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RESEARCH ARTICLE

# A neurobiologically inspired model of social cognition: Memes spreading in the Internet

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**Abstract**
The field of memetics has attracted interdisciplinary attention as a biologically inspired approach to animal communication and sharing of human cultural patterns. Here a formalization of the theory of memes is proposed, making use of a formal language that is adequate to represent neural information processing. This formalization is the basis for our development of a model of social cognition including mathematical tools derived from the field of epidemiology. The model describes processes of communication between individuals of the same biological species, which share the same computational mechanisms of neural information processing. An example of the 'modus operandi' of the model is shown, consisting of a brief study of meme spreading in the Internet. Among the results of this study, we highlight: (1) The operationalization of memetics in a cognitive architecture that is based on biological constraints and possible to be implemented in digital computers; (2) the proposed model of meme spreading in an online social network may be of interest for public organisations, private corporations and people in general; and (3) the limitation of modeling should be considered when interpreting data about any dynamical phenomenon.


## Introduction

The evolution of the human individual began with macroevolutionary events that culminated with the first *Homo* species, about two and a half million years ago. By about 160,000 years ago *Homo sapiens* (White et al., 1997) appeared. They controlled fire, developed agriculture and probably some form of language.

The evolution of the brain is achieved both by increasing the number of neurons and allowing new functional specializations. Brain size increase, however, has a price

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(Blackmore, 1999): oversized brains are expensive to run. Our brains consume 20% of the body energy for a size corresponding to only 2% in weight. The amount of protein and fat necessary for the development of human individuals forced the first members of the Homo genus to increase their meat consumption by means of better hunting strategies, which in turn fed back into increased brain size.

Big brains are dangerous to produce. Human babies have to pass through a narrow birth canal. This implies — in addition to higher maternal and foetal mortality — that the human baby is born prematurely, as compared with other primates. This circumstance has the beneficial consequence that our brain has greater neuronal plasticity, which increases its learning capacity. But this requires continued guidance from parents and forced familial relationships to be strengthened.

The amount of protein and fat necessary for the development of human individuals forced the first members of the Homo genus to increase their meat consumption requiring better hunting strategies taking profit of group activities. According to Power and Schulkin (2009), ''gathering food and bringing it to a communal place where it is shared among the other members of the social network probably is a key evolutionary event''. These and other large-scale collective behaviours stimulated an impressive development of the social brain as a collection of neural circuits to handle other persons' intentions, cooperative actions, fair play and collective decisions (Adolphs, 2009; Rocha, Burattini, Rocha, & Massad, 2009; Tomasello, 1999).

According to Adolphs (2009), evolution shaped us as an essentially social species that share cognitive resources more intensively than other species. We are organisms who understand conspecifics as beings *like ourselves*; we ascribe to them intentional and mental lives like our own. Although a definition of social cohesion is very complex and disputable (see, e.g., OECD, 2011), it certainly involves a sense of belonging to various groups in modern society and being able to communicate in effective ways to sustain collective projects. This sense of belonging is sensitive to how much individual social brains share beliefs, ideas, concepts, myths and icons. These cognitive processes are assumed to depend on the existence of common biological mechanisms of information processing in the individuals belonging to the human species.

## Meme

Humans are capable of imitation. We can copy ideas, habits, skills, behaviours, inventions, song and stories. These are all *memes*, a term which first appears in Richard Dawkins' book *The Selfish Gene* (Dawkins, 1976). Dawkins first thought of '*mimeme*', which had a suitable Greek root, but he wanted a monosyllabic word, which would sound like 'gene' and hence the abbreviation of mimeme into *meme*. The *Oxford English Dictionary* contains the following definition:

**Meme** *An element of a culture that may be considered to be passed on by non-genetic means, esp. imitation.*

In this context, memes are cultural expressions of societies of individuals who share the same biological structures and functions. The content of memes is information (Blackmore, 1999; Ropp, 2015), which is assumed to have a neural basis. Memes are traditionally propagated by direct interaction of individuals, but recently mass media, and specially the Internet, arised as important vehicles for meme spread (JafariAsbagh, Ferrara, Varol, Menczer, & Flammini, 2014; Gal, Shifman, & Kampf, 2015; Kligler-Vilenchik & Thorson, 2015).

Memes — as originally introduced by Dawkins (1976) — are simple pieces of information like genetic viruses. They are held in memory and capable of being copied from memory to another's memory. Because of the cultural diversity of individuals, different people are distinctively affected by memes. Different groups of people share different sets of memes. In this context, memes are important contributors to social cohesion (e.g., Gal et al., 2015; Kligler-Vilenchik & Thorson, 2015).

## Formal grammars

Noam Chomsky (1965) proposed Generative Grammar as a linguistic theory that considers grammar to be a system of rules that is intended to generate exactly those combinations of words that form grammatical sentences in a given language. Chomsky and colleagues have argued that many of the properties of a generative grammar arise from a universal grammar, which is innate to the human brain.

A formal grammar (**G**) is a set of rules for rewriting strings, along with a ''start symbol'' from which rewriting starts (e.g. Hopcroft & Ulmann, 1979).

$\mathbf{G} = (V, \omega, P)$

where

- **V** (the *alphabet*) is a set of symbols containing elements (variables) $v_i$ that can be replaced.
- $\boldsymbol{\omega}$ (*start*, *axiom* or *initiator*) is a string of symbols from **V** defining the initial state of the system.
- **P** is a set of *production rules* or *productions* defining the way variables can be replaced with combinations of constants and other variables:

  $\mathrm{p}: \ \delta \mathrm{v}_i \gamma \rightarrow \delta \mathrm{v}_j \gamma$

- $\delta$, $\gamma$ specify the context for rule application.

