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José Augusto Bagatini

DISCRIMINAÇÃO POR DADOS:

uma análise a partir da literatura científica internacional

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Dissertação apresentada como parte dos requisitos para obtenção do título de Mestre em Ciência da Informação, junto ao programa de Pós-Graduação em Ciência da Informação, Área de Concentração – Produção e Organização da Informação, da Faculdade de Filosofia e Ciências da Universidade Estadual Paulista, Campus de Marília.

Orientador: Prof. Dr. José Augusto Chaves Guimarães

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Dedico este trabalho

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RESUMO

Os dados pessoais assumem papel fundamental na dinâmica socioeconômica contemporânea, tendo como um dos principais aspectos discutidos na atualidade o seu potencial de subsidiar situações discriminatórias. Desse modo, a presente dissertação tem por objetivos: a) caracterizar o universo de produção científica na referida temática a partir dos autores, instituições e países; e b) tecer um panorama da configuração temática dessa literatura de modo a identificar tendências de pesquisa. Para tanto, a pesquisa utiliza como universo bibliográfico as bases de dados Scopus e Web of Science sem um recorte temporal definido, sobre os temas "*data discrimination*", "*algorithmic bias",* "*algorithmic discrimination*" e "*fair algorithms*". Os resultados obtidos possibilitaram, a partir da experiência investigativa, inferir que o domínio de conhecimento analisado incorpora predominantemente dados pessoais, seja sua dimensão comportamental seja no âmbito dos denominados dados sensíveis. Os referidos dados, por sua vez, estão suscetíveis à ação de algoritmos de distintas ordens, sejam eles de relevância, filtragem, preditivos, de ranqueamento social, de recomendação de conteúdos e de classificação aleatória. Tais algoritmos, por sua vez, podem trazer embutidos, em sua programação, vieses discriminatórios relativos a gênero, orientação sexual, raça, nacionalidade, religião, idade, classe social, perfil socioeconômico, aparência física, e posicionamento político.

Palavras-chave: Dados Pessoais. Discriminação por Dados. Discriminação Algorítmica. Análise de Domínio. Organização do Conhecimento.

ABSTRACT

Personal data assume a fundamental role in contemporary socioeconomic dynamics, having as one of the main aspects, its potential to subsidize discriminatory situations. Thus, this MSc thesis aims to: a) characterize the universe of scientific publications in the referred theme in terms of authors, institutions, and countries; and b) to furnish an overview of the thematic configuration of this literature in order to identify its research trends. The research corpus derives from a search without a defined time frame at Scopus and Web of Science databases, under the terms “data discrimination”, “algorithmic bias”, “algorithmic discrimination” and “fair algorithms”. The results obtained made it possible to infer that the knowledge domain analysed predominantly incorporates personal data, whether in its behavioural dimension or the scope of the so-called sensitive data. These data are susceptible to the action of algorithms of different orders, be they relevance, filtering, predictive, social ranking, content recommendation and random classification. Such algorithms can have discriminatory biases in their programming related to gender, sexual orientation, race, nationality, religion, age, social class, socioeconomic profile, physical appearance, and political positioning.

Keywords: Personal Data. Data Discrimination. Algorithm Discrimination. Domain Analysis. Knowledge Organization.

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1 INTRODUÇÃO

Ao longo dos anos de 2018 e 2019 foi desenvolvida a pesquisa de iniciação científica intitulada **A vulnerabilidade dos dados pessoais: uma análise a partir de suas formas de divulgação indevida**, financiada pela Fundação de Amparo à Pesquisa do Estado de São Paulo – FAPESP, a qual teve por objetivos identificar, definir e qualificar o que seja dados pessoais; categorizar os usos que são feitos desses dados a partir de situações de divulgação indevida apontar/sugerir formas de prevenção do cidadão contra o uso indevido de seus dados pessoais. Tal pesquisa, teve como premissa, analisar os danos ao direito à privacidade, levando em conta a vulnerabilidade dos dados pessoais, os quais são constantemente alvos de ações criminosas, e partir de divulgações indevidas, podem causar danos das mais diversas ordens. A partir dos resultados obtidos no desenvolvimento da referida pesquisa, houve um aprofundamento na temática dos dados pessoais, levando assim, a indagações acerca de como os dados pessoais podem subsidiar processos que culminam em uma situação de discriminação, racial, de gênero, socioeconômica, religiosa etc.

Desse modo, para que se possa delimitar conceitualmente o que sejam dados pessoais, necessário se torna recorrer a fontes normativas, dado seu processo de elaboração e sua ampla aplicabilidade[1].

A legislação da União Europeia (GDPR), ao tratar de dados pessoais, os define como sendo:

> [...] informação relativa a uma pessoa singular identificada ou identificável. [...] É considerada identificável uma pessoa singular que possa ser identificada, direta ou indiretamente, em especial por referência a um identificador, como por exemplo um nome, um número de identificação, dados de localização [...] ou a um ou mais elementos específicos da identidade física, fisiológica, genética, mental, económica, cultural ou social dessa pessoa singular (CANADA, 2000; WORLD ECONOMIC FORUM, 2011; EUROPEAN PARLIAMENT; COUNCIL OF THE EUROPEAN UNION, 2016; BRASIL, 2018).

[1] Para tanto, utiliza-se seguinte conjunto de fontes: Regulamento Geral sobre a Proteção de Dados da União Europeia 2016/679 (GDPR); Personal Information Protection and Electronic Documents Act (PIPEDA); Lei nº 13.709, de 14 de agosto de 2018; e relatório Personal Data: the emergence of a new asset class, produzido a partir do World Economic Forum.

A lei canadense (PIPEDA), define dados pessoais como “qualquer informação factual ou subjetiva, registrada ou não, sobre um indivíduo identificável (CANADA, 2000, **tradução nossa)**. Já o relatório produzido pelo World Economic Forum, define como dados pessoais os:

> dados (e metadados) criados por e sobre uma pessoa, compreendendo: dados voluntários: criados e explicitamente compartilhados por indivíduos, exemplo os perfis de redes sociais; dados observados: capturados por gravação de ações de um indivíduo, exemplo os dados de localização ao usar celulares; e dados inferidos: dados sobre um indivíduo baseado em análise de terceiros, exemplo o score financeiro” (WORLD ECONOMIC FORUM, 2011, **tradução nossa).**

Por fim, a Lei nº 13.709, de 14 de agosto de 2018, que dispõe sobre a proteção de dados pessoais no Brasil, define dados pessoais como “informação relacionada a pessoa natural identificada ou identificável” (BRASIL, 2018). O documento ainda define o conceito de dado pessoal sensível como sendo aqueles que tratam “sobre origem racial ou étnica, convicção religiosa, opinião política, filiação a sindicato ou a organização de caráter religioso, filosófico ou político, saúde, vida sexual, genética ou biometria, quando vinculado a pessoa natural” (BRASIL, 2018).

A partir das definições apresentadas, pode-se concluir que os dados pessoais se referem a um conjunto de informações, dados e metadados produzidos a partir do comportamento em ambiente tanto *online* quanto *off-line*, cuja natureza pessoal decorre do fato de serem criados por e sobre uma pessoa singular, natural, identificada ou identificável, de maneira voluntária, observada ou inferida. Os referidos dados revelam-se *sensíveis*, quando relativos a aspectos como convicção religiosa, opinião política, vida sexual, biometria, genética, saúde, origem racial ou étnica e filiação a organização de cunho religioso, político ou filosófico (CANADA, 2000; WORLD ECONOMIC FORUM, 2011; EUROPEAN PARLIAMENT; COUNCIL OF THE EUROPEAN UNION, 2016; BRASIL, 2018).

Os dados pessoais, e ainda mais especificamente os que se enquadram como sensíveis, podem servir como subsídio para processos que objetivam a segregação de um determinado grupo social. Como observado pelo historiador Edwin Black (2001) em sua obra “*IBM and the Holocaust*”, que descreve como dados pessoais, coletados a partir de um censo populacional, serviu como insumo para o holocausto, possibilitando que a Alemanha nazista pudesse identificar, catalogar e

perseguir judeus, ciganos, negros e gays do país. Mais recentemente, a preocupação com a discriminação por dados pode ser verificada em diversos âmbitos, tais como no documento *Big data, algorithms and discrimination*, publicado pela Agência de Direitos Fundamentais da União Europeia (EUROPEAN UNION AGENCY FOR FUNDAMENTAL RIGHTS, 2018), na Proposta de Regulamento do Parlamento Europeu e do Conselho que Estabelece Regras Harmonizadas em Matéria de Inteligência Artificial (EUROPEAN COMMISSION, 2021) e Projeto de Lei nº 21 de 2020 que Estabelece fundamentos, princípios e diretrizes para o desenvolvimento e a aplicação da inteligência artificial no Brasil (BRASIL, 2020).

Portanto, a presente proposta tem por **justificativa** não apenas a atualidade do tema mas, e principalmente, sua relevância científica, pelo fato de lidar com a proteção do cidadão. Outrossim, essa proposta decorre de uma trajetória de pesquisa de iniciação científica junto à Fapesp sobre os dados pessoais e sua vulnerabilidade, o que motivou uma questão específica – a da discriminação por dados – ainda pouco explorada na Ciência da Informação. Nesse contexto, a pesquisa insere-se especificamente no contexto da linha 2 – Produção e Organização da Informação do PPGCI – Unesp, mais especialmente no que se refere à dimensão ética, prevista na ementa da linha, e em especial na vertente da produção da informação.

A vista do exposto, objetiva-se delimitar histórica e conceitualmente e categorizar o que seja discriminação por dados, a partir do panorama sobre a temática na literatura internacional, uma vez que tal tema configura-se especialmente relevante aos saberes e fazeres dos profissionais da informação na atualidade. Desse modo, a presente dissertação tem por objetivos, a partir da referida literatura: a) Identificar, definir e qualificar o que seja discriminação por dados; b) Caracterizar o universo de produção científica na referida temática a partir dos autores, instituições e países; e c) Tecer um panorama da configuração temática dessa literatura de modo a identificar tendências de pesquisa.

Para tanto, esta dissertação parte de uma abordagem teórica dos dados pessoais e de seus impactos na dinâmica social contemporânea para, em seguida, e sob uma dimensão metodológica, adentrar na análise de domínio da produção científica internacional sobre a temática da discriminação por dados. Desse modo, os resultados são apresentados e analisados a partir da caracterização desse domínio em termos autorais, institucionais, geográficos, cronológicos e de veículos de

publicação para, em seguida, prover um panorama temático dessa produção científica valendo-se, para tanto, da análise de conteúdo.

2 REFERENCIAL TEÓRICO: OS USOS DOS DADOS PESSOAIS NA SOCIEDADE CONTEMPORÂNEA E SEUS IMPACTOS NAS ÁREAS CORRELATAS COM A CIÊNCIA DA INFORMAÇÃO

A organização do conhecimento acompanha a história da humanidade, como uma necessidade social para fazer frente a todo conhecimento que se produz e que é socializado para que possa gerar novo conhecimento, em um movimento helicoidal contínuo (GUIMARÃES, 2008). Nesse sentido, Pombo (1998) refere-se a um universo que incorpora a dimensão taxonômica, que remonta a Lineu, no século XVII relativamente aos seres vivos e com reflexos até nossos dias, a dimensão classificatória, que surge com Aristóteles, passando por Bacon, Harris, e os enciclopedistas no intuito de categorizar o conhecimento, e a tradição da Biblioteconomia e da Documentação, voltada ao resgate do conteúdo documental, com Dewey, Brown, Otlet, Ranganathan e tantos outros (SAN SEGUNDO, 1996). Em toda essa trajetória percebe-se a preocupação com a construção de instrumentos de representação.

Como toda atividade humana, a organização do conhecimento, que tradicionalmente vem sendo objeto de estudos, entre outras áreas, da Ciência da Informação e das práticas profissionais a esta relacionadas, tais como a Arquivística e a Biblioteconomia, por vezes lida com os vieses sociais que habitam os responsáveis pela construção dos substitutos do conhecimento, isto é, registros catalográficos, números de classificação, descritores de indexação. Olson (2002), em sua obra "*The Power to name: locating the limits of subject representation in libraries*" chama a atenção para essa questão.

À parte de organizar o mundo ao nosso redor e o conhecimento produzido a partir da análise desse universo, também organizamos e classificamos seres humanos. No âmbito das relações pessoais e privadas, classificamos e organizamos pessoas levando em conta diversos aspectos, tais como parentesco, nível de intimidade, grupos sociais. Com cada grupo agimos e reagimos de uma determinada maneira. Ou seja, não só podemos classificar pessoas, como o fazemos todo tempo com objetivos sociais.

Na mesma lógica, em uma escala maior e levando em conta objetivos administrativos, historicamente governos utilizam-se de técnicas de recenseamento para coleta de dados de sua população que permitam uma visão abrangente das suas características socioeconômicas. O recenseamento/censo mais antigo que se tem

registro ocorreu na China em 2238 a.C., solicitado pelo imperador Yao e com o objetivo de levantar dados sobre a população das lavouras cultivadas do país (IBGE, 2012). Desde então, as tecnologias empregadas nos esforços dos censos evoluíram, tendo passado por uma verdadeira revolução nos anos de 1890, quando Herman Hollerith, estatístico estadunidense de origem alemã, licenciou o uso de suas máquinas de captura e análise de dados em papel perfurado para no censo dos Estados unidos da América. O período estimado para realização desse censo era de aproximadamente dez anos, para coletar e processar todos os dados; entretanto, com as máquinas Hollerith, foi finalizado em apenas três.

A praticidade oferecida pelas máquinas de Hollerith garantiu um enorme sucesso à sua empresa, que em 1924 adotou o nome de IBM, e até os dias de hoje figura entre as grandes empresas de tecnologia do mundo. Após a crise de 1929, a IBM passou a investir em sua internacionalização abrindo, assim, novos mercados ao redor do mundo. Um dos países a receber uma filial, foi a Alemanha, então governada por Adolf Hitler. A relação entre a empresa e o governo nazista foi tão frutífera que o então presidente da IBM, Tomas J. Watson, recebeu diretamente das mãos de Hitler, em 1937, a Medalha da Águia Alemã, a segunda maior honraria que um estrangeiro poderia receber do 3º Reich (BLACK, 2001).

Valendo-se da tecnologia IBM, o governo alemão foi capaz de realizar seu censo populacional com grande velocidade e eficiência. Durante o processo de coleta de dados, ao declarar-se como judeu, os dados sobre esse cidadão e seus familiares eram registrados em cartões perfurados de cor diferente dos demais resultando, assim, na construção de uma ampla e rica base de dados sobre a população judia da Alemanha. Com tantos dados disponíveis, os nazistas conseguiram colocar em prática seu plano de expropriação de bens da comunidade judaica. As máquinas IBM também foram utilizadas nos campos de concentração e, por meio delas, eram gerenciados os prisioneiros e suas atividades. Black (2001), destaca que as máquinas IBM e seus dados gerenciavam até mesmo a alimentação dos prisioneiros, fazendo cálculos para manter os cárceres em nível mínimo de energia para sobrevivência e trabalho forçado, ou seja, os mantinham em seu limite físico de modo que não pudessem oferecer qualquer resistência.

A partir do exposto sobre o caso IBM e o holocausto, nota-se que dados pessoais podem ser empregados em um processo de discriminação, e foram responsáveis por subsidiar o maior genocídio que se tem registro na história.

Com o fim da Segunda Guerra Mundial, diversas tecnologias que nasceram em um contexto militar foram adaptadas para um cenário de relativa paz. Os dados pessoais passaram a ser coletados em diversos âmbitos diferentes, não mais apenas durante os censos populacionais despertando, assim, preocupações já na década de 1960, quando Alan Westin, em sua obra "*Privacy and Freedom*" utiliza o termo *data shadow* para definir os dados pessoais que são registrados e mantidos por empresas e governos em situações cotidianas (WESTIN, 1967). Segundo Saulles (2015), esse conjuntos de dados podem ser divididos em estruturados e não estruturados, os primeiros originados a partir de transações em que uma das partes é a instituição que coleta os dados, tal como uma compra em uma loja, enquanto o segundo grupo diz respeito a dados produzidos a partir de outros tipos de interação, como telefonemas, por exemplo.

Soma-se isso ao desenvolvimento e disseminação da computação pessoal, responsável por uma grande mudança em como produzimos e armazenamos nossos artefatos de memória.

Qualquer forma de captura de um evento, emoção ou pensamento pode ser um item de memória externa uma vez que, fixado em um suporte que tem por função facilitar a recuperação e até mesmo construir uma memória compartilhada, em algum momento facilitará recordar algo com maior precisão estendendo, assim, a própria memória humana e garantindo-lhe portabilidade no espaço e permanência no tempo (SMIT; BARRETO, 2002; MAYER-SCHÖNBERGER, 2011)[2]. Esses artefatos, por muito tempo foram, como preconiza Van Dijck (2007), habitantes de nossas "caixas de sapatos", recipientes que abrigam os mais variados formatos de itens (álbuns fotográficos, cartas, diários, gravações de áudio e vídeo, etc.) e sinalizam o passado. Esses itens, por muito tempo analógicos, ganharam, com o avanço da tecnologia, suas contrapartes digitais e, assim, passaram por uma reformulação completa, levando à necessidade de questionar os impactos das novas mídias nos hábitos de armazenamento e recriação dos artefatos de memória (VAN DIJCK, 2007).

Esse contexto torna-se mais complexo quando ocorre a convergência entre as tecnologias responsáveis pela digitalização da memória e a internet, responsável por

[2] Observa-se que o artigo seminal "As we may think", de Vannevar Bush, publicado em 1945 e considerado um dos marcos da história da Ciência da Computação já mencionava a necessidade de artefatos que pudessem atuar como uma memória externa, auxiliar da memória humana que, por natureza, é limitada.

uma segunda onda de modificações na maneira em que artefatos de memória são produzidos, armazenados e disponibilizados.

Foi primeiro nos blogs e, em um segundo momento, nas redes sociais, que a memória encontrou a possibilidade de se conectar com identidades privadas e públicas, permitindo novas experiências e representações de si mesma e dos outros (VAN DIJCK, 2007; KETELAAR, 2014). Em um terceiro momento, há a disseminação dos serviços de armazenamento em nuvem, um espaço digital conectado à internet e disponibilizado por um provedor para que pessoas físicas ou instituições armazenem seus itens digitais. Desse modo, aos poucos abrimos mão de manter nossas "caixas de sapatos" em nossos armários e entregamos sua guarda a empresas que fornecem os serviços de blog, redes sociais e armazenamento em nuvem, iniciando e intensificando, assim, um processo de "autoerosão do anonimato", descrito por Bauman e Lyon (2012) na obra *Liquid Surveillance: A Conversation*, em que os autores preconizam que a adoção dessas tecnologias foi responsável por nos induzir a tornar público aquilo que é privado, assumir como real o fim da invisibilidade e do anonimato e, por vontade própria, colocarmos em risco nosso direito à privacidade.

Esse evento de "autoerosão da privacidade" ganha contornos ainda mais problemáticos quando se leva em conta que, nas últimas décadas, tecnologias como *smartphones*, *wearables* e a Internet das Coisas se tornaram amplamente difundidas ao redor do mundo gerando, assim, uma quantidade de dados pessoais jamais vista, e sobre os mais variados aspectos da vida humana. Logo, como um caramujo, que incansavelmente carrega sua casa consigo, carregamos conosco nossos dispositivos de vigilância pessoal, sempre conectados e fornecendo dados a empresas e governos alimentando, assim, uma economia voltada à *comoditização* dos dados pessoais e fundamentada no enfraquecimento do direito à privacidade (BAUMAN; LYON, 2012).

Esse modelo econômico de expropriação e uso dos dados pessoais é nada mais que uma faceta do capitalismo, que se fundamenta no enfraquecimento do direito à privacidade tornando, assim, a erosão desse direito, um dos principais desafios a serem enfrentados na contemporaneidade, uma vez que os mecanismos de vigilância se tornam mais presentes e os dados pessoais se tornam mais abrangentes e são mantidos indefinidamente em bancos de memória digital que pertencem a companhias e governos (BAUMAN; LYON, 2012; MAYER-SCHÖNBERGER, 2011). Esses bancos de memória não se contentam mais apenas com dados demográficos, como na primeira metade do século XX pois, como destaca

Mayer-Schönberger (2011), empresas e governos atuam hoje como verdadeiros “buracos negros de dados”, absorvendo e armazenando todo e qualquer dado pessoal. Faz-se, assim, necessário um resgate histórico de como tal cenário se desenvolveu e tornou-se padrão na economia global atual.

A privacidade, enquanto “direito de estar só”, parece ser uma necessidade exclusivamente humana; entretanto, pode ser identificada nas mais distintas espécies. Estudos de comportamento animal e organização social sugerem que a necessidade de privacidade humana pode estar enraizada em suas origens animais, e que compartilhamos com outras espécies vários mecanismos básicos para reivindicar privacidade. Desse modo, todos animais precisam da reclusão individual temporária ou da intimidade de pequenas unidades como elementos para sus sobrevivência, o que leva a concluir que a busca pela privacidade surge nos processos biológicos e sociais de toda a vida, mais especificamente na denominada tendência à territorialidade, na qual um organismo reivindica uma área de terra, água ou ar e a defende contra a intrusão de membros de sua própria espécie (WESTIN, 1967).

A noção de privacidade atualmente adotada pela sociedade ocidental, desenvolveu-se, na visão de Westin (1967), a partir de uma tradição de limitar os poderes de vigilância das autoridades sobre as atividades privadas de indivíduos e grupos, o que remonta aos gregos na história da política ocidental. Ainda segundo o autor, a privacidade pode ser definida como:

> a reivindicação de indivíduos, grupos ou instituições para determinar por si próprios quando, como e em que medida as informações sobre eles são comunicadas a terceiros. Vista em termos da relação do indivíduo com a participação social, a privacidade é a retirada voluntária e temporária de uma pessoa da sociedade em geral por meios físicos ou psicológicos, seja em um estado de solidão ou intimidade de pequeno grupo ou, quando entre grupos maiores, em condição de anonimato ou reserva (WESTIN, 1967, p. 26).

Esse desejo por privacidade nunca é absoluto na medida em que cada indivíduo está continuamente engajado em um processo de ajustamento pessoal no qual ele equilibra o desejo de privacidade com o desejo de divulgação e comunicação de si mesmo aos outros, à luz das condições ambientais e das normas sociais estabelecidas pela sociedade em que vive. Nesse âmbito, a privacidade desempenha quatro funções básicas aos indivíduos: **autonomia pessoal**: relacionada ao desenvolvimento e manutenção do senso de individualidade, a partir do desejo de

evitar ser manipulado ou dominado por outros; **liberação emocional**: a necessidade de o indivíduo ter momentos “fora do palco”, quando pode ser “ele mesmo” e não estar sustentando papeis sociais; **autoavaliação**: a privacidade serve para colocar a consciência em jogo, uma vez que o indivíduo necessita de tempo e espaço para realização de “inventário moral”; e **limitação e comunicação protegida**: fornece ao indivíduo a possibilidade de compartilhar confidências e intimidades com aqueles em quem confia e serve para estabelecer limites necessários de distância mental em situações interpessoais, intimais ou públicas (WESTIN, 1967).

Entretanto, as sociedades contemporâneas trazem consigo elementos que vão de encontro à noção de privacidade, densidade e aglomeração de populações, vida organizacional burocrática, humores populares de alienação e insegurança, instrumentos de vigilância. Especialmente no que diz respeito à vigilância, Westin (1967, p.69) preconiza que a esta pode ser classificada em **vigilância física** (a observação por meio de dispositivos ópticos ou acústicos da localização, atos, fala ou escrita privada de uma pessoa sem seu conhecimento ou contra sua vontade); **vigilância psicológica** (o uso de testes orais ou escritos, dispositivos ou substâncias para extrair de um indivíduo informações que ele não dá de boa vontade, ou não sabe que está revelando); e **vigilância de dados** (a coleta, troca e manipulação de informações documentais sobre indivíduos e grupos por máquinas de processamento de dados).

O autor citado reitera que nenhum desses tipos de vigilância é novo, pois agentes de vigilância pagos remontam à Antiguidade, e que tortura, drogas e testes de mentira ou personalidade também são formas antigas de extrair informação ou implantar sugestões e, em relação aos dados, diversas sociedades no passado já exigiam registro de residência e transações e usavam dossiês e licenças como mecanismo de controle social administrativo. Assim, o que há de novo é o casamento das tecnologias de informação e comunicação (TIC) com os métodos clássicos de vigilância.

As TIC são o elemento central desse novo paradigma principalmente por sua penetrabilidade em todas as esferas de atividade humana. Caracterizando uma ferramenta essencial em um período de reestruturação global do capitalismo, centrado não no conhecimento e na informação propriamente ditos mas na aplicação desses conhecimentos e dessas informações para a geração de outros conhecimentos e de

dispositivos de processamento/comunicação da informação, em um ciclo de realimentação cumulativo entre a inovação e seu uso (CASTELLS, 2009, p. 51).

Mattelart (2002, p. 12), em sua obra *"Historia de la sociedad de la información"*, chama atenção para o fato de que os desenvolvimentos de máquinas inteligentes durante a Segunda Guerra mundial gerou a noção de uma sociedade da informação, termo que começa a figurar nas referências acadêmicas, políticas e econômicas do final dos anos de 1960, assemelhando-se, assim, à leitura realizada por Castells (2009) em *"The Rise of the Network Society"* embora, este prefira afirmar que a sociedade que emerge é uma "sociedade informacional" e não "da informação", pois:

> A economia informacional é um sistema socioeconômico distinto em relação à economia industrial, mas não devido a diferenças nas fontes de crescimento de produtividade. Em ambos os casos, conhecimentos e processamento da informação são elementos decisivos para o crescimento econômico, como pode ser ilustrado pela história da indústria química com base científica ou pela revolução administrativa que criou o Fordismo. _O que é característico é a consequente realização do potencial de produtividade contido na economia industrial madura em razão da mudança para um paradigma tecnológico baseado em tecnologias da informação_. O novo paradigma tecnológico mudou o escopo e a dinâmica da economia industrial, criando uma economia global e promovendo uma nova onda de concorrência entre os próprios agentes econômicos já existentes e também entre eles e uma legião de recém-chegados. Essa nova concorrência, praticada elas empresas, mas condicionada pelo Estado, conduziu a transformações tecnológicas substanciais de processos e produtos que tornaram algumas empresas, setores e áreas mais produtivos. [...] A generalização da produção e da administração baseadas em conhecimentos para toda a esfera de processos econômicos em escala global requer transformações sociais, culturais e institucionais básicas que, se considerarmos o registro histórico de outras revoluções tecnológicas, levarão um certo tempo. É por isso que a economia é informacional e não apenas baseada na informação, pois os atributos culturais e institucionais de todo o sistema social devem ser incluídos na implementação e difusão do novo paradigma tecnológico. A economia industrial também não se baseou apenas no uso de novas fontes de energia de produção, mas no surgimento de uma cultura industrial, caracterizada por uma nova divisão social e técnica do trabalho (CASTELLS, 2009, p. 140).

Um dos principais aspectos desse paradigma preconizado por ambos os autores é o aumento exponencial da capacidade humana para, por meio das TIC, processar dados, o que resultou em benefícios para diversas áreas, possibilitando, assim, a tomada de decisões baseadas em fatos, com índices maiores de lógica e previsibilidade. Entretanto, para que essas tomadas de decisões ocorressem, foi

necessário aumentar significativamente a coleta de dados e a manutenção de registros em todos os campos da sociedade (WESTIN, 1967, p. 121).

Em tom profético, Allan Westin, em sua obra *"Privacy and Power"* chamava a atenção para o fato de que se o aumento da coleta e do processamento de informações não fosse cuidadosamente controlado, poderia levar a um aumento exponencial do poder de vigilância do governo sobre as vidas individuais e as atividades organizacionais (WESTIN, 1967, p. 120). A rigor, tal fato já havia ocorrido no holocausto, mas ainda se encontrava escondido da sociedade civil, vindo a ser exposto com a obra de Black (2001).

A questão dos dados pessoais ganha tanto destaque que, em 1980, o Conselho da Europa aprovou uma Convenção para a proteção das pessoas em relação ao tratamento automatizado de dados pessoais. Nesse mesmo ano, por sua vez, a OCDE (Organização para a Cooperação e Desenvolvimento Económico) adotou, na mesma direção, uma recomendação sobre o fluxo internacional de dados pessoais. Em outubro de 1998, a Directiva da União Europeia relativa à protecção de dados pessoais entra em vigor, sendo considerada pelas autoridades e pelos lobbies de mercado globais norte-americanos como um obstáculo para a criação de bases de dados e a elaboração de perfis precisos e rastreáveis, ferramentas indispensáveis para o comércio eletrônico já em um contexto embrionário da internet (MATTELART, 2002, p. 120).

No ano de 2001, mais precisamente no dia 11 de setembro desse ano, um incidente definiu os rumos da vigilância ao redor do mundo. Após os atentados ao Word Trade Center, o então presidente George W. Bush assina um decreto que permite a órgãos de segurança e inteligência do governo dos Estados Unidos da América interceptarem ligações telefônicas, e-mails e outras comunicações sem necessidade de qualquer autorização, sejam estrangeiras ou estadunidenses. Medidas parecidas foram tomadas por diversos outros países ao redor do mundo, em nome da segurança e da luta contra o terrorismo (MATTELART, 2002).

Tais políticas de vigilância massiva permearam todo o desenvolvimento da internet como hoje conhecemos e contribuíram para definir diretrizes de como a rede mundial de computadores podem fornecer subsídios às ações de espionagem de governos ao redor do mundo. Em 2013, Edward Snowden forneceu ao jornal *The Guardian* documentos que detalhavam o funcionamento do programa PRISM de vigilância da *National Security Agency - NSA*, o que possibilitou, desde 2007, a que

agência tivesse acesso a dados tais como histórico de pesquisa, e-mails completos, arquivos, chats etc. Armazenados em servidores da Google, Facebook, Apple entre outras empresas de tecnologia (GREENWALD; MACASKILL, 2013).

A vigilância que se instaura após o 11 de setembro não possui só os estados como atores pois empresas passam também a dela valerem-se como um meio para obtenção de lucro. Um dos, e na visão de Véliz (2021), o principal protagonista no desenvolvimento do capitalismo de vigilância é a empresa Google (hoje parte do conglomerado Alphabet). A autora destaca que antes da empresa de Mountain View, alguns dados pessoais eram comprados e vendidos esporadicamente; entretanto, a partir de 2003, a companhia passou a utilizar dados pessoais não mais para aprimorar seu principal produto, o buscador de internet homônimo, mas para oferecer publicidade direcionada. Os clientes do Google deixaram, assim, de ser os usuários e passaram a ser os anunciantes, transformando o modelo de exploração de dados pessoais em um dos modelos de negócios mais lucrativos de todos os tempos e inaugurando a economia da vigilância (VÉLIZ, 2021).

Em uma rápida análise do histórico de crescimento do Google e de suas declarações, nota-se que seu modelo de negócio voltado à expropriação de dados pessoais realmente mostra-se lucrativo. Fundada em 1998, oferece serviços e produtos que atendem a quase todas as necessidades de uma pessoa que está inserida em uma sociedade conectada à internet, e até mesmo de empresas e governos. Seu sucesso teve início com o buscador de páginas na internet homônimo, que até hoje é líder absoluto no mercado. Fator preponderante para seu sucesso é o fato de o buscador Google ter uma interface simples, porém com um robusto sistema de funcionamento, atualmente indexando quase toda a *web* e levando em conta as preferências pessoais de cada usuário.

Em 2012, o Google anunciou que, por meio de um robô automatizado, seria capaz de identificar mais de 30 trilhões de endereços únicos da web (URLs) e que o mesmo robô rastreava e indexava mais de 20 bilhões de sites por dia (SULLIVAN, 2012b apud SAULLES, 2015). Além de indexar a web, a empresa também indexa pessoas e anteriormente, em 2007, admitiu que até então havia armazenado todas as consultas de pesquisas já inseridas por seus usuários e todos os resultados em que ele clicou posteriormente (MAYER-SCHÖNBERGER, 2011).

Também em 2012, segundo a própria empresa, seu buscador recebia aproximadamente 38.000 pesquisas por segundo, equivalente a 3.3 bilhões de

pesquisas por dia, mais de 1,2 trilhões de pesquisas por ano (Sullivan, 2012 apud Saulles 2015). Tai dados, combinados com outros como login, cookies, endereços IP etc., tornam o Google capaz de identificar com precisão qualquer pessoa que já tenha utilizado algum dos seus serviços, além de a empresa deter uma memória que detalha minunciosamente toda uma vida humana, coisas que há muito o próprio usuário já havia se esquecido ou descartado. Em suma, o Google sabe mais sobre nós do que podemos lembrar (MAYER-SCHÖNBERGER, 2011). Trata-se, pois, de um conjunto de dados extremamente valioso, de tal modo que, em 2020 a Alphabet, empresa mãe do Google, atingiu a marca de US$ 1 trilhão em valor de mercado, ficando atrás somente da Apple e da Microsoft e à frente da Amazon e da Facebook, as cinco empresas compõem um grupo chamado 5 Big Techs e que, juntas, somavam mais de US$5 trilhões em valor de mercado.

Oferecer serviços gratuitos que têm como moeda de troca a apropriação de dados pessoais dos usuários não é uma prática exclusiva do Google, constituindo um padrão de atuação do mercado da privacidade. Na superfície desse mercado, pode-se dizer que habitam as companhias mais conhecidas e que sabidamente coletam dados pessoais como moeda de troca por seus serviços; entretanto, destaca-se um outro grupo de empresas que raramente é conhecido pela população em geral: as corretoras de dados, que atuam quase que exclusivamente na captura, processamento e comercialização de dados pessoais, ou ainda os serviços de *insight* que utilizam esses dados. Seu *modus operandi* despertou preocupação no órgão estadunidense Federal Trade Comission – FTC, que em 2012, publicou o relatório *Data Brokers: A Call for Transparency and Accountability*, no documento são analisadas as atividades das nove maiores corretoras de dados que atuam no país, as quais são:

1. **Acxiom**: enquanto a maior corretora de dados dos Estados Unidos da América, acumulava em seus bancos de dados em média 1.500 linhas de detalhes sobre a vida pessoal de cada estadunidense, e a cobertura desse base era de 96% da população dos EUA (PARISER, 2012). Vale ressaltar que em 2014 a Acxiom foi alvo do documento descreve a empresa como uma companhia que fornece dados e análises do consumidor para campanhas de marketing e detecção de fraudes. Seus bancos de dados contêm informações sobre 700 milhões de consumidores em todo o mundo com mais de 3.000 tipos de dados para quase todos os consumidores dos EUA (FEDERAL TRADE COMMISSION, 2014). O relatório ainda lista mais outras oito

corretoras que atuam no mercado norte-americano, em ordem de grandeza, sendo a Acxiom a maior, a lista contínua da seguinte forma:

2. **Corelogic**: fornece dados e serviços analíticos para empresas e governo, principalmente informações sobre propriedade, bem como informações financeiras de consumidores. Seus bancos de dados incluem mais de 795 milhões de históricos de transações de propriedades, mais de 93 milhões de hipotecas e cobre mais de noventa e nove por cento das residências dos EUA, mais de 147 milhões de registros;

3. **Datalogix**: fornece às empresas de marketing dados sobre quase todas as famílias dos EUA e mais de um trilhão de dólares em transações de consumidores. Em setembro de 2012, o Facebook anunciou uma parceria com a Datalogix para média a frequência com que um bilhão de usuários do Facebook veem um produto anunciado na rede social e, em seguida, conclui a compra em uma loja de varejo convencional;

4. **eBureau**: fornece pontuação preditiva e serviços analíticos para profissionais de marketing e serviços financeiros para empresas, varejos online e outros. A empresa oferece principalmente produtos que preveem se alguém provavelmente se tornará um cliente lucrativo ou se uma transação provavelmente acarretará fraude. A eBureau fornece aos seus clientes informações extraídas de bilhões de registros de consumidores, e soma à suas bases de dados três bilhões de novos registros a cada mês;

5. **ID Analytics**: fornece serviços de análise projetados principalmente para verificar identidades pessoais ou para determinar se uma transação é provavelmente fraudulenta. As bases da empresa incluem centenas de bilhões de pontos de dados agregados, 1,1 bilhão de dados sobre identidade exclusivos e cobre 1,4 bilhão de transações de consumidores;

6. **Intelius**: fornece às empresas e consumidores verificação de antecedentes e registro públicos. Seus bancos de dados contêm mais de vinte bilhões de registros;

7. **PeekYou**: patenteou uma tecnologia que analisa o conteúdo de mais de sessenta sites de mídia social, fontes de notícias, páginas iniciais e plataformas de blog para fornecer aos clientes perfis detalhados de consumidores;

8. **Rapleaf**: é um agregador de dados que tem pelo menos um ponto de dados associado a mais de oitenta por cento de todos os endereços de e-mail de

consumidores nos EUA. A empresa complementa suas listas de e-mail com idade do titular, sexo, estado civil e trinta outras informações pessoais; e

9. **Recorded Future**: captura e registra os históricos sobre consumidores e empresas em toda a internet e usa essas informações para prever o comportamento futuro desses consumidores e empresas. Em maio de 2014, a Recorded Future teve acesso a informações de mais de 502 mil sites diferentes da internet (FEDERAL TRADE COMMISSION, 2014).

Essas empresas, valem-se do que Acquisti (2013) preconiza como *trade-offs* do mercado da privacidade e alimentam suas bases de dados pessoais a partir de diversas fontes, que capturam dados em situações como: a compra de um bem comum (em que o consumidor pode deixar dados durante a transação financeira); a troca de dados entre os próprios agentes do mercado da privacidade; e o mercado da proteção das informações pessoais (em que consumidores buscam produtos e serviços para gerenciar e proteger seus dados pessoais).

Assim, itens de memória produzidos e armazenados em ambientes digitais e conectados à internet e relativos a dados pessoais das mais variadas naturezas compõem dossiês muito completos sobre nossas personalidades. Esses perfis se tornam cada vez mais completos e são utilizados nas mais diversas áreas, como ocorre com profissionais do marketing que se interessam pelo comportamento humano para compreender desejos e tendências de compra, para posterior utilização de perfis para otimizar a distribuição de publicidade digital garantindo, assim, mais assertividade. O uso aparentemente inofensivo dos dados pessoais para fins de marketing vem causando questionamentos sobre seu potencial danoso, principalmente a partir do envolvimento das empresas Facebook e Cambridge Analityca nas eleições de 2016 nos Estados Unidos da América, quando a propaganda política de Donald Trump utilizou psicográficos sociais construídos a partir de dados pessoais coletados no Facebook sem a devida autorização dos usuários, com o intuito de manipulação de votos.

Em busca de equalizar a relação de poder entre o proprietário dos dados pessoais e os interessados em explorar esses dados, leis que buscam regular o mercado da privacidade passaram a ser desenvolvidas e adotadas ao redor do mundo. A Conferência das Nações Unidas sobre Comércio e Desenvolvimento (Unctad), acompanha o desenvolvimento dessas leis, segundo a sua página Data *Protection and Privacy Legislation Worldwide*, até o ano de 2020, dos 194 países

reconhecidos, 128 já adotaram ou estão em processo de adoção de legislações que contemplam o direito à privacidade e a proteção de dados (UNCTAD, 2020). Na América Latina, o primeiro país a adotar uma lei dessa natureza foi o Chile em 1999, seguido pela Argentina em 2000, e mais recentemente outros países vêm seguindo a tendência, ao exemplo do Uruguai (2008), México (2010), Peru (2011), Colômbia (2012), Brasil (2018), Barbados (2019) e Panamá (2019) (Rodriguez; Alimonti, 2020).

Especificamente no Brasil, a proteção de dados pessoais é discutida desde 2010, a partir do anteprojeto da Lei de Proteção de Dados Pessoais (ALPDP), aprovado como lei oito anos após. Com esse dispositivo legal, a proteção dos dados pessoais no Brasil, antes apenas tangenciada pela Lei de Acesso à Informação, passou a ser objeto de norma específica – a lei n. 13.709, de 14 de agosto de 2018 – , que dispõe sobre a proteção de dados pessoais e altera a lei n. 12.965, de 23 de abril de 2014 (Marco Civil da Internet). Em seu texto, a Lei Geral de Proteção de Dados (LGPD) define como fundamentos: I) o respeito à privacidade; II) a autodeterminação informativa; III) a liberdade de expressão, de informação, de comunicação e de opinião; IV) a inviolabilidade da intimidade, da honra e da imagem; V) o desenvolvimento econômico e tecnológico e a inovação; VI) a livre iniciativa, a livre concorrência e a defesa do consumidor; e VII) os direitos humanos, o livre desenvolvimento da personalidade, a dignidade e o exercício da cidadania pelas pessoas naturais (BRASIL, 2018).

A referida lei aplica-se a qualquer operação de tratamento realizada por pessoa natural ou jurídica de direito público ou privado, independentemente do meio, do país de sua sede ou do país onde estejam localizados os dados, desde que: a) a operação de tratamento seja realizada no território nacional; b) a atividade de tratamento tenha por objetivo a oferta ou o fornecimento de bens, ou serviços ou o tratamento de dados de indivíduos localizados no território nacional; ou c) os dados pessoais objeto de tratamento tenham sido coletados no território nacional (a lei considera coletados no território nacional os dados pessoais cujo titular nele se encontre no momento da coleta) (BRASIL, 2018).

Acerca das exceções do que a lei considera tratamento de dados pessoais, configura-se: realizado por pessoa natural para fins exclusivamente particulares e não econômicos; realizado para fins exclusivamente jornalísticos, artísticos, acadêmicos, de segurança pública, defesa nacional, segurança do Estado, atividades de investigação e repressão de infrações penais, ou provenientes de fora do território

nacional e que não sejam objeto de comunicação, uso compartilhado de dados com agentes de tratamentos brasileiros ou objeto de transferência internacional de dados com outro país que não o de proveniência, desde que o país de proveniência proporcione grau de proteção de dados pessoais adequados ao dos previstos na LGPD (BRASIL, 2018).

Segundo a LGPD, os papéis e responsabilidades dos envolvidos em um processo de tratamento de dados pessoais são: *titular* (pessoa natural a quem se referem os dados pessoais que são objeto de tratamento); *controlador* (pessoa natural ou jurídica, de direito público ou privado, a quem competem as decisões referentes ao tratamento de dados pessoais); *operador* (pessoa natural ou jurídica, de direito público privado, que realiza o tratamento de dados pessoais em nome do controlador); *encarregado* (pessoa indicada pelo controlador para atuar como canal de comunicação entre o controlador, os titulares dos dados e a Autoridade Nacional de Proteção de Dados - ANPD).

Mesmo com a implantação de leis como a LGPD ao redor do mundo, a UNCTAD reforça que, à medida que mais atividades sociais e econômicas acontecem on-line, a importância da privacidade e da proteção de dados é cada vez mais reconhecida; entretanto, continua a se fazer preocupante a coleta, uso e compartilhamento de informações pessoais a terceiros sem aviso prévio ou consentimento dos consumidores (UNCTAD, 2020).

A pandemia de COVID-19 foi responsável por acelerar ainda mais a digitalização de economias e sociedades evidenciando, assim, questões de conectividade e serviços digitais (WORLD ECONOMIC FORUM, 2021). Entretanto, tal situação chamou a atenção também para o fato de que ainda existe uma grande assimetria de acesso à internet e a serviços digitais entre nações. Em resposta a isso, em 2021, durante o Fórum Econômico Mundial foi lançada The EDISON Alliance, que tem como visão a possibilidade de qualquer pessoa participar da economia digital de maneira acessível. Para tanto, busca realizar um movimento global e intersetorial para o desenvolvimento de ações que visem a resultados sociais e econômicos por meio da conectividade e do aperfeiçoamento de investimentos digitais, tendo por abordagem construir uma “rede de redes” para identificar e escalar relacionamentos intersetoriais para impulsionar mudanças e gerar impacto (WORLD ECONOMIC FORUM, 2021).