Formal grammars are frequently classified as (Hopcroft & Ulmann, 1979):

- *Context-free grammars* is a grammar in which the left-hand side of each production rule consists of only a single nonterminal symbol.
- *Regular grammars* is a grammar in which left hand side is again only a single nonterminal symbol, but now the right-hand side is also restricted to be the empty string,

or a single terminal symbol, or a single terminal symbol followed by a nonterminal symbol, but nothing else.
- A recursive grammar is a grammar which contains production rules that are recursive, meaning that expanding a non-terminal according to these rules can eventually lead to a string that includes the same non-terminal again.

L-systems are an example of recursive grammar devised to provide a formal description of the development of multicellular organisms and complex branching structures (e.g., Zamir, 2001). By increasing the recursion level the form slowly 'grows' and becomes more complex. Lindenmayer systems are also popular in the generation of artificial life.

Formal grammars are mathematical constructs in the realm of classic set theory assuming that an element either belongs (1) or does not belong (0) to a give set. For example, any symbol $v_i$ either belongs or not to the set **V**. The word *grammar* belongs to the set of symbols of English language, but the word *gramática* does not, although it is the Portuguese translation of the English word. Sentences and words of real languages are not used in this black/white faction. Most of words may have different meanings; most of sentences have some degree of ambiguity. Because of this, Lee and Zadeh (1969) introduced the theory of Fuzzy Formal Languages based on Fuzzy Set theory (Zadeh, 1965) that assigns a degree of pertinence in the closed interval [0, 1] of each $v_i$ to **V**. As much an element is though to (not) belong to a set, as much this pertinence approaches 1 (0). A degree $\rho$ of possibility defined in the closed interval [0, 1] is assigned to each production rule to express language ambiguity (Massad & Rocha, 2006; Rocha, Françozo, Hadler, & Balduino, 1980; Rocha & Massad, 2006).

Fuzzy formal languages were proposed to be a very adequate formalism to model reasoning taking into consideration the physiology of neural circuits (Rocha et al., 1980; Rocha, 1997; Rocha, Rebelo, & Miura, 1998; Rocha & Massad, 2002; Rocha, Massad, & Pereira, 2005). In this context, memes as information stored in memory are formalized as sentences in the Fuzzy Neural Language modeling brain dynamics. Here we show how this formalization can be done and exemplify the model with a case of meme spreading in the Internet.

## Fuzzy neural grammars

Here, a grammar **G** (Rocha et al., 1998; Rocha et al., 1980) is a structure defined as:

$$\mathbf{G} = \{\mathbf{V_o}, \mathbf{V_n}, \mathbf{V_t}, \mathbf{P}, \boldsymbol{\eta}), \qquad (1)$$

where

(a) $\mathbf{V_o}$: is a finite set of initial or starting symbols or sentences,
(b) $\mathbf{V_t}$: is a finite set of terminal symbols or words,
(c) $\mathbf{V_n}$: is a finite of grammatical classes,
(d) $\boldsymbol{\eta}$: is the empty element, and
(e) **P**: is a set of rewriting rules called the syntax of **G**.

$$\mathbf{p} : \delta \mathbf{s_i} \gamma \rightarrow \delta \mathbf{s_j} \gamma, \quad \mathbf{p} \in \mathbf{P}, \delta, \gamma, \mathbf{s_i}, \mathbf{s_j} \in \mathbf{V_o} \cup \mathbf{V_n} \cup \mathbf{V_t} \cup \boldsymbol{\eta} \qquad (2)$$

In other words, **p** rewrites $\mathbf{s_i}$ as $\mathbf{s_j}$ in the context defined by by $\delta$ and $\gamma$.

The derivation chain $\mathbf{d(s_i, s_j)}$ of the $\mathbf{s_i}$, $\mathbf{s_j} \in \mathbf{V}^*$ is the ordered set of productions required to transform the symbol $\mathbf{s_i} \in \mathbf{V_s}$ into $\mathbf{s_j}$ (Fig. 1). In other words:

$$\mathbf{d}(\mathbf{s_i}, \mathbf{s_j}) = \delta \mathbf{s_i} \gamma \rightarrow \delta \mathbf{s_k} \gamma \ldots \ldots \delta \mathbf{s_l} \gamma \rightarrow \delta \mathbf{s_j} \gamma \qquad (3)$$

Then, a language **L(G)** supported by **G** is the set of all **n** derivation chains $\mathbf{d_i(s_o, s_t)}$, $\mathbf{s_o} \in \mathbf{V_o}$ and $\mathbf{s_t} \in \mathbf{V_t}$, that is:

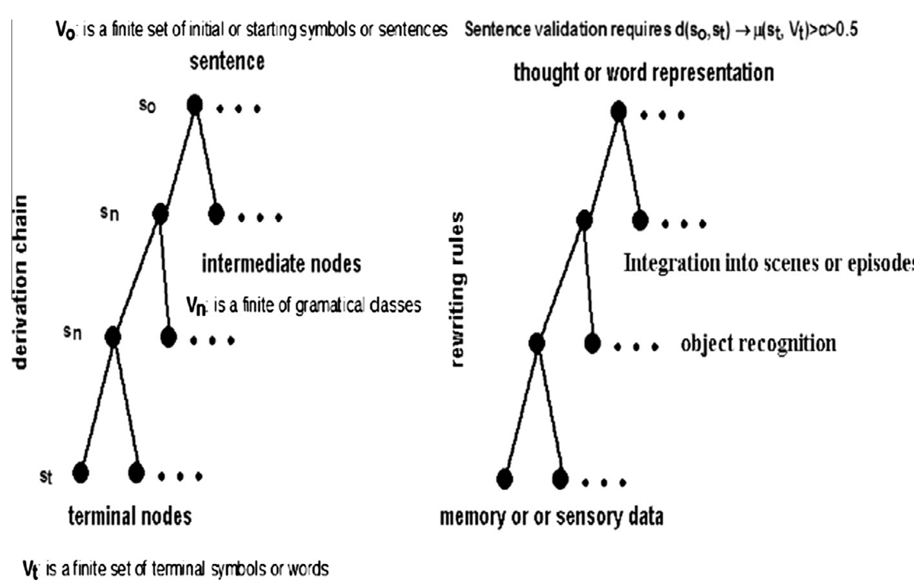


**Fig. 1** Reasoning as production of a Fuzzy Formal Grammar G. $V_o$: set *o* initial symbols $s_o$; $V_n$: set of intermediate symbols $s_n$; $V_t$: set of terminal symbols $s_t$ and $d(s_o, s_t)$: derivation chain rewriting $s_o$ into $s_t$.

$$L(G) = \{d(s_o, s_t) = \delta s_o \gamma \rightarrow \delta s_i \delta \ldots \rightarrow \delta s_t \gamma | s_o \in V_o \text{ and } s_t \in V_t\} \quad (4)$$

The grammar defined so far is called type-0 grammar or $G^0$. Certain restrictions can be imposed on the nature of the productions of a grammar to yield other types of grammars (Hopcroft & Ulmann, 1979). The set of all derivation chains of **L(G)** defines its syntax (Rocha et al., 2005).

The processing of any derivation chain $d(s_o, s_t)$ is a *sequentially ordered* set of rewriting operations, each one involving the following steps:

(1) Matching: a symbol at the left-hand side (e.g. $s_i$) of a prospective rewriting rule (e.g., $s_k \rightarrow s_j$) is matched ($s_o \equiv s_k$) to the symbols of the string $s_i$ being processed. If this matching succeeds, then
(2) Rewriting: the matched $s_i$ is substituted by the right-hand side of the accepted rewriting rule $s_i \equiv s_k \rightarrow s_j$ and finally
(3) Acceptance: the membership degree $\mu_{Vt}(s_i)$ of $s_i$ to $V_t$ is evaluated. If $s_i$ is accepted as belonging to $V_t$, that is, if $s_i = s_t \in V_t$ the rewriting process is ended, and $d(s_o, s_t)$ is assumed to be a well formed formula of **L(G)**.

In this line of reasoning, the following needs to be defined:

(a) The *degree of similarity* (matching) $\mu(s_i, s_k)$ of two strings $s_i$, $s_k$ is a mapping in the cartesian product space $V_s \times V_n \times V_t$ to the closed interval $[0, 1]$ such that:

$$\mu : V_o \times V_n \times V_t \rightarrow [0, 1], \; \mu(s_i, s_k) = 0 \text{ if } s_i \neq s_k, \text{ otherwise } 0 < \mu(s_i, s_k) \quad (5)$$

(b) The *degree of acceptance* $\mu(s_j, V_t)$ of $s_k$ as belonging to $V_t$ is calculated as the maximum degree of similarity $\mu(s_j, s_t)$ of $s_j$ with the strings $s_t \in V_t$. In other words:

$$\mu(s_j, V_t) = \max \mu(s_j, s_t) \quad (6)$$

Sentence validation as a production of **L(G)** requires $d(s_o, s_t) \rightarrow \mu(s_t, V_t) > \alpha > 0.5$. $d(s_o, s_t)$ is a formula of **L(G)** with a degree $\mu(s_o, V_o)$ equal to $\mu(s_j, V_t)$.

**L(G)** may be used to describe the dynamics of a given environment **H**. This is accomplished by making $\mu(s_j, V_t)$ to be dependent on dynamics of **H**. In this context, let **Ł(G | H)** $\subset$ **L(G)** be the language formed by the set of all derivations $d(s_o, s_j)$ that are supported by **G** under the restrictions imposed by the environment **H** because $\mu(s_o, V_o) > \alpha > 0.5$.

We assume that production of sentences accepted by a given grammar requires *processing spaces*, where at least some subsets of $V_o$, $V_n$, $V_t$ are available. We further assume that each processing space **P** is supported by a certain cognitive organ (such as the human brain), or, more generally, a *processing system* **B**, containing processing cells or abstract units **C** that are associated with individual symbols and/or production rules. Let **Ł(G | H, P)** denote the set of sentences about **H** that may be produced and accepted in the processing space **P**. In this context, each processing system **B** will contain many cells of each type **C** and will express a family of languages **Ł(G | H, $C_{m=1 \text{ to } r}$)**, where **m** is the index of the processing space for **G** provided by each type of cell $C_m$ composing the processing system.

An individual processing system **B** is constituted by the family of processing spaces $N_i$ composed by sets of specialized cells. In this approach, the sentences defining **Ł(G | H, $B_i$)** are those describing reasoning computed by a given individual $B_i$ (Fig. 2). In the case of individuals, nodes in Fig. 2 represent the set of cells, and arcs represent connections between these cells. Knowledge is represented by the set of all derivation chains $d(s_i, s_j)$, for which $\mu(s_j, V_t) > \alpha > 0.5$.