Em suma, a Aliança EDISON tem por objetivo, a partir da participação de diversos setores da economia, acelerar a expansão da infraestrutura digital e a implantação da banda larga visando a recuperação da economia e redução das desigualdades (BUCCO, 2021; WORLD ECONOMIC FORUM, 2021). O discurso assumido pela The EDISON Alliance também fornece subsídio para as atividades de expansão de empresas globais do ramo da internet.

Cumpre destacar que, anteriormente à Aliança Edison, diversas companhias já vinham disputando o mercado de acesso à internet travando, assim, uma corrida para definir quem controlará o acesso de bilhões de novos participantes da economia digital.

Por meio do Projeto Aquila, lançado em 2014, o Facebook financiou o desenvolvimento de drones que levariam internet às áreas remotas do planeta, entretanto, por motivos técnicos foi encerrado em 2018 mas, no mesmo ano, a empresa anunciou que lançaria satélites com o mesmo objetivo, em projeto denominado Athena, que segue em execução (JUNQUEIRA, 2018; OLHAR DIGITAL, 2018). Em 2020, anunciou também o lançamento do aplicativo para *smartphones* *Discover*, que fornece conexão gratuita em parceria com empresas de telefonias locais, sendo o Peru o primeiro mercado a receber o projeto (MOTA, 2020). Todos esses projetos fazem parte da iniciativa *Free Basics*, promovida pelo Facebook, que busca oferecer acesso a serviços básicos online sem custo atuando, assim, como um trampolim para uma internet mais inclusiva em que serviços como de notícias, saúde, empregos, comunicação, educação e sobre o governo local são de acesso gratuito (FACEBOOK, 2018). Em concorrência com o Facebook, têm-se a proposta da Starlink que, por meio de satélites, busca alcançar a "conectividade global completa", contando com 1.369 satélites (CASSITA, 2021).[3]

Os esforços para o crescimento global da internet são objeto do relatório *Digital 2019: global digital overview*, produzido pela We Are Social e Hootsuite. Segundo o documento, o número de usuários de internet no mundo saltou de quase dois milhões e meio em 2014 para cerca de quatro milhões e quatrocentos mil em 2019, o que representa uma penetração de 57%, ou seja, mais da metade da população global se conecta à rede mundial de computadores (HOOTSUITE; WE ARE SOCIAL, 2019).

[3] A referida empresa esperava contar com um total de 1700 satélites para 2021, o que ainda não se efetivou.

Especificamente no Brasil, em janeiro de 2020, cerca de 150 milhões de pessoas utilizaram diariamente a internet. Entre os anos de 2018 e 2019, o Brasil foi o décimo país em que a internet mais cresceu, houve um aumento de 7,2%, o que representa quase dez milhões de pessoas; já entre os anos de 2019 e 2020, o número de usuários cresceu 6%, o que representa oito milhões e meio de pessoas que adquiriram o direito de acesso à rede mundial de computadores. Atualmente, a penetração da internet em solo brasileiro é de 71% da população total do país (KEMP, 2020).

No que tange à internet móvel, em 2014 em termos mundiais, representava 26% do tempo total gasto na internet, passando a 48% em 2019, em uma média diária de seis horas e 42 minutos. Nesse contexto, o Brasil registra uma média diária de nove horas e 29 minutos, ocupando, assim, o segundo lugar no *ranking* mundial, ultrapassado apenas pelas Filipinas (HOOTSUITE; WE ARE SOCIAL, 2019).

Destaca-se que grande do tempo conectado à internet refere-se ao uso de redes sociais on-line, havendo assim uma média global diária de duas horas e 16 minutos, enquanto no Brasil a média é de três horas e 34 minutos, ficando somente atrás das Filipinas (HOOTSUITE; WE ARE SOCIAL, 2019). Nesse contexto, especial destaque merece o uso das redes sociais, como Instagram, Facebook, Twitter, acessíveis a 45% da população global. No Brasil, esse índice sobe para 65% da população, com especial destaque para o fato de que, de 2018 para 2019, essas redes angariaram mais de dez milhões de novos usuários (HOOTSUITE; WE ARE SOCIAL, 2019).

Isso posto, fica claro que a expansão da internet continuará sendo acelerada e o objetivo final é a integração total da humanidade na economia digital. Entretanto, esse cenário de hiperconectividade, faz-se notar no emergir de problemáticas relacionadas com os mais diversos campos da Ciência da Informação, tais como as intersecções entre memória e direito ao esquecimento, a proteção do cidadão, e a organização do conhecimento e segregação de minorias sociais.

Numerosos são os estudos acerca da memória, em cujo panorama se destaca, com proeminência, Maurice Halbwachs, filósofo e sociólogo francês que formulou o conceito de memória coletiva, a partir de quem diversos outros autores buscam compreender a memória, como é o caso de Tedesco (2014, p.59) para quem a memória:

> necessita ser entendida como manifestação de um conjunto dinâmico, espaço não só de relação, mas de reinterpretação/renovação de sentido. Sua função está em preservar os elementos do passado que garantem aos sujeitos sua própria continuidade e afirmação identitária, do que propriamente fornecer uma imagem fiel do passado.

Nesse contexto, Le Goff (1990), valendo-se das concepções de Leroi-Gourhan (1981) ressalta três tipos de memória: memória específica (relativa aos comportamentos das espécies animais) memória étnica (que garante a reprodução dos comportamentos nas sociedades humanas) e memória artificial (atualmente de natureza eletrônica, que garante a reprodução de atos mecânicos encadeados.

No caso da memória humana, tem-se um conjunto de funções psíquicas, graças às quais o homem pode atualizar impressões ou informações passadas - ou que ele representa como passadas – o que evidencia a existência de uma linguagem previa para o armazenamento de informações na nossa memória, aspecto que se estende por meio da linguagem falada e da linguagem escrita, saindo dos limites físicos do nosso corpo para no mais das vezes ocupar espaço social em instituições de memória, como bibliotecas, arquivos e museus (LE GOFF, 1990).

É necessário também, destacar que no conjunto de funções psíquicas, estão presentes os processos de seleção, reconfiguração e reordenação de memórias. Além disso, é comum que pessoas manipulem conscientemente seus passados, destruindo fotos, queimando diários etc. Esquecer não é apenas um comportamento individual, fazemos também como sociedade, e nesse caso, o esquecimento social fornece a oportunidade à indivíduos que falharam em algum aspecto, uma segunda chance, possibilitando assim, que através do apagamento de memórias externas, a sociedade possa aceitar que os seres humanos evoluem com o tempo e que temos a capacidade de aprender com experiências passadas e ajustar nossos comportamentos (VAN DIJCK, 2007; MAYER-SCHONBERGER, 2011).

Entretanto, os agentes que compõem o mercado da privacidade vêm, com o tempo, estabelecendo como padrão mercadológico, memórias em que o conceito de temporalidade é distorcido segundo seus interesses, uma vez que, a manutenção de dados pessoais garante a contínua produção de inferências e consequentemente a predição de ações e comportamentos futuros. Mayer-Schonberger (2011) chama atenção para o fato de que: já em 2011 nos Estados Unidos da América, a comunidade médica estava sob pressão econômica e regulatória para digitalizar e enviar décadas de informações pessoais contidas em prontuários para serviços de memória digital.

No mesmo país, agências de aplicação da lei armazenam dados biométricos sobre dezenas de milhões de indivíduos, mesmo que nunca tenham sido acusados de um crime, e a maioria desses registros sensíveis, mas pesquisáveis, nunca são excluídos (MAYER-SCHÖNBERGER, 2011).

Esses bancos de memória geralmente são inacessíveis aos titulares dos dados, e como já alertado tanto por Mayer-Schonberger (2011) quanto por Saulles (2015), em algum momento podem ser usados contra a população. Dificilmente esses dados serão apagados no futuro, ficando assim a indagação sobre se é ético alguma instituição guardar em sua memória digital algo que comprometa o presente e o futuro de uma pessoa afetando diretamente o direito de ser esquecido (SAULLES, 2015).

Desse modo, torna-se necessária uma substituição de abordagem em relação à salvaguarda dos dados pessoais, ou seja, adotar um modelo para o ciclo de vida dos dados pessoais que tenha suas etapas fundamentadas nos direitos à privacidade e de ser esquecido, tal como o proposto por (BAGATINI; GUIMARÃES; SANT'ANA, 2021): a) *coleta*: fase em que os dados pessoais são capturados, em ambiente digital ou físico, de maneira manual ou automatizada. A atividade de coleta deve ser fundamentada por princípios éticos como motivo legítimo, consentimento do titular (ou responsável legal), metodologia de coleta e tipologia dos dados especificadas e publicizadas ao titular no momento da adesão do serviço ou produto; b) *armazenamento*: a unidade de informação deve salvaguardar os dados pessoais por um período limitado, ou seja, até a concretização dos objetivos manifestos no início da coleta.

Os dados pessoais devem ser armazenados em ambiente seguro, com metas e critérios bem definidos de preservação, anonimizados e criptografados. Essa fase também se interliga com a atualização dos dados armazenados pela instituição, e esses dados devem passar por atualizações periodicamente, de modo a estarem sempre completos, corretos e reais; c) *recuperação*: nessa fase ocorre o manuseio dos dados pessoais, por humanos ou sistemas informatizados. Essa atividade deve ser realizada mediante autorização e levar em conta ferramentas de autenticação que possam gerar trilhas e logs detalhados que subsidiem a prestação de contas aos titulares; d) *descarte*: por fim, na fase final ocorre a destruição dos dados, pelo cumprimento do objetivo ou mediante solicitação do titular. Pode também ocorrer a transferência para outra instituição, por necessidade institucional ou também por solicitação do usuário, nesse caso, deve-se levar em conta aspectos como regras

fortes para garantir uma transferência segura e a integridade dos dados, políticas institucionais do recebedor devem ser equivalentes em grau de proteção e a transferência deve ser devidamente informada ao titular[4].

Já em relação a proteção do usuário, preocupante situação nota-se a partir do relatório *National Privacy Test Report*, produzido pela empresa NordVPN, que avalia os hábitos digitais, a consciência sobre privacidade digital e a tolerância a riscos de pessoas ao redor do mundo. Nele, a população brasileira figura em última colocação em relação a hábitos digitais recebendo, assim, notas extremamente baixas nos quesitos *management of app permissions* (37%), *information sharing on social media* (36%), *understanding trade-offs of private data* (30%) e *keeping digital hygiene* (62%) (NORDVPN, 2021). No ranking geral, o Brasil encontra-se em vigésima quinta posição. Preocupante é a constatação de que a população brasileira é a segunda do mundo que mais passa tempo conectado à internet e que também é, a que possui os piores hábitos digitais (HOOTSUITE; WE ARE SOCIAL, 2019; NORDVPN, 2021).

Em busca de minimizar os danos decorrentes das atividades dos usuários da internet, Masur (2020) propõe uma alternativa: a promoção da capacidade crítica de um indivíduo decidir, por si mesmo, quando e dentro de quais limites as informações sobre si devem ser coletadas, analisadas e disseminadas. Tais capacidades, podem ser adquiridas por meio do letramento em privacidade.

O letramento digital e em privacidade caminham geralmente juntos e podem ser entendidos como equivalentes; entretanto, a partir de definições atuais, nota-se que ambos diferem e possuem características bem definidas. Christina Wissinger (2017 p. 379) afirma que, de acordo com a *American Library Association's Digital Literacy Task Force*, o letramento digital é "[...] a capacidade de usar tecnologias de informação e comunicação para encontrar, avaliar, criar e comunicar informações, exigindo habilidades cognitivas e técnicas". Em contrapartida, a autora afirma que as definições para letramento em privacidade possuem enfoque na compreensão das responsabilidades e riscos associados ao compartilhamento de informações online (WISSINGER, 2017). Wissinger propõe, de forma ampla, a definição de Langenderfer e Miyazaki (2009) para letramento em privacidade sendo: "[...] a compreensão que os consumidores têm do cenário de informações com o qual interagem e de suas responsabilidades dentro desse cenário"; a autora ainda

[4] Adaptado de Cavoukian (2006), Romansky (2015), Sant'Ana (2016), Brasil (2018) e Poikola et al. (2020).

apresenta uma definição proposta por Givens (2015) em que o mesmo afirma que o letramento em privacidade é “[...] o nível de compreensão e consciência de como as informações são rastreadas e usadas em ambientes online e como essas informações podem reter ou perder sua natureza privada”.

Já na visão de Bartsch e Dienlin (2016), mesmo o letramento em privacidade sendo um conceito relativamente novo, já se consolida como o:

> [...] conhecimento dos usuários sobre aspectos técnicos da proteção de dados online e sobre leis e diretrizes, bem como práticas institucionais e também sobre a capacidade dos usuários de aplicar estratégias para a regulamentação da privacidade individual e proteção de dados (BARTSCH; DIENLIN, p. 148, 2016, **tradução nossa**).

É a partir do letramento em privacidade que um indivíduo adquire a capacidade de usar as informações sobre como seus dados pessoais serão armazenados, usados ou distribuídos; combinando isso com sua filosofia pessoal sobre quais informações devem ser públicas e privadas, para tomar decisões conscientes acerca do tema (WISSINGER, 2017). Rotman (*apud* Wessinger, 2016) afirmou que uma estrutura de letramento em privacidade deve abordar cinco áreas principais: compreensão, reconhecimento, realização, avaliação e decisão, sendo que:

> [...] a compreensão abrange como as informações pessoais são usadas online. O reconhecimento distingue os vários lugares em que as informações pessoais podem ser compartilhadas online. A percepção se concentra nas consequências do compartilhamento de informações pessoais online. A avaliação aborda os riscos e benefícios do compartilhamento de informações e por último, a decisão se concentra em quando compartilhar essas informações online (WESSINGER, p. 381, 2016, **tradução nossa**).

Entretanto, o conhecimento técnico não é suficiente para motivar mudanças sociais, havendo assim, a necessidade de que as pessoas sejam capazes de refletir e questionar sua cultura e condições sociais a fim de se motivarem a impulsionar reformas sociais (MASUR, 2020). Nesse sentido, o letramento em privacidade assume um papel importante na democracia, ainda mais em sociedades autoritárias, nas quais as pessoas podem ter uma necessidade maior de se proteger contra identificação (MASUR, 2020).

Já no que diz respeito à relação da organização do conhecimento com o potencial de segregação, Hope Olson (2002) em sua obra "*The power to name: locating the limits of subject representation in libraries*", dedica parte do texto para relatar como catálogos de biblioteca podem promover discriminação e marginalização de determinados grupos. Para isso, a autora descreve o caso de três mulheres, Woolf, Fina e Grahn.

Woolf, uma mulher inglesa, buscava recursos informacionais sobre mulheres e a pobreza em sua sociedade, mas o que encontrou foram livros sobre mulheres em lugares "exóticos", mulheres como objetos da atenção masculina, mulheres como seres inferiores e sobre mulheres como superiores de maneiras que beneficiam os outros em detrimento de si mesmas. Fina, uma *chicana*, ou seja, uma estadunidense que possui pais ou antepassados mexicanos, sentiu-se insultada ao ser categorizada por uma biblioteca como "deficiente social", decidiu então tornar-se bibliotecária, e afirma que o catálogo de uma biblioteca não é uma ferramenta neutra, o mesmo é construído e, consequentemente, não representa o conteúdo dos recursos informacionais de maneira neutra ou objetiva, mas seleciona valores para expressão, os quais, geralmente, atendem aos valores das classes dominantes da sociedade. Grahn buscou em uma biblioteca informações sobre homossexualidade, quando tinha 21 anos, em 1961, ao solicitar atendimento aos bibliotecários, os mesmos, segundo seu relato, indignados informaram que livros acerca do tema estavam trancados e poderiam ser acessados somente por professores, médicos, psiquiatras e advogados criminais (OLSON, 2002).

Substitutos do conhecimento, tais como os catálogos de biblioteca, construídos por meio dos processos de representação, isto é, as notações de classificação, termos de indexação, metadados etc. fomentam a mediação entre as necessidades, desejos e demandas de informação dos usuários e os recursos informacionais presentes nos acervos. Quando essa representação não é realizada de uma forma defensável, pode-se enaltecer, censurar, omitir e distorcer informações. Pode-se privar alguém de ser ouvido ou privar alguém de receber informações. Há um poder oculto incorporado ao processo de representação, conforme lembram Milani e Guimarães (2017). Tal poder é denominado por Hope Olson como sendo o "poder de nomear". A representação atribui um nome ou um rótulo ao conteúdo de um recurso informacional e, ao controlar essa representação, controla-se o acesso aos acervos.

Olson (2002) explica que ao se atribuir nomes às coisas, esforços são feitos para que uma autoridade seja imposta sob a linguagem. Esse controle imposto à linguagem não é baseado nas características e necessidades de cada indivíduo, mas em um padrão que ampare uma comunidade de usuários. Pode ser que a criação dessa representação, desse substituto, seja realizada de uma maneira tendenciosa, evocando as crenças e valores éticos do profissional, ou ainda, veiculando preconceitos. Quando os substitutos veiculam preconceitos, tendenciosidades, vieses pode-se dizer que esses substitutos veiculam *biases*.

As *biases* podem fomentar prejuízos às comunidades de usuários ao evocar crenças e princípios de quem está realizando a classificação e a indexação ou de quem construiu um sistema de organização do conhecimento. Essas tendenciosidades podem reforçar preconceitos ou promover desvios na representação causando efeitos danosos aos usuários, principalmente aos que não pertencem às comunidades dominantes (MILANI; GUIMARÃES, 2017).

Invocando Dale Spender, Olson (2002) chama a atenção para o fato de que toda nomeação é necessariamente tendenciosa e a nomeação é um processo de codificação desse viés, de fazer uma seleção do que enfatizar e do que negligenciar com base no uso estrito de materiais já padronizados. Nomear está diretamente conectado à linguagem, a qual, é uma das atividades mais íntimas e políticas, desse modo, o poder de nomear molda e define as instituições que estruturam grande parte de nossas vidas, assim, nomear informação, não é simplesmente representação de informação, mas também a construção dessa informação (OLSON, 2002).

E como já preconizado anteriormente, humanos não são exceção nos processos de nomeação, classificação e representação. E atualmente, são constantemente submetidos a análises por sistemas automatizados, que ao valerem-se de dados pessoais, podem gerar análises e decisões que podem conter vieses e assim, aprofundarem assimetrias no tratamento que um grupo pode receber.

O Conselho de Estado Chinês publicou, em 2014, um documento no qual prevê a criação e implementação de um plano de crédito social. Por meio desse programa, o governo chinês pretende mapear, a partir de dados oriundos de diversas fontes, condutas sociais, financeiras e comportamento tanto *online* quanto *offline*. Cada ação poderá ser categorizada como “aprovada” ou “reprovada”, resultando assim, em soma ou subtração de pontos atribuídos aos cidadãos do país (TUMELERO, 2019). Caso o cidadão perca demasiados pontos, o acesso a serviços de transporte como trens e

aviões, serviços de internet, acesso a hotéis de melhor qualidade, escolas e universidades melhores, vagas de emprego podem ser revogados e, pode até mesmo chegar em situações extremas na qual o nome do cidadão pode ser inserido em listas públicas e mensagens de voz serem exibidas quando uma pessoa liga para o telefone do cidadão mal posicionado no ranking (TUMELERO, 2019).

Cathy O'Neil, doutora em matemática por Harvard, é uma das principais vozes na denúncia sobre como dados aprofundam desigualdades ameaçam a democracia. Para ela, os algoritmos computacionais presentes em diversas atividades da sociedade geram injustiças porque baseiam-se em modelos matemáticos os quais podem reproduzir preconceitos, equívocos e vieses humanos. Esses modelos, segundo O'Neil, são enviesados porque existe alguém que decide o que é importante ou não, e geralmente essas ferramentas são construídas em função da maximização dos lucros, não havendo incentivos para tornar os sistemas mais justos, para ela, o objetivo ético não costuma acompanhar o dinheiro (O'NEIL, 2016).

Em 2018, o Aspen Institute da Espanha e a Fundação Teléfonica realizaram um fórum sobre o impacto dos algoritmos nas democracias. Na ocasião, Cathy O'Neil respondeu diversas perguntas ao jornal El País e citou casos em que houve discriminações por dados e algoritmos. O primeiro caso citado, é referente à demissão com base em decisão de um algoritmo de uma professora estadunidense em Washington, onde a administração do distrito escolar implementou um sistema de pontuação para identificar os professores menos produtivos, resultando em mais de 205 docentes demitidos. Jamais foi publicado o funcionamento e qual conjunto de dados foi utilizado pelo algoritmo para chegar nesses resultados (MENÁRGUEZ, 2018).

Em Wisconsin, é utilizado um algoritmo chamado COMPAS, sigla para *Correctional Offender Management Profiling for Alternative Sanctions,* cujo objetivo é avaliar a probabilidade de um indivíduo voltar a cometer um crime, e através disso, determinar uma pontuação que define a pena. Os dados utilizados pelo sistema são amplos e compreendem desde histórico de prisão de familiares até desempenho escolar do analisado, além disso, o software aplica uma série de questões ao acusado e julga se há ou não "pensamentos criminosos". O funcionamento do programa é secreto, segredo comercial, ou seja, é impossível contestar uma pontuação, afinal, não se pode saber como ela foi obtida. Em uma investigação, a ProPublica, corporação sem fins lucrativos de jornalismo investigativo, identificou que minorias

étnicas recebem pontuações maiores a partir de uma análise comparativa entre os acusados de cor preta e branca com a mesma idade, sexo e ficha criminal. O resultado demonstrou que acusados pretos possuem 45% mais chances do que brancos de receber uma pontuação alta (INSTITUTO HUMANITAS UNISINOS, 2016).

Em 2015, um usuário do Google denunciou que o algoritmo da plataforma havia rotulado a foto de um casal negro com a legenda “gorilas”. Esse mesmo erro aconteceu com o Flickr, serviço de armazenamento e publicação de fotografias quando a plataforma categorizou as fotos de pessoas negras com a *tag* “macacos” (CRUZ, 2021).

A vista do exposto, observa-se que a discriminação por dados constitui aspecto de capital importância na atualidade, com consequências danosas e muitas vezes irreparáveis ao cidadão. Tudo isso leva a crer constituir-se essa temática em um domínio de conhecimento que, como tal, é objeto de pesquisa e de produção científica para que melhor se possa compreender sua dimensão conceitual e seu alcance. Desse modo, a seção a seguir, ocupa-se de explicitar em que medida se efetiva a investigação desse domínio do conhecimento como objeto da literatura internacional no intuito de melhor caracterizá-lo a partir da comunidade e dos veículos científicos responsáveis pela sua materialização.

3 METODOLOGIA

A pesquisa ora proposta caracteriza-se como exploratória e bibliográfica. Sua natureza exploratória decorre do fato de a discriminação por dados ser tema ainda pouco abordado, o que exige um estudo que possa explorar seus aspectos fundamentais. A natureza bibliográfica, por sua vez, decorre do fato de a pesquisa basear-se em fontes bibliográficas (obtenção, análise e sistematização) para sua consecução. Assim, utilizar-se-á de fontes científicas para identificar, definir e qualificar a discriminação por dados.

Visando a atingir os objetivos propostos, a pesquisa utiliza como universo bibliográfico as bases de dados Scopus e Web of Science sem um recorte temporal definido, uma vez que se torna necessário compreender a cronologia dos trabalhos realizados acerca do tema. Desse modo, a busca nas referidas bases, sobre os temas relativos a discriminação, big data e algoritmos em âmbito internacional, para melhor contextualizar e fundamentar a discussão, ocorreu a partir dos termos "*data discrimination*" (82 resultados obtidos na SCOPUS e 25 na WoS), "*algorithmic bias"* (62 resultados obtidos na SCOPUS e 56 na WoS), "*algorithmic discrimination*" (13 resultados obtidos na SCOPUS e 10 na WoS) e "*fair algorithms*" (24 resultados obtidos na SCOPUS e 4 na WoS) com os limitadores "tipo de arquivo: artigo", "acesso: aberto", "estágio de publicação: final" e "linguagem: espanhol, inglês e português" . A pesquisa, obteve assim um corpus preliminar composto por 276 (duzentos e setenta e seis) artigos científicos. Em seguida, procedeu-se a um refinamento eliminando-se duplicações de registros entre ambas as bases de dados (77 itens); documentos em formatos que não artigos de revista (2 relatórios, 1 artigo de opinião, 5 pre-prints e 2 artigos de conferência); e de documentos não recuperáveis ou não mais disponíveis (3 itens) resultando, assim, em um conjunto de 187 artigos.

Em seguida, procedeu-se à leitura do corpus e surpreendentemente verificou-se que havia 129 itens que, embora apresentando palavras-chave relativas ao tema pesquisado, abordavam temáticas outras, o que sinaliza para uma imprecisão na atribuição de palavras-chave. Com isso, o corpus final da pesquisa, composto por artigos que efetivamente tratam a temática pesquisada e, por conseguinte,

representam o referido domínio de conhecimento – a discriminação por dados[5] - compôs-se por 58 itens.

No tocante à análise dos resultados, utiliza-se da análise de domínio, a qual contribui para que se verifique o que é importante ou significativo em um dado campo (tendências, agentes e seus relacionamentos etc.) de modo a que se possa verificar e identificar as condições pelas quais o conhecimento científico se constrói e se socializa bem como as comunidades discursivas que contribuem para seu desenvolvimento (NASCIMENTO; MARTELETO, 2004; DANUELLO, 2007; SMIRAGLIA, 2011).

Especificamente no âmbito da Ciência da Informação, a análise de domínio foi introduzida, e com características próprias, por Hjørland e Albrechtsen, (1995). Em trabalhos posteriores, Hjørland (2002, 2017) aprofunda essa discussão ao caracterizar a análise de domínio como integrante de um paradigma social da Ciência da Informação que tem como pressuposto a existência de uma comunidade discursiva decorrente da divisão social do trabalho, cujos integrantes são membros participantes ativos (essa cumplicidade acadêmica ajuda a definir os limites do domínio), o domínio atua como paralelo às disciplinas, contribuindo para a identificação de uma "ecologia do trabalho" (GUIMARÃES, 2014). Nesse sentido, Hjørland (2002) enunciou um conjunto de 11 "abordagens" para a análise de domínio, nomeadamente: produção de obras de referência; construção de linguagens de indexação; indexação e recuperação da informação; estudo de usuários; estudos bibliométricos; estudos históricos; estudos de gêneros/tipologias documentais; estudos epistemológicos e críticos; estudos terminológicos; comunicação científica; cognição científica; conhecimento especializado e inteligência artificial. Em estudo posterior, o referido autor (HJØRLAND, 2017), incorpora ainda as propostas de Tognoli e Guimarães sobre a proveniência arquivística e de Smiraglia sobre a análise do discurso.

Ainda nesse contexto, vale destacar a contribuição de Tennis (2003), que estabelece limites para o desenvolvimento de uma análise de domínio, propondo áreas de modulação (a extensão do domínio) e áreas de especialidade (a profundidade do domínio) a ser analisado.

Para fins da presente dissertação, o domínio da discriminação por dados será

[5] Esclarece-se, outrossim, que a caracterização do domínio de conhecimento pesquisado - discriminação por dados – contempla, para fins da presente pesquisa, também a atuação de algoritmos.

analisado a partir da produção científica internacional veiculada em artigos de periódicos, em aspectos relativos à comunidade discursiva que produziu esse conhecimento, a suas vinculações institucionais e procedência geográfica e à cronologia dessa produção científica. Para tanto, a análise de domínio pauta-se em uma abordagem de natureza bibliométrica.

Em um segundo momento, procede-se a uma análise de conteúdo para que se possa atingir, em maior profundidade, a dimensão temática do corpus. Elegeu-se o método de Análise de Conteúdo, preconizada por Laurence Bardin (2009) pelo fato de possibilitar uma análise a partir de inferências extraídas do conteúdo de documentos segundo uma categorização deles oriunda, o que, segundo Sales (2008) proporciona, ao mesmo tempo, liberdade ao analista e objetividade de investigação. Esse método constitui-se das fases[6] de pré-análise (construção de um corpus de análise exaustivo, representativo e pertinente e formulação de hipóteses a partir desse corpus tendo por base um processo de categorização por meio do estabelecimento de categorias de análise com traços característicos convergentes), e exploração do material (a partir da leitura do corpus e da extração e descrição de informações), e tratamento dos resultados (a partir da aplicação das categorias ao material extraído do corpus) (GUIMARÃES; SALES, 2010).

A categorização, segundo Bardin (2009), pode ser realizada a partir de dois processos inversos: fornecendo o sistema de categorias a priori ou não fornecendo-o, e obtendo assim, as categorias a partir da análise do corpus. Assim, dada a natureza exploratória da pesquisa, optar-se-á pelo método de classificação a posteriori.

[6] A metodologia de análise de conteúdo (Bardin, 2009) efetiva-se por meio de três etapas consecutivas: pré-análise, exploração do material e tratamento dos resultados e interpretação. Na primeira fase tem-se a definição do corpus de pesquisa e daquilo que nele será buscado, valendo-se de princípios de exaustividade (o corpus na totalidade), representatividade (qualidade do corpus, o que se garante pela reputação das fontes e pelo rigor nas estratégias de busca); c) homogeneidade (no caso, todos foram artigos de periódicos constantes das bases de dados pesquisadas); e d) pertinência: adequação do corpus recuperado aos objetivos da análise. Na segunda fase é quando, a partir do corpus, estabelecem-se as categorias de análise ao passo que, na terceira fase, tem-se o resultado e a interpretação dessa análise.

4 APRESENTAÇÃO E ANÁLISE DOS RESULTADOS

Em busca de identificar a existência de um núcleo de pesquisadores que se ocupam do tema, realizou-se uma análise dos autores dos 58 artigos que compõem o corpus final, chegando-se a um total de 163 autores o que leva a uma média de 2,8 autores por artigo caracterizando uma produção ainda em moldes bastantes tradicionais de autoria, mais similar à das ciências humanas e sociais, uma vez que os temas mais tecnológicos tendem a ter um maior número de autores, como ocorre em áreas como Medicina, Física ou Engenharia.

Nesse contexto, observou-se uma grande pulverização de autores uma vez que apenas um autor - O. Papakyriakopoulos – possui dois artigos sendo que todos os demais figuram em apenas um artigo. Esse dado demonstra, por um lado, que o tema vem sendo objeto de preocupação de distintos universos científicos mas, por outro, que ainda se situa em um patamar inicial de produção científica, sem que se verifiquem publicações reiteradas que representam a trajetória investigativa de um autor nesse tema e nem tampouco a configuração de um núcleo mais representativo de autores nessa temática. Veja-se, a seguir, a distribuição de autores dos 58 artigos:

QUADRO 1: ARTIGOS PUBLICADOS POR AUTOR

Nome do autor	Quantidade de artigos publicados
Papakyriakopoulos, O.	2
Abul-Fottouh, D.	1
Acharya, S. S.	1
Aellen, F. M.	1
Ahmed, S. G.	1
Akter, S.	1
Al-Qirim, N.	1
Antoniou, J.	1
Are, C.	1
Babu, M. C.	1
Bandara, R. J.	1
Begley, C.	1
Begley, K.	1
Biswas, K.	1
Bolander, T.	1
Bonchi, F.	1
Borgesius, F. J. Z.	1
Brooks, C. F.	1
Brooks, L.	1

Castillo, C.	1
Castro, A.	1
Chaudhry, B.	1
Chen, Z. (52)	1
Chen, Z. (90)	1
Costello, C.	1
Custers, B. H. M.	1
De Clercq, E.	1
de Oliveira, F. C. R. M.	1
Dennehy, D.	1
DeVos, A.	1
Donini, M.	1
Du, M.	1
Dua, P.	1
Dwivedi, Y. K.	1
Dylan, J.	1
Elger, B. S.	1
Eom, J.-S.	1
Eslami, M.	1
Evangelo, N. S.	1
Faraci, F. D.	1
Feng, Q. Y.	1
Fennell, P. G.	1
Ferri, C.	1
Fichman, P.	1
Fierrez, J.	1
Fosch-Villaronga, E.	1
Gangadharan, S. P.	1
Gardner, C. C.	1
Gómez, E.	1
Goodman, K. W.	1
Gruzd, A.	1
Gupta, M.	1
Gutiérrez, C. M.	1
Haim, M.	1
Hajian, S.	1
Hegelich, S.	1
Hernández-Orallo, J.	1
Ho, M.-T.	1
Holstein, K.	1
Hu, Q.	1
Hu, X.	1
Iñiguez, G.	1
Ismanto, M.	1
Jeon, W.-T.	1

Jiya, T.	1
Jooste, Y.	1
Kaplan, B.	1
Kavuluru, R.	1
Kehrenberg, T.	1
Kent, D. M.	1
Kerasidou, A.	1
Kertész, J.	1
Khalil, A.	1
Khattak, A. M.	1
Kravets, D.	1
Kristiadi, D. P.	1
Leonardis, A.	1
Lerman, K.	1
Liu, S.	1
Lü, L.	1
Macnish, K.	1
Mantello, P.	1
Mariani, M. S.	1
Martínez-Plumed, F.	1
McQuillan, D.	1
Medo, M.	1
Michael, K.	1
Miron, M.	1
Mishra, B.	1
Montardo, S. P.	1
Morales, A.	1
Mullainathan, S.	1
Nader, K.	1
Nasraoui, O.	1
Neri, M.	1
Nguyen, M.-H.	1
Nieves, D.	1
Niklas, J.	1
Norori, N.	1
Obermeyer, Z.	1
Oneto, L.	1
Ostherr, K.	1
Parra, C. M.	1
Paulus, J. K.	1
Peralta, A. F.	1
Pontil, M.	1
Poulsen, A.	1
Powers, B.	1
Pushpa, S.	1

Qu, H.	1
Quadrianto, N.	1
Ramazzotti, D.	1
Rejaie, R.	1
Rettberg, J. W.	1
Rhoen, M.	1
Rolosana, R.	1
Rosenbaum, H.	1
Rozado, D.	1
Ryan, M.	1
Sajib, S.	1
Santoso, I. R.	1
Schuler, L. G. B.	1
Serrano, J. C. M.	1
Shafto, P.	1
Shawe-Taylor, J.	1
Shen, H.	1
Shmargad, Y.	1
Smith, V.	1
Solomonides, A.	1
Song, M. Y.	1
Søraa, R. A.	1
Srivastava, S.	1
Stahl, B.	1
Starke, G.	1
Subbian, V.	1
Sun, W.	1
Sunarya, P. A.	1
Tang, K.	1
Tino, P.	1
Toepfl, F.	1
Tolan, S.	1
Tzovara, A.	1
Unkel, J.	1
Vera-Rodriguez, R.	1
Verma, S.	1
Vogeli, C.	1
Vuong, Q.-H.	1
Walsh, C. G.	1
Wang, Q.	1
Wang, Y.	1
Warnars, H. L. H. S.	1
Williams, B. A.	1
Xenidis, R.	1
Xu, Z.	1

Yan, S.	1
Yang, F.	1
Yu, S.-E.	1
Zajko, M.	1
Zalewski, M.	1
Zhang, S.	1
Zhang, Y.	1
Zou, N.	1
Zuo, Z.	1

Fonte: Elaborado pelo autor

No que diz respeito à vinculação institucional dos autores, identificou-se um conjunto de 96 universidades (foram excluídas outras instituições, como empresas por exemplo). A seguir, apresenta-se a relação de universidades com dados relativos ao número de autores e ao número de artigos dela provenientes. Esse critério foi adotado para evitar um desvio no que diz respeito ao peso da universidade em relação a temática, uma vez que, por exemplo, um único artigo pode ter cinco autores da mesma instituição. Ou seja, analisa-se abaixo a importância da universidade em relação a quantidade de artigos publicados, e não de autores vinculados a ela.

É interessante observar que apenas cinco universidades publicaram mais de um artigo cada, nomeadamente as universidades europeias de Berna, na Suíça, de Leiden, na Holanda, e de Londres, no Reino Unido, e as universidades estadunidenses de Arizona e da Califórnia. Todas as demais universidades foram responsáveis por apenas um artigo. Já no tocante aos pesquisadores envolvidos nos artigos, observa-se, nas Universidade de Berna e de Hong Kong, um conjunto de 5 pesquisadores, seguido por grupos com 4 pesquisadores cada nas universidades do Texas e Carnegie Mellon (Estados Unidos), Autonoma de Madrid e Politecnica de Valencia (Espanha), Bina Nusantara (Indonésia) e Electronic Science and Technology (China), e de equipes com três pesquisadores nas universidades europeias de Leiden (Holanda), UM (Alemanha), Trinity College Dublin (Irlanda), Basel (Suíça) e Sussex (Reino Unido), norte-americanas de Oregon e South California (Estados Unidos), asiática de Phenikaa (Vietnã), e da Oceania, em Wollongong (Austrália).

Observa-se, outrossim, um quadro de universidades basicamente do hemisfério norte, e em grande parte europeias e norte-americanas, regiões em que a temática tem sido mais tradicionalmente tratada inclusive em instrumentos legais.

QUADRO 2: UNIVERSIDADES E A QUANTIDADE DE ARTIGOS E AUTORES

Nome da Universidade	Artigos	Autores
University of Bern	2	5
University of Arizona	2	4
Leiden University	2	3
University of California	2	2
University of London	2	2
Hong Kong University of Science and Technology	1	5
Bina Nusantara University	1	4
Carnegie Mellon University	1	4
Texas A&M University	1	4
Universidad Autonoma de Madrid	1	4
Universitat Politècnica de València	1	4
University of Electronic Science and Technology of China	1	4
Phenikaa University	1	3
Technical University of Munich	1	3
Trinity College Dublin	1	3
University of Basel	1	3
University of Oregon	1	3
University of Sussex	1	3
University of Wollongong	1	3
University of South California	1	3
Abu Dhabi University	1	2
De Montfort University	1	2
Florida International University	1	2
Indiana University	1	2
Jawaharlal Nehru University	1	2
London School of Economics and Political Science	1	2
Raharja University	1	2
Ritsumeikan Asia Pacific University	1	2
Ryerson University	1	2
Southern University of Science and Technology	1	2
St. Peter's Institute of Higher Education and Research	1	2
Tufts University	1	2
Universidade do Rio de Janeiro	1	2
Universidade Feevale	1	2
Universitat Pompeu Fabra	1	2
University of Birmingham	1	2
University of Louisville	1	2
University of Passau	1	2
Otago Polytechnic	1	1
Aalto University	1	1
Arizona State University	1	1
California State University	1	1
Central European University	1	1

Charles Sturt University	1	1
Chungbuk National University	1	1
City University of Hong Kong	1	1
United Arab Emirates University	1	1
Copenhagen University	1	1
Hangzhou Normal University	1	1
Johns Hopkins University	1	1
Ludwig Maximilian University of Munich	1	1
Louisiana Tech University	1	1
Milano-Bicocca University	1	1
National Research University	1	1
New York University	1	1
NorthShore University	1	1
Norwegian University of Science and Technology	1	1
Ollscoil na hÉireann (National Irish University)	1	1
Princeton University	1	1
Radboud University	1	1
Rice University	1	1
Rutgers University	1	1
Swansea University	1	1
Technical University of Denmark	1	1
The University of British Columbia	1	1
The University of Twente	1	1
Tsinghua University	1	1
University of Central Lancashire Cyprus	1	1
Universidad Autónoma Metropolitana	1	1
Universidad Nacional Autonóma de México	1	1
Universit of Cambridge	1	1
Universität Zürich	1	1
University College London	1	1
University of Applied Sciences and Arts of Southern Switzerland	1	1
University of Bergen	1	1
University of Bristol	1	1
University of Chicago	1	1
University of Fribourg	1	1
University of Geneva	1	1
University of Kentucky	1	1
University of Louisiana	1	1
University of Miami	1	1
University of Michigan	1	1
University of Northampton	1	1
University of Oxford	1	1
University of Pisa	1	1
University of Pretoria	1	1
University of Stavanger	1	1

University of Technology Sydney	1	1
University of Texas	1	1
University of Toronto	1	1
Utrecht University	1	1
Vanderbilt University Medical Center	1	1
Yale University	1	1
Yonsei University	1	1
Zayed University	1	1

Fonte: elaborado pelo autor

Assim como na análise de autores, é possível, a partir do **Quadro 2**, reiterar que a temática é pulverizada, e não possui formado um núcleo de autores e instituições que se debrucem sobre o tema constantemente uma vez que somente cinco, das noventa e seis universidades possuem, vinculados a si, dois artigos.

Em relação aos países das universidades em que os autores estão vinculados, têm-se abaixo a lista ordenada de modo a apresentar aqueles que possuem mais pesquisadores em suas universidades:

QUADRO 3: AUTORES VINCULADOS A UNIVERSIDADES DOS PAÍSES

País	Autores
Estados Unidos	49
Reino Unido	17
Espanha	15
Suíça	12
China	8
Alemanha	6
Hong Kong	6
Indonésia	6
Países Baixos	6
Australia	5
Índia	5
Brasil	4
Canada	4
Irlanda	4
Itália	4
Emirados Árabes	4
Noruega	3
Vietnam	3
Áustria	2
Dinamarca	2
Japão	2
Mexico	2

Coreia do Sul	2
Nova Zelândia	1
Chile	1
Chipre	1
Finlândia	1
Rússia	1
África do Sul	1
Suécia	1

Fonte: elaborado pelo autor

Verifica-se, a partir do exposto no **Quadro 3**, que existe uma forte predominância estadunidense e europeia. Nesse sentido, vale ressaltar que Estados Unidos, Reino Unido, Espanha e Suíça respondem, juntos por 57% da comunidade acadêmica que pesquisa o tema, possuindo mais de uma dezena de pesquisadores cada.

Entretanto, cabe destacar que existe um número razoável de pesquisadores buscando desenvolver o tema em países do "sul socioeconômico"[7], com destaque para China, Indonésia, Índia e Brasil.

Já no que diz respeito aos veículos de publicação do corpus aqui analisado têm-se, abaixo listadas, as revistas científicas que receberam publicações, levando em consideração o número de artigos por elas publicados.