Knowledge that $B_i$ has about its surrounding environment is composed by the set of sentences of **Ł(G | H, $B_i$)** inherited or learned that helps $B_i$ to understand **H** and to behave accordingly (Fig. 3). In this line of reasoning, the knowledge $K_i$ is the set of initial symbols $V_i$ **(H, $B_i$)** for which there exists at least one $d(s_o, s_j)$ with $\mu(s_j, V_t) > \alpha > 0.5$.

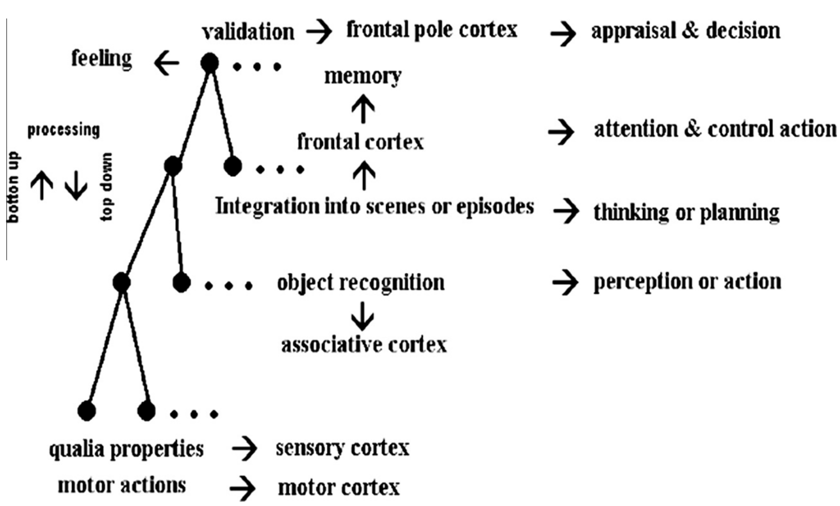


**Fig. 2** Intuitive explanation of a processing space. The diagram refers to **Ł(G | H, $B_i$)** and displays an hypothetical mapping of the language on the human brain.

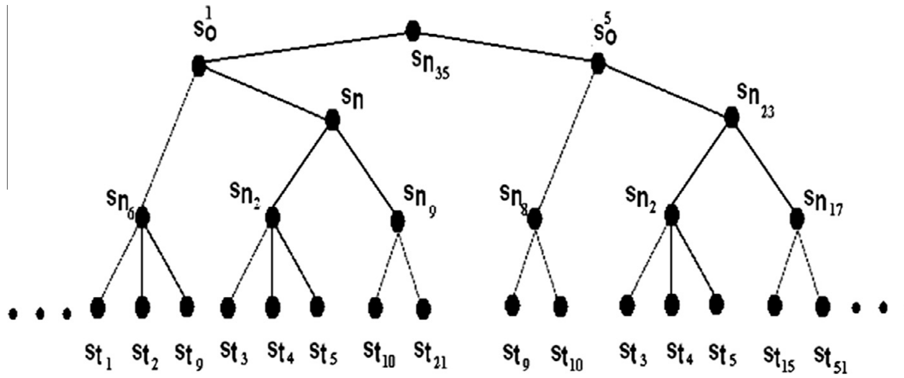


**Fig. 3** $B_i$'s knowledge $K_i$ about H. Initial symbols: $s_o^i$; $S_{ni}V_t$: terminal symbols $s_t i$.

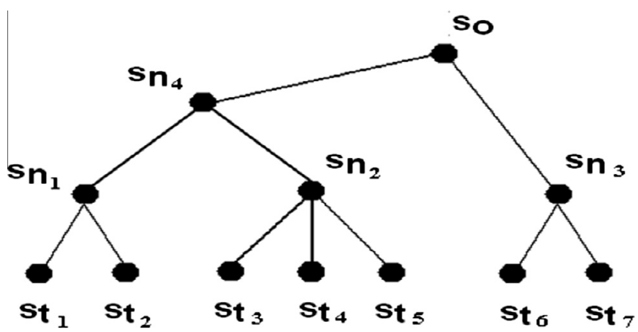


**Fig. 4** A sentence produced by $B_j$. Symbols as in Fig. 3.

Because sentences generated by Ł(**G** | **H, B**$_i$) are dependent on neural connectivity patterns that are changed by learning, the reasoning produced by two individuals $\mathbf{B_i}$ and $\mathbf{B_j}$ depend on their knowledge $\mathbf{K_i}$ and $\mathbf{K_j}$, which resulted from their different learning processes. In this context, knowledge shared by two different individuals $\mathbf{B_i}$ and $\mathbf{B_j}$ is determined by Ł(**G** | **H, B**$_i$) ∩ Ł(**G** | **H, B**$_j$) which in turn is constituted by all $\mathbf{d(s_o^k, s_j)}$ having $\boldsymbol{\mu}(\mathbf{s_j}, \mathbf{V_t} \mid \mathbf{B_{i,}B_m})$ > α > **0.5**.

## The formal meme

Consider two individuals $\mathbf{B_i}$ and $\mathbf{B_j}$ sharing the same grammar **G,** but having different knowledge $\mathbf{K_i}$ and $\mathbf{K_j}$. Now, let $\mathbf{d(s_o^m, s_t \mid B_j)}$ be a sentence (e.g., a thought, an action, etc.) produced by $\mathbf{B_j}$ concerning the environment **H** shared by these two individuals. In this context:

**Definition 1.** $\mathbf{B_i}$ may understand sentence $\mathbf{d(s^m, s_t \mid B_j)}$ produced by $\mathbf{B_j}$ if there exist $\mathbf{d(s_o^n, s_n\ s_t \mid B_j)}$ such that $\boldsymbol{\mu}(\mathbf{s_o^n}, \mathbf{V_o} \mid \mathbf{B_i})$ > α > **0.5** that results into $\mathbf{s_o^n}$ being similar to $\mathbf{s_o^m}$ because $\boldsymbol{\mu}(\mathbf{s_o^m}, \mathbf{s_o^n})$ = ) > α > **0.5.** In the context of **G**, $\mathbf{d(s^m, s_t \mid B_j)}$ is easily understood by $\mathbf{B_i}$ if $\boldsymbol{\mu}(\mathbf{s_o^m}, \mathbf{s_o^n}) \rightarrow \mathbf{1}$ what means that $\mathbf{s_o^m}$, $\mathbf{s_o^n}$ are similar or equal symbols of **Vo** (see Fig. 4).

Let **C** be a community of *p* individuals $\mathbf{B_c}$. The Culture C ($\mathbf{B_c}$), understood as the knowledge shared by individuals, is defined as by $\cap_{\mathbf{c=1\ to\ }p}$ ($\mathbf{K_c}$) and, therefore, determined by those $\mathbf{d(s^m, s_t \mid B_c)}$ for which $\boldsymbol{\mu}(\mathbf{s_o^m}, \mathbf{V_o} \mid \mathbf{B_c})$ > α ≫ **0.5.** Now:

**Definition 2.** Comprehension of any new sentence $\mathbf{d(o^m, s_t \mid B_j)}$ produced by $\mathbf{B_j}$ increases as $\boldsymbol{\mu}(\mathbf{s_o^n}, \mathbf{V_o} \mid$ C($\mathbf{B_c}$)) augments and approaches 1.

Comprehension of $\mathbf{d(s_o^m, s_t \mid H,C)}$ requires the sentence to be copied into the individuals $\mathbf{B_j}$ may be achieved imitation if the set of terminal symbols **st** of the sentence produced by $\mathbf{B_j}$ are observable by $\mathbf{B_i}$. Cells of the $\mathbf{m_i}$ kind allow individuals to copy sentences whose motor output components ($\mathbf{s_i}$ in the sentence produced by $\mathbf{B_j}$) may be observed by means of sensory receptors ($\mathbf{s_i}$ in the sentence copied by $\mathbf{B_i}$). In animals, these cells can be compared to mirror neurons, a kind of neuron present in several mammalian species, with cognitive functions of responding to the observation of a certain behaviour of other animals, and supporting the first animal performing the same action. In humans, mirror neurons were detected at the pre-motor cortex and inferior parietal lobe, being activated in cognitive processes as imitation and language acquisition (Rizzolatti & Craighero, 2004; for a broader view on intentionality issues, see Teixeira & Pereira, 2008). It must be remarked, here, that $\mathbf{d(s_o^n, s_t \mid B_i)}$ may be considered a copy of $\mathbf{d(s_o^m, s_t \mid B_j)}$ iff these two sentences share the majority of their terminal nodes $\mathbf{s_t}$ (Fig. 5; note that node $\mathbf{s_t^5}$ is not a shared node).

Imitation allows transmissions of sentences $\mathbf{d(s_o^m, s_t \mid H,C)}$ having terminal nodes, which are observable by other individuals. Humans use this mechanism to create a language that allows the propagation of **L(G | H,C)** non-observable sentences. Humans produce sounds as terminal nodes that may be copied by using mirror neurons. We learned to map a non-observable sentence $\mathbf{d(s_o^m, s_t \mid H,C)}$ into a observable language sentence $\mathbf{d'(s_o^m, s_t \mid H,C)}$ (Fig. 6) to allow it to be copied by different individuals. Later, humans expanded their capacity to propagate non-observable sentences creating written language. The trick was to map language terminal symbols not into sounds, but into visual symbols.

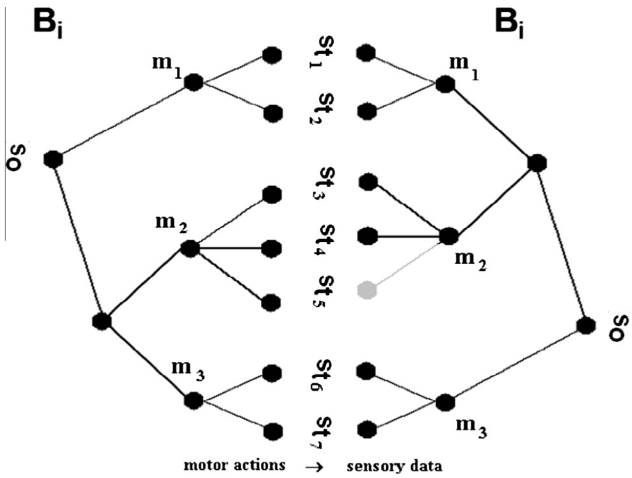


**Fig. 5** How $B_i$ is able to imitate a sentence produced by $B_j$. Symbols as in Fig. 3.

**Definition 3.** $d(s_o^m, s_t \mid H, B_j)$ becomes a formal **meme** in a community **C** if $d(s_o^m, s_t \mid H)$ supporting it, is easily understood by individuals $B_c$ other than $B_j$. Let this be denoted as $m(s_o^m, s_t \mid H, C)$.

Two main systems are used to propagate sentences $d(s_o^m, s_t \mid H, C)$ between individuals $B_c$ sharing same culture **C**:

(a) Mail addressing: Both the sending and the receiving individuals have the capacity to address messages specifically to each other. Imitation and oral language are the main ways used in this type of message addressing, since it is based on inter-individual contact.
(b) Blackboard posting: A given individual delivers messages ($d(s_o^m, s_t \mid H, C)$) that are not specifically addressed to another defined individual, but to those interested in the subject. For such a purpose, messages are posted in channels like books and journals using written language, or more recently they are vehiculated by radios, television, internet, etc., using not only oral and written languages, but also images such as in photography, painting, and videos.