QUADRO 4: QUANTIDADE DE ARTIGO PUBLICADO POR REVISTA CIENTÍFICA

Revista	Ocorrência
AI & Society	3
Information, Communication & Society	2
Plos One	2
Acta Academica	1
Artificial Intelligence and Law	1
Artnodes	1
Bulletin of Electrical Engineering and Informatics	1
Collabra: Psychology	1
Comunicação e Sociedade	1
Digital Medicine	1
EPJ Data Science	1

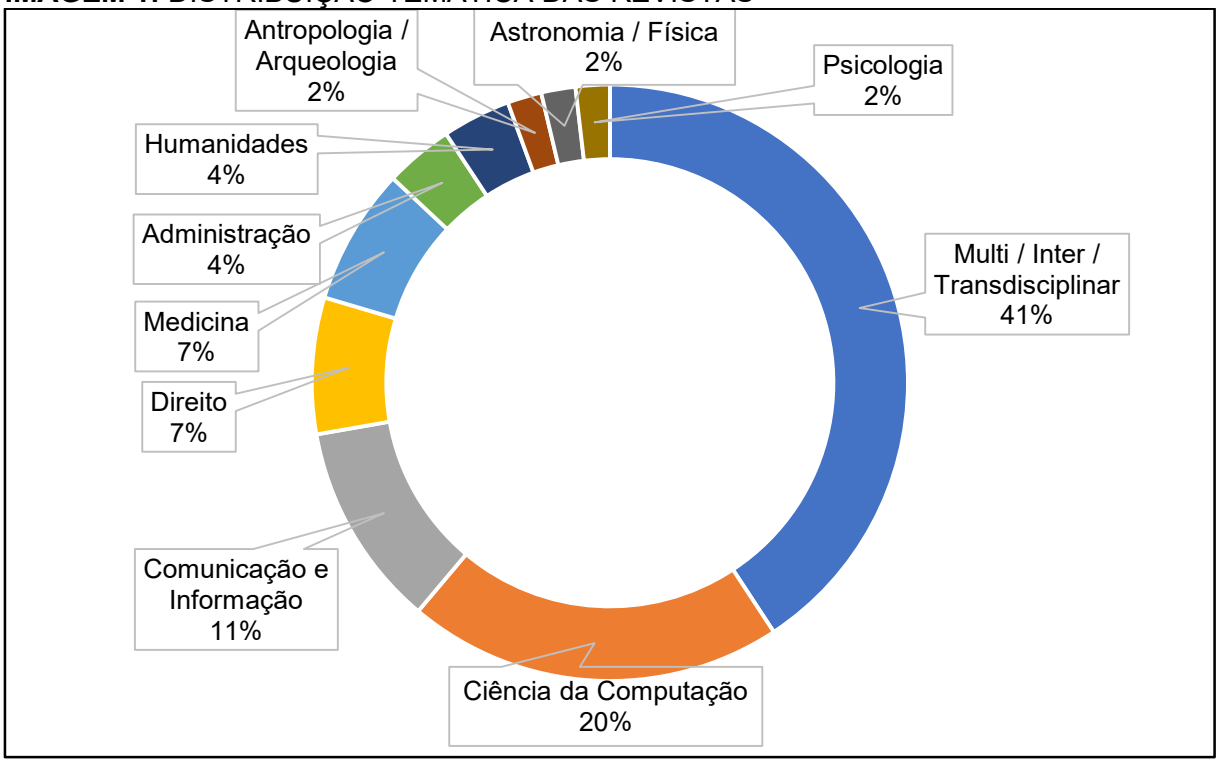
[7] Trata-se de uma divisão do mundo a partir de características socioeconômicas que substituiu a antiga classificação em primeiro, segundo e terceiro mundo. O sul socioeconômico é composto em sua maioria por países que se situam no hemisfério sul com exceções de regiões como a Oceania, por exemplo (LITONJUA, 2012)

Feminist media studies	1
Frontiers in Artificial Intelligence	1
Human Behavior and Emerging Technologies	1
Humanities & Social Sciences Communications	1
IEEE Access	1
IEEE Intelligent Systems	1
IEEE Transactions on Emerging topics in Computational Intelligence	1
IEEE Transactions on Pattern Analysis and Machine Intelligence	1
IEEE Transactions on visualization and computer graphics	1
Information Processing & Management	1
Information Sciences	1
Information Systems Frontier	1
International Data Privacy Law	1
International Information and Library Review	1
International Journal of Data Science and Analytics	1
International Journal of Intelligent Engineering & Systems	1
International Journal of Intelligente Systems	1
International Journal of Medical Informatics	1
JAMIA	1
Journal of Evaluation in Clinical Practice	1
Journal of Global Information Management	1
Journal of Management and Governance	1
Journal of Medical Humanities	1
Journal of Oral Biology and Craniofacial Research	1
Maastricht Journal of European and Comparative Law	1
Medicine, Health Care and Philosophy	1
Neurocomputing	1
Online Social Networks and Media	1
Patterns	1
Journal of Information Policy	1
Philosophy & Technology	1
Physical Review E	1
Proceedings of the ACM on Human-Computer Interaction	1
Proceedings of the Association for Information Science and Technology	1
Psychiatry investigation	1
Revista Chilena de Derecho y Tecnología	1
Revista Tecnologia e Sociedade	1
Science	1
Social Identities	1
Social Philosophy & Policy	1
Social Science Computer Review	1
Sustainability	1
The International Journal of Human Rights	1

Fonte: elaborado pelo autor

Têm-se então, um conjunto de cinquenta e quatro revistas, onde foram publicados cinquenta e oito artigos, demostrando mais uma vez, a pulverização do tema, já que somente três revistas - AI & Society, Information, Communication and Society e PlosOne - publicaram mais de um artigo sobre o tema., sendo que todas as demais publicaram apenas um artigo a respeito. Nesse contexto, vale analisar, a partir daí, a área temática das revistas para que se possa ter um panorama das disciplinas que tradicionalmente vêm sendo mais permeáveis ao tema em estudo.

IMAGEM 1: DISTRIBUIÇÃO TEMÁTICA DAS REVISTAS



Fonte: elaborado pelo autor

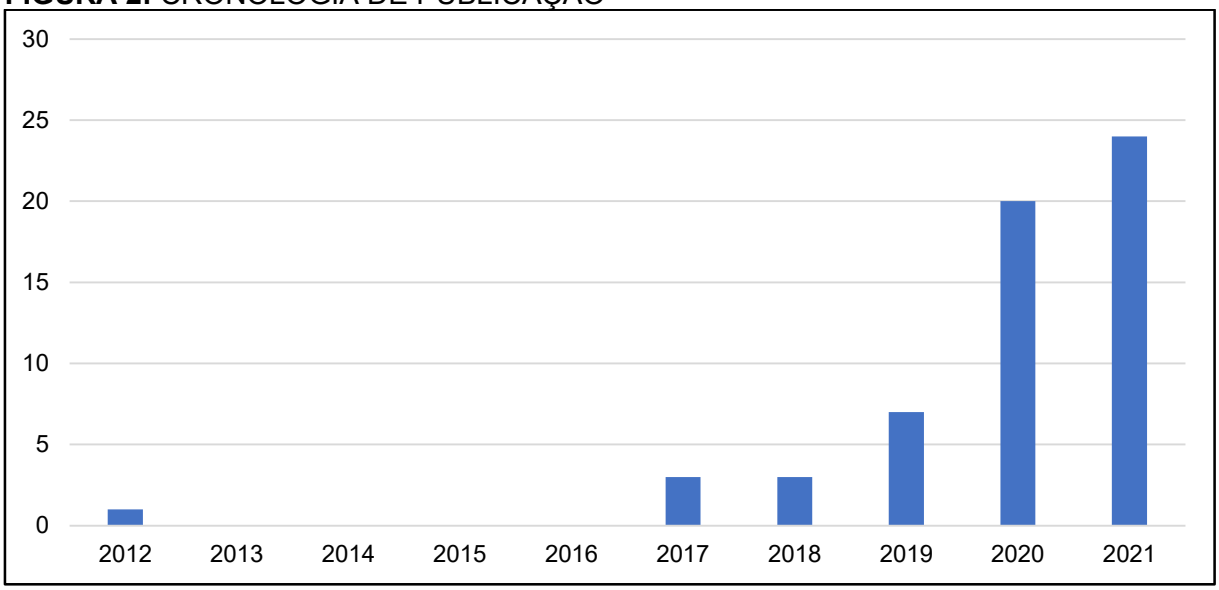
O agrupamento temático das revistas, a partir de áreas do conhecimento a que pertencem, conforme por elas declarado em seu escopo editorial, evidencia uma forte preocupação das revistas de natureza multi, inter e transdisciplinar, com quase metade do universo, o que revela o aspecto transversal dessa temática, atingindo diferentes áreas do conhecimento na sociedade. Isso confirma, ainda, o fato de essa produção ainda se encontrar em consolidação e tematicamente pulverizada. A segunda ocorrência verifica-se em revistas da área de Ciência da Computação (20%), o que já era de se esperar pois as questões afetas a inteligência artificial e à configuração dos algoritmos são tradicionalmente estudadas nessa área. Em terceira posição situam-se as revistas de Comunicação e de Informação (11%), revelando uma

preocupação de esclarecimento do grande público, de alerta aos usuários, e de informação acerca de riscos e danos bem como de medidas para evitá-los.

Em seguida, tem-se revistas que evidenciam um tratamento mais aplicado do tema em seus artigos, como é o caso das áreas de Direito, Medicina, Administração e Psicologia, entre outras. Destaque-se ainda que em quarta posição figuram as áreas de Direito e de Medicina, o que se justifica pelo fato de a temática em estudo envolver direitos e garantias individuais e, por outro lado, pode trazer sérias consequências à saúde e à vida, quando em ambiente hospitalar, por exemplo.

Como explicado na descrição da metodologia, a busca bibliográfica fez-se sem delimitação de data de publicação exatamente pelo fato de ser um tema emergente. Nesse sentido, analisaram-se os anos de publicação dos 58 artigos do corpus para verificar como se seu a evolução quantitativa da preocupação científica com essa temática.

FIGURA 2: CRONOLOGIA DE PUBLICAÇÃO



Fonte: elaborado pelo autor

Como se pode observar, e com exceção de um artigo isolado e de abrangência local (Coreias do Sul e do Norte) relativamente a discriminação para fins de identidade nacional, a produção dessa literatura deu-se basicamente a partir de 2017, ou seja, um ano após a aprovação da legislação europeia de proteção de dados (GDPR). No entanto, com a entrada em vigor da referida regulamentação, em 2018, observa-se, a partir do ano seguinte, um forte crescimento da produção científica nessa temática.

Adentrando no conteúdo temático do corpus da pesquisa, foram analisadas, primeiramente, as palavras-chave dos artigos que, por sua vez, foram categorizadas e agrupadas por meio da análise de conteúdo.

Dessa forma, foi possível estabelecer alguns grupos temáticos das palavras-chave, partindo-se daquele referente ao objeto da pesquisa: os dados e a ação dos algoritmos no âmbito da inteligência artificial (74 ocorrências), e as discriminações e os vieses neles incidem (45 ocorrências).

Em um âmbito mais específico, os artigos apresentam palavras-chave relativas aos contextos e ambiências em que ocorre essa discriminação por dados (62 ocorrências), aos processos e procedimentos específicos ocorríveis (42 ocorrências), às teorias, metodologias e interdisciplinaridades que nortearam as abordagens dos artigos (31 ocorrências).

Permeando necessariamente a questão dos vieses e das discriminações, vem à tona, com forte ocorrência, a dimensão ética das abordagens, aqui inseridos valores, problemas e atributos éticos em discussão (59 ocorrências).

Por fim, dois universos mais específicos se evidenciaram, ainda que de forma bastante menos significativa: a menção explícita à informação (4 ocorrências) e ao comportamento (5 ocorrências) como elementos permeadores da temática.

Veja-se, a seguir, a sistematização das palavras-chave realizada:

QUADRO 5: ANÁLISE DE CONTEÚDO DAS PALAVRAS-CHAVE

Categoria temática e respectivas palavras-chave	Ocorrências
Dados, Algortimos e Inteligência Artificial: Algorithm (Algorithmic (distribution) stability / Algorithmic accountability / Algorithmic discrimination / Algorithmic colonisation / Algorithmic decision making / Algorithmic filtering / Algorithmic video editing / Recommender algorithm / Algorithmic fairness/ Fair algorithm / Fairness in algorithm / Randomized algorithm / Algorithmic bias / Algorithm Bias) / Artificial intelligence (Responsible AI / Connectionist AI / Symbolic AI / AI ethics / Emotional AI) / Data /Data science / Big data / Data imputation / Data protection law / Data standards / Data visualization / Personal data / GDPR – General Data Protection Regulation	74
Vieses e discriminação: Bias (Classification bias / Cognitive bias / Confirmation bias / Gender bias / Racial bias / Sample bias / Survey bias / Algorithmic bias / Algorithm Bias) / Discrimination (Algorithmic discrimination / Discrimination discovery / Sorrouding discrimination / Statistical discrimination)	45
Processos / Ações: Profiling / Signaling / Measurement/ Modeling / Topic modeling/ Collaborative filtering / Ranking / Social ranking / Feature selection / Natural language processing / Predictive modeling / Biometrics / Risk assessment / Networking / Automated management / Shared decision-making / Algorithmic decision making / Automated decision	42

making / Human decision making / Shared decision-making/ Face analysis / Facial analysis / Facial recognition / Face recognition / Deep learning /Machine learning / Gender classifier / Gender stereotyping / Automated gender recognition	
Teorias, Metodologias e Interdisciplinaridades: Bayesian analysis / Case studies / Empirical studies / Omitted variables / Agent-based testing / Survey / Network analysis / Social network analysis / Neo-platonism / Pragmatism / Realism / Standpoint theory / Constrained Bayesian network / PAC-Bayes / Predictive analytics / Predictive models / Demographic parity / Randomized classifier / Philosophy of Science / Sociology / Cybernetics / Design / Medicine / Computational Social Science / Culture / Cross-cultural perception / Counterculture	31
Contextos e ambiências específicos: Academic libraries / Caste / Dalits / Elections / LGBTQAI+ /Pole dance / Uber / Vaccination / Hyperactive users / Open Science / Civil Society / Electronic fetal monitoring / Smart information System (SIS) / Participatory Science / Protest / Recommender systems / Recommendation systems / Neural networks / Complex networks / Digital platforms / Sociotechnical systems / Social machines / Sustainable development goals (SDGs) / ASHA - American Speech – Language – Hearing Association / GDPR – General Data Protection Regulation / Social Media / Instagram / Twiter /YouTube / Shadowban / Online social networks / Latin America / European Union / Russia / North Korea/ Mexico / Territory / Lower-middle-income-countries (LMICS)/ Global Health / Health care / Health disparities algorithms / Health technology/ Behavioral health / Digital health / Narrative medicine / Mental health / Social determinants of health / Search engines / Yandex / Google / Politics (Political communication / Political data Science / Political information / Political machines) Policies (Technological policy)	62
Dimensão ética (incluindo atributos, valores e problemas): Ethics / AI ethics / Ethical AI / Ethics of dating / Ethics of technology / Prejudice / Racism / Authoritarianism / Colonialism / Missing values / Digital activism / Equality (Principle of equality / Equality of opportunity) / Inequality / Popularity inequality / Privacy / Privacy preserving data analysis / Surveillance-privacy / Differential privacy Surveillance (Surveillance capitalism / Surveillance-privacy / Digital surveillance / Racial surveillance)/ Fairness /Algorithmic fairness / Fair algorithm / Fairness in algorithm / Fairness pattern / Unfairness / Justice / Criminal justice / Digital justice / Criminal recidivism / Non-discrimination law / Legal resilience / Duty of care / GDPR – General Data Protection Regulation / Explainability / Popularity / Interpretability / Trust / Social identity / National Identity	59
Informação: Disinformation / Misinformation / Information evaluation / Information literacy	04
Comportamento: Human behavior / Behavioral health / Online Behavioral Advertising / Human computer interaction (HCI) / Human-centered computing	05

Fonte: elaborado pelo autor

Em seguida, e buscando recuperar possíveis abordagens não representadas no universo das palavras-chave, procedeu-se a uma análise de conteúdo dos títulos e dos resumos dos artigos por serem essas as partes textuais em que os autores buscam descrever de forma sintética o tema, o objeto e o objetivo de seus artigos.

Assim, e de forma similar à análise de conteúdo realizada com as palavras-chave, identificaram-se oito categorias temáticas, nomeadamente:

A. os tipos de vieses discriminatórios,
B. as ambiências de contextos de aplicação e de realização;
C. os valores e problemas éticos envolvidos;
D. os tipos de algoritmos abordados;
E. os tipos de dados envolvidos;
F. as ferramentas e instrumentos concebidos e utilizados;
G. a menção explícita a metodologias específicas: e
H. as interações e consequências desse tema.

Desse modo, apresenta-se, a seguir, a classificação do conteúdo dos artigos, com as respectivas categorias, subcategorias e os artigos que a elas se referem:

QUADRO 6: ANÁLISE DE CONTEÚDO DOS TÍTULOS E RESUMOS DOS ARTIGOS

Tipos de vieses discriminatórios:

- de gênero e de orientação sexual: (FOSCH-VILLARONGA et al., 2021), (MARTÍNEZ-PLUMED et al., 2021), (SCHULER; MONTARDO, 2020), (KHALIL et al., 2020), (GUPTA; PARRA; DENNEHY, 2021), (ROZADO, 2020);
- de raça: (OBERMEYER et al., 2019), (MARTÍNEZ-PLUMED et al., 2021), (SCHULER; MONTARDO, 2020), (KHALIL et al., 2020), (OSTHERR, 2020), (GUPTA; PARRA; DENNEHY, 2021), (ZAJKO, 2021), (MCQUILLAN, 2018), (EVANGELO; OLIVEIRA, 2021), (BONCHI; MISHRA; RAMAZZOTTI, 2017), (ROZADO, 2020);
- de nacionalidade: (MARTÍNEZ-PLUMED et al., 2021), (AKTER et al., 2021), (CASTRO, 2020), (YU; EOM; JEON, 2012);
- de religião: (ROZADO, 2020), (AKTER et al., 2021)
- de idade: (AKTER et al., 2021), (KHALIL et al., 2020);
- de classe social e perfil socioeconômico: (SCHULER; MONTARDO, 2020), (AKTER et al., 2021), (VERMA; ACHARYA, 2018), (WILLIAMS; BROOKS; SHMARGAD, 2018), (EVANGELO; OLIVEIRA, 2021), (ROZADO, 2020)
- de aparência física: (ROZADO, 2020);
- de posição política: (ROZADO, 2020), (PAPAKYRIAKOPOULOS; SERRANO; HEGELICH, 2020);
- cognitivos: (YAN, 2021);
- sociais: (ZAJKO, 2021);
- interseccionais: (XENIDIS, 2020);
- de banimento em mídias sociais - Shadowban: (ARE, 2021).

Ambiências e Contextos de aplicação e realização

- Sistemas de saúde (diagnósticos, terapêuticos e prognósticos): (OBERMEYER et al., 2019), (KERASIDOU, 2021), (STARKE; DE CLERCQ; ELGER, 2021), (NORORI et al., 2021), (PAULUS; KENT, 2020), (BEGLEY; BEGLEY; SMITH, 2021), (WALSH et al., 2020);
- Sistemas criminais: (ZAJKO, 2021), (MIRON et al., 2021), (CASTRO, 2020);
- Sistemas organizacionais / corporativos: (BOLANDER, 2019), (GANGADHARAN; NIKLAS, 2019);

- Sistemas eleitorais: (UNKEL; HAIM, 2019);
- Sistemas legais / normativos: (GUTIÉRREZ, 2021), (XENIDIS, 2020)-EU, (RHOEN; FENG, 2018)-GDPR;
- Mídias sociais: Twitter: (FOSCH-VILLARONGA et al., 2021), Facebook (RETTBERG, 2020; COSTELLO et al., 2021), Instagram (ARE, 2021), YouTube (ABUL-FOTTOUH; SONG; GRUZD, 2020; RETTBERG, 2020);
- Yandex (motor de busca do estado russo): (KRAVETS; TOEPFL, 2021);
- Google's PageRank = Rankings algorítmicos baseados em popularidade: (ZHANG et al., 2019);
- Sistemas de Reconhecimento Facial: (KHALIL et al., 2020);
- Biometria / Emotion AI: (MANTELLO et al., 2021);
- Objetivos de Desenvolvimento Sustentável da ONU: (RYAN et al., 2020).

Valores e Problemas éticos envolvidos

- Transparência algorítmica: (ABUL-FOTTOUH; SONG; GRUZD, 2020), (BOLANDER, 2019), (ZHANG et al., 2019);
- Responsabilidade algorítmica: (ROSENBAUM; FICHMAN, 2019);
- justiça e confiabilidade algorítmica: (ROSENBAUM; FICHMAN, 2019), (DU et al., 2020), (KRISTIADI et al., 2020), (KEHRENBERG; CHEN; QUADRIANTO, 2020), (PAULUS; KENT, 2020), (ZHANG et al., 2021), (OSTHERR, 2020), (SUN; NASRAOUI; SHAFTO, 2020);
- Transparência e interoperabilidade nas decisões algorítmicas: (BOLANDER, 2019), (ZHANG et al., 2021);
- Colonização algorítmica: (JOOSTE, 2021);
- Práticas digitais opressivas: (JOOSTE, 2021);
- Capitalismo da vigilância: (JOOSTE, 2021).

Tipos de algoritmos envolvidos

- Algoritmos de Relevância Pública (ARP): (SCHULER; MONTARDO, 2020);
- Algoritmos colaborativos de filtragem: (MCQUILLAN, 2018), (NADER, 2020)
- Algoritmos preditivos: (PAULUS; KENT, 2020), (FENNELL; ZUO; LERMAN, 2019), (XENIDIS, 2020);
- Algoritmos de ranqueamento social: (EVANGELO; OLIVEIRA, 2021), (ZHANG et al., 2021);
- Algoritmos de recomendação de conteúdos em mídias sociais: (ABUL-FOTTOUH; SONG; GRUZD, 2020), (PAPAKYRIAKOPOULOS; SERRANO; HEGELICH, 2020), (GUPTA; PARRA; DENNEHY, 2021);
- Efficient Discrimination Prevention and Rule Protection Algoritms: (BABU; PUSHPA, 2018);
- Classificadores aleatórios:(ONETO et al., 2020).

Tipos de dados envolvidos

- Dados pessoais: (RETTBERG, 2020);
- Dados comportamentais: (FENNELL; ZUO; LERMAN, 2019), (COSTELLO et al., 2021);
- Dados sensíveis: (RHOEN; FENG, 2018), (ONETO et al., 2020).

Ferramentas e Instrumentos concebidos e utilizados

- SensitiveNets (rede neural de preservação da privacidade para eliminar informação sensível): (MORALES, 2019);
- DiscriLens (ferramenta de visualização interativa): (WANG et al., 2021);
- Situated Data Analysis: (RETTBERG, 2020);
- *Outside in: exile at home:* (CASTRO, 2020)

Metodologias / Procedimentos

- Feature Space Decomposition - FSD: (FENNELL; ZUO; LERMAN, 2019);

Interações e consequências

- Efeitos dos algoritmos na transferência da informação e na formação de opinião (PERALTA et al., 2021);
- Interação de pessoas e algoritmos (ecossistemas sócio-algorítmicos) e da política nas máquinas sociais (PAPAKYRIAKOPOULOS, 2022).

Fonte: elaborado pelo autor

Outras reflexões subjacentes à discriminação por dados se fizeram presentes, relativas às relações de poder entre empresas, plataformas e usuários (RETTBERG, 2020), aos elementos ocultos nas tecnologias de filtragem de conteúdo (PERALTA et al., 2021), à importância do estudo da terminologia e da natureza dos vieses para neutralizar discriminações algorítmicas (ROZADO, 2020), à caracterização da Ciência de Dados como um Neoplatonismo tecnológico na medida em que a discriminação algorítmica pode transformar predições em direito de preferência e as pessoas envolvidas nisso correm o risco de uma abstração de responsabilidade e de gerarem "descuidos" (MCQUILLAN, 2018), à discussão da privacidade como uma contribuição das ciências humanas para a inteligência artificial (OSTHERR, 2020), à necessidade de realização de auditorias em sistemas algorítmicos (SHEN et al., 2021) e à importância do desenvolvimento de *media literacy* em usuários e principalmente em bibliotecários como forma de fazer frente aos vieses algorítmicos (GARDNER, 2019).

Em face aos dados apresentados, e em busca de corroborar ou não a inferência de que a discussão relativa ao tema se encontra pulverizada foi realizada, então, uma análise das referências de 56 dos 58 artigos que compõem o corpus final. Dois artigos não foram analisados por seu formato não possibilitar a extração de suas referências.

Foram analisadas então, a partir de um conjunto de 3.665 referências, provenientes de 56 artigos, a quantidade de autocitações presentes em cada um desses textos.

QUADRO 7: CITAÇÕES E AUTOCITAÇÕES DO CORPUS FINAL

Nome do artigo	Citações	Autocitações	% de autocitações
The long-term impact of ranking algorithms in growing networks	41	14	34,15%

SensitiveNets: Learning agnostic representations with application to face images	40	7	17,50%
Effect of algorithmic bias and network structure on coexistence, consensus, and polarization of opinions	67	10	14,93%
Evolution and impact of bias in human and machine learning algorithm interaction	82	12	14,63%
Exposing the probabilistic causal structure of discrimination	45	6	13,33%
Dissecting racial bias in an algorithm used to manage the health of populations	53	7	13,21%
Social identity and perceptions about health care service provisioning by and for the dalits in india	38	5	13,16%
Predicting and explaining behavioral data with structured feature space decomposition	46	6	13,04%
The Shadowban Cycle: an autoethnography of pole dancing, nudity and censorship on Instagram	63	8	12,70%
Randomized learning and generalization of fair and private classifiers from PAC-Bayes to stability and differential privacy	122	15	12,30%
Stigma, biomarkers, and algorithmic bias: recommendations for precision behavioral health with artificial intelligence	93	10	10,75%
A little bird told me your gender: Gender inferences in social media	108	11	10,19%
Ethics of artificial intelligence in global health: explainability, algorithmic bias and trust	20	2	10,00%
Shared decision-making and maternity care in the deep learning age: acknowledging and overcoming inherited defeaters	40	4	10,00%
Tuning Fairness by Balancing Target Labels	41	4	9,76%
Visual analysis of discrimination in machine learning	73	6	8,22%
Bosses without a heart: socio-demographic and cross-cultural determinants of attitude toward Emotional AI in the Workplace	123	10	8,13%
Everyday Algorithm Auditing: Understanding the Power of Everyday Users in Surfacing Harmful Algorithmic Behaviors	101	8	7,92%
Questioning racial and gender bias in AI-based recommendations: do espoused national cultural values matter?	133	10	7,52%

Situated data analysis: a new method for analysing encoded power relationships in social media platforms and apps	83	6	7,23%
Outside in: exile at home. Na algorithmic discrimination system	14	1	7,14%
Political communication on social media: A tale of hyperactive users and bias in recommender systems	86	6	6,98%
Tuning EU equality law to algorithmic discrimination: Three pathways to resilience	129	9	6,98%
Predicting Mental Health From Followed Accounts on Twitter	44	3	6,82%
Googling politics: Parties, Sources, and Issue Ownerships on Google in the 2017 German Federal Election Campaign	62	4	6,45%
Decentering technology in discourse on discrimination	47	3	6,38%
Gauging reference and source bias over time: how Russia's partially state-controlled search engine Yandex mediated na anti-regime protest event	32	2	6,25%
The ethical balance of using smart information systems for promoting the United Nations' sustainable development goals	98	6	6,12%
Predictably unequal: understanding and addressing concerns that algorithmic clinical prediction may increase health disparities	50	3	6,00%
Missing the missing values: The ugly duckling of fairness in machine learning	89	5	5,62%
Evaluating causes of algorithmic bias in juvenile criminal recidivism	58	3	5,17%
Teaching algorithmic bias in a Credit-Bearing Course	22	1	4,55%
The black social ranking experience at Uber: a racialized reflection on contemporary surveillance	23	1	4,35%
Addressing Algorithmic Bias in AI-Driven Customer Management	24	1	4,17%
Addressing bias in big data and AI for health care: A call for open science	74	3	4,05%
Fairness in Deep Learning: A computational perspective	28	1	3,57%
Artificial Intelligence and medical humanities	170	6	3,53%
Examining algorithmic biases in YouTube's recommendations of vaccine videos	33	1	3,03%
Political machines: a framework for Studying politics in social machines	142	3	2,11%

Towards a pragmatist dealing with algorithmic bias in medical machine learning	55	1	1,82%
Strengthening legal protection against discrimination by algorithms and artificial intelligence	129	2	1,55%
Why the 'Computer says no': illustrating big data's discrimination risk through complex system science	103	1	0,97%
A survey on neural network interpretability	150	1	0,67%
Conservative AI and social inequality: conceptualizing alternatives to bias through social theory	78	0	0,00%
Dating through the filters	27	0	0,00%
Surveillance capitalism as white world-making	43	0	0,00%
What do we loose when machines take the decisions?	17	0	0,00%
Wide range screening of algorithmic bias in word embedding models using large sentiment lexicons reveals underreported bias types	26	0	0,00%
A política das máquinas: vieses em algoritmos de relevância pública	8	0	0,00%
Data Science as Machinic Neoplatonism	68	0	0,00%
La discriminación em uma sociedad automatizada: Contribuciones desde América Latina	92	0	0,00%
Framework for developing algorithmic fairness	27	0	0,00%
Investigatin bias in facial analysis systems: a systematic review	56	0	0,00%
How algorithms discriminate based on data they lack: challenges, solutions, and policy implications	89	0	0,00%
An efficient discrimination prevention and rule protection algorithms avoid direct and indirect data discrimination in web mining	24	0	0,00%
The Factors Affecting the development of national identity as South Korean in North Korean refugees living in South Korea	36	0	0,00%

Fonte: elaborado pelo autor

Nota-se a partir dos dados expostos que, a média de autocitação em cada artigo é de 4,07 e o percentual médio de 6,30%.

Considerando que a literatura internacional considera como aceitável um índice de autocitação de até 15% das referências, tem-se que apenas dois artigos do corpus

ultrapassam esse patamar – com respetivamente 34,15% e 17,50% de autocitações, revelando que a literatura sobre o tema vem buscando enriquecer-se com fontes externas. Por outro lado, o baixo índice de autocitações novamente evidencia o fato de ser uma área de pesquisa ainda jovem em que não foi ainda possível formar um corpo de autores e obras seminais.

A partir da análise das 3.665 referências, foi possível identificar um conjunto de 3.637[8] autores, os quais foram citados 5.135 vezes.

Em relação à autoria do conjunto de referências, ao ser aplicado o conceito do Elitismo de Price, que determina que a raiz quadrada do número total de autores é um critério para separar os autores mais profícuos dos menos, teve como resultado um grupo de 63 pesquisadores, que possuem seis ou mais citações. A raiz quadrada do total 3.637 autores é 60.3075451333; entretanto, o autor de número 60 possui 6 citações, desse modo, optou-se por utilizar esse número de citações como valor de corte obtendo-se, assim, um conjunto de 63 autores que representam a "elite" dessa bibliografia, segundo (PRICE; BEAVER, 1966).

A lista dos referidos autores apresenta-se da seguinte maneira:

QUADRO 8: OS 63 AUTORES MAIS CITADOS NO CORPUS FINAL

	Nome do autor	Total de citações
1	Barocas, S.	20
2	Dwork, C.	20
3	Hardt, M.	20
4	Buolamwini, J.	18
5	Zemel, R.	16
6	Calders, T.	15
7	Friedler, S. A	15
8	Angwin, J.	14
9	Gebru, T.	14
10	Roth, A.	14
11	Ruggieri, S.	14
12	Mullainathan, S.	13
13	Pedreschi, D.	13
14	Turini, F.	12
15	Corbett-Davies, S.	11

[8] Para tanto, foram considerados como autores citados os primeiros, segundos e últimos autores. Tal critério foi adotado levando em conta as ponderações de Helgesson (2020), o qual preconiza que a ordem de importância na autoria de trabalhos científicos se configura da seguinte maneira (do mais importante para o menos importante): primeiro autor, último altor, segundo autor, terceiro autor e os subsequentes, penúltimo autor.

16	Kamiran, F.	11
17	Kirchner, L.	11
18	Wang, Y. X.	11
19	Larson, J.	10
20	Wu, Y.	10
21	Kleinberg, J.	9
22	Selbst, A.	9
23	Valera, I.	9
24	Venkatasubramanian, S.	9
25	Zafar, M. B.	9
26	Chouldechova, A.	8
27	Gummadi, K. P.	8
28	Kim, B.	8
29	Mittelstadt, B. D.	8
30	Narayanan, A.	8
31	Obermeyer, Z.	8
32	Sandvig, C.	8
33	Chang, K. W.	7
34	Crawford, K.	7
35	Flammini, A.	7
36	Floridi, L.	7
37	Kusner, M. J.	7
38	Price, E.	7
39	Scheidegger, C.	7
40	Srebro, N.	7
41	Bengio, Y.	6
42	Benjamin, R.	6
43	Bryson, J. J.	6
44	Caliskan, A.	6
45	Goel, S.	6
46	Huq, A.	6
47	Kosinski, M.	6
48	Lum, K.	6
49	Menczer, F.	6
50	Mitchell, M.	6
51	Müller, K.-R.	6
52	Nissenbaum, H.	6
53	Pierson, E.	6
54	Raghavan, M.	6
55	Riedl, J.	6
56	Samek, W.	6
57	Wachter, S.	6
58	Wallach, H.	6

59	Watts, D. J.	6
60	Wilson, C.	6
61	Zhang, X.	6
62	Zhou, B.	6
63	Zou, J.	6

Fonte: elaborado pelo autor

Já em relação as 5.135 citações, é possível identificar que, os 63 autores, que representam 1,7% do total de pesquisadores, foram responsáveis por 577 citações, ou seja, 11% do total. Por outro lado, 2.919 autores foram citados apenas uma vez, sendo que esse valor representa 80% das citações totais. Tal situação reforça mais uma vez a dispersão da temática, não havendo ainda um conjunto de obras que subsidiem de maneira expressiva a literatura aqui analisada.

Dos autores do corpus de 58 artigos analisados no presente trabalho, somente dois figuraram entre os 3.637, sendo eles Powers, B. e Haijan, S., ambos com apenas uma citação cada.

Desse modo, os resultados aqui apresentados corroboram a hipótese de que o tema ainda se encontra em desenvolvimento, sendo os principais indícios a dispersão das fontes utilizadas pelos autores, a baixa produção científica acerca do tema pelos autores analisados, a pulverização em veículos de comunicação científica e áreas do saber, a quantidade total de artigos recuperados e a evolução cronológica da quantidade de publicações.

5 CONCLUSÃO

A experiência investigativa desenvolvida na presente dissertação permitiu observar que o domínio de conhecimento analisado incorpora predominantemente dados pessoais, seja sua dimensão comportamental seja no âmbito dos denominados dados sensíveis. Os referidos dados, por sua vez, estão suscetíveis à ação de algoritmos de distintas ordens, sejam eles de relevância, filtragem, preditivos, de ranqueamento social, de recomendação de conteúdos e de classificação aleatória. Tais algoritmos, por sua vez, podem trazer embutidos, em sua programação, vieses discriminatórios relativos a gênero, orientação sexual, raça, nacionalidade, religião, idade, classe social, perfil socioeconômico, aparência física, e posicionamento político.

As abordagens aplicadas a partir da literatura evidenciam a prevalência de preocupações acerca da temática analisada em ambiências específicas tais como Sistemas de saúde, Sistemas legais, Sistemas organizacionais, Sistemas eleitorais, Mídias sociais e Sistemas Biométricos.

Relativamente às consequências éticas dessa temática, evidenciam-se valores relativos à transparência, responsabilidade, justiça, confiabilidade e interpretabilidade algorítmica e a preocupação com problemas relativos à colonização algorítmica, práticas digitais opressivas e, em última análise, ao denominado “Capitalismo da vigilância”.

Como resultado, esse contexto pode levar a consequências relativas aos efeitos dos algoritmos na transferência da informação e na formação de opinião e ao grau de interação de pessoas e algoritmos (nos denominados ecossistemas sócio-algorítmicos) e do desenvolvimento da política em estruturas sociais.

Isto posto, torna-se evidente o fato de que os algoritmos desenvolvidos que utilizam dados pessoais como base de conhecimento para geração de análises e tomadas de decisão são suscetíveis a vieses de diversas ordens – oriundos de seu processo de programação - o que pode culminar em situações discriminatórias a um determinado sujeito ou grupo, isso porque análises que partem dessa tipologia de dados podem não levar em conta, no momento da organização desse conhecimento ou na construção das regras que regem o algoritmo, questões primordiais no que diz respeito a equidade social.

Portanto, questões relativas à Ciência da Informação, tais como as já apresentadas (gestão do ciclo de vida dos dados, desenvolvimento da capacidade crítica do usuário, organização do conhecimento, entre outras), assumem papel importante no debate aqui proposto.

Assim sendo, a temática ainda carece de uma maior verticalização em diversas outras questões, tais como a da autodeterminação informativa, a categorização e comparação dos vieses que surgem a partir das atividades algorítmicas, e como os ferramentais da Organização do Conhecimento podem subsidiar a construção de base de dados pessoais.

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7 APÊNDICES

APÊNDICE A: Corpus preliminar obtido a partir do termo "*Algorithmic bias*"

N	Base	Ano	Revista	Palavras-chave	Autores	Filiação	País
1	SCOPUS	2021	Information Processing and Management	Gender	E. Fosch-Villaronga	Leiden University	Holanda
				Twitter	A. Poulsen	Charles Sturt University	Australia
				Social Media	R. A. Søraa	Norwegian University of Science and Technology	Noruega
				Inference	B. H. M. Custers	Leiden University	Holanda
				Gender classifier	-	-	-
				Automated gender recognition system	-	-	-
				Privacy	-	-	-
				Algorithmic bias	-	-	-
				Discrimination	-	-	-
				LGBTQAI+	-	-	-
				Gender stereotyping	-	-	-
				Online Behavioral Advertising	-	-	-
2	SCOPUS	2019	Vietnam Journal of Computer Science	Sustainable design	V.M. Xanat	The University of Tsukuba	Japão
				Social networks	Y. Toshimasa	The University of Tsukuba	Japão
				Computational intelligence	-	-	-
				Information retrieval	-	-	-
				Multicriteria decision-making	-	-	-
3	SCOPUS	2021	International Journal of Interactive Multimedia and Artificial Intelligence	Algorithmic Bias	L. Boeschoten	Ultrecht University	Netherlands
				Fair Machine Learning	E.-J. van Kesteren	Ultrecht University	Netherlands
				Latent Variable Model	A. Bagheri	Ultrecht University	Netherlands
				Measurement Error	D. L. Oberski	Ultrecht University	Netherlands
				Measurement Invariance	-	-	-

				-	-	-	-
4	SCOPUS	2021	Frontiers in Artificial Intelligence	Artificial Intelligence	R. R. Fletcher	Massachusetts Institute of Technology	United States
				Machine Learning		University of Massachusetts Medical School	United States
				Bias	A. Nakeshimana	Massachusetts Institute of Technology	United States
				Fairness	O. Olubeko	Massachusetts Institute of Technology	United States
				Appropriate use	-	-	-
				Global Health	-	-	-
				Ethics	-	-	-
				Medicine	-	-	-
5	SCOPUS	2021	Energies	Artificial intelligence	V. Marinakis	National Technical University of Athens	Greece
				Data democratisation	T. Koutsellis	National Technical University of Athens	Greece
				Energy data spaces	A. Nikas	National Technical University of Athens	Greece
				Interoperability	H. Doukas	National Technical University of Athens	Greece
				Data sharing	-	-	-
				Energy management	-	-	-
				Decarbonisation	-	-	-
				Decision support	-	-	-
6	SCOPUS	2019	Asian Bioethics Review	Artificial intelligence	T. Lysaght	National University of Singapore	Singapore
				Big data	H. Y. Vicki Xafis	Nanyang Technology University	Singapore
				Clinical decision-making support systems	V. Xafis	National University of Singapore	Singapore
				Professional governance	K. Y. Ngiam	National University Hospital	Singapore
				Bioethics	-	-	-
7	SCOPUS	2021	Humanities & Social Sciences	-	A. Checco	The University of Sheffield	United Kingdom
				-	L. Bracciale	University of Rome Tor Vergata	Italy

			Communications	-	P. Loreti	University of Rome Tor Vergata	Italy
				-	S. Pinfield	The University of Sheffield	United Kingdom
				-	G. Bianchi	University of Rome Tor Vergata	Italy
8	SCOPUS	2021	Communications in Nonlinear Science and Numerical Simulation	PageRank	M. Cui	Southwest Minzu University	China
				Algorithmic bias	M. S. Mariani	Universität Zürich	Switzerland
				Networks	M. Medo	University Hospital of Bern	Switzerland
				Ranking algorithms		University of Bern	Switzerland
9	SCOPUS	2019	IEEE Access	Facial analysis	B. Taati	University Health Network	Canada
				Older adults		University of Toronto	Canada
				Dementia		Vector Institute for Artificial Intelligence	Canada
				Facial landmark detection	S. Zhao	University Health Network	Canada
				Facial action units	A. B. Ashraf	University Health Network	Canada
				-		University of Manitoba	Canada
				-	A. Asgarian	University Health Network	Canada
				-		University of Toronto	Canada
				-	M. E. Browne	University of Regina	Canada
				-	K. M. Prkachin	University of Northern British Columbia	Canada
				-	A. Mihailidis	University Health Network	Canada
				-		University of Toronto	Canada
				-	A. T. Hadjistavropoulos	University of Regina	Canada
10	SCOPUS	2019	Plos One	-	A. Sîrbu	University of Pisa	Italy
				-		New York University Abu Dhabi	United Arab Emirates
				-	D. Pedreschi	University of Pisa	Italy
				-	F. Giannotti	Instituto di Scienza e Tecnologie dell'Informazione "A. Faedo"	Italy
				-	J. Kertész	Central European University	Hungary

				-		Budapest University of Technology and Economics	Hungary
11	SCOPUS	2020	Internet Policy Review	Valuew sensitive design	J. Simon	Universität Hamburg	Germany
				Algorithmic bias	P.-H. Wong	Universität Hamburg	Germany
				Human valuews	G. Rieder	Universität Hamburg	Germany
				Fairness	-	-	-
				Fairness	-	-	-
				Fairness in machine learning	-	-	-
12	SCOPUS	2019	Management Science	Algorithmic bias	A. Lambrecht	London Business School	United Kingdom
				Online advertising	C. Tucker	Massachusetts Institute of Technology	Estados Unidos
				Algorithms	-	-	-
				Artificial intelligence	-	-	-
				-	-	-	-
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				-	-	-	-
				-	-	-	-
			Plos One	-	A. Thiem	University of Lucerne	Switzerland

13	SCOPUS	2020		-	L. Mkrtchyan	University of Lucerne	Switzerland
				-	T. Haesebrouck	Ghent University	Belgium
				-	D. Sanchez	LINK Institute	Switzerland
				-	-	-	-
14	SCOPUS	2020	Springer Synthese	Bias	G.M. Johnson	New Yourk University	Estados Unidos
				Algorithmic bias	-	-	-
				Social bias	-	-	-
				Machine bias	-	-	-
				Implicit bias	-	-	-
15	SCOPUS	2021	Big Data & Society	Machine learning	J. L. Davis	The Australian National University	Australia
				Algorithmic bias	A. Williams	University of Michigan	Estados Unidos
				Intersectionality		University of Notre Dame	Estados Unidos
				Artificial intelligence	M. W. Yang	The Australian National University	Australia
				Critical race theory	-	-	-
				Fair machine learning	-	-	-
16	SCOPUS	2019	Ecology and Evolution	Algorithm-derived biases	W. Zhang	Henan University	China
				Basal mineral-matter reference systems		Chinese Academy of Sciences	China
				Equivalent mineral-matter volume	Y. Chen	Hunan University of Science and Technology	China
				Reference systems		University of Chinese Academy of Sciences	China
				SOC comparability	L. Shi	Henan University	China
				Soil organic carbon	X. Wang	Qinghai University	China
				Soil volume change	Y. Liu	Peking University	China
				-	R. Mao	Jiangxi Agricultural University	China
				-	X. Rao	Chinese Academy of Sciences	China
				-	Y. Lin	Chinese Academy of Sciences	China
				-	Y. Shao	Henan University	China

				-		Chinese Academy of Sciences	China
				-	X. Li	Chinese Academy of Sciences	China
				-	C. Zhao	Henan University	China
				-	S. Liu	Chinese Academy of Sciences	China
				-	W. Zhu	The State University of New York	Estados Unidos
				-	X. Zou	University of Puerto Rico	Puerto Rico
				-	S. Fu	Henan University	China
				-		Chinese Academy of Sciences	China
17	SCOPUS	2021	Technology in Society	Artificial intelligence	V. Galaz	Royal Swedish Academy of Sciences	Sweden
				Climate change		Stockholm University	Sweden
				Sustainability	M. A. Centeno	Princeton University	Estados Unidos
				Systemic risks	P. W. Callahan	Princeton University	Estados Unidos
				Anthropocene	A. Causevic	Royal Swedish Academy of Sciences	Sweden
				Resilience		Stockhol Environment Institute	Sweden
				Social-ecological systems	T. Patterson	Princeton University	Estados Unidos
				Automation	I. Brass	University College London	United Kingdom
				Digitalization	S. Baum	Global Catastrophic Risk Institute	Estados Unidos
				-	D. Farber	Pennsylvania State University	Estados Unidos
				-	J. Fischer	Leuphana Universitaet Lueneburg	Germany
				-	D. Garcia	Medical University of Vienna	Austria
				-	T. McPhearson	Royal Swedish Academy of Sciences	Sweden
				-		Stockholm University	Sweden
				-		New School	Estados Unidos
				-		Cary Institute of Ecosystem Studies	Estados Unidos
				-	D. Jimenez	CGIAR Plataform of ig Data in Agriculture	Colombia
				-		Universidad Icesi	Colombia
				-	B. King	CGIAR Plataform of ig Data in Agriculture	Colombia
				-	P. Larcey	University of Cambridge	United Kingdom