## A Formal sentence becomes a meme

Acceptance of $d(s_o^m, s_t \mid H, C)$ as a sentence of $L(G \mid H, B_i)$ implies in classifying it as a pleasurable or harmful one. In the case of human mind/brain, this operation involves the reward and punishment systems (including the dopamine-activated nuclei and frontal cortical areas, as discussed in Krawczyk, Gazzaley, and D'Esposito (2007)). If $s_o^m$ promotes a better adaptation of $B_i$ to **H** then a degree of benefit $\beta(d(s_o^m, s_t))$ is assigned to the sentence. In the same way if $s_o^m$ may endanger adaptation of $B_i$ to **H** then a degree of risk $\rho(d(s^mo, s_t))$ is assigned to the sentence. This classifies sentence $d(s^mo, s_t \mid H, C)$ in two distinct sets of antagonic sentences. In addition, if both $\beta(d(s_o^m, s_t))$ and $d(s_o^m, s_t \mid H, C)$ tend to zero, then $d(s^mo, st \mid H, C)$ is considered a sentence not belonging to $L(G \mid H, B_i)$.

In this context, it is possible now to rank sentences $d(s_o^m, s_t \mid H, C)$, $d(s_o^n, s_t \mid H, C)$ resulting in the same or similar set of terminal symbols according to their associated benefit/risk $\beta(d(s_o^m, s_t))$, $\beta(d(s_o^n, s_t))$ ($\rho(d(s_o^m, s_t))$, $\rho(d(s_o^n, s_t))$). These sentences $d(s_o^m, s_t)$, $d(s_o^n, s_t)$ are alternative interpretations about **H**, as described by $V_t$.

Now, the following definition can be made:

**Proposition 1.** *A meme $m(s_o^m, s_t \mid H, C)$ has either a high benefit $\beta(d(s_o^m, s_t))$ or a high risk $\rho(d(s_o^m, s_t))$, and therefore is conceived to be respectively pleasurable or unpleasant. In the first case, $m(s_o^m, s_t \mid H, C)$ is probably copied by $B_c$ because it promotes happiness, in the sense of increasing his/her pleasure (although we do not directly address the semantics of the proposed formal language, the concept of*

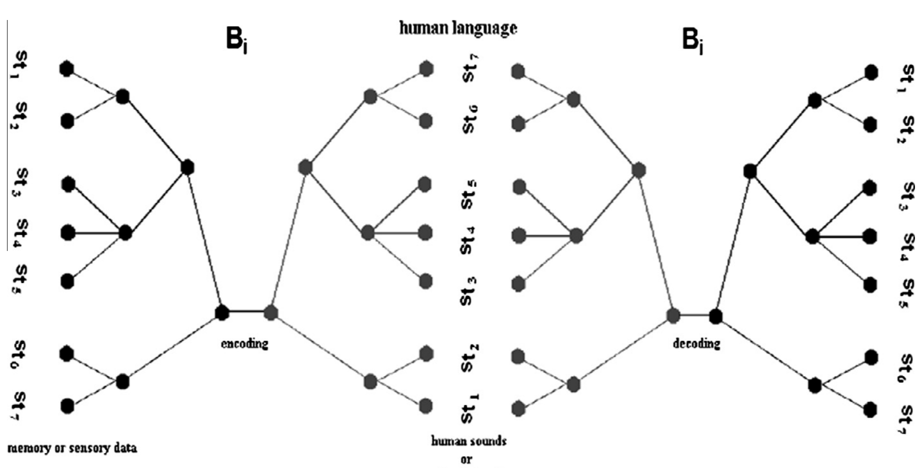


**Fig. 6** Using human language to propagate sentences of Ł(G | H, C). Symbols as in Fig. 3.

*''happiness'' refers to psychological states of agents receiving and interpreting the messages carried by sentences of the language). In the second case,* $\mathbf{m(s_o^m, s_t \mid H, C)}$ *is also probably copied by* $\mathbf{B_c}$ *because it warns about danger to* $\mathbf{B_c}$.

Consider two $\mathbf{d(s_o^m, s_t)}$, $\mathbf{d(s_o^n, s_t)}$ sentences of $\mathbf{L(G \mid H, C)}$ as having different probabilities $p(s_o^m)$, $p(s_o^n)$ of being interpretations of H. In this context, the expected benefits for $\mathbf{d(s_o^m, s_t)}$, $\mathbf{d(s_o^n, s_t)}$ being the most adequate actual interpretation of $\mathbf{H}$ are estimated as:

$$(1 - p(s_o^m)^* \beta(\mathbf{d}(s_o^m, s_t))) \text{ and } (1 - p(s_o^n)^* \beta(\mathbf{d}(s_o^n, s_t)))$$

In the same line of reasoning, the expected risks for $\mathbf{d(s_o^m, s_t)}$, $\mathbf{d(s_o^n, s_t)}$ being the most adequate actual interpretention of $\mathbf{H}$ are estimated as:

$$(1 - p(s_o^m)^* \rho(\mathbf{d}(s_o^m, s_t))) \text{ and } (1 - p(s_o^n)^* \rho(\mathbf{d}(s_o^n, s_t)))$$

In addition, let the values of $\mathbf{p(s_o^m)}$, $\mathbf{p(s_o^n)}$ be dependent on actual contexts $\mathbf{H_{t,}}$ which are defined as subsets of $\mathbf{H}$. Let there be assumed that $\mathbf{p(s_o^m) > p(s_o^n)}$ is true for most of the context $\mathbf{H_t}$ of $\mathbf{H}$, but the reverse $\mathbf{p(s_o^m) < p(s_o^n)}$ being true to the remaining contexts $\mathbf{H_r}$.