				-	K. Levy	Cornell University	United Kingdom
18	SCOPUS	2019	Journal of global health	-	T. Panch	Harvard University	Estados Unidos
				-		Wellframe	Estados Unidos
				-	H. Mattie	Harvard University	Estados Unidos
				-	R. Atun	Harvard University	Estados Unidos
19	SCOPUS	2020	Artnodes	Art	M. Tromble	San Francisco Art Institute	Estados Unidos
				Artificial intelligence	-	-	-
				AI	-	-	-
				Embodiment	-	-	-
				Feelthink	-	-	-
				Metaphor	-	-	-
20	SCOPUS	2021	Future Internet	Gender bias	N. Alshareef	North Carolina A & T State University	Estados Unidos
				Presentation attack detection	X. Yuan	North Carolina A & T State University	Estados Unidos
				Debiasing variational autoencoder	K. Roy	North Carolina A & T State University	Estados Unidos
				Convolutional neural network	M. Atay	Wiston-Salem State University	Estados Unidos
21	SCOPUS	2020	Big Data & Society	Critical algorithm studies	P. Polack	University of California	Estados Unidos
				Predictive policing	-	-	-
				Design studies	-	-	-
				Algorithmic bias	-	-	-
				Algorithmic opacity	-	-	-
				Algorithmic accountability	-	-	-
22	SCOPUS	2021	JAMA Network Open	-	Y. Park	IBM Research	Estados Unidos
				-	J. Hu	IBM TJ Watson Research Center	Estados Unidos
				-	M. Singh	IBM TJ Watson Research Center	Estados Unidos

				-	I. Sylla	IBM Research	Estados Unidos
				-	I. Dankwa-Mullan	IBM Watson Health	Estados Unidos
				-	E. Koski	IBM TJ Watson Research Center	Estados Unidos
				-	A. K. Das	IBM Research	Estados Unidos
23	SCOPUS	2021	Tapuya: Latin American Science, Technology and Society	Algorithms	O. J. M. Castañeda	Universidad del Rosario	Colombia
				Cervical cancer	-	-	-
				Data practices	-	-	-
				Health economics	-	-	-
				HPV vaccines	-	-	-
				Algorithmic bias	-	-	-
				Markov chain Monte Carlo (MCMC)	-	-	-
24	SCOPUS	2021	AI & Society	Bias	M. Zajko	The University of British Columbia	Canada
				Inequality	-	-	-
				Sociology	-	-	-
				Fairness	-	-	-
				Politics	-	-	-
				Colonialism	-	-	-
25	SCOPUS	2021	Social Philosophy & Policy	Algorithmic filtering	K. Nader	University of Texas	Estados Unidos
				Algorithmic bias	-	-	-
				Collaborative filtering	-	-	-
				Ethics of dating	-	-	-
				Ethics of technology	-	-	-
26	SCOPUS	2020	Philosophy & Technology	Algorithmic bias	P.-H. Wong	Universität Hamburg	Germany
				Machine Learning	-	-	-
				Fairness	-	-	-

				Democratization	-	-	-
				Accountability for reasonableness	-	-	-
27	SCOPUS	2016	The astrophysical Journal	Planetary systems	L. Pueyo	Space Telescope Science Institute	Estados Unidos
				Techniques: image processing	-	-	-
28	SCOPUS	2019	Science	-	Z. Obermeyer	University of California	Estados Unidos
				-	B. Powers	Brigham and Women's Hospital	Estados Unidos
				-	C. Vogeli	Massachusetts General Hospital	Estados Unidos
				-	S. Mullainathan	University of Chicago	Estados Unidos
29	SCOPUS	2021	Physical Review E	-	A. F. Peralta	Central European University	Austria
				-	M. Neri	Complexity Science Hub	Austria
				-	J. Kertész	Aalto University School of Science	Finland
				-	G. Iñiguez	Universidad Nacional Autonóma de México	Mexico
30	SCOPUS	2021	Journal of Oral Biology and Craniofacial Research	Artificial intelligence	A. Kerasidou	University of Oxford	United Kingdom
				Global Health	-	-	-
				Lower-middle-income-countries (LMICS)	-	-	-
				Explainability	-	-	-
				Algorithmic bias	-	-	-
				Trust	-	-	-
31	SCOPUS	2021	Artificial Intelligence and Law	Criminal recidivism	M. Miron	European Commission's Joint Research Centre	Spain
				Machine learning	S. Tolan	European Commission's Joint Research Centre	Spain
				Algorithmic fairness	E. Gómez	European Commission's Joint Research Centre	Spain
				Risk assessment		Universitat Pompeu Fabra	Spain
				Criminal justice	C. Castillo	Universitat Pompeu Fabra	Spain
				Automated decision making	-	-	-

32	SCOPUS	2021	Proceedings of the ACM on Human-Computer Interaction	Human-centered computing	H. Shen	Carnegie Mellon University	EUA
				Human computer interaction (HCI)	A. DeVos	Carnegie Mellon University	EUA
				Empirical studies in HCI	M. Eslami	Carnegie Mellon University	EUA
				-	K. Holstein	Carnegie Mellon University	EUA
33	SCOPUS	2020	Plos One	-	W. Sun	University of Louisville	EUA
				-	O. Nasraoui	University of Louisville	EUA
				-	P. Shafto	Rutgers University	EUA
				-	-	-	-
				-	-	-	-
				-	-	-	-
34	SCOPUS	2020	International Journal of Medical Informatics	Misinformation	D. Abul-Fottouh	University of Toronto	Canada
				Disinformation	M. Y. Song	Ryerson University	Canada
				Vaccination	A. Gruzd	Ryerson University	Canada
				YouTube	-	-	-
				Network analysis	-	-	-
				Social med	-	-	-
				Recommender algorithm	-	-	-
35	SCOPUS	2021	Social Science Computer Review	Search engines	J. Unkel	LMU Munich	Germany
				Algorithmic bias	M. Haim	University of Stavanger	Norway
				Political information	-	-	-
				Elections	-	-	-
				Agent-based testing	-	-	-
36	SCOPUS	2021	Phylosophy of the Social Sciences	Economic design	P. van Basshuysen	Leibniz University Hannover	Germany
				Engineering	-	-	-

				Plumbing	-	-	-
				Normative modeling	-	-	-
				Algorithmic bias	-	-	-
				-	-	-	-
				-	-	-	-
				-	-	-	-
				-	-	-	-
37	SCOPUS	2020	International Journal of Intelligente Systems	Algorithmic bias	F. Martínez-Plumed	Joint Research Centre (European Commisision)	Spain
				Confirmation bias		Universitat Politècnica de València	Spain
				Data imputation	C. Ferri	Universitat Politècnica de València	Spain
				Fairness	D. Nieves	Universitat Politècnica de València	Spain
				Missing values	J. Hernández-Orallo	Universitat Politècnica de València	Spain
				Sample bias		Universit of Cambridge	United Kingdom
				Survey bias	-	-	-
38	SCOPUS	2021	Patterns				
39	SCOPUS	2012	BMC Research Notes	-	G. L. Rosen	Drexel University	USA
				-	T. Y. Lim	Drexel University	USA
40	SCOPUS	2020	Liber Quarterly	Digital humanities	T. Willaert	Universiteit Brussel	Belgium
				Data studies	G. Roumans	Faculty of Arts	Belgium
				Wikipedia	-	-	-
				Wikidata politics	-	-	-
41	SCOPUS	2020	Proceedings of the ACM on Human-	Decision-formation	K. Burghardt	USC Information Science Institute	USA
				Crowd-wisdom	T. Hogg	Institute for Molecular Manufacturing	USA

			Computer Interaction	Algorithmic instability	R. M. D'Souza	University of California	USA
				Algorithmic bias	K. Lerman	USC Information Science Institute	USA
				-	M. Pósfai	Central European University	Hungary
				-		University of California	USA
42	SCOPUS	2020	European Journal of Comparative Law and Governance	Privatization	S. Ranchordás	University of Groningen	Netherlands
				Social Welfare	Y. Schuurmans	Leiden University	Netherlands
				Algorithmic bias	-	-	-
				Data-driven decision-making	-	-	-
				Discrimination	-	-	-
				Surveillance	-	-	-
43	SCOPUS	2020	Online Social Networks and Media	Social media	O. Papakyriakopoulos	Technical University of Munich	Germany
				Political communication	J. C. M. Serrano	Technical University of Munich	Germany
				Hyperactive users	S. Hegelich	Technical University of Munich	Germany
				Recommendation systems	-	-	-
				Algorithmic bias	-	-	-
				Recommender systems	-	-	-
				Topic modeling	-	-	-
				Computational social science	-	-	-
				Political data science	-	-	-
				Agenda setting	-	-	-
44	SCOPUS	2020	Digital Medicine	-	J. K. Paulus	Tufts University	USA
				-	D. M. Kent	Tufts University	USA
45	SCOPUS	2019	EPJ Data Science	Computational social science	P. G. Fennell	University of South California	USA
				Empirical studies	Z. Zuo	University of South California	USA
				Online social networks		City University of Hong Kong	Hong Kong

				Human behavior	K. Lerman	University of South California	USA
				Feature selection	-	-	-
				-	-	-	-
				-	-	-	-
				-	-	-	-
				-	-	-	-
46	SCOPUS	2021	Collabra: Psychology	Emotions	C. Costello	University of Michigan	USA
				Social network analysis	S. Srivastava	University of Oregon	USA
				Online social networks	R. Rejaie	University of Oregon	USA
				Machine learning	M. Zalewski	University of Oregon	USA
				Data science	-	-	-
				Mental health	-	-	-
47	SCOPUS	2020	Journal of the American Society for Mass Spectrometry	PRESnovo	K. DeLaney	University of Wisconsin	USA
				de novo Sequencing	W. Cao	University of Wisconsin	USA
				Tandem mass spectrometry	Y. Ma	University of Wisconsin	USA
				Neuropeptide	M. Ma	University of Wisconsin	USA
				Peptide identification	Y. Zhang	University of Wisconsin	USA
				Motif	L. Li	University of Wisconsin	USA
48	SCOPUS	2019	Systematic and Applied Microbiology	Bacillales	P. De Maayer	University of the Witwatersrand	South Africa
				Lactobacillales	H. Aliyu	Karlsruhe Institute of Technology	Germany
				Bacillaceae	D. A. Cowan	University of Pretoria	South Africa
				Phylogenomics	-	-	-
				16S rRNA gene	-	-	-
				Core protein phylogeny	-	-	-
			Nature	-	C. Tannenbaum	Université de Montréal	Canada

49	SCOPUS	2019		-	R. P. Ellis	University of Exeter	United Kingdom
				-	F. Eyssel	Universität Bielefeld,	Germany
				-	J. Zou	Stanford University	USA
				-		Chan-Zuckerberg Biohub	USA
				-	L. Schiebinger	Stanford University	USA
50	SCOPUS	2020	Humanities & Social Sciences Communications	-	J. W. Rettberg	University of Bergen	Norway
				-	-	-	-
				-	-	-	-
				-	-	-	-
51	SCOPUS	2021	Acta Academica	Surveillance capitalism	Y. Jooste	University of Pretoria	South Africa
				Digital surveillance	-	-	-
				Racial surveillance capitalism	-	-	-
				Algorithmic bias	-	-	-
				Algorithmic colonisation	-	-	-
52	SCOPUS	2019	International Information & Library Review	Algorithmic bias	C. C. Gardner	California State University	USA
				Information literacy	-	-	-
				Evaluating information	-	-	-
				Academic libraries	-	-	-
53	SCOPUS	2018	Proceedings of the Association for Information Science and Technology	Algorithmic Bias	C. Wilkie	University of Glasgow	United Kingdom
				Information Retrieval	Leif Azzopardi	University of Strathclyde	United Kingdom
				Search Engine Bias	-	-	-
54	SCOPUS	2019	Information Sciences	Complex networks	S. Zhang	University of Electronic Science and Technology of China	China
				Ranking	M. Medo	University of Electronic Science and Technology of China	China
				Popularity and quality		University of Bern	Switzerland

				Popularity inequality		University of Fribourg	Switzerland
				Algorithmic bias	L. Lü	University of Electronic Science and Technology of China	China
				-		Hangzhou Normal University	China
				-	M. S. Mariani	University of Electronic Science and Technology of China	China
				-		Universität Zürich	Switzerland
55	SCOPUS	2020	Sustainability	Smart information System (SIS)	M. Ryan	KTH Royal Institute of Technology	Sweden
				Sustainable development goals (SDGs)	J. Antoniou	UCLan Cyprus	Cyprus
				Ethics	L. Brooks	De Montfort University	United Kingdom
				Case studies	T. Jiya	University of Northampton	United Kingdom
				Impact	K. Macnish	The University of Twente	Netherlands
				-	B. Stahl	De Montfort University	United Kingdom
56	SCOPUS	2020	Frontiers in Psychology	Learning machine	M. Boman	KTH Royal Institute of Technology	Sweden
				Machine learning	J. Downs	King's College London	United Kingdom
				Multi-modal learning	A. Karali	KTH Royal Institute of Technology	Sweden
				Mental health		NVIDIA Corporation	United Kingdom
				Maternal unresponsiveness	S. Pawlby	Bethlem Royal Hospital	United Kingdom
				Mind-mindedness		Maudsley National Health Service Trust	United Kingdom
57	SCOPUS	2021	Medicine, Health Care and Philosophy	Artificial intelligence	G. Starke	University of Basel	Switzerland
				Machine learning	E. De Clercq	University of Basel	Switzerland
				Pragmatism	B. S. Elger	University of Basel	Switzerland
				Philosophy of Science		University of Geneva	Switzerland
				Algorithmic bias	-	-	-
				Fairness	-	-	-
58	SCOPUS	2020	Frontiers in Artificial Intelligence	Algorithmic bias	T. Kehrenberg	University of Sussex	United Kingdom
				Fairness	Z. Chen	University of Sussex	United Kingdom

				Machine learning	N. Quadrianto	University of Sussex	United Kingdom
				Demographic parity		National Research University Higher School of Sconomics	Russia
				Equality of opportunity	-	-	-
				-	-	-	-
				-	-	-	-
				-	-	-	-
59	SCOPUS	2019	Journal of Management and Governance	Artificial intelligence (AI)	T. Bolander	Technical University of Denmark	Denmark
				Connectionist AI	-	-	-
				Symbolic AI	-	-	-
				Explainability	-	-	-
				Trust	-	-	-
				Algorithmic bias	-	-	-
				Algorithmic decision making	-	-	-
				Human decision making	-	-	-
60	SCOPUS	2020	Plos One	-	D. Rozado	Otago Polytechnic	New Zealand
				-	-	-	-
				-	-	-	-
				-	-	-	-
				-	-	-	-
				-	-	-	-
61	SCOPUS	2021	Communications of the ACM	-	K. Sakaguchi	Allen Institute for AI	USA
				-	R. L. Bras	Allen Institute for AI	USA
				-	C. Bhagavatula	Allen Institute for AI	USA
				-	Y. Choi	University of Washington	USA
				-		Allen Institute for AI	USA

62	WoS	2020	Revista Tecnologia e Sociedade	Algoritmos	L. G. B. Schuler	Universidade Feevale	Brasil
				Plataformas digitais	S. P. Montardo	Universidade Feevale	Brasil
				Viés algoritmico	-	-	-
				Preconceito	-	-	-
63	WoS	2021	Journal of Global Information Management	AI Ethics	S. Akter	University of Wollongong	Australia
				Algorithm Bias	Y. K. Dwivedi	Swansea University	United Kingdom
				Artificial intelligence	K. Biswas	University of Wollongong	Australia
				Machine Learning	K. Michael	Arizona State University	USA
				Responsible AI	R. J. Bandara	University of Wollongong	Australia
				-	S. Sajib	University of Technology Sydney	Australia
64	WoS	2021	Patterns	Artificial intelligence	N. Norori	University of Bern	Switzerland
				Deep learning		University of Bristol	United Kingdom
				Health care	Q. Hu	University of Bern	Switzerland
				Bias	F. M. Aellen	University of Bern	Switzerland
				Open science	F. D. Faraci	University of Applied Sciences and Arts of Southern Switzerland	Switzerland
				Participatory science	A. Tzovara	University of Bern	Switzerland
				Data standards		University of California	USA
65	WoS	2020	Artnodes	Artificial intelligence	R. West	University of North Texas	USA
				Machine learning: AI	A. Burbano	Universidad de los Andes	Colombia
				ML	-	-	-
				Arts	-	-	-
				Design	-	-	-
66	WoS	2021	Human Behavior and Emerging Technologies	AI	S. Yan	Beaver Country Day School	USA
				Algorithmic bias	-	-	-
				Cognitive bias	-	-	-

				Facial recognition	-	-	-
				Feedback	-	-	-
				Social influence	-	-	-
				Prejudice	-	-	-
				Technology use	-	-	-
67	WoS	2020	Journal of Medical Humanities	Digital health	K. Ostherr	Rice University	USA
				Natural language processing	-	-	-
				Narrative medicine	-	-	-
				Social determinants of health	-	-	-
				Health technology	-	-	-
				Big data	-	-	-
68	WoS	2019	Journal of Medical Internet Research	Artificial intelligence	J. Shaw	Institute for Health System Solutions and Virtual Care	Canada
				Machine learning		University of Toronto	Canada
				Implementation science	F. Rudzics	St Mhicael's Hospital	Canada
				Ethics	T. Jamieson	Institute for Health System Solutions and Virtual Care	Canada
				-		St Mhicael's Hospital	Canada
				-	A. Goldfarb	University of Toronto	Canada
69	WoS	2021	Jama Network Open	-	J. Coquet	Stanford University School of Medicine	USA
				-	N. Bievre	Stanford University	USA
				-	V. Billaut	Stanford University	USA
				-	M. Seneviratne	Stanford University School of Medicine	USA
				-		Stanford University	USA
				-	C. J. Magnani	Stanford University School of Medicine	USA
				-	S. Bozkurt	Stanford University School of Medicine	USA
				-	J. D. Brooks	Stanford University School of Medicine	USA
				-	T. Henandez-Boussard	Stanford University School of Medicine	USA

70	WoS	2021	AI & Society	Automated management	P. Mantello	Ritsumeikan Asia Pacific University	Japan
				Emotional AI	Manh-Tung Ho	Ritsumeikan Asia Pacific University	Japan
				Bayesian analysis		Phenikaa University	Vietnam
				Cross-cultural perception	Minh-Hoang Nguyen	Phenikaa University	Vietnam
				-	Quan-Hoang Vuong	Phenikaa University	Vietnam
71	WoS	2021	Information, Communication & Society	Search engines	D. Kravets	University of Passau	Germany
				Algorithmic bias	F. Toepfl	University of Passau	Germany
				Google	-	-	-
				Yandex	-	-	-
				Russia	-	-	-
				Protest	-	-	-
				Authoritarianism	-	-	-
72	WoS	2019	BMC Medicine	-	C. J. Kelly	Google Health	United Kingdom
				-	A. Karthikesalingam	Google Health	United Kingdom
				-	M. Suleyman	DeepMind	United Kingdom
				-	G. Corrado	Google Health	USA
				-	D. King	Google Health	United Kingdom
73	WoS	2021	AI & Society	Political machines	O. Papakyriakopoulos	Princeton University	USA
				Social machines	-	-	-
				Sociotechnical systems	-	-	-
				Algorithmic bias	-	-	-
				Tech policy	-	-	-
				Cybernetics	-	-	-
				Artificial intelligence	-	-	-
				Design	-	-	-

				Algorithms	-	-	-
74	WoS	2021	Information Systems Frontier	Artificial intelligence	M. Gupta	Florida International University	USA
				Recommender systems	C. M. Parra	Florida International University	USA
				Culture	D. Dennehy	NUI Galway	Ireland
				Racial bias	-	-	-
				Gender bias	-	-	-
				Responsible AI	-	-	-
				Algorithmic bias	-	-	-
				Ethical AI	-	-	-
75	WoS	2019	Humanities	Participation	A. Mihai	University of Bucharest	Romania
				Shakespeare online	-	-	-
				Field of cultural production	-	-	-
				Youtube	-	-	-
				Romanian users	-	-	-
				Local	-	-	-
76	WoS	2020	Journal of Evaluation in Clinical Practice	Algorithmic bias	K. Begley	Trinity College Dublin	Ireland
				Artificial intelligence	C. Begley	Trinity College Dublin	Ireland
				Duty of care	V. Smith	Trinity College Dublin	Ireland
				Electronic fetal monitoring	-	-	-
				Epistemic defeaters	-	-	-
				Shared decision-making	-	-	-
77	WoS	2020	JAMIA	Behavioral health	C. G. Walsh	Vanderbilt University Medical Center,	USA
				Ethics	B. Chaudhry	University of Louisiana at Lafayette,	USA
				Predictive modeling	P. Dua	Louisiana Tech University,	USA
				Artificial intelligence	K. W. Goodman	University of Miami,	USA

				Precision medicine	B. Kaplan	Yale University	USA
				Health disparities algorithms	R. Kavuluru	University of Kentucky	USA
				Mental health	A. Solomonides	NorthShore University HealthSystem	USA
				-	V. Subbian	University of Arizona	USA
78	WoS	2021	Personal and Ubiquitous Computing	Artificial intelligence	S. Borsci	University of Twente	Netherlands
				AI		Imperial College of London	United Kingdom
				Chatbots	A. Malizia	University of Pisa	Italy
				Conversational agents		Molde University	Norway
				Interaction satisfaction	M. Schmettow	University of Twente	Netherlands
				Usability	F. vander Velde	University of Twente	Netherlands
				User experience	G. Tariverdiyeva	Backbase	Netherlands
				Human-Computer interaction (HCI)	D. Balaji	University of Amsterdam	Netherlands
				Evaluation	A. Chamberlain	University of Nottingham	United Kingdom
				Autonomy	-	-	-
				Design	-	-	-
				Satisfaction	-	-	-
				Trust	-	-	-
79	WoS	2021	Feminist media studies	Shadowban	C. Are	University of London	United Kingdom
				Instagram	-	-	-
				Algorithm bias	-	-	-
				Pole dance	-	-	-
				Digital activism	-	-	-
				-	-	-	-
				-	-	-	-

APÊNDICE B: Corpus preliminar obtido a partir do termo "*Algorithmic discrimination*"

N	Base	Nome	Ano	Revista	Palavras-chave	Autores	Filiação	País
80	SCOPUS	Algorithmic accountability and digital justice: a critical assessment of technical and sociotechnical approaches	2019	Proceedings of the Association for Information Science and Technology	Algorithmic accountability	H. Rosenbaum	Indiana University	USA
					Digital justice	P. Fichman	Indiana University	USA
					-	-	-	-
					-	-	-	-
					-	-	-	-
					-	-	-	-
81	SCOPUS	Data Science as Machinic Neoplatonism	2017	Philosophy & Technology	Machine Learning	D. McQuillan	University of London	United Kingdom
					Algorithms	-	-	-
					Data Science	-	-	-
					Counterculture	-	-	-
					Standpoint theory	-	-	-
					Agential realism	-	-	-
					Neo-platonism	-	-	-
					Biga data	-	-	-
					Participation	-	-	-
					Agency	-	-	-
82	SCOPUS	Decentering technology in discourse on discrimination	2019	Information, Communication & Society	Big data	S. P. Gangadharan	London School of Economics and Political Science	United Kingdom
					Surveillance/privacy	J. Niklas	London School of Economics and Political Science	United Kingdom
					Algorithms	-	-	-
					Civil society	-	-	-
					Discrimination	-	-	-
					Justice	-	-	-
83	SCOPUS	La discriminación em uma	2021	Revista Chilena de	Principio de igualdad	C. M. Gutiérrez	Independente	Chile
					Discriminación	-	-	-

		sociedad automatizada: Contribuciones desde América Latina		Derecho y Tecnología	Inteligencia artificial	-	-	-
					América Latina	-	-	-
					Toma de decisiones automatizadas	-	-	-
84	SCOPUS	Exposing the probabilistic causal structure of discrimination	2017	International Journal of Data Science and Analytics	Discrimination discovery	F. Bonchi	ISI Foundation	Italy
					Algorithmic discrimination	S. Hajian	Eurecat-Technology Centre of Catalonia	Spain
					Probabilistic causation	B. Mishra	New York University	USA
					Constrained Bayesian network	D. Ramazzotti	Milano-Bicocca University	Italy
					Random Walks	-	-	-
85	SCOPUS	Framework for developing algorithmic fairness	2020	Bulletin of Electrical Engineering and Informatics	Algorithmic discrimination	D. P. Kristiadi	Raharja University	Indonesia
					Fair algorithmic	P. A. Sunarya	Raharja University	Indonesia
					Fairness in algorithm	M. Ismanto	Bina Nusantara University	Indonesia
					Fairness pattern	J. Dylan	Bina Nusantara University	Indonesia
					-	I. R. Santoso	Bina Nusantara University	Indonesia
					-	H. L. H. S. Warnars	Bina Nusantara University	Indonesia
86	SCOPUS	Investigatin bias in facial analysis systems: a systematic review	2020	IEEE Access	Algorithmic discrimination	A. Khalil	Abu Dhabi University	United Ara Emirates
					Classification bias	S. G. Ahmed	Abu Dhabi University	United Ara Emirates
					Facial analysis	A. M. Khattak	Zayed University	United Ara Emirates
					Bias	N. Al-Qirim	College of Information Technology	United Ara Emirates
					Unfariness	-	-	-
87	SCOPUS	Outside in: exile at home. Na algorithmic discrimination system	2020	Artnodes	Machine learning	A. Castro	Universidad Autónoma Metropolitana	Mexico
					Decision systems	-	-	-
					Algorithmic video editing	-	-	-
					Mexican citizenship during WWII	-	-	-
					Identity	-	-	-
					Territory	-	-	-

88	SCOPUS	SensitiveNets: Learning agnostic representations with application to face images	2021	IEEE Transactions on Pattern Analysis and Machine Intelligence	Face recognition	A. Morales	Universidad Autonoma de Madrid	Spain
					Face analysis	J. Fierrez	Universidad Autonoma de Madrid	Spain
					Biometrics	R. Vera-Rodriguez	Universidad Autonoma de Madrid	Spain
					Deep learning	R. Rolosana	Universidad Autonoma de Madrid	Spain
					Agnostic	-	-	-
					Algorithmic discrimination	-	-	-
					Bias	-	-	-
					Privacy	-	-	-
89	SCOPUS	Strengthening legal protection against discrimination by algorithms and artificial intelligence	2020	The International Journal of Human Rights	Artificial intelligence	F. J. Z. Borgesius	Radboud University	Netherlands
					Machine learning	-	-	-
					Algorithm	-	-	-
					GDPR	-	-	-
					Data protection law	-	-	-
					Discrimination	-	-	-
90	SCOPUS	Tuning EU equality law to algorithmic discrimination: Three pathways to resilience	2020	Maastricht Journal of European and Comparative Law	Algorithmic discrimination	R. Xenidis	Copenhagen University	Dinamarca
					Non-discrimination law	-	-	-
					Equality	-	-	-
					Algorithms	-	-	-
					Machine learning	-	-	-
					Artificial intelligence	-	-	-
					Profiling	-	-	-
					Predictive analytics	-	-	-
					European Union	-	-	-
					Legal resilience	-	-	-
91	SCOPUS		2021		Machine Learning	Q. Wang	Hong Kong University of Science and Technology	Hong Kong

		Visual analysis of discrimination in machine learning		IEEE Transactions on visualization and computer graphics	Discrimination	Z. Xu	Hong Kong University of Science and Technology	Hong Kong
					Data visualization	Z. Chen	Hong Kong University of Science and Technology	Hong Kong
					-	Y. Wang	Hong Kong University of Science and Technology	Hong Kong
					-	S. Liu	Tsinghua University	China
					-	H. Qu	Hong Kong University of Science and Technology	Hong Kong
92	WoS	A survey on neural network interpretability	2021	IEEE Transactions on Emerging topics in Computational Intelligence	Machine learning	Y. Zhang	Southern University of Science and Technology	China
					Neural networks	P. Tino	University of Birmingham	United Kingdom
					Interpretability	A. Leonardis	University of Birmingham	United Kingdom
					Survey	K. Tang	Southern University of Science and Technology	China
93	WoS	Fairness in Deep Learning: A computational perspective	2020	IEEE Intelligent Systems	Predictive models	M. Du	Texas A&M University	USA
					Deep learning	F. Yang	Texas A&M University	USA
					Modeling	N. Zou	Texas A&M University	USA
					Measurement	X. Hu	Texas A&M University	USA
					Face recognition	-	-	-
					Neurons	-	-	-
94	WoS	How algorithms discriminate based on data they lack: challenges, solutions, and policy implications	2018	Journal of Information Policy	Algorithmic discrimination	B. A. Williams	University of Arizona	USA
					Statistical discrimination	C. F. Brooks	University of Arizona	USA
					Signaling	Y. Shmargad	University of Arizona	USA
					Omitted variables	-	-	-
					Personal data	-	-	-

APÊNDICE C: Corpus preliminar obtido a partir do termo "*Data discrimination*"

N°	Origem	Nome	Ano	Revista	Palavras-chave	Autores	Filiação	País
95	SCOPUS	A closed-form neural network for discriminatory feature extraction from high-dimensional data	2001	Neural networks	Dimensionality reduction	A. Talukder	California Institute of Technology	USA
					Discrimination	D. Casasent	Carnegie Mellon University	USA
					Feature extraction (nonlinear)	-	-	-
					Neural networks	-	-	-
					Nonlinear transform	-	-	-
					Pattern recognition	-	-	-
96	SCOPUS	A Factor-Graph-Based TOA Location Estimator	2012	IEEE Transactions on Wireless Communications	TOA	H. Jhi	Minghsin University of Science and Technology	Taiwan
					Location tracking	J. Chen	National Kaohsiung Normal University	Taiwan
					Kalman filter	C. Lin	Kun Shan University	Taiwan
					Extended Kalman filter	C. Huang	Minghsin University of Science and Technology	Taiwan
					Factor graph	-	-	-
					Soft-information	-	-	-
					Sum-product algorithm	-	-	-
					Data screening	-	-	-
					Data discrimination	-	-	-
97	SCOPUS	A pseudo-nearest-neighbor approach for missing data recovery on Gaussian random data sets	2002	Pattern Recognition Letters	Missing data	X. Huang	University of Nebraska at Omaha	USA
					Missing data recovery	Q. Zhu	University of Nebraska at Omaha	USA
					Data imputation	-	-	-
					Data clustering	-	-	-
					Gaussian data distribution	-	-	-
					Data mining	-	-	-
					-	-	-	-

					-	-	-	-
					-	-	-	-
98	SCOPUS	A Risk-Based Measure of Time-Varying Prognostic Discrimination for Survival Models	2017	Biometrics	Biomakers	C. J. Liang	University of Washington	USA
					Cox regression	P. J. Heagerty	University of Washington	USA
					Discrimination	-	-	-
					Longitudinal analysis	-	-	-
					Predictive accuracy	-	-	-
					Survival	-	-	-
99	SCOPUS	A speaker verification backend with robust performance accross conditions	2022	Computer Speech & Language	Speaker verification	L. Ferrer	Instituto de Investigación em Ciencias de la Computación	Argentina
					Probabilistic linear discriminant analysis	M. McLaren	Speech Technology and Research Lab	USA
					Robust calibration	N. Brümmer	Omilia Conversational Intelligence	Greece
					-	-	-	-
100	SCOPUS	Acoustic and reservoir properties of microporous carbonate rocks: Implication of micrite particle size and morphology	2014	JGR Solid Earth	-	J. B. Regnet	Université de Cergy-Pontoise	France
					-	P. Robion	Université de Cergy-Pontoise	France
					-	C. David	Université de Cergy-Pontoise	France
					-	J. Fortin	Laboratoire de Géologie de l'Ecole Normale Supérieure	France
					-	B. Brigaud	Université Paris Sud	France
					-	B. Yven	-	France
101	SCOPUS	A framework for unsupervised change	2017	International Journal of Pervasive	Activity recognition	S. A. Bashir	Robert Gordon University	United Kingdom

		detection in activity recognition		Computing and Communications				
					Change detection		Federal University of Technology Minna	Nigeria
					Concept drift	A. Petrovski	Robert Gordon University	United Kingdom
					Machine Learning	D. Doolan	Birmigham City University	United Kingdom
					Model Adaptation	-	-	-
102	SCOPUS	A Machine Learning and Cross-Validation Approach for the Discrimination of Vegetation Physiognomic Types Using Satellite Based Multispectral and Multitemporal data	2017	Scientifica	-	R. C. Sharma	Tokyo University of Information Sciences	Japan
					-	K. Hara	Tokyo University of Information Sciences	Japan
					-	H. Hirayama	Tokyo University of Information Sciences	Japan
103	SCOPUS	Analysis of distribution disturbances and arcing faults using the crest factor	1995	Eletric Power Systems Research	Fault analysis	C. J. Kim	The University of Swam	South Korea
					Arcing faults	B. D. Russell	Texas A&M University	USA
					Waveform distortion	-	-	-
					Crest factor	-	-	-
104	SCOPUS	An efficient discrimination prevention and rule protection algorithms avoid direct and indirect data discrimination in web mining	2018	International Journal of Intelligent Engineering & Systems	Discrimination	M. C. Babu	St. Peter's Institute of Higher Education and Research	India
					Anti-discrimination	S. Pushpa	St. Peter's Institute of Higher Education and Research	India
					Rule protection	-	-	-
					Rule generation	-	-	-
					Support	-	-	-
					Confidence	-	-	-

105	SCOPUS	Na evaluation of the rate constants for the adsorption of the defective phage PBS Z to Bacillus subtilis	1982	-				
106	SCOPUS	Approximate empirical kernel map-based iterative extreme learning machine for clustering	2020	Neural Computing and Applications	Maximum margin clustering	C. Chen	University of Macau	China
					Extreme learning machine	C. Vong	University of Macau	China
					Approximate empirical kernel map	P. Wong	University of Macau	China
					Kernel learning	K. Tai	University of Macau	China
					Compact model	-	-	-
107	SCOPUS	A proposal of quantum data representation to improve the discrimination power	2019	Natural Computing	Quantum representation	R. B. de Souza	Universidade Federal do Cariri	Brazil
					Data discrimination power	E. J. S. Pereira	Universidade Federal Rural de Pernambuco	Brazil
					Machine learning	M. P. Cipolletti	Universidad Nacional Del Sur	Argentina
					Preprocessing data	T. A. E. Ferreira	Universidade Federal Rural de Pernambuco	Brazil
					Classification	-	-	-
108	SCOPUS	Architectural analysis of oral cancer, dysplastic, and normal epithelia	2004	Cytometry Part A	Epithelium	G. Landini	The University of Birmingham	United Kingdom
					Image analysis	I. E. Othman	The University of Birmingham	United Kingdom
					Cancer	-	-	-
					Precancer	-	-	-
					Architecture	-	-	-
					Graph theory	-	-	-
109	SCOPUS	Ares spectrometer	1986					

110	SCOPUS	A signal detection theory analysis of a category judment experiment	1970	Perception & Psychophysics	-	E. F. Shipley	University of Pennsylvania	USA
					-	-	-	-
					-	-	-	-
					-	-	-	-
111	SCOPUS	Avian colour vision: effects of variation in receptor sensitivity and noise data on model predictions as compared to behavioural results	2009	Vision Research	O. Lind	Lund University	Sweden	
					A. Kelber	Lund University	Sweden	
					-	-	-	
					-	-	-	
112	SCOPUS	Binary sequence matching system based on cross-phase modulation and four-wave mixing in highly nonlinear fibers	2020	Optical Engineering	Photonic firewall	Y. Liu	Beijing University of Posts and Tellecommunications	China
					Sequence matching	X. Li	Beijing University of Posts and Tellecommunications	China
					Cross-phase modulation	Y. Tang	Beijing University of Posts and Tellecommunications	China
					Four-wave mixing	Z. Shi	Beijing University of Posts and Tellecommunications	China
					Highly nonlinear fiber	S. Huang	Beijing University of Posts and Tellecommunications	China
113	SCOPUS	Chunking for massive nonlinear kernel classification	2008	Optimization Methods and Software	Classification	O. L. Mangasarian	University of Wisconsin	EUA
					Nonlinear kernel	M. E. Thompson	University of Wisconsin	EUA
					Massive datasets	-	-	-
					Linear programming	-	-	-
					Dual penalty	-	-	-

114	SCOPUS	Classification with discrete and continuous variables via general mixed-data models	2011	Journal of Applied Statistics	Error rate	A. R. de Leon	University of Calgary	Canada
					General location model	A. Soo	University of Calgary	Canada
					Grouped continuous model	T. Williamson	University of Calgary	Canada
					Maximum likelihood	-	-	-
					Measurement level	-	-	-
					Minimum distance probability	-	-	-
					Misclassification probability	-	-	-
					Plug-in estimates	-	-	-
115	SCOPUS	Composite-Graph-Based sparse subspace clustering for machine fault diagnosis	2020	IEEE Transactions on Instrumentation and Measurement	Blocky-diagonal constraint	C. Sun	Xi'na Jiaotong University	China
					Composite graph	X. Chen	Xi'na Jiaotong University	China
					Machine fault diagnosis	R. Yan	Xi'na Jiaotong University	China
					Sparse subspace clustering (SSC)	R. X. Gao	Case Western Reserve University	USA
116	SCOPUS	Contrast Driven Elastica for Image Segmentation	2016	IEEE Transactions on Image Processing	Euler elastica	N. Y. El-Zehiry	Siemens Healthcare	USA
					Weighted curvature	L. Grady	HeartFlow Inc.	USA
					Combinatorial optimization		Siemens	USA
					Primal formulation	-	-	-
					Image segmentation	-	-	-
117	SCOPUS	Cross-National validation of prognostic models predicting sickness absence and the added value of work environment variables	2014	Journal of Occupational Rehabilitation	Absenteeism	C. A. M. Roelen	ArboNed Occupational Health Service	Netherlands
					Decision support techniques		VU University Medical Center	Netherlands
					Health care sector		University of Groningen	Netherlands
					Reproducibility of results	C. M. Stapelfeldt	Public Health and Quality Improvement	Denmark

					Sick leave	C. V. Nielsen	Aarhus University	Denmark
					Workload	C. Jensen	Norwegian University of Science and Technology	Norway
118	SCOPUS	Determination of kinetic parameters from chemical relaxation data: discrimination between coupled two-step binding reactions differing in stoichiometry	1994	European Biophysics Journal	Chemical relaxation	C. Bremer	Max-Planck-Institut fiir Biophysik	Germany
					Relaxation kinetics	E. Grell	Max-Planck-Institut fiir Biophysik	Germany
					Two-step binding reactions	-	-	-
					Relaxation times	-	-	-
					Kinetic parameters	-	-	-
119	SCOPUS	Discovering all associations in discrete data using frequent minimally infrequent attribute sets	2012	Discrete Applied Mathematics	Data discrimination	E. Eisenschmidt	Universität Magdeburg	Germany
					Frequent sets	U. Haus	Institute for Operations Research	Switzerland
					Boolean functions	-	-	-
					Systems biology	-	-	-
120	SCOPUS	Discrimination ability of time-domain feature and rules for arrhythmia classification	2012	Mathematical and Computational Applications	Arrhythmia	U. Arikan	Boğaziçi University	Turkey
					ECG	F. Gürgen	Boğaziçi University	Turkey
					Rule extraction	-	-	-
					Hot spot algorithm	-	-	-
					Classification	-	-	-
					Naive Bayes	-	-	-
					C4.5	-	-	-
					Multilayer perceptron (MLP) and support vector machines (SVM)	-	-	-

121	SCOPUS	Discrimination of vegetation types in alpine sites with ALOS Palsar-, RADARSAT-2-, and lidar-derived information	2013	International Journal of Remote Sensing	-	G. V. Laurin	Tor Vergata University of Rome	Italy
					-		Euro- Mediterranean Center for Climate Change	Italy
					-	F. D. Frate	Tor Vergata University of Rome	Italy
					-	L. Pasolli	EURAC Research Institute for Applied Remote Sensing	Italy
					-	C. Notarnicola	EURAC Research Institute for Applied Remote Sensing	Italy
					-	L. Guerriero	Tor Vergata University of Rome	Italy
					-	R. Valentini	University of Tuscia	Italy
					-		Euro- Mediterranean Center for Climate Change	Italy
122	SCOPUS	Discriminative clustering via extreme learning machine	2015	Neural networks	Discriminative clustering	G. Huang	Tsinghua university	China
					Extreme learning machine	T. Liu	Nanyang Technological University	Singapore
					K-means	Y. Yang	Nanyang Technological University	Singapore
					Linear discriminant analysis	Z. Lin	Nanyang Technological University	Singapore
					-	S. Song	Tsinghua university	China
					-	C. Wu	Tsinghua university	China
123	SCOPUS	Dynamic contrast-enhanced MRI of synovitis in knee osteoarthritis: repeatability, discrimination and sensitivity to change in a prospective experimental study	2021	European Radiology	-	J. W. MacKay	University of Cambridge	UK
					-	F. S. Nezhad	Bioxydyn Limited	UK
					-	T. Rifai	Norfolk & Norwich University Hospital	UK
					-	J. D. Kaggie	University of Cambridge	UK
					-	J. H. Naish	Bioxydyn Limited	UK

					-	C. Roberts	Bioxydyn Limited	UK
					-	M. J. Graves	University of Cambridge	UK
					-	J. C. Waterton	University of Manchester	UK
					-	R. L. Janiczek	GlaxoSmithKline	UK
					-	A. R. Roberts	GlaxoSmithKline	UK
					-		Antaros Medical	Sweden
					-	A. McCaskie	University of Cambridge	UK
					-	F. J. Gilbert	University of Cambridge	UK
					-	G. J. M. Parker	University College London	Uk
124	SCOPUS	Electrochemical product detection of na asymmetric convective polymerase chain reaction	2009	Biosensors and Bioelectronics	Heated platinum wire	H. Duwensee	University of Rostock	Germany
					Asymmetric thermo-convective PCR	M. Mix	University of Rostock	Germany
					Thermal simulation	M. Stubbe	University of Rostock	Germany
					Fluid flow simulation	J. Gimsa	University of Rostock	Germany
					Osmium tetroxide bipyridine	M. Adler	Research Institute for the Biology of Farm Animals	Germany
					Voltammetric hybridization detection	G. Flechsig	University of Rostock	Germany
125	SCOPUS	ESR Dosimetry of Irradiated Ascorbic Acid	1997	Pharmaceutical Research	Radiosterilization	J. P. Basly	UFR de Pharmacie	France
					ascorbic acid	I. Longy	UFR de Pharmacie	France
					ESR	M. Bernard	UFR de Pharmacie	France
					Dosimetry	-	-	-
					Decay of radicals	-	-	-
126	SCOPUS	Extensible pattern matching via a lightweight language extension						

127	SCOPUS	Extensions of LDA by PCA misture model and class-wise features	2003	Pattern Recognition				
128	SCOPUS	Facilitated Gate setting by sequential dot plot scanning	2015	Cytometry Part A				
129	SCOPUS	Who Global Report on Falls Prevention in Older Age	2007	excluído (formato do documento não corresponde a um artigo científico, é um relatório)				
130	SCOPUS	Fast on-line speech/voiceband-data discrimination for statistical multiplexing of data with telephone conversations	1986	IEEE Transactions on communications	Telephony	C. Roberge	University of Sherbrooke	Canada
					Speech processing	J.-P. Adoul	University of Sherbrooke	Canada
					Baseband	-	-	-
					Speech recognition	-	-	-
					Signal processing	-	-	-
					Pattern classification	-	-	-
					Data mining	-	-	-
					Phase change materials	-	-	-
					Event detection	-	-	-
					Modems	-	-	-
131	SCOPUS	Generalized orthogonal locality preserving projections for nonlinear fault detection and diagnosis	2009	Chemometrics and intelligent laboratory systems	Fault detection	J.-D. Shao	Zhejiang University	China
					Fault diagnosis	G. Rong	Zhejiang University	China
					Nonlinear dimensionality reduction	J. M. Lee	University of Alberta	Canada
					Structure preserving	-	-	-
					Kernel methods	-	-	-

132	SCOPUS	Global burned-land estimation in Latin America using modis composite data	2008	Ecological Applications	Biomass burning	E. Chuvieco	Universidad de Alcalá	Spain
					Burn area index	S. Opazo	Universidad de Alcalá	Chile
					Brun scars	W. Sione	Universidad de Luján	Argentina
					Burned area		Universidad de Entre Rios	Argentina
					Forest fires	H. del Valle	Centro Nacional Patagónico	Argentina
					Latin America		Comisión Nacional de Ciencia y Tecnología	Argentina
					MODIS	J. Anaya	Universidad de Medellín	Colombia
					Normalized burn ratio	C. Di Bella	Instituto de Clima y Agua	Argentina
					Remote sensing	I. Cruz	Comisión Nacional para el Conocimiento y Uso de la Biodiversidad	Mexico
					-	L. Manzo	Universidad Nacional Autónoma de México	Mexico
					-	G. López	Comisión Nacional para el Conocimiento y Uso de la Biodiversidad	Mexico
					-	N. Mari	Instituto de Clima y Agua	Argentina
					-	F. González-Alonso	Centro de Investigación Forestal	Spain
					-	F. Morelli	Instituto Nacional de Pesquisas Espacias	Brazil
					-	A. Setzer	Instituto Nacional de Pesquisas Espacias	Brazil
					-	I. Csiszar	University of Maryland	USA
					-	J. Kanpandegi	Instituto de Clima y Agua	Argentina
					-	A. Bastarrika	Universidad del País Vasco	Spain
					-	R. Libonati	Instituto Nacional de Pesquisas Espacias	Brazil
133	SCOPUS	High-Gain Digital Speech Interpolation with Adaptive differential PCM Encoding	1982	IEEE Transactions on communications	Speech	Y. Yatsuzuka	Kokusai Denshin Denwa Company Limited	Japan
					Interpolation		COMSAT Laboratories	USA
					Phase change materials	-	-	-

					Encoding	-	-	-
					Sampling methods	-	-	-
					Detectors	-	-	-
					Signal detection	-	-	-
					Time measurement	-	-	-
					Satellites	-	-	-
					Frequency conversion	-	-	-
134	SCOPUS	High-performance liquid chromatographic-mass spectrometric determination of methamphetamine and amphetamine enantiomers, desmethylselegiline and selegiline, in hair samples of long-term methamphetamine abusers or selegiline users	2006	Journal of Analytical Toxicology	-	K. Nishida	Criminal Investigation Laboratory	Japan
					-	S. Itoh	Criminal Investigation Laboratory	Japan
					-	N. Inoue	Asaki Hospital	Japan
					-	K. Kudo	Kyushu University	Japan
					-	N. Ikeda	Kyushu University	Japan
135	SCOPUS	Hydrodesulphurization of Thiophene Over a NiO-MoO3-Al2O3 Catalyst	1978	The Canadian Journal of Chemical Engineering				
136	SCOPUS	Influence of radiation treatment on dobutamine	1998	International Journal of Pharmaceutics	Dobutamine	J. P. Basly	Laboratoire de Chimie Analytique et Bromatologie	France
					ESR	I. Basly	Laboratoire de Chimie Analytique et Bromatologie	France
					Dosimetry	M. Bernard	Laboratoire de Biophysique Pharmaceutique	France
					Decay of radicals	-	-	-
					Nonhomogeneous kinetics	-	-	-

137	SCOPUS	Intensity mapping curve to diminish the effects of illumination variations	2016	Signal, Image and Video Processing	Illumination variation	M. Ezoji	Babol University of Technology	Iran
					Intensity mapping	K. Faez	Amirkabir University of Technology	Iran
138	SCOPUS	Investigating pre-analytical requirements for serum and plasma based infrared spectro-diagnostic	2019	Journal of Biophotonics	Biofluids	L. Lovergne	Université de Reims	France
					FTIR spectroscopy		University of Strathclyde	UK
					Plasma	J. Lovergne	University of Strathclyde	UK
					Pre-analytical requirements	P. Bouzy	Université de Reims	France
					Standardisation	V. Untereiner	Université de Reims	France
					Serum	M. Offroy	Université de Reims	France
					Water	R. Garnotel	Université de Reims	France
					Interference correction		CHU de Reims	France
					-	G. Thiéfin	Université de Reims	France
					-		CHU de Reims	France
					-	M. J. Baker	University of Strathclyde	UK
					-	G. D. Sockalingum	Université de Reims	France
139	SCOPUS	Kernel self-optimization learning for kernel-based feature extraction and recognition	2014	Information Sciences	Kernel method	J.-B. Li	Harbin Institute of Technology	China
					Data-dependent kernel	Y.-H. Wang	Harbin Institute of Technology	China
					Kernel self-optimization	S.-C. Chu	Flinders University of South Australia	Australia
					Kernel principal component analysis	J. F. Roddick	Flinders University of South Australia	Australia
					Kernel discriminant analysis	-	-	-
					Kernel locality preserving projection	-	-	-
140	SCOPUS	Kinetic analysis of thermogravimetric data;	1984	Thermochimica Acta	-	A. R. Salvador	Universidad Complutense	Spain

		discrimination of integral models						
					-	E. G. Calvo	Universidad Complutense	Spain
					-	A. I. Gulias	Universidad del País Vasco	Spain
					-	-	-	-
					-	-	-	-
141	SCOPUS	Lateral enhancement in adaptive metric learning for functional data	2014	Neurocomputing	Learning vector quantization	T. Villmann	University of Applied Sciences Mittweida	Germany
					Relevance learning	M. Kaden	University of Applied Sciences Mittweida	Germany
					Matrix learning	D. Nebel	University of Applied Sciences Mittweida	Germany
					Expert knowledge	M. Riedel	University of Applied Sciences Mittweida	Germany
					Functional data	-	-	-
142	SCOPUS	Learning representations for object classification using multi-stage optimal component analysis	2008	Neural Networks	Dimension reduction	Y. Wu	Florida State University	USA
					Linear data representations	X. Liu	Florida State University	USA
					Feature selection	W. Mio	Florida State University	USA
					Object recognition	-	-	-
					Object classification	-	-	-
					Optimal component analysis	-	-	-
143	SCOPUS	Massive data discrimination via linear support vecto machines	2007	Optimization Methods and Software	Support vector machines	P. S. Bradley	University of Wisconsin	USA
					Linear programming chunking	O. L. Mangasarian	University of Wisconsin	USA
144	SCOPUS	Methods for digital analysis of AVHRR Sea Ice Images	1992	IEEE Transactions on Geoscience and Remote Sensing	Image analysis	B. A. Burns	Universitat Bremen	Germany
					Sea ice	M. Schmidt-Grottrup	Alfred Wegener Institute of Polar na Marine Research	Germany

					Sea measurements	T. Viehoff	Alfred Wegener Institute of Polar na Marine Research	Germany
					Size measurement	-	-	-
					Image resolution	-	-	-
					Radiometry	-	-	-
					Digital images	-	-	-
					Area measurement	-	-	-
					Reflectivity	-	-	-
					Frequency	-	-	-
145	SCOPUS	Microsimulation model to predict incremental value of biomarkers added to prognostic models	2018	JAMIA	Risk	K. M. Pencina	Brigham and Women's Hospital, Boston	USA
					Correlation	R. B. D'Agostino	Boston University	USA
					Performance	R. S. Vasan	Boston University	USA
					Synthetic cohorts	M. J. Pencina	Duke University School of Medicine	USA
146	SCOPUS	Minority manifold regularization by stacked auto-encoder for imbalanced learning	2021	Expert System with Applications	Regularized auto-encoder	N. Farajian	University of Kashan	Iran
					Imbalanced data classification		University of Eyvanekey	Iran
					Feature learning	P. Adibi	University of Isfahan	Iran
					-	-	-	-
147	SCOPUS	Molecular identification and biometric analysis of Macaronesian archipelago stocks of Beryx splendens	2005	Fisheries research	Alfonsino	S. Schönhuth	Universidad Complutense de Madrid	Spain
					Mitochondrial DNA	Y. Álvarez	Universidad Complutense de Madrid	Spain
					Beryx splendens	V. Rico	Instituto Canario de Ciencias Marinas	Spain
					Haplotypes	J. A. González	Instituto Canario de Ciencias Marinas	Spain

					Canary Islands	J. I. Santana	Instituto Canario de Ciencias Marinas	Spain
					Azores	E. Golveia	Direcção de Serviços e Investigação das Pescas	Portugal
					Madeira	J. M Lorenzo	Universidad de Las Palmas de Gran Canaria	Spain
					Macaronesian achipelagos	J. M. Bautista	Universidad Complutense de Madrid	Spain
					Easterns atlatic	-	-	-
148	SCOPUS	Non-destructive evaluation of the adhesive fillet size in a T-peel joint using ultrasonic Lamb waves and a linear network for data discrimination	1995	Measurement Science and Technology	-	U. Bork	Keele University	UK
					-	R. E. Challis	Keele University	UK
149	SCOPUS	On some variants of locality preserving projection	2016	Neurocomputing	Locality preserving projection	G. Shikkenawis	Dhirubhai Ambani Institute of Information and Communication Technology	India
					Subspace analysis	S. K. Mitra	Dhirubhai Ambani Institute of Information and Communication Technology	India
					Dimensionality reduction	-	-	-
					Data discrimination	-	-	-
150	SCOPUS	Probability description of single droplet events at high pressures: droplet-wall collision case	2011	Journal of Natural Gas Science and Egineering	Multiphase flow	P. M. Dupuy	Norwegian University of Science and Technology	Norway
					Probabilistic	M. Fernandino	Norwegian University of Science and Technology	Norway
					Separations	H. A. Jakobsen	Norwegian University of Science and Technology	Norway
					High pressure	H. F. Svendsen	Norwegian University of Science and Technology	Norway
					Natural gas	-	-	-
					Stochastic	-	-	-

151	SCOPUS	Probability of severe postpartum hemorrhage in repeat cesarean deliveries: a multicenter retrospective study in China	2021	Scientific Reports	-	L. Du	The Third Affiliated Hospital of Guangzhou Medical University	China
					-		Key Laboratory for Reproduction and Genetics of Guangdong Higher Education Institutes	China
					-	L. Feng	Huazhong University of Science and Technology	China
					-	S. Bi	The Third Affiliated Hospital of Guangzhou Medical University	China
					-		Key Laboratory for Reproduction and Genetics of Guangdong Higher Education Institutes	China
					-		(mais 23 autores)	
152	SCOPUS	Protocol for the derivation and external validation of a 30-day mortality risk prediction model for older patients having emergency general surgery (PAUSE score-Probability of mortality Associated with Urgent/emergent general Surgery in oldEr patients score)	2019	BMJ Open	-	S. Feng	The Ottawa Hospital	Canada
					-	C. Van Walraven	The Ottawa Hospital	Canada
					-	M. Lalu	The Ottawa Hospital	Canada
					-	H. Moloo	The Ottawa Hospital	Canada
					-	R. Musselman	The Ottawa Hospital	Canada
					-	D. McIsaac	The Ottawa Hospital	Canada
153	SCOPUS	Quality assessment of data discrimination using self-organizing maps	2014	Journal of Biomedical Informatics	Artificial intelligence	A. Mekler	The Bonch-Bruevich Saint-Petersburg State University of Telecommunications	Russia
					Classification	D. Schwarz	The Bonch-Bruevich Saint-Petersburg State University of Telecommunications	Russia

					Data mining	-	-	-
					Feature selection	-	-	-
					Self-organizing maps	-	-	-
					Artificial neural networks	-	-	-
154	SCOPUS	Selective Oxidation of n-butane to Maleic Anhydride	1991					
155	SCOPUS	Setting up a hydrological model of Alberta: data discrimination analyses prior to calibration	2015	Environmental Modelling & Software	SWAT	M. Faramarzi	University of Alberta	Canada
					Watershed modeling	R. Srinivasan	Texas A&M University	USA
					Climate data	M. Iravani	University of Alberta	Canada
					Hydrological processes	K. D. Bladon	University of Alberta	Canada
					Geo-spatial data		Oregon State University	USA
					-	K. C. Abbaspour	Swiss Federal Institute of Aquatic Science and Technology	Switzerland
					-	A. J. B. Zehnder	Alberta Innovates-Energy and Environment Solutions	Canada
					-		Nanyang Technological University	Singapore
					-	G. G. Goss	University of Alberta	Canada
156	SCOPUS	Social identity and perceptions about health care service provisioning by and for the dalits in india	2017	Social Identities	Dalits	S. Verma	Jawaharlal Nehru University	India
					Caste	S. S. Acharya	Jawaharlal Nehru University	India
					Social identity		Indian Institute of Dalit Studies	India
					Discrimination	-	-	-
					ANM	-	-	-
					ASHA	-	-	-

157	SCOPUS	Solution Structure and Acetyl-lysine binding activity of the GCN5 Bromodomain	2000	Journal of Molecular Biology	Transcriptional activator	B. P. Hudson	Skaggs Institute for Chemical Biology	USA
					Histone	M. A. Martinez-Yamout	Skaggs Institute for Chemical Biology	USA
					Chromatin	H. J. Dyson	Skaggs Institute for Chemical Biology	USA
					Transcription	P. E. Wright	Skaggs Institute for Chemical Biology	USA
158	SCOPUS	Some Interesting Central Asian Events on the Ms : mb Diagram	1972	Geophysical Journal International	-	T. Landers	Massachusetts Institute of Technology	USA
					-	-	-	-
159	SCOPUS	Spatio-temporal coherence based technique for near-real time sea-ice identification from scatterometer data	2011	Journal of the Indian Society of Remote Sensing	Sea-Ice identification	S. R. Oza	Space Applications Centre	India
					Scatterometer	R. K. K. Singh	Space Applications Centre	India
					QuikSCAT	N. K. Vyas	Space Applications Centre	India
					Spatio-temporal coherence	B. S. Gohil	Space Applications Centre	India
						A. Sarkar	Space Applications Centre	India
160	SCOPUS	Spectral and Structural measures of Northwest Forest Vegetation at Leaf to landscape scales	2004	Ecosystems	Remote sensing	D. A. Roberts	University of California	USA
					Canopy architecture	S. L. Ustin	University of California	USA
					Leaf area index	S. Ogunjemiyo	University of California	USA
					Albedo	J. Greenberg	University of California	USA
					Conifer forests	S. Z. Dobrowski	University of California	USA
					Broadleaf deciduous forests	J. Chen	University of Toledo	USA
					Spatial scace	T. M. Hinckley	University of Washington	USA
					AVIRIS	-	-	-
					Imaging spectroscopy	-	-	-

161	SCOPUS	Systematic kinetic modeling of the propyl tert-butyl ether synthesis reaction	2019	Chemical Engineering Journal	Kinetic modeling	J. H. Badia	University of Barcelona	Spain
					Propyl tert-butyl ether	C. Fité	University of Barcelona	Spain
					Amberlyst 35	R. Bringué	University of Barcelona	Spain
					Multimodel inference	M. Iborra	University of Barcelona	Spain
					-	F. Cunill	University of Barcelona	Spain
162	SCOPUS	The black social ranking experience at Uber: a racialized reflection on contemporary surveillance	2021	Comunicação e Sociedade	Social ranking	N. S. Evangelo	Universidade do Rio de Janeiro	Brazil
					Uber	F. C. R. M. de Oliveira	Universidade do Rio de Janeiro	Brazil
					Racism	-	-	-
					Surveillance	-	-	-
163	SCOPUS	The Factors Affecting the development of national identity as South Korean in North Korean refugees living in South Korea	2012	Psychiatry investigation	North Korean Refugee	S.-E. Yu	Johns Hopkins University	USA
					National Identity	J.-S. Eom	Chungbuk National University	Republic of Korea
					Sorrouding discrimination	W.-T. Jeon	Yonsei University	Republic of Korea
					Networking	-	-	-
					Trauma experience	-	-	-
164	SCOPUS	Toward improved aesthetics and data discrimination for treemaps via color schemes	2017	Color Research and Application	Aesthetics	Y. Xie	Sichuan University	China
					Color scheme		China West Normal University	China
					Discrimination	T. Lin	Sichuan University	China
					Treemap	R. Chen	Sichuan University	China
					-	Z. Chen	Sichuan University	China

165	SCOPUS	Ultraviolet-electrical erasing response characteristics of Ag@SiO2 core-shell functional floating gate organic memory	2021	Organic Electronics	Floating gate organic memory	X. Guo	Lanzhou University	China
					Ag@SiO2 core-shell nanomaterial	W. Zhang	Lanzhou Jiaotong University	China
					Integrated functional layer	J. Yin	Lanzhou University	China
					Ultraviolet erasing	Y. Xu	Lanzhou University	China
					-	Y. Bai	Lanzhou University	China
					-	J. Yang	Lanzhou University	China
166	SCOPUS	Voiceband Signal Classification Using Statistically Optimal Combinations of Low-Complexity Discriminant Variables	1999	IEEE Transactions on communications	Pattern classification	J. S. Sewall	LSI Logic Corporation	Canada
					Passband	B. F. Cockburn	University of Alberta	Canada
					Telecommunication traffic	-	-	-
					Speech processing	-	-	-
					Baseband	-	-	-
					Modems	-	-	-
					Facsimile	-	-	-
					Demodulation	-	-	-
					Statistical analysis	-	-	-
					Telephony	-	-	-
167	SCOPUS	Wavelength dispersive X-ray fluorescence (WDXRF) and chemometric investigation of human hair after cosmetic treatment	2018	X-Ray spectrometry	-	M. C. Santos	Universidade Estadual Paulista	Brazil
					-	M. A. Sperança	Universidade Federal de São Carlos	Brazil
					-	F. M. V. Pereira	Universidade Estadual Paulista	Brazil

168	SCOPUS	Why the 'Computer says no': illustrating big data's discrimination risk through complex system science	2018	International Data Privacy Law	-	M. Rhoen	Leiden University	Netherlands
					-	Q. Y. Feng	Utrecht University	Netherlands
169	SCOPUS	Without quality presence-absence data, discrimination metrics such as TSS can be misleading measures of model performance	2018	Journal of Biogeography	-	B. Leroy	Sorbonne Universités	France
					-		Université de Caen Normandie	France
					-		Université des Antilles	France
					-	R. Delsol	Sorbonne Universités	France
					-		Université de Caen Normandie	France
					-		Université des Antilles	France
					-	B. Hugueny	Université de Toulouse	France
					-	C. N. Meynard	Université Montpellier	France
					-	C. Barhoumi	Sorbonne Universités	France
					-		Université de Caen Normandie	France
					-		Université des Antilles	France
					-	M. Barbet-Massin	Université Paris-Sud	France
					-	C. Bellard	Sorbonne Universités	France
					-		Université de Caen Normandie	France
					-		Université des Antilles	France
170	WoS	Chromatic discrimination in the presence of incremental and decremental rod pedestals	2008	Visual Neuroscience	Chromatic discrimination	D. Cao	The University of Chicago	USA
					Rod pedestal	A. J. Zele	Queensland University of Technology	Australia
					Mesopic	J. Pokorny	The University of Chicago	USA

					Rod-cone interaction	-	-	-
					Post-receptoral pathways	-	-	-
171	WoS	Deriving probabilistic SVM Kernels from flexible statistical mixture models and its application to retinal images classification	2018	IEEE Access	Retinal images	S. Bourouis	Taif University	Saudi Arabia
					Scaled Dirichlet mixture	A. Zaguia	Taif University	Saudi Arabia
					SVM	N. Bouguila	Concordia University	Canada
					Generative-discriminative learning	R. Alroobaea	Taif University	Canada
					MDL	-	-	-
					Probabilistic kernels	-	-	-
172	WoS	Discrimination of Switchgrass cultivars and nitrogen treatments using pigment profiles and hyperspectral leaf reflectance data	2012	Remote sensing	Hyperspectral	A. J. Foster	Oklahoma State University	USA
					Pigments	V. G. Kakani	Oklahoma State University	USA
					Reflectance	J. Ge	Oklahoma State University	USA
					Vegetation indices	J. Mosali	The Samuel Roberts Noble Foundation, Inc.	USA
					Switchgrass			
173	WoS	Eigenvector Weighting Function in Face Recognition	2011	Discrete Dynamics in Nature and Society	-	P. Y. Han	Multimedia University	Malaysia
					-	A. T. B. Jin	Yonsei University	Korea
					-		Sunway University	Malaysia
					-	L. H. Siong	Multimedia University	Malaysia
174	WoS	Increasing the effectiveness of handwritten manipuri Meetei-Mayek character	2019	Sādhanā	Manipuri Meetei-Mayek (script)	K. Nongmeikapam	Indian Institute of Information Technology Manipur	India

		recognition using multiple-HOG-feature descriptors						
					Multilayer perceptron	W. K. Kumar	North Eastern Regional Institute of Science and Technology	India
					Feedforward artificial neural network	O. N. Meetei	National Institute of Technology	India
					Histogram of oriented gradient (HOG)	T. Tuithung	National Institute of Technology	India
					Linear multiclass support vector machine (SVM)	-	-	-
					-	-	-	-
175	WoS	Magnesium deficiency decreases biomass water-use efficiency and increases leaf water-use efficiency and oxidative stress in barley plants	2016	Plant and Soil	Magnesium	M. Tränkner	Institute of Applied Plant Nutrition	Germany
					Water use efficiency		University of Goettingen	Germany
					Carbon discrimination	B. Jákli	Institute of Applied Plant Nutrition	Germany
					Oxidative stress		University of Goettingen	Germany
					Barley	E. Tavakol	Institute of Applied Plant Nutrition	Germany
					-		University of Goettingen	Germany
					-	C.-Martin Geilfus	KU Leuven	Belgium
					-	I. Cakmak	Sabanci University	Turkey
					-	K. Dittert	Institute of Applied Plant Nutrition	Germany
					-		University of Goettingen	Germany
					-	M. Senbayram	Institute of Applied Plant Nutrition	Germany
					-		Harran University	Turkey
176	WoS	Membrane transport processes analyzed by a highly parallel nanopore chip system at single protein resolution	2016	Journal of Visualized Experiments	-	M. Urban	Goethe University Frankfurt	Germany

					-	M. Von der Brüggen	Nanospot GmbH	Germany
					-	R. Tampé	Goethe University Frankfurt	Germany
					-	-	-	-
177	WoS	Multi-layer network utilizing rewarded spike time dependent plasticity to learn a foraging task	2017	PLOS Computational Biology	-	P. Sanda	University of California	USA
					-	S. Skorheim	HRL Laboratories	USA
					-	M. Bazhenov	University of California	USA
					-	-	-	-
					-	-	-	-
					-	-	-	-
178	WoS	Wages, employment, and statistical discrimination: evidence from the laboratory	2014	Economic Inpuiry	-	D. L. Dickinson	Appalachian State University	USA
					-	R. L. Oaxaca	University of Arizona	USA

APÊNDICE D: Corpus preliminar obtido a partir do termo "*Fair algorithms*"

N°	Origem	Nome	Ano	Revista	Palavras-chave	Autores	Filiação	País
179	SCOPUS	A bayesian network approach for cybersecurity risk assesment implementing and extending the fair model	2019	Computers & Security	Cybersecurity risk assessment	J. Wang	Queen Mary University	United Kingdom
					FAIR model	M. Neil	Agena Ltd	United Kingdom
					Bayesian networks	N. Fenton	Agena Ltd	United Kingdom
					Monte Carlo simulation	-	-	-
					Risk aggregation	-	-	-
					Adversarial risk analysis	-	-	-
					Game Theory	-	-	-
180	SCOPUS	An interference coordination-based distributed resource allocation scheme in heterogeneous cellular networks	2017	IEEE Access	-	Q. Song	Northeastern University	China
					-	X. Wang	Dalian University of Technology	China
					-	T. Qiu	Dalian University of Technology	China
					-	Z. Ning	Dalian University of Technology	China
181	SCOPUS	A new processing approach for scheduling time minimization in 5G-iOT Networks	2021	International Journal of Intelligent Engineering & Systems	5G	A. M. Mahmood	University of Technology-Iraq	Iraq
					IoT	A. R. Kareem	University of Technology-Iraq	Iraq
					Scheduling algorithms	-	-	-
					Proportional fair algorithm	-	-	-
					Spark framework	-	-	-
					Scalability	-	-	-
					Parallel processing	-	-	-
182	SCOPUS	An improved dynamic joint resource allocation algorithm based on SFR	2016	Algorithms	Joint resource allocation	Y. Li	Harbin Engineering University	China
					Soft frequency reuse	X. Diao	Harbin Engineering University	China
					Inter-cell interference	G. Dong	Harbin Engineering University	China
					LTE	F. Ye	Harbin Engineering University	China
					Interior sector Partition	-	-	-

183	SCOPUS	Na optimal boundary fair scheduling	2014	Real-Time Systems	-	G. Nelissen	Polytechnic Institute of Porto	Portugal
					-	H. Su	The University of Texas	USA
					-	Y. Guo	The University of Texas	USA
					-	D. Zhu	The University of Texas	USA
					-	V. Nélis	Polytechnic Institute of Porto	Portugal
					-	J. Goossens	Université Libre de Bruxelles	Belgium
184	SCOPUS	Bounded-Bypass Mutual Exclusion with Minimum Number of Registers	2009	IEEE Transactions on Parallel and Distributed Systems	Time factors	S.-H. Chen	SpringSoft, Inc	Taiwan
					Memory management	T.-L. Huang	National Chiao Tung University	Taiwan
					Registers	-	-	-
					Real time systems	-	-	-
					Algorithm design and analysis	-	-	-
					Scheduling algorithm	-	-	-
					Resource management	-	-	-
					Automotive engineering	-	-	-
					Control systems	-	-	-
					Mobile computing	-	-	-
185	SCOPUS	Chasm in Hegemony: explaining and reproducing disparities in homophilous networks	2021	Proceedings of the ACM on Measurement and Analysis of Computing Systems	Structural bias in social networks	Y. Zhang	Columbia University	USA
					Fairness of fake news detection	J. X. Han	Massachusetts Institute of Technology	USA
					-	I. Mahajan	Columbia University	USA
					-	P. Bengani	Columbia University	USA
					-	A. Chaintreau	Columbia University	USA
186	SCOPUS	Downlink Scheduling with guarantees on the probability of short-term throughput	2009	IEEE Transactions on Wireless Communications	Downlink	N. Chen	University of California	USA
					Throughput	S. Jordan	University of California	USA
					Delay	-	-	-

					Tail	-	-	-
					Probability	-	-	-
					Wireless communication	-	-	-
					Wireless networks	-	-	-
					Time measurement	-	-	-
					System performance	-	-	-
					Costs	-	-	-
187	SCOPUS	Equitable selection in bilateral matching markets	2005	Theory and Decision	Matching markets	A. Romero-Medina	Universidad Carlos III de Madrid	Spain
					Fair distribution	-	-	-
					Fair algorithm	-	-	-
					-	-	-	-
					-	-	-	-
					-	-	-	-
					-	-	-	-
188	SCOPUS	Exponential MLWDF (EXP-MLWDF) Downlink scheduling algorithm evaluated in LTE for high mobility and dense area scenario	2018	International Journal of Electrical and Computer Engineering	LTE	I. Angri	National Institute of Posts and Telecommunications	Morocco
					MLWDF	M. Mahfoudi	Superior School of Technology	Morocco
					QoS	A. Najid	National Institute of Posts and Telecommunications	Morocco
					Radio resource management	M. El Bekkali	Superior School of Technology	Morocco
					Real time traffic	-	-	-
					Scheduling algorithms	-	-	-
189	SCOPUS	FAIR: A fast algorithm for document image restoration	2013	IEEE Transactions on Pattern Analysis and Machine Intelligence				

190	SCOPUS	Green and fair workload distribution in geographically distributed datacenters	2013	Journal of Green Engineering	Datacenter	R. Y. Alawnah	Kuwait University	Kuwait
					Green computing	I. Ahmad	Kuwait University	Kuwait
					Cloud computing	E. A. Alrashed	Kuwait University	Kuwait
					SLA	-	-	-
					Fairness	-	-	-
					Optimization	-	-	-
					Langrage	-	-	-
191	SCOPUS	Implementation of Max-SNR opportunistic scheduling in cross layer design	2019	International Journal of Engineering and Advanced Technology	Cross-layer design	T. Praveena	Department of CSE	India
					Opportunistic scheduling	G. S. Nagaraja	Department of CSE	India
					Strict-priority	-	-	-
					Max-Min	-	-	-
					QoS	-	-	-
					SNR	-	-	-
					QualNet	-	-	-
192	SCOPUS	Maximum-largest wighted delay first algorithm for heterogenous traffic in 4G networks	2018	Indonesian Journal of Electrical Engineering and Informatics	LTEA	E. M. A. Esheikh	International Islamic University Malaysia	Malaysia
					Mac protocol	M. H. Habaebi	International Islamic University Malaysia	Malaysia
					M-LWDF	H. A. M. Ramli	International Islamic University Malaysia	Malaysia
					Multimedia	M. H. A. Arafa	International Islamic University Malaysia	Malaysia
					Scheduling	K. I. Ahmed	International Islamic University Malaysia	Malaysia
193	SCOPUS	Randomized learning and generalization of fair and private classifiers from PAC-Bayes to stability and differential privacy	2020	Neurocomputing	Algorithmic fairness	L. Oneto	University of Pisa	Italy
					Privacy preserving data analysis	M. Donini	Amazon	USA
					Generalization	M. Pontil	Instituto Italiano di Tecnologia	Italy
					Randomized classifier	J. Shawe-Taylor	University College London	United Kingdom
					PAC-Bayes	-	-	-

					Algorithmic (distribution) stability	-	-	-
					Randomized algorithm	-	-	-
					Differential privacy	-	-	-
194	SCOPUS	Scheduling of QoS Guaranteed Services in DS-CDMA Uplink Networks: Modified Weighted G-Fair Algorithm	2004	excluído (conference paper)				
195	SCOPUS	Security and Authentication through Text Encryption and Decryption based on Substitution Method	2019	International Journal of Innovative Technology and Exploring Engineering (IJITEE)				
196	SCOPUS	Snap-stabilizing committee coordination	2016	Journal of Parallel and Distributed Computing	Distributed algorithms	B. Bonakdarpour	McMaster University	Canada
					Snap-stabilization	S. Devismes	Université Joseph Fourier	France
					Self-stabilization	F. Petit	UPMC Sorbonne Universités	France
					Committee coordination	-	-	-
197	SCOPUS	User-level performance of channel-aware scheduling algorithms in wireless data networks	2005	IEEE/ACM Transactions on Networking	Blocking probabilities	S. Borst	Center of Mathematics and Computer Science	Netherlands
					Channel-aware scheduling		Bell Laboratories	USA
					Elastic traffic		Eindhovan University of Technology	Netherlands
					Insensitivity	-	-	-
					Processor sharing	-	-	-
					Proportional fair scheduling	-	-	-

					Response times	-	-	-
					Stability	-	-	-
					Throughput	-	-	-
					Wireless data network	-	-	-
198	SCOPUS	Virtual reality over wireless networks: quality-of-service model and learning-base resource management	2018	IEEE Transactions on communications	Virtual reality	M. Chen	Beijing University of Posts and Telecommunications	China
					Resource management	W. Saad	Wireless@VT	USA
					Machine learning	C. Yin	Beijing University of Posts and Telecommunications	China
					-	-	-	-
					-	-	-	-
					-	-	-	-
					-	-	-	-
					-	-	-	-
199	SCOPUS	Efficient fair algorithms for message communication	2009	Simulation Modelling Practice and Theory	Capacity allocation	S. Gorinsky	Washington University	USA
					Efficient message communication	E. J. Friedman	Cornell University	USA
					Minimal avarege delay	S. Henderson	Cornell University	USA
					Fair algorithm	C. Jechlitschek	Intel GmbH	Germany
					Slack system	-	-	-
200	SCOPUS	Fair algorithms for selecting citizens' assemblies	2021	Nature	-	B. Flanigan	Carnegie Mellon University	USA
					-	P. Gölz	Carnegie Mellon University	USA
					-	A. Gupta	Carnegie Mellon University	USA
					-	B. Hennig	Sortition Foundation	United Kingdom
					-	A. D. Procaccia	Harvard University	USA

APÊNDICE E: Referências extraídas de 56 artigos de 58 que compõem o corpus final

1. Article 29 Working Party, A29WP (2014). Opinion 06/2014 on the notion of legitimate interest of the data controller under Article 7 of Directive 95/46/EC. 844/14/ EN, WP 217, adopted 9 April 2014, https://ec.europa.eu/justice/article-29/documentation/opinion-recommendation/files/2014/wp217_en.pdf.
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2656. The example is also discussed in Barocas and Selbst, 'Big Data's Disparate Impact', 682.
2657. There is no evidence of such practices, although from a technical perspective such price discrimination is easy. There was, however, a travel and booking site that showed more expensive hotels to Apple users and cheaper ones to PC users (D. Mattioli, 'On Orbitz, Mac Users Steered to Pricier Hotels', Wall Street Journal, 23 August 2012).
2658. W.L. Perry et al., 'Predictive Policing: The Role of Crime Forecasting in Law Enforcement Operations', 2013, https://www.rand.org/content/dam/rand/pubs/research_reports/RR200/RR233/RAND_RR233.pdf (accessed January 19, 2020). See also A.G. Ferguson, The Rise of Big Data Policing: Surveillance, Race, and the Future of Law Enforcement (NYU Press, 2017).
2659. Wachter, 'Affinity Profiling and Discrimination by Association'.
2660. While the European Convention on Human Rights has some horizontal effect, the Convention does not directly regulate discrimination in the private sector.
2661. Z. CLipton, 'From AI to ML to AI: On Swirling Nomenclature & Slurried Thought', June 5, 2018, http://approximatelycorrect.com/2018/06/05/ai-ml-ai-swirling-nomenclature-slurried-thought/ (accessed January 19, 2020). See also M. Jordan, 'Artificial Intelligence—The Revolution Hasn't Happened Yet', April 2018, https://medium.com/@mijordan3/artificial-intelligence-the-revolution-hasnt-happened-yet-5e1d5812e1e7 (accessed January 19, 2020).
2662. (emphasis added).
2663. A qualification of indirect discrimination requires the showing by the applicant of a 'particular disadvantage', which might be difficult given the speed, scale and lack of transparency of algorithmically assisted decision-making. In addition, justifications can be invoked by the defendant, which leads to a proportionality exercise in which the Court balances an objective and legitimate aim with the disadvantage caused.
2664. A.L. Hoffmann, 'Where fairness fails: data, algorithms, and the limits of antidiscrimination discourse', 22 Information, Communication & Society (2019), p. 906.
2665. According to Hepple, '[w]hile substantive equality affords opportunities to people who have been in the past disproportionately excluded, without disturbing the underlying social framework that denies them genuine choice and generates inequitable outcomes, transformative equality is aimed at the dismantling of systemic inequalities and the eradication of […] disadvantage'. B.A. Hepple, Equality: The New Legal Framework (Hart Publishing, 2011). See also D. Möckli, International human rights law (OUP, 2014).
2666. An important element of such contextual assessments is the notion of power, see e.g. C.A. MacKinnon, 'Substantive Equality: a Perspective', 96 Minnesota Law Review (2011); S. Fredman, 'Substantive equality revisited', 14 International Journal of Constitutional Law (2016); C.A. MacKinnon, 'Substantive equality revisited: A reply to Sandra Fredman', 14 International Journal of Constitutional Law (2016); S. Fredman, 'Substantive equality revisited: A rejoinder to Catharine MacKinnon', 14 International Journal of Constitutional Law (2016).
2667. Art. 14 ECHR provides that '[t]he enjoyment of the rights and freedoms set forth in this Convention shall be secured without discrimination on any ground such as sex, race, colour, language, religion, political or other opinion, national or social origin, association with a national minority, property, birth or other status'.
2668. Art. 19 TFEU; Directive 2000/43/EC; Directive 2000/78/EC; Council Directive 2004/113/EC of 13 December 2004 implementing the principle of equal treatment between men and women in the access to and supply of goods and services, [2004] OJ L 373; Directive 2006/54/EC of the European Parliament and of the Council of 5 July 2006 on the implementation of the principle of equal opportunities and equal treatment of men and women in matters of employment and occupation (recast), [2006] OJ L 204/23. Art. 21 of the Charter has a broader scope of protection, see section 1.C. for an analysis.
2669. Article 2(1)(b) of Directive 2006/54/EC, Article 2(b) of Directive 2004/113/EC and Article 2(2)(b) of Directive 2000/43/EC and 2000/78/EC.
2670. B.A. Williams, C.F. Brooks and Y. Shmargad, 'How Algorithms Discriminate Based on Data They Lack: Challenges, Solutions, and Policy Implications', 8 Journal of Information Policy (2018), p. 82–83. The authors explain that the reliance on statistical correlations make 'prediction', 'imputation' and the identification of 'proxy variables' possible.
2671. C. D'Ignazio and L.F. Klein, Data feminism (MIT Press, 2020).
2672. C. Kilpatrick, 'Article 21- Non-Discrimination', in S. Peers et al. (eds), The EU Charter of Fundamental Rights A Commentary (Hart Publishing, 2014), s. 21.43.
2673. C. O'Neil, Weapons of math destruction: how big data increases inequality and threatens democracy.

2674. C. Sheppard, 'Grounds of Discrimination: Towards an Inclusive and Contextual Approach', 80 Canadian Bar Review (2001), p. 903; S. Fredman, Intersectional discrimination in EU gender equality and non-discrimination law, European Network of legal scholars in gender equality and non-discrimination and European Commission, 10; G. Calvès, L'inflation legislative des motifs illicites de discrimination: essai d'analyse fonctionnelle (2018), p. 154; D. Pothier, 'Connecting Grounds of Discrimination to Real People's Real Experiences', 13 Canadian Journal of Women and the Law (2001), p. 3.
2675. Case C-13/05 Sonia Chacón Navas v Eurest Colectividades SA, para. 56 and Case C-354/13 Fag og Arbejde (FOA) v Kommunernes Landsforening (KL), para. 36. Art 21 prohibits discrimination on 'any ground such as sex, race, colour, ethnic or social origin, genetic features, language, religion or belief, political or any other opinion, membership of a national minority, property, birth, disability, age or sexual orientation'.
2676. Case C-13/05 Sonia Chacón Navas v Eurest Colectividades SA, para. 56.
2677. Case C-13/05 Sonia Chacón Navas v Eurest Colectividades SA, EU: C:2006:456; Case C-354/13 Fag og Arbejde (FOA) v Kommunernes Landsforening (KL), EU: C:2014:2463.
2678. Case C-144/04 Werner Mangold v Rüdiger Helm. This situation arose because the transposition deadline of Directive 2000/78/EC had not yet passed in Germany at the time of the facts.
2679. Case C-144/04 Werner Mangold v Rüdiger Helm, EU: C:2005:709; Case C-555/07 Seda Kücükdeveci v Swedex GmbH & Co. KG, EU: C:2010:21; Case C-441/14 Dansk Industri (DI), acting on behalf of Ajos A/S v Estate of Karsten Eigil Rasmussen, EU: C:2016:278.
2680. Case C-152/11 Johann Odar v Baxter Deutschland GmbH.
2681. Case C-177/88 Elisabeth Johanna Pacifica Dekker v Stichting Vormingscentrum voor Jong Volwassenen (VJV-Centrum) Plus, EU: C:1990:383.
2682. Case C-303/06 S. Coleman v Attridge Law and Steve Law EU: C:2008:415.
2683. Case C-354/13 Fag og Arbejde (FOA) v Kommunernes Landsforening (KL), para. 58–60. See L. Waddington, 'Case C-13/05, Chacón Navas v. Eurest Colectividades SA, judgment of the Grand Chamber of 11 July 2006, EU: C:2006:456', 44 Common Market L Rev (2007).
2684. Case C-354/13 Fag og Arbejde (FOA) v Kommunernes Landsforening (KL).
2685. Case C-363/12 Z. v A Government department and The Board of management of a community school, para. 92.
2686. Case C-414/16 Vera Egenberger contre Evangelisches Werk für Diakonie und Entwicklung eV, EU: C:2018:257 and Case C-68/17 IR v JQ, EU: C:2018:696.
2687. Case C-415/10 Galina Meister v Speech Design Carrier Systems GmbH, EU: C:2012:217.
2688. Case C-443/15 David L. Parris v Trinity College Dublin and Others.
2689. Case C-443/15 David L. Parris v Trinity College Dublin and Others, EU: C:2016:897.
2690. Case C-54/07 Centrum voor gelijkheid van kansen en voor racismebestrijding v Firma Feryn NV, EU: C:2008:397 and Case C-507/18 NH v Associazione Avvocatura per i diritti LGBTI - Rete Lenford, EU: C:2019:922.
2691. Case C-668/15 Jyske Finans A/S v Ligebehandlingsnævnet, acting on behalf of Ismar Huskic EU: C:2017:278, para. 20.
2692. Case C-81/12 Asociaţia Accept v Consiliul Naţional pentru Combaterea Discriminării, EU: C:2013:275.
2693. Case C-83/14 "CHEZ Razpredelenie Bulgaria" AD v Komisia za zashtita ot diskriminatsia EU: C:2015:480.
2694. Case C-83/14 "CHEZ Razpredelenie Bulgaria" AD v Komisia za zashtita ot diskriminatsia, EU: C:2015:480, para. 57.
2695. Council Directive 2000/43/EC of 29 June 2000 implementing the principle of equal treatment between persons irrespective of racial or ethnic origin, [2000] OJ L 180, recital (14); Council Directive 2000/78/EC establishing a geenral framework for equal treatment in employment and occupation, [2000] OJ L 303, recital (3).
2696. D. Schiek, 'Organising EU Equality Law Around the Nodes of 'Race', Gender and Disability', in A. Lawson and D. Schiek (eds), EU Non-Discrimination Law and Intersectionality: Investigating the Triangle of Racial, Gender and Disability Discrimination (Ashgate Publishing, 2011), p. 19.
2697. Direct discrimination is a situation in which 'one person is treated less favourably on grounds of [sex, racial or ethnic origin, religion or belief, disability, age or sexual orientation] than another is, has been or would be treated in a comparable situation'. See Article 2(2)(a) of the Race Equality Directive 2000/43/EC and the Employment Equality Directive 2000/78/EC, Article 2(a) of the Gender Goods and Services Directive 2004/113/EC and 2(1)(a) of the Gender Equality (Recast) Directive 2006/54/EC.
2698. E. Bribosia, I. Rorive and J. Hislaire, 'Article 21: Non Discrimination', in F. Picod, S. van Drooghenbroeck and C. Rizcallah (eds), Charte des droits fondamentaux de l'Union européenne: Commentaire article par article (Bruylant, 2017), p. 37 and I. Rorive, Le droit européen de la non-discrimination mis au tempo de critères singuliers: Enjeux, effets et perspectives, p. 40. On the application of an intersectional approach based on the general principle of non-discrimination, see also S. Robin-Olivier, 'Interdiction des discriminations fondées sur l'âge, protection du droit au recours juridictionnel effectif et liberté de circulation des travailleurs: feux croisés sur une réforme, mais pas d'intersectionnalité', RTDeur Revue trimestrielle de droit européen (2020).
2699. ECtHR, Aydin v. Turkey, Judgment of 25 September 1997, Application no. 23178/94.
2700. ECtHR, Kiyutin v. Russia, Judgment of 10 March 2011, Application no. 2700/10.
2701. ECtHR, M.S.S. v. Belgium and Greece, Judgment of 21 January 2011, Application no. 30696/09.
2702. Eligibility to non-discrimination protection is not necessarily linear, it might depend on the specific context of a given measure, which might condition the presence or lack of harmful effects.
2703. Elsewhere termed a 'self-fulfilling prophecy', see W. Fröhlich and I. Spiecker genannt Döhmann, 'Können Algorithmen diskriminieren?', Verfassungsblog (2018), <https://verfassungsblog.de/koennen-algorithmen-diskriminieren/>.
2704. European Commission, A Union of Equality: Gender Equality Strategy 2020–2025 COM (2020) 152 final, 2.
2705. For a reconstruction of these debates, see e.g. D.W. Carbado et al., 'INTERSECTIONALITY Mapping the Movements of a Theory', 10 Du Bois Review: Social Science Research on Race (2013); A.-M. Hancock, Intersectionality: an intellectual history (OUP, 2016); P. Hill Collins and S. Bilge, Intersectionality (Polity Press, 2016); D.W. Carbado and C.I. Harris, 'Intersectionality at 30: Mapping the Margins of Anti-Essentialism, Intersectionality, and Dominance Theory', 132 Harvard law review (2019).
2706. For instance, by returning a larger proportion of pornographic images for racialized female groups compared to white female groups.
2707. From a procedural point of view, these cases also provide an interesting route to addressing algorithmic discrimination since they establish that associations and organisations with a legitimate interest have 'standing to bring legal proceedings for the enforcement of [non-discrimination] obligations'. The involvement of such collective actors could ease the burden of proof in cases of algorithmic discrimination. Case C-507/18 NH v Associazione Avvocatura per i diritti LGBTI - Rete Lenford, para. 65 and Case C-54/07 Centrum voor gelijkheid van kansen en voor racismebestrijding v Firma Feryn NV, para. 27.