**Proposition 2.** *Given* $\beta(\boldsymbol{d}(s_o^m, s_t)) > \beta(\boldsymbol{d}(s_o^n, s_t)$, *alternation from* $\boldsymbol{H_t}$ *to* $\boldsymbol{H_r}$ *increases the happiness of* $\boldsymbol{B_c}$.

**Proposition 3.** *Given that* $\rho(\boldsymbol{d}(s_o^m, s_t)) > \rho(\boldsymbol{d}(s_o^n, s_t)$, *alternation from* $\boldsymbol{H_t}$ *to* $\boldsymbol{H_r}$ *promotes relief for* $\boldsymbol{B_c}$.

In such a line of reasoning:

**Proposition 4.** *The spread of a meme* $\boldsymbol{m(s_o^m, s_t \mid H, C)}$ *increases if alternation from* $\boldsymbol{H_t}$ *to* $\boldsymbol{H_r}$ *promotes either happiness or relief for* $\boldsymbol{B_c}$.

Alternation from $\mathbf{H_t}$ to $\mathbf{H_r}$ may be real or simulated. Jokes $\mathbf{j(s_o^n, s_t \mid s_o^m, s_t)}$ are built to simulate alternation from $\mathbf{H_t}$ to $\mathbf{H_r}$ in order to promote either happiness or relief. Jokes may be ranked from successful to unsuccessful depending how they really simulate alternation from $\mathbf{H_t}$ to $\mathbf{H_r}$.

**Proposition 5.** *Successful jokes* $\boldsymbol{j(s_o^n, s_t \mid s_o^m, s_t)}$ *related to* $\boldsymbol{d(s_o^m, s_t)}$, $\boldsymbol{d(s_o^n, s_t)}$ *become memes because they promote either happiness or relief.*

Humour theories stress that the pleasure triggered by jokes and satires is mostly dependent on the presentation of a incongruity and its resolution. Incongruity arises because opposing interpretations $\mathbf{s_o^n}$, $\mathbf{s_t}$, $\mathbf{s_o^m}$, $\mathbf{s_t}$ of a given $\mathbf{j^s(s_o^n, s_t \mid s_o^m, s_t)}$ are signalled. One of them, e.g. $\mathbf{s_o^n, s_t}$, has high probability of being true compared to the other, e.g. $\mathbf{s_o^n, s_t}$. The first interpretation is the usual one, but the actual context for sentence decoding favours the less probable as the resolution of the joke.

Humour theories they can be grouped in three major families: (a) Cognitive theories propose that humour depends on incongruity and its resolution; (b) psychoanalytical models assume humour to arise from a tension-release mechanism; and (c) social theories highlight the importance of aggression, disparagement and the confirmation of superiority in humour, focusing attention on the interpersonal and often adversarial nature of humour games.

The social approach is especially cogent for our study of memetics. According to, humour develops in a multi-agent setting with opponents competing in a game of thrusts and parries; wittiness becomes the symbol of intellectual and social superiority. In this context, political satire contributes to enhance social adhesion by clearly highlighting group differences and promoting cohesion within each group either throughout pleasure (social superiority) or hate (social inferiority).

## Meme spreading in the Internet

### The memes

''A culpa é do FHC'' (''The blame is on FHC'') is a open Facebook page in Portuguese language that anyone can access and post messages (Site: https://www.facebook.com/aculpaedofhc). ''FHC'' is Fernando Henrique Cardoso, Brazil´s President before the rise of the Workers' Party (Partido dos Trabalhadores — PT) in 2003. The Worker's Party keeps the federative power since 2002, having reelected President Luis Inacio Lula da Silva in 2006. President Dilma Roussef, belonging to the same party, was first elected in 2010, and then reelected in 2014.

The page contains messages of political satire, based on the Worker's Party frequent argumentative strategy of putting the blame of all Brazilian problems on FHC, the last President belonging to another party (Fig. 7). The satire is encoded in both visual and verbal languages.

**Fig. 7** Former Brazilian presidents and the analysed meme. FHC (right) enthrones Lula (left) in January 1st, 2003. The meme proposes to contrast the usual task of power transmission with the less probable semantic decoding proposed by the page's central argument (blaming FHC). Since Brazilian politics favour the latter interpretation, the meme is interpreted as being funny. Public photo taken by *Agência Brasil*; downloaded from http://diariodoaco.com.br/noticia/95609-10/brasil-e-mundo/lula-quer-aproximacao- com-fhc. Access in August 27, 2015.

As in other Facebook pages, when the viewer likes the post he/she can click ''Like'' and can also click ''Share''. If he/she clicks the latter the posting is copied in his/her page and can be seen by all (if the page is Public) or by Facebook friends only (if the page is Private). FHC page acts as both blackboard for meme spreading because it is public, and mail addressing because people may send meme copies to their friends.

We monitored the site from February 21, 2015 to April 9, 2015. Meme exposure was accounted by the number of posts. In our analysis of the dynamics of memes we considered that if the person ''likes'' the post then she was ''infected'' (Massad et al., 2013). If she shared the post, then she became a diffusion vector.