2708. I. Rorive, Le droit européen de la non-discrimination mis au tempo de critères singuliers: Enjeux, effets et perspectives (Défenseur des Droits, 2018), p. 36.
2709. Ibid, p. 11.
2710. Ibid, p. 19.
2711. Ibid, p. 502, p. 504.
2712. Ibid, para. 153.
2713. Ibid, para. 153.
2714. Ibid, para. 157.
2715. Ibid, para. 80.
2716. Ibid.
2717. In addition, the Court will be offered an opportunity to reconsider its stance on intersectional discrimination with the pending WABE case, which posed the question of indirect discrimination on the grounds of religion and/or gender, see Case C-804/18 IX v WABE e. V (pending).
2718. In addition, those groups are already potentially economically more vulnerable as habits such as sports, nutrition, sleep or lifestyle are deeply linked to class – for instance those who have the means to reside in well-connected areas gain 'leisure' time to perform these activities while poorer groups might be forced to dedicate this time to commuting.
2719. In fact, the very purpose of profiling and predictive algorithms is to discriminate. Identifying and using difference patterns within a given population is neither morally wrong nor unlawful per se, as only certain forms of discrimination – based on protected categories – are considered both morally and legally wrong.
2720. It even renders the detection of such discrimination more difficult by removing the labels used to visualize and measure bias.
2721. It has been argued that the notion of 'multiple discrimination' covers various forms of additive, compounded, sequential and intersectional discrimination. See e.g. S. Burri and D. Schiek, Multiple Discrimination in EU Law. Opportunities for legal responses to intersectional gender discrimination?, European Commission (July 2009) and S. Fredman, Intersectional discrimination in EU gender equality and non-discrimination law, European Network of legal scholars in gender equality and non-discrimination and European Commission. By contrast, some commentators distinguish multiple and intersectional discrimination, see e.g. T. Makkonen, Multiple, compound and intersectional discrimination: bringing the experiences of the most marginalized to the fore, Institute For Human Rights, Äbo Akademi University (2002).
2722. Jyske Finans, para. 16-21. On the composite nature of the protected ground of 'racial and ethnic origin' and the relevance of data such as nationality, patronym, country of birth, cultural background, religion, etc. as well as a critique of the Court's decision in Jyske Finans, see e.g. L. Farkas, The meaning of racial or ethnic origin in EU law: between stereotypes and identities, European Commission (2017), p. 55, 87, 112–113.
2723. Jyske Finans, para. 19.
2724. K. Crenshaw, 'Demarginalizing the Intersection of Race and Sex: A Black Feminist Critique of Antidiscrimination Doctrine, Feminist Theory, and Antiracist Politics', 1989 The University of Chicago Legal Forum (1989); K. Crenshaw, 'Mapping the Margins: Intersectionality, Identity Politics, and Violence against Women of Color', 43 Stan L Rev (1990); P.H. Collins, Black Feminist Thought: Knowledge Consciousness and the Politics of Empowerment (Unwin Hyman, 1990); T. Grillo, 'Anti-Essentialism and Intersectionality: Tools to Dismantle the Master's House Symposium: Looking to the 21st Century: Under-Represented Women and the Law', 10 Berkeley Women's LJ (1995). See also the comparator problem and judges' refusal to create a 'super-remedy' in DeGraffenreid v. General Motors Assembly Div., Etc., 413 F. Supp. 142 (E.D. Mo. 1976).
2725. L. Alexander, 'What makes wrongful discrimination wrong? Biases, preferences, stereotypes, and proxies', 141 University of Pennsylvania Law Review (1992); see also F.F. Schauer, Profiles, probabilities, and stereotypes (Belknap Press, 2003).
2726. M. Ali et al., 'Discrimination Through Optimization: How Facebook's ad Delivery Can Lead to Skewed Outcomes', Proceedings of the ACM on Human-Computer Interaction (2019), https://arxiv.org/pdf/1904.02095.pdf, p. 2.
2727. M. Kusner et al., 'Counterfactual Fairness', 31st Conference on Neural Information Processing Systems, p. 4.
2728. M. Leese, 45 Security Dialogue (2014), p. 501.
2729. M. Leese, 45 Security Dialogue (2014), p. 505.
2730. M. Mann and T. Matzner, 'Challenging algorithmic profiling: The limits of data protection and anti-discrimination in responding to emergent discrimination', 6 Big Data & Society (2019), p. 2, p. 6.
2731. M. Mann and T. Matzner, 6 Big Data & Society (2019), 7.
2732. M. Mann and T. Matzner, 6 Big Data & Society (2019), p. 7.
2733. On 'feedback loops' or 'feedback effects', see P.T. Kim, 'Data-Driven Discrimination at Work', 48 William & Mary Law Review (2017), p. 882; on redundant encodings, see C. Dwork et al., 'Fairness through awareness', Proceedings of the 3 rd innovations in theoretical computer science conference (2012), p. 226.
2734. On pervasive social sorting, see e.g. S. Zuboff, The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power; C. O'Neil, Weapons of math destruction: how big data increases inequality and threatens democracy.
2735. On stereotyping as discrimination, see e.g. R.J. Cook and S. Cusack, Gender Stereotyping. Transnational Legal Perspectives (University of Pennsylvania Press, 2010).
2736. Opinion of Advocate General Kokott in Case C-443/15 David L. Parris v Trinity College Dublin and Others, EU: C:2016:493, para. 4.
2737. Opinion of Advocate General Mengozzi in Case C-528/13 Geoffrey Léger v Ministre des Affaires sociales, de la Santé et des Droits des femmes and Etablissement français du sang, EU: C:2014:2112, para. 44 (emphasis added).
2738. Representational and access injustices can also pervade much more intimate spheres, as a study of the matching algorithms of online dating apps show: on OK Cupid, 'Asian men and black women are least likely to receive messages or responses'. See J. Hutson et al., 'Debiasing Desire: Addressing Bias & Discrimination on Intimate Platforms', 2 Proceedings of the ACM on Human-Computer Interaction (2018) and C.R. Schwartz, 'Trends and variation in assortative mating: Causes and consequences', 39 Annu Rev Sociol (2013), p. 451.
2739. S. Noble, Algorithms of Oppression: How Search Engines Reinforce Racism (NYU Press, 2018).
2740. S. Wachter, 35 Berkeley Technology Law Journal (2020).
2741. S. Zuboff, The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power (Profile Books, 2019)
2742. See A. Ward, 'The Impact of the EU Charter of Fundamental Rights on Anti-Discrimination Law: More a Whimper than a Bang?', 20 Cambridge Yearbook of European Legal Studies (2018).
2743. See also A.L. Hoffmann, 22(7) Information, Communication & Society (2019), p. 907.

2744. See C. Tilly, Durable Inequality (University of California Press, 1998); N. Fraser, 'From Redistribution to Recognition? Dilemmas of Justice in a 'Post-Socialist' Age', 212 New Left Review (1995); I. M. Young, Justice and the Politics and Difference (Princeton University Press, 1990); I. Solanke, Discrimination as Stigma: A Theory of Anti-Discrimination Law (Hart Publishing, 2017).
2745. See Council, 'Proposal for a Council Directive on implementing the principle of equal treatment between persons irrespective of religion or belief, disability, age or sexual orientation (consolidated text)' ST 9481/17, 1 June 2017.
2746. See D. Pothier, 'Connecting Grounds of Discrimination to Real People's Real Experiences', 13 Canadian Journal of Women and the Law (2001) and D. Gilbert, 'Unequaled: Justice Claire L'Heureux-Dube's Vision of Equality and Section 15 of the Charter', 15 Can J Women & L (2003).
2747. See e.g. A. Lambrecht and C. Tucker, 'Algorithmic Bias? An Empirical Study of Apparent Gender-Based Discrimination in the Display of STEM Career Ads', 65 Management Science (2019).
2748. See e.g. C. Calude and G. Longo, 'The Deluge of Spurious Correlations in Big Data', 22 Foundations of Science (2017), p. 595–612. Machine learning algorithms are trained to identify patterns based on statistical correlations but cannot differentiate these from causal relationships, which might lead to situations were correlations are treated as causal and enforced as relevant variables in decision-making. This is the mechanism behind so-called 'feedback loops', see P.T. Kim, 48 William & Mary Law Review (2017), p. 882.
2749. See e.g. C. O'Neil, Weapons of math destruction: how big data increases inequality and threatens democracy (Crown, 2016); B.A. Williams, C.F. Brooks and Y. Shmargad, Journal of Information Policy (2018), p. 82 and 90.
2750. See e.g. C. Ridgeway, 'Why Status Matters for Inequality', 79 American Sociological Review (2014).
2751. See e.g. L. Alexander and K. Cole, 'Discrimination by proxy', 14 Const Comment (1997).
2752. See e.g. L. Jaume-Palasí, 'Diskriminierung hängt nicht vom Medium ab', Algorithm Watch (2017), <https://algorithmwatch.org/diskriminierung-haengt-nicht-vom-medium-ab/>.
2753. See e.g. N. Vigdor, 'Apple Card Investigated After Gender Discrimination Complaints', The New York Times (2019), <https://www.nytimes.com/2019/11/10/business/Apple-credit-card-investigation.html> and L. Kelion, 'Apple's 'sexist' credit card investigated by US regulator', BBC (2019), https://www.bbc.co.uk/news/business-50365609.
2754. See e.g. S. Barocas and A.D. Selbst, 104 California law review (2016); S.G. Mayson, 'Bias In, Bias Out', University of Georgia School of Law Legal Studies Research Paper No 2018-35 (2018) An example of prejudiced algorithmic model can be found in the story of Dr. Selby, see e.g. S. Wachter-Boettcher, Technically wrong: Sexist apps, biased algorithms, and other threats of toxic tech (WW Norton & Company, 2017), p. 6 and R.Q. Allen and D. Masters, Algorithms, Apps & Artificial Intelligence: The next frontier in discrimination law (Cloisters 2018), p. 12–13.
2755. See e.g. S. Moreau, 'What is discrimination?', 38 Philosophy & Public Affairs (2010); D. Hellman and S. Moreau, Philosophical foundations of discrimination law (OUP, 2013); L. Alexander, 141 University of Pennsylvania Law Review (1992); K. Lippert-Rasmussen, 'The badness of discrimination', 9 Ethical Theory and Moral Practice (2006); K. Lippert-Rasmussen, Born free and equal?: a philosophical inquiry into the nature of discrimination (OUP, 2014); T. Khaitan, A Theory of Discrimination Law (OUP, 2015); I. Solanke, Discrimination as Stigma: A Theory of Anti-Discrimination Law.
2756. See e.g. T.Z. Zarsky, 'Understanding discrimination in the scored society', 89 Wash L Rev (2014); T.Z. Zarsky, 'An Analytic Challenge: Discrimination Theory in the Age of Predictive Analytics', 14 ISJLP (2017); S. Barocas and A.D. Selbst, 'Big Data's Disparate Impact', 104 California Law Review (2016); F.J. Zuiderveen Borgesius, 'Strengthening legal protection against discrimination by algorithms and artificial intelligence', The International Journal of Human Rights (2020); J. Kleinberg et al., 'Discrimination in the age of algorithms', NBER Working Paper No 25548 (2019).
2757. See e.g. the analysis of 'fattism' as a form of discrimination in I. Solanke, Discrimination as Stigma: A Theory of Anti-Discrimination Law.
2758. See e.g. V. Eubanks, Automating inequality: how high-tech tools profile, police, and punish the poor (St. Martin's Press, 2018).
2759. See ibid, p. 82.
2760. See ibid, para. 76–77.
2761. See ibid.
2762. See ibid.
2763. See J. Buolamwini and T. Gebru, Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification, Proceedings of Machine Learning Research (2018).
2764. See K. Crenshaw, The University of Chicago Legal Forum (1989).
2765. See Opinion of Advocate General Maduro in Case C-303/06 S. Coleman v Attridge Law and Steve Law, EU: C:2008:61.
2766. See P. Westen, 'The Empty Idea of Equality', 95 Harvard Law Review (1982).
2767. See P.H. Collins, Black Feminist Thought: Knowledge Consciousness and the Politics of Empowerment.
2768. See P.T. Kim, 48 William & Mary Law Review (2017), p. 873.
2769. See S. Besson, 'La vulnérabilité et la structure des droits de l'Homme. L'exemple de la jurisprudence de la Cour Européenne des Droits de l'Homme', in L. Burgorgue-Larsen (ed), La vulnérabilité saisie par les juges en Europe, vol Cahiers Européens n°7 (Editions Pedone, 2014), p. 69 and O. M. Arnardóttir, 'Vulnerability under Article 14 of the European Convention on Human Rights', 4 Oslo Law Review (2017).
2770. See S. Choudhry, 'Distribution vs. Recognition: The Case of Antidiscrimination Laws', 9 George Mason Law Review (2000).
2771. See S. Noble, Algorithms of Oppression: How Search Engines Reinforce Racism.
2772. See S. Wachter, 'Affinity Profiling and Discrimination by Association in Online Behavioural Advertising', 35 Berkeley Technology Law Journal (2020), p. 44–45.
2773. See the example opening this article: M. Ali et al., 'Discrimination Through Optimization: How Facebook's ad Delivery Can Lead to Skewed Outcomes' (2019), p. 2.
2774. The consequences of social sorting based on behavioural data have been discussed against the background of Foucaldian accounts of biopolitics and the disciplining of society, see e.g. M. Leese, 'The new profiling: Algorithms, black boxes, and the failure of anti-discriminatory safeguards in the European Union', 45 Security Dialogue (2014).
2775. The Court compared the applicant to commissioning fathers and to non-disabled workers in two separate instances, see Case C-363/12 Z. v A Government department and The Board of management of a community school, para. 52 and 77–81.
2776. The Horizontal Directive would extend the scope of the current Framework Directive 2000/78/EC to the supply and consumption of goods and services, see European Commission, Proposal for a Council Directive on implementing the principle of equal treatment between persons irrespective of religion or belief, disability, age or sexual orientation COM(2008) 426 final OJ C303/8, European Union.
2777. This can in and of itself give rise to abuses, see e.g. ibid.

2778. This formula can be traced back to K. Crenshaw, The University of Chicago Legal Forum (1989), p. 140.
2779. This situation would in itself escape the grasp of EU non-discrimination law because socio-economic status is not a protected ground under EU secondary law. It is nevertheless protected in the national law of certain EU Member States.
2780. To counter this, disaggregated data about intersectional patterns of discrimination should be made available. For instance, the accuracy of a predictive system should not only be assessed as an aggregate but also broken down in relation to e.g. gender, race and the intersection of gender and race. This demand has been made repeatedly with regard to intersectional discrimination to trace intra-group disadvantage. Most recently, this point has been recognized in relation to gender-based violence in European Commission, A Union of Equality: Gender Equality Strategy 2020–2025 COM (2020) 152 final: 'To get a complete picture of gender-based violence, data should be disaggregated by relevant intersectional aspects and indicators such as age, disability status, migrant status and rural-urban residence.'
2781. To give just one example, a 2015 Eurobarometer on discrimination in the EU indicated that, in the general population, around one fourth of all discriminations declared were multiple in nature. See European Commission, Special Eurobarometer 437: Discrimination in the EU in 2015 (European Union, 2015).
2782. "Equal Employment Opportunity Commission", 1978.
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2784. A. Cabrera, W. Epperson, F. Hohman, M. Kahng, J. Morgenstern and D. H. Chau, "Fairvis: Visual analytics for discovering intersectional bias in machine learning", arXiv preprint arXiv:1904.05419, 2019.
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2789. B. Alsallakh, W. Aigner, S. Miksch and H. Hauser, "Radial sets: Interactive visual analysis of large overlapping sets", IEEE Transactions on Visualization and Computer Graphics, vol. 19, no. 12, pp. 2496-2505, 2013.
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APÊNDICE F: Autores extraídos das de 3437 referências

N	Autor	Citações	N	Autor	Citações	N	Autor	Citações	N	Autor	Citações
1	Barocas, S.	20	911	Barber, V.	1	1821	Harada, M.	1	2731	Pine, K.	1
2	Dwork, C.	20	912	Barberá, P.	1	1822	Harbin, C. W. L.	1	2732	Pinsof, D.	1
3	Hardt, M.	20	913	Baretto, A.	1	1823	Hardle, W. K.	1	2733	Pinto, P.	1
4	Buolamwini, J.	18	914	Bargavi, P.	1	1824	Harich, K. R.	1	2734	Pip, W.	1
5	Zemel, R.	16	915	Barnard, E.	1	1825	Haridasan, M.	1	2735	Pisani, R.	1
6	Calders, T.	15	916	Barnes, P.	1	1826	Härkönen, E.	1	2736	Pitassi, T.	1
7	Friedler, S. A	15	917	Barnett, R.	1	1827	Harman, C. T.	1	2737	Pitcan, M.	1
8	Angwin, J.	14	918	Barnett, V.	1	1828	Harper, F. M.	1	2738	Pitkin, K.	1
9	Gebru, T.	14	919	Baro, X.	1	1829	Harper, S. R.	1	2739	Pitoura, E.	1
10	Roth, A.	14	920	Baroglio, C.	1	1830	Harris, K. D.	1	2740	Pitt, C.	1
11	Ruggieri, S.	14	921	Baron, R. S.	1	1831	Harrison, D.	1	2741	Pizzato, L.	1
12	Mullainathan, S.	13	922	Baronchelli, A.	1	1832	Hartmann, B.	1	2742	Plaisant, C.	1
13	Pedreschi, D.	13	923	Baron-Cohen, S.	1	1833	Hasan, B.	1	2743	Plant, E. A.	1
14	Turini, F.	12	924	Barr, A.	1	1834	Hasanuzzaman, M.	1	2744	Plantin, J.-C.	1
15	Corbett-Davies, S.	11	925	Barrat, A.	1	1835	Hasebrink, U.	1	2745	Plotkina, D.	1
16	Kamiran, F.	11	926	Barreca, S.	1	1836	Haselton, M. G.	1	2746	Plumerault, H. L. B.	1
17	Kirchner, L.	11	927	Barry, C. L.	1	1837	Hashemi, M.	1	2747	Png, M.-T.	1
18	Wang, Y. X.	11	928	Bartlett, A.	1	1838	Hashimoto, D. A.	1	2748	Poggio, T.	1
19	Larson, J.	10	929	Bartlett, J.	1	1839	Haslam, A. S.	1	2749	Pogrebna, G.	1
20	Wu, Y.	10	930	Barton, M. B.	1	1840	Haslam, C.	1	2750	Pollak, S. D.	1
21	Kleinberg, J.	9	931	Barzel, B.	1	1841	Hassan, S.	1	2751	Pollard, C.	1
22	Selbst, A.	9	932	Basch, C. E.	1	1842	Hatef, E.	1	2752	Pollet, T. V.	1
23	Valera, I.	9	933	Basch, C. H.	1	1843	Hausen, S.	1	2753	Pons, P.	1
24	Venkatasubramanian, S.	9	934	Baskin, W.	1	1844	Haydock, M.	1	2754	Pontil, M.	1
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26	Chouldechova, A.	8	936	Bates, W.	1	1846	Hazarika, D.	1	2756	Popejoy, A. B.	1
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28	Kim, B.	8	938	Batty, M.	1	1848	He, L.	1	2758	Popović, R.	1
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30	Narayanan, A.	8	940	Baumann, E.	1	1850	Hecht, B.	1	2760	Poria, S.	1
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34	Crawford, K.	7	944	Beaulieu-Jones, B. K.	1	1854	Hegelich, S.	1	2764	Prabhakaran, V.	1
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38	Price, E.	7	948	Bedeian, A. G.	1	1858	Heine, S. J.	1	2768	Premack, D.	1
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53	Pierson, E.	6	963	Benkler, Y.	1	1873	Herlocker, J. L.	1	2783	Puri, I. K.	1
54	Raghavan, M.	6	964	Bennett, W. L.	1	1874	Hern, A.	1	2784	Purpura, A.	1
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67	Bolukbasi, T.	5	977	Bernier, E.	1	1887	Hindman, M.	1	2797	Radhakrishnan, V. B.	1
68	Breiman, L.	5	978	Bernot, J.	1	1888	Hing, E.	1	2798	Radicchi, F.	1
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70	Feldman, M.	5	980	Berry, D. S.	1	1890	Hintz, A.	1	2800	Raff, E.	1
71	Green, B.	5	981	Berry, P.	1	1891	Hirschfeld, E.	1	2801	Rafiei, M. H.	1
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85	Silva, R.	5	995	Bickel, P. J.	1	1905	Hojatpour, Y.	1	2815	Randall, V.	1
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87	Smith, M.	5	997	Biemann, C.	1	1907	Holm, S.	1	2817	Rao, K. D.	1
88	Sutskever, K. I.	5	998	Bien, J.	1	1908	Holme, P.	1	2818	Rao, M.	1
89	Torralba, A.	5	999	Bienenstock, E.	1	1909	Holstein, K.	1	2819	Rashotte, J.	1
90	Tucker, C. E.	5	1000	Bigelow, J.	1	1910	Holtham, E.	1	2820	Ratha, N.	1
91	Vedaldi, A.	5	1001	Bigo, D.	1	1911	Honeywell, L.	1	2821	Rathgeb, C.	1
92	Wang, T.	5	1002	Bilmes, J.	1	1912	Hong, P.	1	2822	Ratkiewicz, J.	1
93	Zhang, L.	5	1003	Binns, R.	1	1913	Honneth, A.	1	2823	Rauss, P. J.	1
94	Zhao, J.	5	1004	Birch, L.	1	1914	Honnibal, M.	1	2824	Ravenell, K. L.	1
95	Akaho, S.	4	1005	Bird, S.	1	1915	Hoodbhoy, Z.	1	2825	Raver, J. L.	1
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97	Bau, D.	4	1007	Bischoff, K.	1	1917	Hopman, S. M. J.	1	2827	Ravuri, S. R.	1
98	Berendt, B.	4	1008	Bishop, C. M.	1	1918	Horkheimer, M.	1	2828	Razaviyayn, M.	1
99	Birhane, A.	4	1009	Bishop, S.	1	1919	Horn, M.	1	2829	Razee, H.	1
100	Bogen, M.	4	1010	Bittner, L.	1	1920	Hosenuzzaman, M.	1	2830	Reda, C.	1
101	Borum, R.	4	1011	Bjerring, J. C.	1	1921	Hoskins, A.	1	2831	Reddy, V.	1
102	Castillo, C.	4	1012	Björkqvist, K.	1	1922	Hoskisson, A.	1	2832	Redelmeier, D.	1
103	Chaudhuri, K.	4	1013	Black, W. C.	1	1923	Hosmer, D. W.	1	2833	Redmiles, E. M.	1
104	Chen, C.	4	1014	Blackstock, C.	1	1924	House, R.	1	2834	Redner, S.	1
105	Custers, B.	4	1015	Blanch, M.	1	1925	Hovy, D.	1	2835	Reed, A. L.	1
106	Datta, A.	4	1016	Blanden, J.	1	1926	Hovy, E.	1	2836	Reese, P. P.	1

107	Dean, J.	4	1017	Blank, G.	1	1927	Howansky, K.	1	2837	Rei, M.	1
108	Eguíluz, V. M.	4	1018	Blank, R. M.	1	1928	Howard, A.	1	2838	Reichenbach, H.	1
109	Ferrara, E.	4	1019	Blank, G.	1	1929	Howard, P. N.	1	2839	Reichenbach, M.	1
110	Forth, A. E.	4	1020	Blankenship, D. M.	1	1930	Howard, S. B.	1	2840	Rempala, D. M.	1
111	Fortunato, S.	4	1021	Blaser, R.	1	1931	Howe, C. L.	1	2841	Ren, D.	1
112	Friedman, B.	4	1022	Blei, D. M.	1	1932	Howe, P. D.	1	2842	Ren, L.	1
113	Friedman, J. H.	4	1023	Blex, C.	1	1933	Howes, A.	1	2843	Renken, J.	1
114	Galstyan, A.	4	1024	Blodgett, S. L.	1	1934	Hsieh, C.-J.	1	2844	Renn, O.	1
115	Germain, P.	4	1025	Bloemen, O.	1	1935	Hu, H.	1	2845	Renooij, S.	1
116	Goodfellow, I. J.	4	1026	Blomberg, S. N.	1	1936	Hu, X.	1	2846	Requena, I.	1
117	Goodman, B. W.	4	1027	Blum, A.	1	1937	Huang, A.	1	2847	Resnick, P.	1
118	Gutwirth, S.	4	1028	Blyth, C. R.	1	1938	Huang, C.-D.	1	2848	Rhose, S.	1
119	Hastie, T.	4	1029	Boccaletti, S.	1	1939	Huang, J.	1	2849	Riaz, N.	1
120	Hinton, G. E.	4	1030	Bochner, A. P.	1	1940	Huang, Y.	1	2850	Ribeiro, M. H.	1
121	Hu, L.	4	1031	Bock, C.	1	1941	Huang, Z.-G.	1	2851	Ribeiro-Neto, B.	1
122	Joseph, M.	4	1032	Bodkhe, S.	1	1942	Huberman, B. A.	1	2852	Ricanek, K.	1
123	Kamishima, T.	4	1033	Bodo, B.	1	1943	Hudelot, C.	1	2853	Ricardo, S.	1
124	Kearns, M.	4	1034	Bodria, F.	1	1944	Hufman, A. H.	1	2854	Rice, P.	1
125	Konstan, J. A.	4	1035	Body, J.	1	1945	Hufman, W. H.	1	2855	Richerson, P. J.	1
126	Lambrecht, A.	4	1036	Boellstorff, T.	1	1946	Huibers, T.	1	2856	Richman, L. S.	1
127	Leskovec, J.	4	1037	Boerman, S. C.	1	1947	Hume, D.	1	2857	Richtárik, P.	1
128	Loftus, J. R.	4	1038	Boes, J.	1	1948	Humphreys, K. L.	1	2858	Riediger, M.	1
129	Madras, D.	4	1039	Bogaardt, M.-J.	1	1949	Hunt, N.	1	2859	Riedmiller, M.	1
130	McPherson, M.	4	1040	Bogle, S.	1	1950	Husain, M.	1	2860	Rieg, T.	1
131	Mehrabi, N.	4	1041	Bogost, I.	1	1951	Hussain, A.	1	2861	Rieke, N.	1
132	Messing, S.	4	1042	Boguñá, M.	1	1952	Hussain, M. S.	1	2862	Ringelheim, J.	1
133	Mikolov, T.	4	1043	Bohn, B.	1	1953	Husserl, E.	1	2863	Ringland, N.	1

134	Morstatter, F.	4	1044	Bojanowski, P.	1	1954	Huston, P.	1	2864	Rinzivillo, S.	1
135	Oh, S. S.	4	1045	Bolam, M.R.	1	1955	Hutchings, V. L.	1	2865	Ripley, M. B.	1
136	Phillips, P. J.	4	1046	Bonawitz, K.	1	1956	Hutchins, J.	1	2866	Rivera-Rodriguez, A.J.	1
137	Powers, B.	4	1047	Bond, C. H. L.	1	1957	Hutchinson, B.	1	2867	Rivero-Arias, O.	1
138	Raji, I. D.	4	1048	Bond, M. H.	1	1958	Hutson, J.	1	2868	Roberge, J.	1
139	Rajkomar, A.	4	1049	Bonezzi, A.	1	1959	Huttenlocher, D.	1	2869	Roberson, A. M.	1
140	Russo, F.	4	1050	Bonferroni, C.	1	1960	Hwang, C. P.	1	2870	Roberto, U.	1
141	Scheuerman, M. K.	4	1051	Booth, C.	1	1961	Hwang, D.-U.	1	2871	Roberts, B. W.	1
142	Selbst, A. D.	4	1052	Borenstein, J.	1	1962	Hyde, J. S.	1	2872	Roberts, E.	1
143	Shadbolt, N.	4	1053	Borges, J.	1	1963	Hyland, S. L.	1	2873	Roberts, L. W.	1
144	Smith-Lovin, L.	4	1054	Borgesius, F. Z.	1	1964	Idrees, H.	1	2874	Robertson, R. E.	1
145	Stillwell, D.	4	1055	Boser, B. E.	1	1965	Illouz, E.	1	2875	Robicquet, A.	1
146	Tibshirani, R.	4	1056	Bossman, J.	1	1966	Indregard, A. M. R.	1	2876	Robinson, A.	1
147	Varol, O.	4	1057	Bostrom, N.	1	1967	Indurkhya, N.	1	2877	Robles, C.	1
148	Vayena, E.	4	1058	Botello, A. P.	1	1968	Inukollu, V. N.	1	2878	Robnett, B.	1
149	Wang, D. H.	4	1059	Botsis, T.	1	1969	Iosifescu, D. V.	1	2879	Rodgers, P.	1
150	Watson, D. S.	4	1060	Bouguila, N.	1	1970	Irani, K.	1	2880	Rodrigues, T.	1
151	Zisserman, A.	4	1061	Bourdieu, P.	1	1971	Irani, Z.	1	2881	Rodriguez, C. J.	1
152	Žliobaitė, I.	4	1062	Bourke, R.	1	1972	Irwin, G. A.	1	2882	Rodriguez-Lonebear, D.	1
153	Adamic, L. A.	3	1063	Bourré-Tessier, J.	1	1973	Irwin, L.	1	2883	Rogers, R.	1
154	Allo, P.	3	1064	Bousquet, O.	1	1974	Ishwar, P.	1	2884	Rogers, W. H.	1
155	Alsallakh, B.	3	1065	Bouter, L. M.	1	1975	Isin, E.	1	2885	Rojas, H.	1
156	Bakshy, E.	3	1066	Bouwmans, T.	1	1976	Islam, M.A.	1	2886	Roland, F. G.	1
157	Barrett, L. F.	3	1067	Bowen, D. J.	1	1977	Ismail, Z.	1	2887	Romani, S.	1
158	Bonchi, F.	3	1068	Box, G. E. P.	1	1978	Ito, M.	1	2888	Romanillos, G.	1
159	Bonilla-Silva, E.	3	1069	Boyatzis, R. E.	1	1979	Ivanov, V.	1	2889	Romano, A.	1
160	Branham, S. M.	3	1070	Boyce, W. T.	1	1980	Ives, B.	1	2890	Romanov, A.	1

161	Browne, S.	3	1071	Boyd, R.	1	1981	Jabłonowska, A.	1	2891	Rombach, I.	1
162	Burge, M. J.	3	1072	Boyer, K. W.	1	1982	Jabri, S.	1	2892	Romero, D. M.	1
163	Burrell, J.	3	1073	Boza, V.	1	1983	Jack, R. E.	1	2893	Romero-Tris, C.	1
164	Calmon, F.	3	1074	Brandt, E.	1	1984	Jackson, J. E.	1	2894	Rommelfanger, K. S.	1
165	Caruana, R.	3	1075	Brants, S.	1	1985	Jadbabaie, A.	1	2895	Rommetveit, K.	1
166	Castellano, C.	3	1076	Braun, V.	1	1986	Jafarzadeh, H.	1	2896	Ron, D.	1
167	Castro, V. M.	3	1077	Bray, F.	1	1987	Jagielski, M.	1	2897	Ronanki, R.	1
168	Chen, J.	3	1078	Bray, P.	1	1988	Jain, S.	1	2898	Rorive, I.	1
169	Chen, Y.	3	1079	Brendan, F. K.	1	1989	Jaja, B. N. R.	1	2899	Rosa, N.	1
170	Clune, J.	3	1080	Brender, J.	1	1990	Jamshidi, M. B.	1	2900	Rosa, P.	1
171	Cook, J. M.	3	1081	Brenner, E.	1	1991	Janizek, J.	1	2901	Rosch, E.	1
172	Cotter, A.	3	1082	Brenner, J.	1	1992	Jannach, D.	1	2902	Roscher, R.	1
173	Courville, A.	3	1083	Brentnall, L.	1	1993	Jao, I.	1	2903	Rose, S.	1
174	Covington, B. P.	3	1084	Bresnick, J.	1	1994	Jarrett, K.	1	2904	Rosenblat, A.	1
175	Cukier, K.	3	1085	Bressgott, T.	1	1995	Javed, S.	1	2905	Rosenblueth, A.	1
176	Danks, D.	3	1086	Brewer, P.	1	1996	Javidan, M.	1	2906	Rosenbluth, F. M.	1
177	Dantcheva, A.	3	1087	Brewin, C. R.	1	1997	Jawad, A. S.	1	2907	Rosenfeld, M. J.	1
178	Dey, K.	3	1088	Brey, P.A.	1	1998	Jawaid, H.	1	2908	Rosner, D. K.	1
179	Dodds, P. S.	3	1089	Bribosia, E.	1	1999	Jędrzejewski, A.	1	2909	Rost, K.	1
180	Domingo-Ferrer, J.	3	1090	Brickell, J.	1	2000	Jefrey, W.	1	2910	Rosvall, M.	1
181	Doshi-Velez, F.	3	1091	Brieghel, C.	1	2001	Jeh, G.	1	2911	Rougier, M.	1
182	Dressel, J.	3	1092	Brinker, T. J.	1	2002	Jenkins, H.	1	2912	Rouhizadeh, M.	1
183	Dua, D.	3	1093	Briones, R.	1	2003	Jenkins, J. L.	1	2913	Rouse, C.	1
184	Farid, H.	3	1094	Brkan, M.	1	2004	Jensen, M. H.	1	2914	Roussin, C. J.	1
185	Feldman, V.	3	1095	Brock, A.L.	1	2005	Jensen, T. B.	1	2915	Rowe, D. C.	1
186	Fernández-Delgado, A.	3	1096	Broder, A.	1	2006	Jeong, S.-J.	1	2916	Roy, B.	1
187	Flaxman, S.	3	1097	Brody, J. G.	1	2007	Jestico, B.	1	2917	Roy, D.	1

188	Graepel, T.	3	1098	Broeders, D.	1	2008	Jetten, J.	1	2918	Roychowdhury, V. P.	1
189	Graff, C.	3	1099	Brooks, C. F.	1	2009	Jeung, D. Y.	1	2919	Rubin, D. B.	1
190	Grote, T.	3	1100	Brosius, H.	1	2010	Jewkes, R.	1	2920	Rubinfeld, D. L.	1
191	Guttag, J. V.	3	1101	Brossard, E.	1	2011	Jia, M.	1	2921	Rubinov, I.	1
192	Haim, M.	3	1102	Brougham, D.	1	2012	Jia, Y.	1	2922	Rudder, C.	1
193	Hamidi, F.	3	1103	Brown, A.	1	2013	Jiang, F.	1	2923	Rudin, C.	1
194	Hannak, A.	3	1104	Brown, B.	1	2014	Jiang, H.	1	2924	Rudolph, J. W.	1
195	Hauser, H.	3	1105	Brown, N. M.	1	2015	Jiang, J.-J.	1	2925	Rudzicz, F.	1
196	Heidari, H.	3	1106	Brown, W.	1	2016	Jiang, R.	1	2926	Ruesch, J.	1
197	Horvitz, E.	3	1107	Brundage, M.	1	2017	Jiang, S.	1	2927	Rugh, J. S.	1
198	Hubert, B. M.	3	1108	Bruno, F.	1	2018	Jiao, J.	1	2928	Rukavina, S.	1
199	Iliadis, A.	3	1109	Brynjolfsson, E.	1	2019	Jin, Z.	1	2929	Rumberger, J. L.	1
200	Introna, L. D.	3	1110	Bryone, K.	1	2020	Jiskrova, G. K.	1	2930	Rumsfeld, J. S.	1
201	Isaac, W.	3	1111	Bryson, K.	1	2021	Jiyoung, W.	1	2931	Ruppert, E.	1
202	Jabbari, S.	3	1112	Buckeley, C.	1	2022	Joachims, T.	1	2932	Russel, S. J.	1
203	Johnson, K. L.	3	1113	Budd, K.	1	2023	John, O. P.	1	2933	Russell, J. Á.	1
204	Kagal, L.	3	1114	Buettner, R.	1	2024	Johnson, J. A.	1	2934	Russell, J. C.	1
205	Karypis, G.	3	1115	Bulat, A.	1	2025	Johnson, M.	1	2935	Russell, S.J.	1
206	Khosla, A.	3	1116	Buntain, C.	1	2026	Jones, K.	1	2936	Russo, G.	1
207	Kittur, A.	3	1117	Buntine, W.	1	2027	Jong, L.	1	2937	Ruthotto, L.	1
208	Klare, B. F.	3	1118	Burbano, A.	1	2028	Joo, S.	1	2938	Ruths, D.	1
209	Lacasse, A.	3	1119	Burdge, B. J.	1	2029	Jordon, J.	1	2939	Ryszka, D.	1
210	Lakkaraju, H.	3	1120	Burke, J.	1	2030	Jørgensen, D. R.	1	2940	Sabatine, M. S.	1
211	Laviolette, F.	3	1121	Burke, O.	1	2031	Joshua, L.	1	2941	Sacco, T.	1
212	Lazer, D.	3	1122	Burke, R.	1	2032	Jost, J. T.	1	2942	Sackett, P. R.	1
213	Li, Y.	3	1123	Burns, T.	1	2033	Joyce, M. L.	1	2943	Sadiq, S.	1
214	Liu, C. H.	3	1124	Busch, C.	1	2034	JuLeigh, P.	1	2944	Sadowski, P.	1

215	London, A. J.	3	1125	Busch, J.	1	2035	Jung, J.	1	2945	Sagiroglu, S.	1
216	Louizos, C.	3	1126	Buse, K.	1	2036	Jung, S. K.	1	2946	Sagonas, C.	1
217	Mann, M.	3	1127	Bygrave, L. A.	1	2037	Junger, M.	1	2947	Saheeda, A.	1
218	Manyika, J.	3	1128	Cabanas, E.	1	2038	Junglas, I.	1	2948	Sahu, A.	1
219	Mathivanan, P.	3	1129	Cable, J.	1	2039	Jurgens, P.	1	2949	Sai, C. L.	1
220	Matzner, T.	3	1130	Cabral, H. J.	1	2040	Just, N.	1	2950	Saigí-Rubió, F.	1
221	Mcauley, J.J.	3	1131	Cabrera, A.	1	2041	Kachel, S.	1	2951	Saindane, H. M.	1
222	McMahan, H. B.	3	1132	Cabrera, A. A.	1	2042	Kahng, M.	1	2952	Sajjad, H.	1
223	Meira, S. R.	3	1133	Cacioppo, J. T.	1	2043	Kaibara, M.	1	2953	Sakuma, J.	1
224	Mohammad, S. M.	3	1134	Caldarelli, G.	1	2044	Kairouzv, P.	1	2954	Salamon, L. M.	1
225	Murray-Rust, D.	3	1135	Calderone, K. L.	1	2045	Kalai, A. T.	1	2955	Salanitro, A.	1
226	Nguyen, A. D.	3	1136	Calude, C.	1	2046	Kalakota, R.	1	2956	Saleh, T.	1
227	Pastor-Satorras, R.	3	1137	Calvo, R. A.	1	2047	Kalibatseva, Z.	1	2957	Salehi, N.	1
228	Patil, D. J.	3	1138	Camacho-Collados, J.	1	2048	Kaliouby, R. E.	1	2958	Salehinejad, H.	1
229	Pazzani, M. J.	3	1139	Camaj, L.	1	2049	Kalish, M. L.	1	2959	Salgado, M.	1
230	Pechenizkiy, M.	3	1140	Cambria, E.	1	2050	Kamal, M. M.	1	2960	Salihu, H. M.	1
231	Pentland, A. S.	3	1141	Camilli, G.	1	2051	Kamar, E.	1	2961	Salimi, A.	1
232	Poornima, K.	3	1142	Camino, R. D.	1	2052	Kamilaris, A.	1	2962	Salisbury, E. J.	1
233	Preibusch, S.	3	1143	Campa, S.	1	2053	Kanade, T.	1	2963	Salman, S.	1
234	Rieke, A.	3	1144	Campbell, A.	1	2054	Kanamori, K.	1	2964	Saltelli, A.	1
235	Robertson, D.	3	1145	Cancelmo, C.	1	2055	Kane, C. F.	1	2965	Saltz, J. S.	1
236	Robinson, D. G.	3	1146	Candanedo, L. M.	1	2056	Kangarloo, H.	1	2966	Salvanes, K. G.	1
237	Romei, A.	3	1147	Cao, B.	1	2057	Kansagara, D.	1	2967	San Miguel, M.	1
238	Ross, A.	3	1148	Cao, H.	1	2058	Kaplan, A.	1	2968	Sanchez, A.	1
239	Roth, D.	3	1149	Cao, Q.	1	2059	Karahalios, K.	1	2969	Sánchez-Jankowski, M.	1
240	Roy, J.F.	3	1150	Capdevila, M.	1	2060	Karahanna, E.	1	2970	Sanders, D.	1
241	Rubin, J.	3	1151	Caplan, R.	1	2061	Karhade, A. V.	1	2971	Sandra, G.	1

242	Sakuma, J.	3	1152	Capps, J.	1	2062	Karim, A.	1	2972	Sankaranarayanan, S.	1
243	Salakhutdinov, R.	3	1153	Capsuto, S.	1	2063	Karpathy, A.	1	2973	Santos, D. P.	1
244	Saldivar, E.	3	1154	Caragea, D.	1	2064	Karpuzoglu, E.	1	2974	Sapiezynski, P.	1
245	Schiebinger, L.	3	1155	Caramanis, C.	1	2065	Kartakoullis, A.	1	2975	Saposnik, G.	1
246	Schwartz, H. A.	3	1156	Carbonell, I. M.	1	2066	Karthikesalingam, A.	1	2976	Saramäki, J.	1
247	Setiono, R.	3	1157	Cardiff, C. F.	1	2067	Kassam, I.	1	2977	Sarathy, R.	1
248	Sharma, A.	3	1158	Cardoso, F. M.	1	2068	Katajisto, J.	1	2978	Sareen, S.	1
249	Shavlik, J. W.	3	1159	Cardoso, T.	1	2069	Katon, J. G.	1	2979	Saria, S.	1
250	Skeem, J.	3	1160	Cardullo, P.	1	2070	Katzenbach, C.	1	2980	Saribay, S. A.	1
251	Smart, P.	3	1161	Carlos, S.	1	2071	Kaufmann, E.	1	2981	Sarker, A.	1
252	Sontag, D.	3	1162	Carolan, M.	1	2072	Kaukiainen, A.	1	2982	Sarshar, N.	1
253	Suresh, H.	3	1163	Carpendale, S.	1	2073	Kaul, R.	1	2983	Sartorius, N.	1
254	Suresh, V.	3	1164	Carr, N.	1	2074	Kaun, A.	1	2984	Sarwar, B.	1
255	Swersky, K.	3	1165	Carrell, D. S.	1	2075	Kaushal, A.	1	2985	Sarwar, S.	1
256	Tang, X.	3	1166	Carter, R. A.	1	2076	Kavukcuoglu, K.	1	2986	Sarwat, M.	1
257	Taylor, L.	3	1167	Casalicchio, G.	1	2077	Kawaguchi, A.	1	2987	Sarwate, A.D.	1
258	Thakurta, A.G.	3	1168	Casilli, A. A.	1	2078	Kawulok, M.	1	2988	Satyanarayanan, M.	1
259	Trielli, D.	3	1169	Caspi, A.	1	2079	Kaya, A.	1	2989	Saul, L. K.	1
260	Varshney, K. R.	3	1170	Cassel, J.	1	2080	Keck, P. E.	1	2990	Savova, G.	1
261	Verma, S.	3	1171	Castelle, M.	1	2081	Keeys, M. R.	1	2991	Sayre, M. R.	1
262	Vespignani, A.	3	1172	Castelli, M.	1	2082	Kell, D. B.	1	2992	Scantamburlo, T.	1
263	Vidal, R.	3	1173	Castelló, X.	1	2083	Kellis, M.	1	2993	Schacht, C.	1
264	Wainberg, M.	3	1174	Castillo, J.	1	2084	Kelly, C. J.	1	2994	Schaefer, D. R.	1
265	Wei, D.	3	1175	Castoriadis, C.	1	2085	Kelly, M.	1	2995	Schafer, J. B.	1
266	Weinberger, K. Q.	3	1176	Castro-Gómez, S.	1	2086	Kelly, J.	1	2996	Schafer, J. L.	1
267	Weller, A.	3	1177	Catanzaro, M.	1	2087	Keltner, D.	1	2997	Schaffer, M. M.	1
268	Whittaker, M.	3	1178	Cave, S.	1	2088	Kemelmacher-Shlizerman, I.	1	2998	Schaub, M.	1

269	Wu, X.	3	1179	Cebrian, M.	1	2089	Kennedy, M.	1	2999	Schenck-Gustafsson, K.	1
270	Yosinski, J.	3	1180	Ceccio, J.	1	2090	Kennedy-Hendricks, A.	1	3000	Scherr, S.	1
271	Zhou, A.	3	1181	Celi, L.A.	1	2091	Kerr, I.	1	3001	Schiano, D.	1
272	Zúñiga, H. G.	3	1182	Cella, D.	1	2092	Kerstin, D.	1	3002	Schiebinger, L.	1
273	Abramson, C. M.	2	1183	Cerquides, J.	1	2093	Kertesz, J.	1	3003	Schipper, B. C.	1
274	Adam, H.	2	1184	Chae, J. M.	1	2094	Kessel, P.	1	3004	Schmidt, J.-H.	1
275	Adamic, L. A.	2	1185	Chan, J.	1	2095	Kesselheim, A. S.	1	3005	Schmitt, N. W.	1
276	Adams, J.	2	1186	Chan, S.	1	2096	Kettinger, W. J.	1	3006	Schmitz, H.	1
277	Adebayo, J.	2	1187	Chandak, P.	1	2097	Keum, M. J.	1	3007	Schnabel, K. U.	1
278	Adler, N. E.	2	1188	Chandraharan, E.	1	2098	Keuroghlian, A.S.	1	3008	Schneeberger, D.	1
279	Adolphs, R.	2	1189	Chaney, A. J. B.	1	2099	Keyes, E. F.	1	3009	Schneeweiss, S.	1
280	Adomavicius, G.	2	1190	Chang, B.	1	2100	Khaitan, T.	1	3010	Schneider, G.	1
281	Agan, A.	2	1191	Chang, C.-I.	1	2101	Khaloufi, H.	1	3011	Schneider, T. D.	1
282	Ahmad, M.	2	1192	Chang, S. J.	1	2102	Khamis, A.	1	3012	Schneier, B.	1
283	Ajunwa, I.	2	1193	Chang, Y.-W.	1	2103	Khan, S. A.	1	3013	Schölkopf, B.	1
284	Allen, A.	2	1194	Chapman, J.	1	2104	Khandani, E.	1	3014	Scholz, F.W.	1
285	Alpaydin, E.	2	1195	Charles-Pauvers, B.	1	2105	Khanna, B.	1	3015	Schönfeld, M.V.	1
286	Alsan, M.	2	1196	Charon, R.	1	2106	Khanna, P.	1	3016	Schor, J. B.	1
287	Ammenwerth, E.	2	1197	Chau, D. H.	1	2107	Kharrazi, H.	1	3017	Schott, C. L.	1
288	Ananny, M.	2	1198	Chau, P. Y.	1	2108	Khaw, K.-T.	1	3018	Schroeter, T.	1
289	Ancona, M.	2	1199	Chaudhari, J.	1	2109	Khedkar, A. P.	1	3019	Schubert, L.	1
290	Anderson, C.	2	1200	Chaudhari, N.	1	2110	Khetan, A.	1	3020	Schüll, N. D.	1
291	Andrews, R.	2	1201	Chauvin, A.	1	2111	Khozin, S.	1	3021	Schuman, H.	1
292	Arendt, F.	2	1202	Chen, A. M.	1	2112	Kia-Keating, M.	1	3022	Schuster, A.	1
293	Arnaboldi, V.	2	1203	Chen, C.-h.	1	2113	Kibbe, M. R.	1	3023	Schutt, R.	1
294	Baeza-Yates, R.	2	1204	Chen, E. S.	1	2114	Kiciman, E.	1	3024	Schwartz, C.R.	1
295	Baker, S.	2	1205	Chen, F.	1	2115	Kiel, D.	1	3025	Schwartz, R. C.	1

296	Baldwin, R.	2	1206	Chen, G.	1	2116	Kietzmann, J.	1	3026	Schwarz, N.	1
297	Banaji, M. R.	2	1207	Chen, J. A.	1	2117	Kifer, D.	1	3027	Scullard, P.	1
298	Bartel, P. A.	2	1208	Chen, L.	1	2118	Kilpatrick, C.	1	3028	Seaver, N.	1
299	Bateson, G.	2	1209	Chen, P.	1	2119	Kim, A. J.	1	3029	Seefeldt, C.	1
300	Batra, D.	2	1210	Chen, R.	1	2120	Kim, C	1	3030	Segolene, T.	1
301	Beck, C.	2	1211	Chen, S.-Y.	1	2121	Kim, H.	1	3031	Seitz, S.	1
302	Bell, R.	2	1212	Chen, X.	1	2122	Kim, J.	1	3032	Selala, M. K.	1
303	Bell, S.	2	1213	Chen, Z.	1	2123	King, D.	1	3033	Selbst, A. D.	1
304	Bellamy, R. K.	2	1214	Cheng, J.	1	2124	King, I.	1	3034	Seldin, Y.	1
305	Benbasat, I.	2	1215	Cheng, P.	1	2125	King, J.	1	3035	Seligman, M. E. P.	1
306	Benitez, J. M.	2	1216	Cheng, Z.	1	2126	Klein, J.	1	3036	Semaan, B.	1
307	Bennett, J.	2	1217	Chenok, D.	1	2127	Klein, T.	1	3037	Senders, J. T.	1
308	Berens, P.	2	1218	Chiang, C. K.	1	2128	Kleinberg, J.	1	3038	Sengupta, B.	1
309	Berk, R.	2	1219	Chiappa, S.	1	2129	Kleinlein P.	1	3039	Seo, J.	1
310	Berners-Lee, T.	2	1220	Chiappetta, M.	1	2130	Kline, T. L.	1	3040	Sequeira, R.	1
311	Bertot, J. C.	2	1221	Chierichetti, F.	1	2131	Klinke, A.	1	3041	Seth, K.	1
312	Bidgoly, J. A.	2	1222	Chintala, S.	1	2132	Klohnen, E. C.	1	3042	Settles, B.	1
313	Billsus, D.	2	1223	Chipman, H. Á.	1	2133	Kluckhohn, C.	1	3043	Setty, S.	1
314	Binder, A.	2	1224	Chishti, M.A.	1	2134	Klumbyte, G.	1	3044	Severinghaus, J. W.	1
315	Binns, R.	2	1225	Choi, E.	1	2135	Knittel, C. R.	1	3045	Sezgin, M.	1
316	Birnholtz, J.	2	1226	Choi, K.-H.	1	2136	Knoche, M.	1	3046	Shalev-Shwartz, S.	1
317	Black, J. S.	2	1227	Choi, S. W.	1	2137	Knox, D.	1	3047	Shalit, U.	1
318	Blasimme, A.	2	1228	Choo, H. Y.	1	2138	Ko, S. J.	1	3048	Shanavas, K. A.	1
319	Blenn, N.	2	1229	Chowdhury, R.	1	2139	Koen, L.	1	3049	Shapira, B.	1
320	Blix, E.	2	1230	Chow-White, P. A.	1	2140	Kofi, K.	1	3050	Shardanand, U.	1
321	Bonilla, E. V.	2	1231	Christakis, N. A.	1	2141	Koh, P. W.	1	3051	Sharfstein, J. M.	1
322	Bonneau, R.	2	1232	Christin, A.	1	2142	Kohler-Hausmann, I.	1	3052	Sharif, A. M.	1

323	Bowker, G. C.	2	1233	Chronaki, C.	1	2143	Koike-Akino, T.	1	3053	Shaw, D. L.	1
324	Boyd, D.	2	1234	Chu, X.	1	2144	Kolhe, V. L.	1	3054	Shaw, J.	1
325	Bozdag, E.	2	1235	Chui, M.	1	2145	Kombe, F.	1	3055	Shearer, E.	1
326	Bremond, F.	2	1236	Chung, C.	1	2146	Kong, J. S.	1	3056	Sheats, K.	1
327	Broussard, M.	2	1237	Chung, J. Y.	1	2147	Kononenko, I.	1	3057	Sheikh, K.	1
328	Brubaker, J. R.	2	1238	Chung, P.-C.	1	2148	Konrad, J.	1	3058	Shen, J.	1
329	Bruna, J.	2	1239	Chun-Ju, H.	1	2149	Koops, B.	1	3059	Shen, L.	1
330	Buregio, V.	2	1240	Churchwell, K.	1	2150	Kopecky, J.	1	3060	Shen, Y.	1
331	Burgess, J.	2	1241	Ciampaglia, G. L.	1	2151	Koren, Y.	1	3061	Shepherd, T.	1
332	Butler, J.	2	1242	Cifor, M.	1	2152	Korfiatis, P.	1	3062	Sheppard, S. D.	1
333	Cai, Z.	2	1243	Cimini, G.	1	2153	Kornienko, O.	1	3063	Sheth, B.	1
334	Campolo, A.	2	1244	Cinelli, M.	1	2154	Kosara, R.	1	3064	Shi, N.	1
335	Carter, G.	2	1245	Cios, K. J.	1	2155	Kothari, P.	1	3065	Shim, J.	1
336	Castro, J. L.	2	1246	Cisło, J.	1	2156	Kotzian, B. J.	1	3066	Shimomura, N.	1
337	Cave, M.	2	1247	Citro, C. F.	1	2157	Kouki, P.	1	3067	Shirado, H.	1
338	Centola, D.	2	1248	Claassen, T.	1	2158	Kowalski, R. M.	1	3068	Shmargad, Y.	1
339	Cernadas, E.	2	1249	Clancy, C. M.	1	2159	Kraaij, W.	1	3069	Shmueli, E.	1
340	Char, D. S.	2	1250	Clapham, R.	1	2160	Krafft, T. D.	1	3070	Shneiderman, B.	1
341	Charles, C. R.	2	1251	Clare, H.	1	2161	Kramer, A. D. I.	1	3071	Shoerio, M.	1
342	Chen, H. L.	2	1252	Clark, C.	1	2162	Kranton, R. E.	1	3072	Shoham, Y.	1
343	Chen, I. Y.	2	1253	Clarke, A. E.	1	2163	Kreimeyer, K.	1	3073	Sholla, S.	1
344	Chen, K.	2	1254	Clarke, B.	1	2164	Krishnan, R.	1	3074	Shoval, P.	1
345	Chen, M. C.	2	1255	Clarke, V.	1	2165	Krishnan, S.	1	3075	Shrem, G.	1
346	Chen, W.	2	1256	Clary, E. G.	1	2166	Kristensen, D. B.	1	3076	Shrestha, Y. R.	1
347	Cheng, C. T.	2	1257	Clayton, J. A.	1	2167	Kroeber, A. L.	1	3077	Shrof, R.	1
348	Chi, E. H.	2	1258	Clayton, P. R.	1	2168	Kross, E.	1	3078	Siapera, E.	1
349	Chin, M. H.	2	1259	Clopton, J.	1	2169	Kruijf, J. D.	1	3079	Siegel, A. L.	1

350	Churchill, E. F.	2	1260	Coenen, L.	1	2170	Kruikemeier, S.	1	3080	Sijben, E.	1
351	Ciampaglia, G.L.	2	1261	Cohen, J.	1	2171	Krumholz, M.	1	3081	Silakari, S.	1
352	Clifton, C.	2	1262	Cohen, S.	1	2172	Kruskal, W. H.	1	3082	Silva, G. M.	1
353	Cogswell, M.	2	1263	Cohen, T. S.	1	2173	Krutzinna, J.	1	3083	Silva, L.	1
354	Coppersmith, G. A.	2	1264	Cohen, W.	1	2174	Kuechler, B.	1	3084	Silva, P. A.	1
355	Cotten, S. R.	2	1265	Cohen, J.	1	2175	Kuhn, T. S.	1	3085	Silver, D.	1
356	Counts, S.	2	1266	Cohn, J. F.	1	2176	Kukutai, T.	1	3086	Silverman, M. G.	1
357	Cowgill, B.	2	1267	Colak, A.	1	2177	Kulkarni, A.	1	3087	Simonetto, P.	1
358	Cowls, J.	2	1268	Cole, K.	1	2178	Kulshrestha, J.	1	3088	Simonyan, K.	1
359	Cramer, H.	2	1269	Cole, M. S.	1	2179	Kulynych, B.	1	3089	Simperl, E.	1
360	Creager, E.	2	1270	Colizza, V.	1	2180	Kumar, R.	1	3090	Simpson, E.	1
361	Creager, E.	2	1271	Collins, C.	1	2181	Kumari, S.V.	1	3091	Sinanc, D.	1
362	Cui, B.	2	1272	Collins, F.S.	1	2182	Kundaje, A.	1	3092	Sinclair, M.	1
363	D'Ignazio, C.	2	1273	Collins, H.	1	2183	Kundnani, A.	1	3093	Sinclair, T.	1
364	Danah, B.	2	1274	Comandé, G.	1	2184	Kunz, T. P.	1	3094	Singh, J.	1
365	Das, A.	2	1275	Combs, G.	1	2185	Kurgan, L. A.	1	3095	Singh, J. P.	1
366	Davoust, A.	2	1276	Concannon, C.	1	2186	Kushniruk, A. W.	1	3096	Singh, M.	1
367	De Choudhury, M.	2	1277	Conover, M.	1	2187	Kvapilova, L.	1	3097	Sinha, G.	1
368	De Hert, P.	2	1278	Conradt, R.	1	2188	Kwon, H. S.	1	3098	Sink, A.	1
369	De Roure, D.	2	1279	Conti, M.	1	2189	Lacoste, A.	1	3099	Sinsky, C. A.	1
370	de Vreese, C. H.	2	1280	Converse, P. E.	1	2190	Lagerspetz, K.	1	3100	Sırbu, A.	1
371	Dean, S.	2	1281	Conway, D.	1	2191	Lagoze, C.	1	3101	Sivakumar, G.	1
372	De-Arteaga, M.	2	1282	Cook, B. L.	1	2192	Lai, Y.-C.	1	3102	Sivarajah, U.	1
373	Deng, W.	2	1283	Cook, D.	1	2193	Lalmas, M.	1	3103	Sjoding, M. W.	1
374	Denton, E.	2	1284	Cook, J. M.	1	2194	Lan, C.	1	3104	Skiera, B.	1
375	DeVito, M. A.	2	1285	Cook, R. J.	1	2195	Lan, Y.	1	3105	Skitka, L. J.	1
376	Devroye, L.	2	1286	Cooper, R. L.	1	2196	Lanckriet, G. R.	1	3106	Skogerbø, E.	1

377	Diakopoulos, N.	2	1287	Coram, M.	1	2197	Lander, E.	1	3107	Slechten, L.	1
378	Diederich, J.	2	1288	Corander, J.	1	2198	Lang, A.	1	3108	Sloan, L.	1
379	Dobbe, R.	2	1289	Coravos, A.	1	2199	Langford, J.	1	3109	Slobogin, C.	1
380	Dow, S. P.	2	1290	Corbett, J.	1	2200	Langley, P.	1	3110	Smart, A.	1
381	Duchesnay, É.	2	1291	Corbett, L. E.	1	2201	Langlois, G.	1	3111	Smeaton, A. F.	1
382	Dudık, M.	2	1292	Corney, M.	1	2202	Langner, O.	1	3112	Smith, B.	1
383	Dugelay, J.-L.	2	1293	Cornish, H.	1	2203	Langville, A.	1	3113	Smith, C. L.	1
384	Dunbar, R.	2	1294	Cornwall, A.	1	2204	Lanning, S.	1	3114	Smith, T. W.	1
385	Durrani, N.	2	1295	Correa, T.	1	2205	Larradet, F.	1	3115	Smith, V.	1
386	Edwards, L.	2	1296	Corrigan, P. W.	1	2206	Larson, D. B.	1	3116	Smith, W. R.	1
387	Ellis, B. H.	2	1297	Cortes, C.	1	2207	Larson, J.	1	3117	Smith-Doerr, L.	1
388	Engebretsen, M.	2	1298	Cossy-Gantner, A.	1	2208	Larsson, A. O.	1	3118	Smolenski, D. J.	1
389	Erhan, D.	2	1299	Costa-jussa, M.R.	1	2209	Larus, J.	1	3119	Smolka, B.	1
390	Evans, J. A.	2	1300	Cotter, K.	1	2210	Lasecki, W.	1	3120	Smyth, R.	1
391	Fan, X.	2	1301	Cotterell, R.	1	2211	Lasko, T. A.	1	3121	Snape, P.	1
392	Fawzi, N.	2	1302	Courset, R.	1	2212	Lasswell, H. D.	1	3122	Snyder, C. F.	1
393	Feng, Z. k.	2	1303	Courtois, C.	1	2213	Latapy, M.	1	3123	Snyder, M.	1
394	Fong, R. C.	2	1304	Cowan, T. L.	1	2214	Latzer, M.	1	3124	Soatto, S.	1
395	Frey, B. J.	2	1305	Crandall, J. W.	1	2215	Laumer, S.	1	3125	Socher, R.	1
396	Galletta, D. F.	2	1306	Cranor, L. F.	1	2216	Lauriault, T. P.	1	3126	Sokolowski, S. W.	1
397	Gao, J.	2	1307	Cranshaw, J.	1	2217	Lausen, G.	1	3127	Solomon, S.	1
398	Garcia, D.	2	1308	Craven, M.	1	2218	LaVeist, T. A.	1	3128	Song, C.	1
399	Garcia, E. A.	2	1309	Crawford, J. T.	1	2219	Law, E.	1	3129	Song, D.	1
400	Garcia, P.	2	1310	Crawford, P.	1	2220	Law, M. R.	1	3130	Song, L.	1
401	Garcia-Gathright, J.	2	1311	Crawford, K.	1	2221	Le, Q. V.	1	3131	Song, M.	1
402	Gardner, J. R.	2	1312	Crayton, E.	1	2222	Leary, M. R.	1	3132	Song, R.	1
403	Garg, N.	2	1313	Criado, N.	1	2223	Leavitt, R. A.	1	3133	Sood, V.	1

404	Giannotti, F.	2	1314	Cristianini, N.	1	2224	Lederman, R.	1	3134	Sophie, H.	1
405	Gilbert, J. E.	2	1315	Crivelli, C.	1	2225	Ledig, C.	1	3135	Sowell, E. R.	1
406	Gillespie, T.	2	1316	Croft, B.	1	2226	Ledley, R. S.	1	3136	Sowell, E. R.	1
407	Gilpin, L. H.	2	1317	Cromwell, J.	1	2227	Lee, B.	1	3137	Sparks, J. V.	1
408	Glenn, I.	2	1318	Crone, S. F.	1	2228	Lee, C.	1	3138	Speckmann, B.	1
409	Graham, J. W.	2	1319	Cronkite, D.	1	2229	Lee, C.-C.	1	3139	Speier, A.	1
410	Granka, L.	2	1320	Crowcroft, J.	1	2230	Lee, D. S.	1	3140	Spenkuch, J. L.	1
411	Grant, A.	2	1321	Crowley, M.	1	2231	Lee, H. W.	1	3141	Speybroeck, N.	1
412	Greenwald, A. G.	2	1322	Cueto, R. M.	1	2232	Lee, M. S. A.	1	3142	Spiegel, M.	1
413	Grey, S.	2	1323	Culver, S. M.	1	2233	Lee, S.	1	3143	Spong, C. Y.	1
414	Grgic-Hlaca, N.	2	1324	Cunneen, M.	1	2234	Lef, J.	1	3144	Springenberg, J. T.	1
415	Gross, M.	2	1325	Cunningham, P.	1	2235	Lehavot, K.	1	3145	Squartini, T.	1
416	Guha, A.	2	1326	Cuocolo, R.	1	2236	Leibrand, S.	1	3146	Sra, S.	1
417	Guidotti, R.	2	1327	Curcin, V.	1	2237	Leigh, B. P.	1	3147	Sridharan, K.	1
418	Günnemann, S.	2	1328	Curran, J.R.	1	2238	Lemeshow, S.	1	3148	Srikant, R.	1
419	Gupta, A. K.	2	1329	Curren, M. T.	1	2239	Lenartowicz, T.	1	3149	Sriperumbudur, B. K.	1
420	Gürses, S.	2	1330	Currie, L. M.	1	2240	Leng, T.	1	3150	Stacey, J.	1
421	Gutmann, M. U.	2	1331	Cusack, S.	1	2241	Leon, P. G.	1	3151	Stamos, A.	1
422	Hagerty, A.	2	1332	Cusimano, M. D.	1	2242	Leong, F. T. L.	1	3152	Stanyer, J.	1
423	Halfaker, A.	2	1333	Cutrona, C. E.	1	2243	Lepper, M. R.	1	3153	Stappers, P. J.	1
424	Hall, E.	2	1334	Cvijanovich, N. Z.	1	2244	Lerman, K.	1	3154	Stark, L.	1
425	Hall, W.	2	1335	Cynthia, L.	1	2245	Lesaffre, E.	1	3155	Starr, S.	1
426	Han, J.	2	1336	Czerwinski, M.	1	2246	Lesko, L. J.	1	3156	State, R.	1
427	Hancock, J. T.	2	1337	D'Arcy, J.	1	2247	Leslie, D.	1	3157	Steele, C. M.	1
428	Handcock, M. S.	2	1338	Dabady, M.	1	2248	Letouzé, E.	1	3158	Steenbeek, W.	1
429	Hanna, A.	2	1339	D'Agostino, R. B.	1	2249	Levick, D.	1	3159	Steffens, M. C.	1
430	Hayashi, Y.	2	1340	Dahbi, A.	1	2250	Levy, D. A.	1	3160	Stegwee, R.	1

431	He, H.	2	1341	Dahinten, V. S.	1	2251	Lewandowsky, S.	1	3161	Stehr, N.	1
432	He, K.	2	1342	Dahmash, A. B.	1	2252	Lewis, D.	1	3162	Stein, M. B.	1
433	Helberger, N.	2	1343	Dallora, A. L.	1	2253	Lewis, J. E.	1	3163	Stein, M.-K.	1
434	Hendler, J.	2	1344	Dalton, C. M.	1	2254	Lewis, S. C.	1	3164	Steiner, M.	1
435	Henrich, J.	2	1345	Dalvi, F.	1	2255	Lewis, T.	1	3165	Steiner, M.	1
436	Heo, J.	2	1346	Damerji, H.	1	2256	Li, C.	1	3166	Steinke, T.	1
437	Hildebrandt, M.	2	1347	Dandapat, S. K.	1	2257	Li, F.	1	3167	Stephen, M. A.	1
438	Hilterman, E. L.	2	1348	Danforth, C. M.	1	2258	Li, H.	1	3168	Stern, M. J.	1
439	Hirsh, H.	2	1349	Dang, S.	1	2259	Li, H.	1	3169	Sternberg, M. J. E.	1
440	Hoffmann, A.L.	2	1350	Dangelico, R.M.	1	2260	Li, N.	1	3170	Stevens, A.	1
441	Hofstede, G. J.	2	1351	Dang-Xuan, L.	1	2261	Li, T.	1	3171	Stewart, B. M.	1
442	Holzinger, A.	2	1352	Danker-Hopfe, H.	1	2262	Li, W.	1	3172	Stewart, W.	1
443	Hong, S.	2	1353	Dantu, R.	1	2263	Li, X.-Y.	1	3173	Stieglitz, S.	1
444	Hsu, D. J.	2	1354	Darrell, T.	1	2264	Lian, D.	1	3174	Stinghal, A.	1
445	Hua, G.	2	1355	DasGupta, S.	1	2265	Lian, X.-C.	1	3175	Stockdale, K. C.	1
446	Huan, J.	2	1356	Daston, L.	1	2266	Liao, K.-C.	1	3176	Stöger, K.	1
447	Hubbard, B.	2	1357	Daugherty, P. R.	1	2267	Liao, W.	1	3177	Stokes, D. E.	1
448	Hughes, M. C.	2	1358	Davies, P.	1	2268	Liberati, A.	1	3178	Stone, P. J.	1
449	Hunter, D. R.	2	1359	Davis, F. D.	1	2269	Librenza-Garcia, D.	1	3179	Storkey, A.	1
450	Huys, Q. J. M.	2	1360	Davis, M.	1	2270	Lichtenstein, G.	1	3180	Stormo, G. D.	1
451	Ienca, M.	2	1361	Davis, S. E.	1	2271	Lied, H.	1	3181	Street, W. N.	1
452	Immorlica, N.	2	1362	Dawson, A.	1	2272	Lim, K. H.	1	3182	Strobelt, H.	1
453	Iyengar, S.	2	1363	Dawson, G. S.	1	2273	Lin, B.-R.	1	3183	Strogatz, S. H.	1
454	Jaeger, P. T.	2	1364	Day, N.	1	2274	Lin, C.-J.	1	3184	Strohman, T.	1
455	Jain, P.	2	1365	Day, S.	1	2275	Lin, F.	1	3185	Stromback, J.	1
456	Janet, V.	2	1366	de Arruda, H. F.	1	2276	Lin, S. Y.	1	3186	Štrumbelj, E.	1
457	Jensen, R. E.	2	1367	De Bruyn, A.	1	2277	Lind, L. K.	1	3187	Struyf, A.	1

458	Jernigan, C.	2	1368	de Campos, A. D.	1	2278	Linden, G.	1	3188	Stucke, M. E.	1
459	Jobin, A.	2	1369	De Castro, L.	1	2279	Lindenberger, U.	1	3189	Stukas, A. A.	1
460	Johansson, F. D.	2	1370	De Fátima Marin, H.	1	2280	Ling, Y.	1	3190	Sturdivant, R. X.	1
461	Johndrow, J.	2	1371	De Figueiredo, R. J. P.	1	2281	Link, C. L.	1	3191	Su, H.	1
462	Johndrow, J.	2	1372	De Filippi, P.	1	2282	Linsell, L.	1	3192	Su, J. K.	1
463	Johnson, D. R.	2	1373	de Groot, V.	1	2283	Lipson, H.	1	3193	Subhashini, U.	1
464	Johnston, R. B.	2	1374	De la Hoz-Correa, A.	1	2284	Lisetti, C.	1	3194	Such, J. M.	1
465	Jolly, M.	2	1375	de Oliveira, S.	1	2285	List, R.	1	3195	Suchecki, K.	1
466	Jordan, M. I.	2	1376	De Saussure, F.	1	2286	Little, R. J.	1	3196	Suchman, L.	1
467	Joynt Maddox, K. E.	2	1377	De Schutter, O.	1	2287	Little, T. D.	1	3197	Sun, T.	1
468	Kahneman, D.	2	1378	De Vel, O.	1	2288	Liu, F.	1	3198	Sundararajan, M.	1
469	Kalenichenko, D.	2	1379	De Waal, M.	1	2289	Liu, G.	1	3199	Sundararaman, T.	1
470	Kallus, N.	2	1380	Debortoli, S.	1	2290	Liu, J.	1	3200	Sunstein, C. R.	1
471	Kannan, P. K.	2	1381	Deffuant, G.	1	2291	Liu, P. J.	1	3201	Sunstein, C.R.	1
472	Kastrup, V.	2	1382	Delahaye-Duriez, A.	1	2292	Liu, S.	1	3202	Surette, R.	1
473	Kay, M.	2	1383	Delbanco, T.	1	2293	Liu, W.	1	3203	Suri, S.	1
474	Kennedy, H.	2	1384	Dell'Acqua, F.	1	2294	Liu, X.	1	3204	Sushil, K. S.	1
475	Kenneth, J.	2	1385	DellaVigna, S.	1	2295	Liu, X.-Y.	1	3205	Susto, G. A.	1
476	Kenthapadi, K.	2	1386	Demack, S.	1	2296	Liu, Y.	1	3206	Suzuki, Y.	1
477	Khemmarat, S.	2	1387	DeMets, D. L.	1	2297	Liu, Z.	1	3207	Svendsen, C.	1
478	Kilbertus, N.	2	1388	DeMichele, M.	1	2298	Lo, A. W.	1	3208	Sviggum, O.	1
479	Kim, J.	2	1389	Demiralp, C.	1	2299	Loader, B. D.	1	3209	Swami, A.	1
480	Kim, S. H.	2	1390	Dencik, L.	1	2300	Locock, L.	1	3210	Swinburne, N.	1
481	King, R. D.	2	1391	Deng, Y.	1	2301	Lodge, M.	1	3211	Swinger, N.	1
482	King, W. R.	2	1392	Deng, Z.	1	2302	Loftus, J.	1	3212	Sydnor., J. R.	1
483	Kirby, S.	2	1393	Dent, A.	1	2303	Loftus, J.	1	3213	Syed-Abdul, S.	1
484	Kiritchenko, S.	2	1394	Denton, E.	1	2304	Logg, J. M.	1	3214	Sylvester, J.	1

485	Kitchin, R.	2	1395	Denyer, D.	1	2305	Lohani, V.	1	3215	Syme, S. L.	1
486	Klein, D. B.	2	1396	Depper, A.	1	2306	Longo, D. L.	1	3216	Szegedy, C.	1
487	Klein, L. F.	2	1397	Deramaix, D.	1	2307	Longo, G.	1	3217	Szolovits, P.	1
488	Konecny, J.	2	1398	Deshmukh, V. M.	1	2308	Longoni, C.	1	3218	Taati, B.	1
489	Kozlowski, A. C.	2	1399	Deshpande, M.	1	2309	Lopes, D. S.	1	3219	Tackett, J. L.	1
490	Krauth, K.	2	1400	Desjardins, M.	1	2310	López, B.	1	3220	Tackett, M. J.	1
491	Kuester, B.	2	1401	Desmarais, S. L.	1	2311	López, M.	1	3221	Taddeo, M.	1
492	Kumar, N.	2	1402	Desouza, K. C.	1	2312	Lorenz-Spreen, P.	1	3222	Tajfel, H.	1
493	Lahey, B. B.	2	1403	DesRoches, C.	1	2313	Loreto, V.	1	3223	Takagi, T.	1
494	Lambiotte, R.	2	1404	Devane, D.	1	2314	Lorigo, L.	1	3224	Talwalkar, A.S.	1
495	Lan, S.	2	1405	Devine, P. G.	1	2315	Loscalzo, J.	1	3225	Taly, A.	1
496	Langlotz, C. P.	2	1406	Dewar, N.	1	2316	Losh, E. M.	1	3226	Tamang, S.	1
497	Lapuschkin, S.	2	1407	Dezfouli, A.	1	2317	Lou, Y.	1	3227	Tan, B.	1
498	Latora, V.	2	1408	Dhakar, M.	1	2318	Louie, A. K.	1	3228	Tan, C.	1
499	Learned-Miller, E.	2	1409	Dheeru, D.	1	2319	Lovallo, D.	1	3229	Tan, S.	1
500	LeCun, Y.	2	1410	Dhurandhar, A.	1	2320	Love, P. E.	1	3230	Tanangunan, R. M. D. V.	1
501	Lee, D. D.	2	1411	Diamandis, P.	1	2321	Lowry, S.	1	3231	Taniskidou, E. K.	1
502	Lee, M. K.	2	1412	Dias-Oliva, T.	1	2322	Lu, B.-L.	1	3232	Tannenbaum, C.	1
503	Lee, S. T.	2	1413	Díaz de Valdés, J.	1	2323	Lubaroff, D. M.	1	3233	Tarolli, C.	1
504	Lee, S.-I.	2	1414	Dibben, C.	1	2324	Lucas, W.	1	3234	Tatham, R. L.	1
505	Lefevere, J.	2	1415	Dickson, B.	1	2325	Ludman, A. J.	1	3235	Tatonetti, N. P.	1
506	Lehr, D.	2	1416	Dickson, R. P.	1	2326	Ludwiczuk, B.	1	3236	Tatsunori, B.	1
507	Lei, J.	2	1417	Dignum, V.	1	2327	Lugosi, G.	1	3237	Tavarea, S.	1
508	Leiserson, M.	2	1418	Dillahunt-Aspillaga, C.	1	2328	Luo, J.	1	3238	Tedesco. S.	1
509	Lemoine, B.	2	1419	Dillen, J.	1	2329	Luo, L.	1	3239	Teeple, S.	1
510	Lepri, B.	2	1420	Dimitrakakis, C.	1	2330	Luo, X. R.	1	3240	Tegmark, M.	1
511	Li, B.	2	1421	Dinev, T.	1	2331	Luong, B. T.	1	3241	Teich, J.	1

512	Li, J.	2	1422	Dinkla, K.	1	2332	Luong, B.T.	1	3242	Teredesai, A.	1
513	Li, O.	2	1423	Dionisio, S.	1	2333	Lupton, D.	1	3243	Terry, D.	1
514	Liang, P.	2	1424	Dipper, S.	1	2334	Lusted, L. B.	1	3244	Tesafaye, T.	1
515	Light, B.	2	1425	Dive, R. T.	1	2335	Lustig, C.	1	3245	Tetlock, P. E.	1
516	Lin, H. W.	2	1426	Dixit, P.	1	2336	Luukkaala, T.	1	3246	Thakur, R.	1
517	Lin, Y.-R.	2	1427	Dixon-Woods, M.	1	2337	Lynch, T.	1	3247	Thaler, A.	1
518	Lipton, Z. C.	2	1428	Doerr, C.	1	2338	Lyons, M.	1	3248	Thaler, R. H.	1
519	Little, M. A.	2	1429	Dohan, D.	1	2339	Ma, H.	1	3249	Theis, L.	1
520	Liu, A.	2	1430	Doktorchik, C.	1	2340	Ma, R.	1	3250	Thekumparampil, K.K.	1
521	Liu, H.	2	1431	Dombrowski, A.-K	1	2341	MacDonald, G.	1	3251	Theodoridis, Y.	1
522	Liu, H.	2	1432	Domingos, P.	1	2342	MacDonald, H. Z.	1	3252	Therese, J.	1
523	Liu, K.	2	1433	Donahue, J.	1	2343	MacDonald, M.	1	3253	Thi, C.	1
524	Liu, L. T.	2	1434	Donaldson, S. I.	1	2344	Machin, A.	1	3254	Thomas, P.	1
525	Loch, K.	2	1435	Dong, L.	1	2345	Mackenzie, D.	1	3255	Thomas, R. J.	1
526	Lodewijks, H.	2	1436	Dong, S.	1	2346	MacKinnon, C. A.	1	3256	Thompson, B.	1
527	Lowenkamp, C.	2	1437	Donini, M.	1	2347	MacLean, T. L.	1	3257	Thompson, E.	1
528	Lowry, P. B.	2	1438	Donneyong, M.	1	2348	Macmillan, L.	1	3258	Thorat, N.	1
529	Ludwig, J.	2	1439	Donovan, J.	1	2349	Macpherson, G.	1	3259	Thornham, H.	1
530	Luo, P.	2	1440	Donthu, N.	1	2350	Macy, M. W.	1	3260	Thornicroft, G.	1
531	Lyytinen, K.	2	1441	Dorak, M. T.	1	2351	Madaio, M. A.	1	3261	Thorson, K.	1
532	Maes, P.	2	1442	Doran, D.	1	2352	Madan, A.	1	3262	Thrall, J. H.	1
533	Magin, M.	2	1443	Dorfman, P.	1	2353	Madathil, K. C.	1	3263	Thurman, N.	1
534	Maheswaran, D.	2	1444	Dorie, V.	1	2354	Madbouly, A. I.	1	3264	Tiidenberg, K.	1
535	Maia, T. V.	2	1445	Dosovitskiy, A.	1	2355	Madden, K.	1	3265	Tilly, C.	1
536	Mancuhan, K.	2	1446	Dotsch, R.	1	2356	Madras, N.	1	3266	Tilton, L.	1
537	Marchand, M.	2	1447	Dou, Z.	1	2357	Magassa, L.	1	3267	Timan, T.	1
538	Massey, D. S.	2	1448	Doursat, R.	1	2358	Magin, M.	1	3268	Tindana, P.	1

539	Matthews, I.	2	1449	Dragan, A. D.	1	2359	Magnus, D.	1	3269	Tipping, M. E.	1
540	Matuszek, C.	2	1450	Dragojevic, M.	1	2360	Magrabi, F.	1	3270	Tippins, N. T.	1
541	Mayer-Schönberger, V.	2	1451	Draude, C.	1	2361	Magruder, J.	1	3271	Titano, J. J.	1
542	McCoy, S.	2	1452	Dredze, M. H.	1	2362	Mahdavi, M.	1	3272	Tobin, A.	1
543	McDaniel, P.	2	1453	Drozd, A.	1	2363	Mahlouly, D.	1	3273	Tobler, C.	1
544	McNamara, D.	2	1454	Drozdowski, P.	1	2364	Mahmoud, A.	1	3274	Tobler, P. N.	1
545	McSharry, P. E.	2	1455	Druck, A.	1	2365	Mahmoudi, D.	1	3275	Tolan, S.	1
546	Merico, D.	2	1456	D'Souza, S. W.	1	2366	Mahoney, M. R.	1	3276	Tomlinson, G.	1
547	Millsap, R. E.	2	1457	Du, J.	1	2367	Maier, C.	1	3277	Tonelli, M.	1
548	Minematsu, T.	2	1458	Duarte, J. L.	1	2368	Majumder, N.	1	3278	Toom, V.	1
549	Mirjalili, V.	2	1459	Dubec, P.	1	2369	Makhortykh, M.	1	3279	Tope, D.	1
550	Mistree, B. F. T.	2	1460	Duggan, M.	1	2370	Makse, H. A.	1	3280	Topi, H.	1
551	Mitchell, S.	2	1461	Duguay, S.	1	2371	Maldonad, T. A.	1	3281	Toprak, M.	1
552	Moeller, J.	2	1462	Duhamel, P.	1	2372	Malgieri, G.	1	3282	Torkashvand, R. R.	1
553	Mojsilovic, A.	2	1463	Dulhanty, C.	1	2373	Malhotra, S.	1	3283	Torralba, A.	1
554	Monahan, J.	2	1464	Dunn, A.	1	2374	Malin, B.	1	3284	Torre, L. G.	1
555	Monreale, A.	2	1465	Dunphy, D. C.	1	2375	Mallat, S.	1	3285	Towell, G. G.	1
556	Montavon, G.	2	1466	Dürrenmatt, D. J.	1	2376	Malte, Z.	1	3286	Townend, J.	1
557	Moore, P. V.	2	1467	Dutta, S.	1	2377	Mandl, K. D.	1	3287	Tran, D.	1
558	Morris, M.	2	1468	Dutton, W. H.	1	2378	Mangasarian, O. L.	1	3288	Tranfield, D.	1
559	Muñoz, C.	2	1469	Dutton, W. H.	1	2379	Manimaran, J.	1	3289	Trapnell, P. D.	1
560	Munson, S. A.	2	1470	Dweck, C. S.	1	2380	Manjón, J. A.	1	3290	Traue, H. C.	1
561	Nan, X.	2	1471	Dworzynski, K.	1	2381	Manning, C.	1	3291	Trawalter, S.	1
562	Newman, S. T.	2	1472	Dwyer, T.	1	2382	Mannor, S.	1	3292	Treanor, J. J.	1
563	Nicholls, T. L.	2	1473	Eardley, A.	1	2383	Manoharan, P.	1	3293	Treem, J.	1
564	Niu, W. J.	2	1474	Earle, J.	1	2384	Mansukhani, N. A.	1	3294	Tresch, A.	1
565	Niyogi, P.	2	1475	Eastwood, C.	1	2385	Mantas, C. J.	1	3295	Treusch, P.	1

566	Nosek, B. A.	2	1476	Ebner, N.	1	2386	Mantelero, A.	1	3296	Trevisan, F.	1
567	Nyrup, R.	2	1477	Eckert, C.	1	2387	Manuel, J.	1	3297	Trigeorgis, G.	1
568	Ohm, P.	2	1478	Edge, V. L.	1	2388	Marks, J. S.	1	3298	Tripathi, K. K.	1
569	Oliver, M. N.	2	1479	Edwards, H.	1	2389	Marsella, S.	1	3299	Tsaparas, P.	1
570	Oliver, N.	2	1480	Effing, R.	1	2390	Martens, J.-B.	1	3300	Tsintzou, V.	1
571	O'Madadhain, J.	2	1481	Efros, A. A.	1	2391	Martin, U.	1	3301	Tsioutsiouliklis, K.	1
572	Ong, C.S.	2	1482	Ehrenfeucht, A.	1	2392	Marx, C. T.	1	3302	Tsunokai, G. T.	1
573	Oztireli, C.	2	1483	Ehrgott, M.	1	2393	Maserejian, N. N.	1	3303	Tsybakov, A.B.	1
574	Paglen, T.	2	1484	Eichstaedt, J. C.	1	2394	Massengale, J.	1	3304	Tu, K.	1
575	Paltemaa, L.	2	1485	Eivazzadeh, S.	1	2395	Mastro, D.	1	3305	Tubaro, P.	1
576	Pan, B.	2	1486	Elazar, Y.	1	2396	Matkovic, K.	1	3306	Tucker, J. A.	1
577	Paris, S.	2	1487	Eldan, R.	1	2397	Matsuoka, S.	1	3307	Tucker, R. P.	1
578	Park, G.	2	1488	Elenko, E.	1	2398	Mattar, M.	1	3308	Tufekci, Z.	1
579	Parker, M.	2	1489	Elhadad, N.	1	2399	Matteson, M. L.	1	3309	Tuimala, R.	1
580	Passarella, A.	2	1490	Elisseeff, A.	1	2400	Matthew-Juarez, P.	1	3310	Turnball, D.	1
581	Passos, E.	2	1491	Elkind, M. S. V.	1	2401	Matthews, D. B.	1	3311	Turner, K.	1
582	Pedregosa, F.	2	1492	Elkins, Z.	1	2402	Mattie, H.	1	3312	Turner, J. C.	1
583	Perra, N.	2	1493	Ellemers, N.	1	2403	Mattos, L. S.	1	3313	Tuval, C.	1
584	Philbin, J.	2	1494	Elliott, M. T.	1	2404	Mattu, S.	1	3314	Tuzhilin, A.	1
585	Pink, S.	2	1495	Ellis, E.	1	2405	Matz, S.	1	3315	Tversky, A.	1
586	Pleiss, G.	2	1496	Ellis, R. P.	1	2406	Maurer, A.	1	3316	Tyler, C.	1
587	Plumb, G.	2	1497	Ellis, C.	1	2407	Mavrodiev, P.	1	3317	Uchino, S.	1
588	Poell, T.	2	1498	Ellwood-Lowe, M.E.	1	2408	Maydeu-Olivares, A.	1	3318	Uddin, M. F.	1
589	Potash, E.	2	1499	Elmer, G.	1	2409	Mayo-Muñoz, X.	1	3319	Ujiie, M. K.	1
590	Quadrianto, N.	2	1500	Elms, H.	1	2410	Mãžller, K. R.	1	3320	Ulbricht, L.	1
591	Quattrociocchi, W.	2	1501	Else-Quest, N. M.	1	2411	Mazumder, A.	1	3321	Ulleberg, P.	1
592	Rainie, L.	2	1502	Emanuel, E.	1	2412	Mazzocco, K.	1	3322	Ungar, L. H.	1

593	Raschka, S.	2	1503	Embrick, G.	1	2413	Mcafee, A.	1	3323	Unkel, J.	1
594	Rathouz, P. J.	2	1504	Emdin, C. A.	1	2414	McArdle, G.	1	3324	Unwin, A.	1
595	Reardon, S. F.	2	1505	Emerson, J. W.	1	2415	McCall, N.	1	3325	Ur, B.	1
596	Reddy, S.	2	1506	Emirbayer, M.	1	2416	McCarthy, B.	1	3326	Urato, C.	1
597	Reidhead, M.	2	1507	Enders, C. K.	1	2417	McCauley, D.	1	3327	Urman, A.	1
598	Reisdorf, B. C.	2	1508	Eneanya, N. D.	1	2418	McCombs, M. E.	1	3328	Urueña, A.	1
599	Riche, N. H.	2	1509	Engelhardt, E.	1	2419	McCoy, T. H.	1	3329	Usher, K.	1
600	Ridgeway, C. L.	2	1510	Engelmann, S.	1	2420	McCulloch, R. E.	1	3330	Ustun, B.	1
601	Rifkin, R.	2	1511	Engelsen, B. A.	1	2421	McDonald, A. M.	1	3331	Usunier, N.	1
602	Roberts, D.	2	1512	Engesser, S.	1	2422	McDowell, M. J.	1	3332	Uszkoreit, H.	1
603	Roberts, H.	2	1513	Englander, H.	1	2423	McDuff, D.	1	3333	Vaage, K.	1
604	Robertson, R. E.	2	1514	Enli, G. S.	1	2424	McGill, K.	1	3334	Vaddi, R.	1
605	Robinson, L.	2	1515	Ensign, D.	1	2425	M'charek, A.	1	3335	Vadhan, S.	1
606	Rocha, L. E. C.	2	1516	Epperson, W.	1	2426	McKelvey, F.	1	3336	Vadillo, M. A.	1
607	Rojas-Carulla, M.	2	1517	Epstein, R.	1	2427	McKevitt, S.	1	3337	Vaishnavi, V.	1
608	Ruckenstein, M.	2	1518	Epstein, R.	1	2428	McKinlay, J. B.	1	3338	Vaithianathan, R.	1
609	Ryu, H. J.	2	1519	Erickson, B. J.	1	2429	McNee, S. M.	1	3339	Valaee, S.	1
610	Saleiro, P.	2	1520	Ernberg, G.	1	2430	McRae, A. F.	1	3340	Valanis, B. G.	1
611	Salganik, M. J.	2	1521	Ertl, A.	1	2431	McSherry, F.	1	3341	Valentino, N. A.	1
612	Salton, G.	2	1522	Escalera, S.	1	2432	Meaney, M. J.	1	3342	Van Aelst, P.	1
613	Sargin, E.	2	1523	Escarce, J. J.	1	2433	Medin, D. L.	1	3343	Van Alstyne, M.	1
614	Schapire, R. E.	2	1524	Escobar, G.	1	2434	Meeder, B.	1	3344	van de Velde, R. N.	1
615	Schermer, B. W.	2	1525	Escóssia, L.	1	2435	Megías, D.	1	3345	Van Den Driessche, G.	1
616	Scholkopf, B.	2	1526	Eslami, M.	1	2436	Mehrotra, R.	1	3346	van den Heever, M.	1
617	Scholtes, I.	2	1527	Esnaola, N. F.	1	2437	Mehta, D.	1	3347	Van Der Gaag, L. C.	1
618	Schroff, F.	2	1528	Espinosa, A.	1	2438	Meissner, J.	1	3348	van der Lee, R.	1
619	Schulz, S.	2	1529	Esposito, A.	1	2439	Mello, M. M.	1	3349	van der Nagel, E.	1

620	Schwalbe, N.	2	1530	Esser, F.	1	2440	Mendenhall, R.	1	3350	van der Schaar, M.	1
621	Schweitzer, F.	2	1531	Esteva, A.	1	2441	Mendes, E.	1	3351	Van der Veeken, S.	1
622	Selvaraju, R. R.	2	1532	Etminan, N.	1	2442	Mendoza, I.	1	3352	van der Vlist F. N.	1
623	Seung, H. S.	2	1533	Ettehad, D.	1	2443	Meng, L.	1	3353	Van Eck, B.M.A.	1
624	Shahrezaye, M.	2	1534	Evangelopoulos, N.	1	2444	Mercea, D.	1	3354	van Es, B.	1
625	Shamir, O.	2	1535	Evans, B.	1	2445	Merchant, R. M.	1	3355	Van Everdingen, Y. M.	1
626	Shao, L.	2	1536	Evans-Lacko, S.	1	2446	Merks, J. H. M.	1	3356	Van Hoboken, J.	1
627	Sharma, A.	2	1537	Evaristo, R.	1	2447	Merolli, M.	1	3357	van Holsteyn, J. J. M.	1
628	Sharmanska, V.	2	1538	Everson, H. T.	1	2448	Meshram, P.	1	3358	Van Kleek, M.	1
629	Shimada, A.	2	1539	Ezrachi, A.	1	2449	Metaxa, D.	1	3359	van Knippenberg, A.	1
630	Shmatikov, V.	2	1540	Ezzy, D.	1	2450	Metaxa, D.	1	3360	Van Rijsbergen, C. J.	1
631	Silberg, J.	2	1541	Fabris, A.	1	2451	Metz, C.	1	3361	van Ryn, M.	1
632	Simon, H.	2	1542	Fahey, M.	1	2452	Metzinger, T.	1	3362	Van Vanik, P.	1
633	Sinatra, R.	2	1543	Falch, M.	1	2453	Metzl, J. M.	1	3363	Vance, A.	1
634	Singh, A.	2	1544	Faltys, M.	1	2454	Metzler, D.	1	3364	Vance, S. L.	1
635	Smith, A.	2	1545	Fan, L. M.	1	2455	Mian, A.	1	3365	Vandenhof, C.	1
636	Smith, K.	2	1546	Fan, W.	1	2456	Mianjy, P.	1	3366	Vandervieren, E.	1
637	Smith-Loud, J.	2	1547	Fantino, A. M.	1	2457	Micallef, L.	1	3367	Varadarajan, R.	1
638	Smyth, P.	2	1548	Farah, M. J.	1	2458	Michela, A. B.	1	3368	Varela, F. J.	1
639	Soeller, G.	2	1549	Farinella, G.	1	2459	MikolaitisPreuss, R. A.	1	3369	Varian, H. R.	1
640	Song, S.	2	1550	Faris, R.	1	2460	Mikolajczyk, A.	1	3370	Varner, M.	1
641	Song, Y.	2	1551	Farnadi, G.	1	2461	Milena, G. A.	1	3371	Varpio, L.	1
642	Speicher, T.	2	1552	Farràs, O.	1	2462	Milfont, T. L.	1	3372	Varshney, K.R.	1
643	Srite, M.	2	1553	Fauci, A. S.	1	2463	Miller, B. N.	1	3373	Varshney, L. R.	1
644	Srivastava, N.	2	1554	Fawzi, A.	1	2464	Miller, V.	1	3374	Vásquez, J.	1
645	Stark, B.	2	1555	Fayyad, U.	1	2465	Milne, D. N.	1	3375	Vassilvitskii, S.	1
646	Starnini, M.	2	1556	Fei, W.	1	2466	Milner, A.	1	3376	Vaughan, J. W.	1

647	Steyvers, M.	2	1557	Fei-Fei, L.	1	2467	Minkov, M.	1	3377	Vaughan, L.	1
648	Stone, C. J.	2	1558	Feiner, J. R.	1	2468	Minnier, J.	1	3378	Vaughan, M.	1
649	Strakowski, S. M.	2	1559	Feldheim, V.	1	2469	Minsky, S.	1	3379	Vazquez, F.	1
650	Straub, D.	2	1560	Feliciano, C.	1	2470	Minson, J. A.	1	3380	Vázquez, J.	1
651	Strohmaier, M.	2	1561	Feller, D. J.	1	2471	Mintzes, B.	1	3381	Vazsonyi, A. T.	1
652	Sumartojo, S.	2	1562	Fenton, N.	1	2472	Miron, M.	1	3382	Vehtari, A.	1
653	Sun, J.	2	1563	Ference, B. A.	1	2473	Mirzaey, M.	1	3383	Veit, A.	1
654	Suttie, M.	2	1564	Fergus, P.	1	2474	Misra, S.	1	3384	Velmurugan, T.	1
655	Sweeney, L.	2	1565	Fergus, R.	1	2475	Mittal, A.	1	3385	VeneKlasen, L.	1
656	Taddy, M.	2	1566	Fernandez-Dols, J.	1	2476	Mittelstadt, B.D.	1	3386	Ventura, R. V.	1
657	Talwalkar, A. S.	2	1567	Fernández-Gracia, J.	1	2477	Mnih, A.	1	3387	Verba, S.	1
658	Taniguchi, R.-I.	2	1568	Fernandez-Luque, L.	1	2478	Mnih, V.	1	3388	Verdouw, C.	1
659	Tenenbaum, J. B.	2	1569	Fernando, S. C.	1	2479	Moffat, A.	1	3389	Verduyn, P.	1
660	Thatcher, J.	2	1570	Ferolie, J.	1	2480	Moffitt, T. E.	1	3390	Verghese, A.	1
661	Therneau, T. M.	2	1571	Ferree, M. M.	1	2481	Mohammed, A. T.	1	3391	Vertan, C.	1
662	Thomas, O.	2	1572	Ferretti, L.	1	2482	Mohan, S.	1	3392	Verykios, V. S.	1
663	Thorat, S.	2	1573	Ferris, T. G.	1	2483	Mohay, G.	1	3393	Vignoles, A.	1
664	Tian, Y.	2	1574	Ferryman, K.	1	2484	Moher, D.	1	3394	Viljoen, S.	1
665	Tickle, A. B.	2	1575	Fessell, D.	1	2485	Mokdad, A. H.	1	3395	Vimla, L.	1
666	Tishkoff, S.	2	1576	Feudtner, C.	1	2486	Molenberghs, G.	1	3396	Vincent, G. M.	1
667	Tschantz, M. C.	2	1577	Feutry, C.	1	2487	Molitor, D.	1	3397	Vincent, N.	1
668	Tzimiropoulos, G.	2	1578	Fienberg, S. E.	1	2488	Möller, D. T.	1	3398	Vincent, P.	1
669	Uleman, J. S.	2	1579	Figueira, J.	1	2489	Möller, J.	1	3399	Vinck, P.	1
670	Ullman, J.	2	1580	Figueroa, M.	1	2490	Molnar, C.	1	3400	Vinny, P.W.	1
671	Ulrich, B.	2	1581	Filippone, M.	1	2491	Molyneux, S.	1	3401	Vinterbo, S. A.	1
672	Valley, T. S.	2	1582	Finch, D.	1	2492	Mónica, G.	1	3402	Vinuesa, R.	1
673	van Dijck, J.	2	1583	Findlay, J. N.	1	2493	Montfort, N.	1	3403	Vishnu, V. Y.	1

674	Van Esch, P.	2	1584	Fink, C.	1	2494	Moody, G. D.	1	3404	Viswanathan, V.	1
675	van Hell, J. G.	2	1585	Fioretti, C.	1	2495	Moon, T.	1	3405	Vivaldo, G.	1
676	Van Mieghem, P.	2	1586	Fiscella, K.	1	2496	Moore, A.	1	3406	Voda, A.I.	1
677	van Nieuwenhuizen, C.	2	1587	Fischer, R.	1	2497	Moore, D. A.	1	3407	Vogel, B.	1
678	Vapnik, V. N.	2	1588	Fischetti, M.	1	2498	Moore, E.	1	3408	Voigt, K.-I.	1
679	Varoquaux, G.	2	1589	Fisher, E. S.	1	2499	Moore, J. H.	1	3409	Volfovsky, A.	1
680	Veale, M.	2	1590	Fisher, K.	1	2500	Moosavi-Dezfooli, S.-M.	1	3410	Volinsky, C.	1
681	Venkatesh, V.	2	1591	Fitzmaurice, G.	1	2501	Mopuri, K. R.	1	3411	Volker, B.	1
682	Verwer, S.	2	1592	Flannery, D. J.	1	2502	Morales, G. D. F.	1	3412	Volpp, K. G.	1
683	Vicario, M. D.	2	1593	Fleming, T. R.	1	2503	Moran, D.	1	3413	von Euler, M.	1
684	Viswanath, P.	2	1594	Fletcher, R.	1	2504	Morawski, M.	1	3414	von Stemann, J. H.	1
685	Vuori, J. A.	2	1595	Florea, C.	1	2505	Mordvintsev, A.	1	3415	von Wangenheim, F.	1
686	Wagner, B.	2	1596	Florea, L.	1	2506	Moreau, S.	1	3416	Vorobeychik, Y.	1
687	Wagner, C.	2	1597	Flynn, K.	1	2507	Moreno, Y.	1	3417	Vosoughi, S.	1
688	Wagner, T. J.	2	1598	Foa, E. B.	1	2508	Morewedge, C. K.	1	3418	Vyas, C. M.	1
689	Wahl, B.	2	1599	Folke, F.	1	2509	Morgan, S. G.	1	3419	W. Zheng	1
690	Waks, L.	2	1600	Font, J. E.	1	2510	Moriyama, T.	1	3420	Waarts, E.	1
691	Wäldchen, S.	2	1601	Fookes, C.	1	2511	Morone, F.	1	3421	Wachs, S.	1
692	Walgrave, S.	2	1602	Ford, M. E.	1	2512	Morota, G.	1	3422	Wachter, R. M.	1
693	Wallach, H.	2	1603	Forsati, R.	1	2513	Moroz, I. M.	1	3423	Wagemans, T.	1
694	Wang, H.	2	1604	Fossa, A. J.	1	2514	Morris, M. E.	1	3424	Wagenmakers, E.-J.	1
695	Wang, M.	2	1605	Foster, M.	1	2515	Mosier, K. L.	1	3425	Waldinger, R.	1
696	Wang, R.	2	1606	Fountaine, T.	1	2516	Moskowitz, G. B.	1	3426	Walker, J.	1
697	Wang, W.	2	1607	Fox, A. M.	1	2517	Mu€ller, K.-R.	1	3427	Walker, S.	1
698	Warkentin, M.	2	1608	Fox, E. A.	1	2518	Mubin, O.	1	3428	Wallis, W. A.	1
699	Wiese, D.	2	1609	Frank, E.	1	2519	Mueller, J. C.	1	3429	Walter, M.	1
700	Wolfert, S.	2	1610	Frank, M. J.	1	2520	Muk, A.	1	3430	Walther, A.	1

701	Yang, J.	2	1611	Franks, P.	1	2521	Mukherjee, S.	1	3431	Walton, G. M.	1
702	Yang, K.-C.	2	1612	Fraser, N.	1	2522	Mukhlish, F.	1	3432	Wanamaker, M.	1
703	Yao, S.	2	1613	Freedman, D.	1	2523	Müller, J.M.	1	3433	Wang, F.	1
704	Yin, H.	2	1614	Freiler, W.	1	2524	Müller, O.	1	3434	Wang, J.	1
705	Yinger, J.	2	1615	Frenkel, S.	1	2525	Mulligan, D. K.	1	3435	Wang, L.	1
706	Yoo, J. S.	2	1616	Freund, Y.	1	2526	Mullins, M.	1	3436	Wang, P.	1
707	Yoon, I. J.	2	1617	Frey, B.J.	1	2527	Mulvehill, A. M.	1	3437	Wang, S.	1
708	You, S.	2	1618	Frick, J.	1	2528	Muneeb, A.	1	3438	Wang, Y.	1
709	Yudell, M.	2	1619	Friedlander, M. P.	1	2529	Munoz, C.	1	3439	Wang, Z.	1
710	Zafeiriou, S.	2	1620	Friedman, A.	1	2530	Muñoz, M. A.	1	3440	Ward, A.	1
711	Zhang, B. H.	2	1621	Friedman, L. D.	1	2531	Muñoz-Leiva, F.	1	3441	Wareham, N.	1
712	Zhang, Q.	2	1622	Friedman, B.	1	2532	Muntés-Mulero, V.	1	3442	Warmington, P.	1
713	Zhao, S.	2	1623	Friston, K. J.	1	2533	Munzel, A.	1	3443	Watson, P.	1
714	Zhong, R. Y.	2	1624	Froemelt, A.	1	2534	Murdock, V.	1	3444	Watson, R.	1
715	Zhou, R.	2	1625	Frossard, P.	1	2535	Murphy, S. N.	1	3445	Wattenberg, M.	1
716	Zhu, S.	2	1626	Fryzlewicz, P.	1	2536	Murray, S. G.	1	3446	Watts, D. J.	1
717	Zhu, S.-C.	2	1627	Fuller, S.	1	2537	Musakwa, W.	1	3447	Waylen, G.	1
718	Zweig, M.	2	1628	Fullerton, S. M.	1	2538	Mussenden, S.	1	3448	Wear, D.	1
719	Aakhus, M.	1	1629	Fung, B.	1	2539	Naaz, R.	1	3449	Weaver, C.	1
720	Aaniya, A.	1	1630	Fuster, A.	1	2540	Nabi, M.	1	3450	Weaver, D. H.	1
721	Abbas, K.	1	1631	Gabarron, E.	1	2541	Nadeem, M.	1	3451	Weber, W.	1
722	Abbe, A.	1	1632	Gaboardi, M.	1	2542	Nafus, D.	1	3452	Wechsler, H.	1
723	Abdelaziz, K.	1	1633	Gabry, J.	1	2543	Nagpal, G.	1	3453	Wedding, J.	1
724	Abdilla, A.	1	1634	Gadi, T.	1	2544	Nagpal, S.	1	3454	Wedel, M.	1
725	Abdollahpouri, H.	1	1635	Gagne, J. J.	1	2545	Nail, R.	1	3455	Weedon, J.	1
726	Abe, N.	1	1636	Gaines, S.	1	2546	Nalepa, J.	1	3456	Weeks, B.E.	1
727	Abnousi, F.	1	1637	Gajane, P.	1	2547	Nam, T.	1	3457	Weerakkody, V.	1

728	Abouelmehdi, K.	1	1638	Gal, U.	1	2548	Nambisan, S.	1	3458	Wei, K.-K.	1
729	Abraham, K.	1	1639	Galanter, J.	1	2549	Natarajan, P.	1	3459	Wei, X.	1
730	Abràmof, M. D.	1	1640	Galič, M.	1	2550	Navarra, S. V.	1	3460	Weijia, S.	1
731	Abrams, D. M.	1	1641	Galison, P.	1	2551	Navathe, A. S.	1	3461	Weinberg, E.	1
732	Abrams, M.	1	1642	Galuba, W.	1	2552	Naveen, M. S.	1	3462	Weinberger, E.	1
733	Aczel, B.	1	1643	Gamer, M.	1	2553	Nayar, S. K.	1	3463	Weisbuch, G.	1
734	Adams, T. E.	1	1644	Gamon, M.	1	2554	Neau, D.	1	3464	Weiss, S. M.	1
735	Adebimpe, V. R.	1	1645	Gangl, C.	1	2555	Nellaker, C.	1	3465	Weitzel, T.	1
736	Adeli, H.	1	1646	Gao, L.	1	2556	Nelson, T.	1	3466	Welch, H. G.	1
737	Adewole, S.	1	1647	Gao, W.	1	2557	Nematzadeh, A.	1	3467	Weld, D.	1
738	Adnan, A. A. Z.	1	1648	Gara, M. A.	1	2558	Nerenz, D. R.	1	3468	Welling, M.	1
739	Adorno, T. W.	1	1649	Garcea, G.	1	2559	Nerenz, D.R.	1	3469	Wells, M.	1
740	Agamben, G.	1	1650	García, M.	1	2560	Nerini, F. F.	1	3470	Welser, W. I.	1
741	Agarwal, A.	1	1651	García, S.	1	2561	Nettle, D.	1	3471	Weltzer, W.	1
742	Agarwal, S.	1	1652	Garcia, V. C.	1	2562	Newell, C.	1	3472	Wen, J. R.	1
743	Ågerfalk, P. J.	1	1653	García-García, J.	1	2563	Newman, K.	1	3473	Weng, L.	1
744	Agius, R.	1	1654	Garcke, J.	1	2564	Newman, L. S.	1	3474	Wentworth, W. M.	1
745	Agrawal, N.	1	1655	Garg, A. X.	1	2565	Newman, M. E.	1	3475	Werner, R. M.	1
746	Agrawal, R.	1	1656	Gargeya, R.	1	2566	Newman, N.	1	3476	Wernimont, J.	1
747	Aguilar, A.	1	1657	Garies, S.	1	2567	Newman, K. S.	1	3477	West, C.	1
748	Aha, D.	1	1658	Garrett, S. B.	1	2568	Ng, A.Y.	1	3478	West, R.	1
749	Ahlers, D.	1	1659	Garrick, O.	1	2569	Ngan, M.	1	3479	West, S. M.	1
750	Ahmedt-Aristizabal, D.	1	1660	Gary, S.	1	2570	Nguyen, C.	1	3480	Westbrook, T.	1
751	Ahn, U. R.	1	1661	Gaut, A.	1	2571	Nguyen, P. A.	1	3481	Westenberg, M. A.	1
752	Ahn, Y.	1	1662	Gawade, P.	1	2572	Nguyen, X.	1	3482	Wetherill, L.	1
753	Aiello, G.	1	1663	Gawehn, E.	1	2573	Ni, M.	1	3483	Wexler, J.	1
754	Aigner, W.	1	1664	Gay, G.	1	2574	Nichols, D.	1	3484	Whetten, J.	1

755	Airhihenbuwa, C. O.	1	1665	Ge, L.	1	2575	Nicosia, V.	1	3485	White, K.	1
756	Ajana, B.	1	1666	Ge, Y.	1	2576	Niculescu-Mizil, A.	1	3486	Whiteson, D.	1
757	Akamatsu, S.	1	1667	Gebru, T.	1	2577	Nieborg, D.	1	3487	Whittaker, M.	1
758	Akerlof, G. A.	1	1668	Gehlenborg, L. N.	1	2578	Niedlich, C.	1	3488	Whittlestone, J.	1
759	Akotirene, C.	1	1669	Geiger, R. S.	1	2579	Niehoff, M.	1	3489	Wichern, D.	1
760	Akvik, A.	1	1670	Geiß, S.	1	2580	Nielsen, M. B.	1	3490	Wickham, H.	1
761	Alabdulkareem, M.	1	1671	Gelfand, M. J.	1	2581	Nielsen, R. K.	1	3491	Widom, J.	1
762	Alabort-i-Medina, J.	1	1672	Geman, S.	1	2582	Nieuwenhuis, M.	1	3492	Wiebe, N.	1
763	Alber, M.	1	1673	Gentzkow, M.	1	2583	Niewiadomski, R.	1	3493	Wiener, N.	1
764	Albino, V.	1	1674	George, E. I.	1	2584	Nigon, J.	1	3494	Wieringa, J.	1
765	Albright, L.	1	1675	George, A.	1	2585	Nikolov, D.	1	3495	Wijnhoven, F.	1
766	Alcoff, L. M.	1	1676	Gerberding, J. L.	1	2586	Ning, X.	1	3496	Wilchek-Aviad, Y.	1
767	Alegria, S. N.	1	1677	Gergle, D.	1	2587	Nisbett, R. E.	1	3497	Wildberger, A. M.	1
768	Alexander, L.	1	1678	Gerlitz, C.	1	2588	Nishant, R.	1	3498	Wilkens, J.	1
769	Alexandrova, A.	1	1679	Getoor, L.	1	2589	Noaman, A. Y.	1	3499	Wilkins, S.	1
770	Alfirevic, Z.	1	1680	Geyer, R. C.	1	2590	Noman, M.	1	3500	Wilkinson, C.	1
771	Ali, J.	1	1681	Geyik, S. C.	1	2591	Norenzayan, A.	1	3501	Williams, B.A.	1
772	Alipanahi, B.	1	1682	Ghani, R.	1	2592	Noriega-Campero, A.	1	3502	Williams, C.	1
773	Alison, D. M.	1	1683	Ghassemi, M.	1	2593	Norman, D. A.	1	3503	Williams, D.	1
774	Alix-Garcia, J.	1	1684	Gherheș, V.	1	2594	Norvig, P.	1	3504	Williams, J.	1
775	Aljarah, I.	1	1685	Ghiara, V.	1	2595	Norvig, P.	1	3505	Williams, J. D.	1
776	Allen, C.	1	1686	Ghorbani, A. A.	1	2596	Nothman, J.	1	3506	Williams, M. C.	1
777	Allen, J.	1	1687	Ghosh, R.	1	2597	Nouiehed, M.	1	3507	Williams, O.	1
778	Allen, K.	1	1688	Ghosh, S. M.	1	2598	Novillo-Ortiz, D.	1	3508	Williamson, B.	1
779	Allen, M.	1	1689	Ghouri, A. M.	1	2599	Nowalk, M. P.	1	3509	Williamson, J.	1
780	Almeida, S.	1	1690	Giannakopoulos, K.	1	2600	Nowok, B.	1	3510	Williamson, R.C.	1
781	Almeida, V.	1	1691	Giese, D.	1	2601	Nuland, W.	1	3511	Williamson, T.	1

782	Almklov, P.	1	1692	Gil, E. B.	1	2602	Nunes, A. R.	1	3512	Willison, R.	1
783	Almoaiqel, M.	1	1693	Gilbert Welch, H.	1	2603	Nuytemans, M.	1	3513	Wilson, A. G.	1
784	Alper, B.	1	1694	Gilbert, N.	1	2604	Nuzum, R.	1	3514	Wilson, D.	1
785	Alsaleh, D. A.	1	1695	Gil-Fournier, A.	1	2605	Nyka€nen, P.	1	3515	Wilson, H. J.	1
786	Al-Shedivat, M.	1	1696	Gilichinsky, M.	1	2606	Oates, S.	1	3516	Wilson, K.	1
787	Altaf, S.	1	1697	Gillborn, D.	1	2607	Obozintsev, L.	1	3517	Wilson, P.	1
788	Altman, D.	1	1698	Gillen, P.	1	2608	Obrad, C.	1	3518	Wilson, C.	1
789	Altman, R.	1	1699	Gilmartin, S. K.	1	2609	O'Callaghan, D.	1	3519	Wilton, L. S.	1
790	Alvero, A.	1	1700	Gilmer, J.	1	2610	O'Connell, J. W.	1	3520	Winant, H.	1
791	Alvi, M.	1	1701	Gina, N.	1	2611	Odajima, K.	1	3521	Windekilde, I.	1
792	Amann, J.	1	1702	Ging, D.	1	2612	O'Grady, M. J.	1	3522	Winter, J.	1
793	Amaral, F.	1	1703	Gladkova, A.	1	2613	O'Hare, G. M. P.	1	3523	Winters, M.	1
794	Amati, G.	1	1704	Glaisyer, T.	1	2614	Ohlund, L.	1	3524	Witkowski, B.	1
795	Ambler, S.	1	1705	Glance, N.	1	2615	Ohnuma, T.	1	3525	Witten, I. H.	1
796	Amershi, S.	1	1706	Glass, J.	1	2616	Øian, P.	1	3526	Wojtas, M.	1
797	Amiri, M.	1	1707	Gleeson, J. P.	1	2617	Oikonomou, E. K.	1	3527	Wolberg, W. H.	1
798	Amiry, A.	1	1708	Glick, P.	1	2618	Ojha, U.	1	3528	Wolfe, C.	1
799	Amorim, D.	1	1709	Glickman, D.	1	2619	Okamoto, K.	1	3529	Wong, A.	1
800	Amos, B.	1	1710	Glize, E.	1	2620	Okdie, B. M.	1	3530	Wong, H. R.	1
801	Amrieh, E. A.	1	1711	Glynn, R. J.	1	2621	Okereke, O. I.	1	3531	Wong, S.-L. Z.	1
802	Amy, S.	1	1712	Goggin, G.	1	2622	Olah, C.	1	3532	Wong, W. F.	1
803	Anas, N.	1	1713	Goh, G.	1	2623	Olsen, M. A.	1	3533	Wongkoblap, A.	1
804	Anderer, P.	1	1714	Goker, B.	1	2624	Olteanu, A.	1	3534	Woo, H.	1
805	Anderson, B. B.	1	1715	Golbeck, J.	1	2625	Olver, M. E.	1	3535	Wood, D.	1
806	Anderson, H. D.	1	1716	Goldberg, D.	1	2626	Omi, M.	1	3536	Woodcock, J.	1
807	Anderson, J.	1	1717	Goldberg, K.	1	2627	Oneto, L.	1	3537	Wood-Harper, T.	1
808	Anderson, M.	1	1718	Goldberg, Y.	1	2628	Ong, S. L.	1	3538	Woodruf, G.	1

809	Andrejevic, M.	1	1719	Goldfarb, A.	1	2629	Onnela, J.-P.	1	3539	Woolley, S. C.	1
810	Angiolillo, J.	1	1720	Goldin, C.	1	2630	Ono, R.	1	3540	Wormith, J.	1
811	Ankerst, D. P.	1	1721	Goldsmith-Pinkham, P.	1	2631	Ooms, G.	1	3541	Wozniak, J. R.	1
812	Ansari, U.	1	1722	Goldstein, D. G.	1	2632	Oppenheimer, C.	1	3542	Wright, D. L.	1
813	Ansolabehere, S.	1	1723	Gollust, S. E.	1	2633	Ordonez, V.	1	3543	Wright, E. M.	1
814	Antal, T.	1	1724	Gomes, A.	1	2634	Oren, E.	1	3544	Wu, A.	1
815	Antonakos, E.	1	1725	Gomez-Rodriguez, M.	1	2635	Orestis, P.	1	3545	Wu, A. H. B.	1
816	Antonialli, D.	1	1726	Gomez-Uribe, C. A.	1	2636	O'Riordan, T.	1	3546	Wu, H.	1
817	Antonio, A. L.	1	1727	Gong, S.	1	2637	Ortega-Campos, E.	1	3547	Wu, M.	1
818	Appelbaum, P. S.	1	1728	Gonzalez, C. M.	1	2638	Oruch, R.	1	3548	Wu, T.	1
819	Appelman, Y. E. A.	1	1729	Gonzalez, D.	1	2639	Osheroff, J.	1	3549	Wu, Z.	1
820	Applegate, B.	1	1730	Gonzalez-Hernandez, G.	1	2640	Osoba, A. O.	1	3550	Wu, Z. S.	1
821	Aral, S.	1	1731	Goodenday, L. S.	1	2641	Østerlie, T.	1	3551	Wyatt, R.	1
822	Araujo, T.	1	1732	Goodman, B.W.	1	2642	O'Sullivan, D.	1	3552	Wyckmans, A.	1
823	Araya, A. A.	1	1733	Goodwin, J.	1	2643	Otakore, O.	1	3553	Wymant, C.	1
824	Archambault, D.	1	1734	Goodwin, R. D.	1	2644	O'Toole, A. J.	1	3554	Xia, P.	1
825	Ardèvol-Abreu, A.	1	1735	Gopoian, J. D.	1	2645	Ottoni, R.	1	3555	Xiang, A.	1
826	Arenas, E. A.	1	1736	Gordon, D. F.	1	2646	Ourselin, S.	1	3556	Xiang, Y.	1
827	Arezoumand, Z.	1	1737	Gosling, S. D.	1	2647	Over, P.	1	3557	Xiao, S.	1
828	Argo, J. J.	1	1738	Gotlib, I. H.	1	2648	Overdorf, R.	1	3558	Xie, X.	1
829	Argyle, L. P.	1	1739	Gottfried, J.	1	2649	Owen, G.	1	3559	Xu, D.	1
830	Arikan, B.	1	1740	Goyal, Y.	1	2650	Ozment, A.	1	3560	Xu, H.	1
831	Arimura, H.	1	1741	Graefe, A.	1	2651	Paasonen, S.	1	3561	Xu, J.	1
832	Arista, N.	1	1742	Graells-Garrido, E.	1	2652	Pacchiano, A.	1	3562	Xu, W.	1
833	Armstrong, D. G.	1	1743	Graham, G.	1	2653	Pace, W. D.	1	3563	Yan, Q.	1
834	Armstrong, K.	1	1744	Gramopadhye, A.K.	1	2654	Page, J.	1	3564	Yang, C.	1
835	Arnadottir, J.	1	1745	Granovsky, B. L.	1	2655	Pager, D.	1	3565	Yang, F.	1

836	Arnaout, O.	1	1746	Grant-Vallone, E. J.	1	2656	Pak, C.	1	3566	Yang, G.	1
837	Arnholt, M. W.	1	1747	Grappi, S.	1	2657	Pakhomov, S.	1	3567	Yang, Q.	1
838	Arnold, T. B.	1	1748	Grasso, C.	1	2658	Pal, C. J.	1	3568	Yang, S.	1
839	Aronson, J.	1	1749	Gravante, G.	1	2659	Pallud, J.	1	3569	Yang, W.	1
840	Arora, R.	1	1750	Grave, E.	1	2660	Palm, E.	1	3570	Yang, Y.	1
841	Arriagada, E.	1	1751	Gray, M. L.	1	2661	Palmer, R. E.	1	3571	Yao, M.	1
842	Arrieta, B.	1	1752	Graziani, G. C.	1	2662	Palomäki, O.	1	3572	Yasseri, T.	1
843	Arsi, S.	1	1753	Greco, S.	1	2663	Pan, J. S.	1	3573	Yates, K.	1
844	Arthurs, N.	1	1754	Green, S.	1	2664	Pan, R.	1	3574	Yazdany, J.	1
845	Asch, D. A.	1	1755	Greenberg, A.	1	2665	Pan, Y.	1	3575	Ye, L.	1
846	Ashar, S. M.	1	1756	Greenberg, J.	1	2666	Panch, T.	1	3576	Yee, K.-P.	1
847	Ashby, W. R.	1	1757	Greene, D.	1	2667	Pandharipande, P. V.	1	3577	Yeh, C.-K.	1
848	Ashe, S. D.	1	1758	Gregg, P.	1	2668	Pang, R.	1	3578	Yeung, K.	1
849	Ashley, F.	1	1759	Gregor, S.	1	2669	Pantic, M.	1	3579	Yin, X.	1
850	Ashley, K. D.	1	1760	Grevet, C.	1	2670	Papapanagiotou, P.	1	3580	Yoo, B.	1
851	Asi, Y. M.	1	1761	Griffin, G. P.	1	2671	Papernot, N.	1	3581	Yoon, D. Y.	1
852	Athey, S.	1	1762	Grinblat, Y.	1	2672	Parapatics, S.	1	3582	York, J.	1
853	Atkinson, A. J. Jr.	1	1763	Grochowski, M.	1	2673	Pardalos, P. M.	1	3583	You, X.	1
854	Atkinson, B.	1	1764	Gross, R.	1	2674	Pardo, T. A.	1	3584	Young, M.	1
855	Atkinson, E. J.	1	1765	Grosse, K.	1	2675	Parekh, K.	1	3585	Young, R.	1
856	Attewell, P.	1	1766	Grossklags, J.	1	2676	Parikh, R. B.	1	3586	Young, T.	1
857	Attride-Stirling, J.	1	1767	Grother, P.	1	2677	Parikka, J.	1	3587	Youyou, W.	1
858	Auber, D.	1	1768	Grouin, C.	1	2678	Park, J. H.	1	3588	Ysabel, G.	1
859	Auffarth, B.	1	1769	Groves, R. M.	1	2679	Park, Y.	1	3589	Yu, C.	1
860	Aurora, V.	1	1770	Grundy, S.	1	2680	Park, J. S.	1	3590	Yu, L.	1
861	Austwick, M. Z.	1	1771	Gruss, S.	1	2681	Parkhi, O. M.	1	3591	Yuan, J.	1
862	Avci, B.	1	1772	Gu, Y.	1	2682	Parks, D.	1	3592	Yuan, Q.	1

863	Axhausen, K. W.	1	1773	Guadagno, R. E.	1	2683	Parks, M.	1	3593	Yuan, S.	1
864	Ayres, M.	1	1774	Guerra, S.	1	2684	Parris, T.	1	3594	Yucesoy, B.	1
865	Azad, T.	1	1775	Guillemin, M.	1	2685	Parush, A.	1	3595	Yun, C.	1
866	Azizpour, H.	1	1776	Guillory, J. E.	1	2686	Paschen, U.	1	3596	Yunus, N. K. Y.	1
867	Ba, J.	1	1777	Gulshan, V.	1	2687	Pasquale, F.	1	3597	Yurochkin, M.	1
868	Baatarjav, E. A.	1	1778	Gummadi, K.P.	1	2688	Pasti, R.	1	3598	Zadrozny, B.	1
869	Babaian, T.	1	1779	Gundotra, N.	1	2689	Patel, J.	1	3599	Zahedi, F. M.	1
870	Babenko, A.	1	1780	Gunning, D.	1	2690	Patel, A. R.	1	3600	Zaldívar-Basurto, F.	1
871	Babu, R. V.	1	1781	Guo, C. J.	1	2691	Patten, S.	1	3601	Zang, J.	1
872	Bach, S.	1	1782	Guo, Y.	1	2692	Paul, J. M.	1	3602	Zarsky, T.	1
873	Bachorowski, J.	1	1783	Gupta, I.	1	2693	Paulus, M. P.	1	3603	Zeiler, M.	1
874	Backstrom, L.	1	1784	Gupta, M.	1	2694	Paunesku, D.	1	3604	Zeller, T. J.	1
875	Bacon, D.	1	1785	Gupta, N.	1	2695	Pavri-Garcia, K. V.	1	3605	Zeng, J.	1
876	Badgeley, M.	1	1786	Guryan, J.	1	2696	Payrovnaziri, S. N.	1	3606	Zhan, A.	1
877	Baehrens, D.	1	1787	Guterman, S.	1	2697	Peacock, C.	1	3607	Zhan, X. X.	1
878	Baeßler, B.	1	1788	Guy, L. S.	1	2698	Pearl, J.	1	3608	Zhang, H.	1
879	Bagdasaryan, E.	1	1789	Guyon, I. M.	1	2699	Pease, A.	1	3609	Zhang, J.	1
880	Bagheri, M. A.	1	1790	Gyoba, J.	1	2700	Pedapati, T.	1	3610	Zhang, K.	1
881	Bagozzi, R. P.	1	1791	Györfi, L.	1	2701	Pei, J.	1	3611	Zhang, Q.-S.	1
882	Bagrow, J.P.	1	1792	Gyte, G. M. L.	1	2702	Pei, Z.	1	3612	Zhang, S.	1
883	Bahadori, M. T.	1	1793	Haar, J.	1	2703	Peng, L.	1	3613	Zhang, Y.	1
884	Baiely, T.	1	1794	Haas, L.	1	2704	Penn, G.	1	3614	Zhang, Z.	1
885	Bail, C. A.	1	1795	Haber, E.	1	2705	Pennington, J.	1	3615	Zhang, Z.-K.	1
886	Bailey, P.	1	1796	Hackman, D. A.	1	2706	Penzel, T.	1	3616	Zhao, Z.	1
887	Bain, M.	1	1797	Hackney, R.	1	2707	Perer, A.	1	3617	Zheng, K.	1
888	Bair, E.	1	1798	Hadjiharalambous, S.	1	2708	Perez, M. S.	1	3618	Zheng, S.	1
889	Baker, C.	1	1799	Hadley, T. D.	1	2709	Perillo, T.	1	3619	Zheng, Z.	1

890	Bakker, J.	1	1800	Haeffele, B. D.	1	2710	Perlis, R. H.	1	3620	Zhou, T.	1
891	Bakker, M.	1	1801	Haenlein, M.	1	2711	Perrault, R. T.	1	3621	Zhou, T. C.	1
892	Bakshy, E.	1	1802	Hagg, E.	1	2712	Pessach, D.	1	3622	Zhou, X.	1
893	Balabanović, M.	1	1803	Haidt, J.	1	2713	Petretta, M.	1	3623	Zhou, Y.	1
894	Balakrishnan, A.	1	1804	Haines, A.	1	2714	Petrocik, J. R.	1	3624	Zhou, Z.-H.	1
895	Balayla, J.	1	1805	Hair, J. F.	1	2715	Petter, S.	1	3625	Ziegler, C. N.	1
896	Baldi, P.	1	1806	Hamke, A. K.	1	2716	Pettit, R. W.	1	3626	Zintgraf, L. M.	1
897	Baldoni, M.	1	1807	Hammel, E.A.	1	2717	Peugh, J. L.	1	3627	Žliobaitė, L.	1
898	Balfour, R.	1	1808	Hammerschmidt, C. A.	1	2718	Peus, C. V.	1	3628	Zmud, R. W.	1
899	Ball, K.	1	1809	Hammond, P.	1	2719	Pfeffer, J.	1	3629	Zoepf, S.	1
900	Ballenger, G.	1	1810	Hampson, S.	1	2720	Pfister, H.	1	3630	Zohar, D.	1
901	Banegas, M. P.	1	1811	Hamtini, T.	1	2721	Pfitzner, R.	1	3631	Zohar, N.	1
902	Banet-Weiser, S.	1	1812	Hanani, U.	1	2722	Philipp, B.	1	3632	Zou, H.	1
903	Banner, O.	1	1813	Hancox, J.	1	2723	Phillips, R.	1	3633	Zucker, J.	1
904	Bansal, G.	1	1814	Hankin, C.	1	2724	Phillips, S. J.	1	3634	Zügner, D.	1
905	Bantilan, N.	1	1815	Hansen, B.	1	2725	Phillips-Wren, G.	1	3635	Zweig, K. A.	1
906	Barabási, A.-L.	1	1816	Hansen, D.	1	2726	Phithakkitnukoon, S.	1	3636	Zweigenbaum, P.	1
907	Barad, K.	1	1817	Hansen, G. J.	1	2727	Piantanida, P.	1	3637	Zybert, P.	1
908	Barassi, V.	1	1818	Hanson, L.	1	2728	Picard, R. W.	1			
909	Barbaro, M.	1	1819	Hansson, S. O.	1	2729	Pilehvar, M. T.	1			
910	Barbash, F.	1	1820	Hao, M.	1	2730	Pilkonis, P. A.	1			