## Application of the model

The success of a joke $\mathbf{j(s_o^n, s_t \mid s_o^m, s_t)}$ to be copied by individuals lies on its capacity to produce happiness. In this context, this success depends on $\mathbf{B_c}$ being able to alternate between contexts $\mathbf{H_t}$, $\mathbf{H_r}$. Different $\mathbf{B_c}$s may have different capacities to flip between $\mathbf{H_t}$, $\mathbf{H_r}$. Therefore, different $\mathbf{B_c}$s may have a different susceptibility of being *infected* by (or to copy) $\mathbf{j(s_o^n, s_t \mid s_o^m, s_t)}$.

Once $\mathbf{j(s_o^n, s_t \mid s_o^m, s_t)}$ is copied by $\mathbf{B_c}$ it will be maintained in memory and may be repeatedly remembered to recreate happiness. However, in memory it is subject to forgetting, such that after some period of time $\mathbf{B_c}$ may be infected by $\mathbf{j(s_o^n, s_t \mid s_o^m, s_t)}$ or any other similar $\mathbf{j^s(s_o^n, s_t \mid s_o^m, s_t)}$. In this context, meme spread may be modelled by the SIRS (Susceptible-Infected-Recovered-Susceptible) approach (Anderson & May, 1991).

The model is described by the following ordinary, first order, non-linear differential equations:

$$\begin{aligned}
\frac{dS(t)}{dt} &= -\lambda_1 S - \mu S + \mu N + \sigma R + \alpha I - \lambda_2 S\theta(t-\varphi) \\
\frac{dI(t)}{dt} &= +\lambda_1 S - (\mu + \alpha + \gamma) I + \lambda_2 S\theta(t-\varphi) \\
\frac{dR(t)}{dt} &= \gamma I - (\mu + \sigma) R \\
N &= S + I + R
\end{aligned} \tag{7}$$

where

(a) $\lambda_i,\ (i = 1, 2)$ is the incidence-density rate, also known in the mathematical epidemiology terminology as ''f orce-of-infection'' (or copy easiness). It determines the number of new ''cases'' per time unit, denoting the number of new copies and the velocity of meme spread;
(b) $\sigma$ is the rate at which ''recovered'' individuals turn into the susceptible state after once cycle of the outbreak. In the present case, it is equivalent to forgetting;
(c) $\gamma$ is the ''recovered'' rate or the rate at which individuals ''infected'' with a given meme forget it; and
(d) $\mu$ is the ''mortality rate'' given by the number of individuals who are removed from the community. Here, it is related with people that do not visit the FHC page;
(e) $\alpha$ is the ''condition-specific mortality rate'' given by the rate at which a given meme is removed forever from the community. Here, it is related to posts removed from the FHC page;
(f) $\theta$ is the Heaviside function, which is equal to zero until $t = \varphi$, and is equal to 1 afterwards (it is introduced here to mimic the two outbreaks when the second one begins at $\varphi = 3$).

We assumed a continuous function for meme spread velocity (the force of infection) $\lambda_i,\ (i = 1, 2)$ with the following form:

$$\lambda_i = \lambda_{0_i} \exp\left(-\frac{(t - A_i)^2}{\mathrm{var}_i}\right), \tag{8}$$

which has the same shape as a ''Gaussian'' probability density function with a mean equal to $A_i,\ (i = 1, 2)$ and variance equal to $\mathrm{var}_i,\ (i = 1, 2)$.

We fitted the model with parameter values in Table 1 such that the actual number of observations was reproduced. Note that the actual number of observations is represented in the model by the incidence $\lambda_i S(t),\ (i = 1, 2)$.

Table 2 shows the actual number of new ''infections'' by the meme per week.

**Table 1** Initial conditions (IC) and parameters' values.

| IC/Parameter | Value |
|---|---|
| $S(0)$ | $4 \times 10^6$ |
| $I(0)$ | 10 |
| $R(0)$ | 0 |
| $\mu$ | 0.01 weeks$^{-1}$ |
| $\sigma$ | $1 \times 10^{-4}$ weeks$^{-1}$ |
| $\alpha$ | 0.05 weeks$^{-1}$ |
| $\gamma$ | 0.6 weeks$^{-1}$ |
| $\lambda_{0_1}$ | $3.25 \times 10^{-3}$ weeks$^{-1}$ |
| $\lambda_{0_2}$ | $7.00 \times 10^{-3}$ weeks$^{-1}$ |
| $A_1$ | 2.5 weeks |
| $A_2$ | 6.3 weeks |
| $\mathrm{var}_1$ | $4.9 \times 10^{-1}$ |
| $\mathrm{var}_2$ | $5.1 \times 10^{-1}$ |

**Table 2** Actual number of observations.

| Week | Observations |
|---|---|
| 1 | 1527 |
| 2 | 973 |
| 3 | 10,036 |
| 4 | 6745 |
| 5 | 1.745 |
| 6 | 4.670 |
| 7 | 23.330 |
| 8 | 13.150 |
| 9 | 5.523 |
| 10 | 3.539 |

Fig. 8 shows the spreading function carried by the forces of infection, according to the actual number of observations.

In Fig. 9 we show the model's result compared with the actual number of observations.

We calculated the Effective Reproduction Number or Effective Copy Number. $R(t)$ is the number of secondary copies (infections) each infective individual generates in each instant of time. It is defined as the product of the Basic Reproduction Number $R_0$ times the proportion of susceptible individuals at that instant of time, $S(t)/N(t)$. The Basic Reproduction Number for this model is given by:

$$R_0 = \frac{\beta N}{(\mu + \gamma + \alpha)}, \tag{9}$$

where $\beta$ is the potentially infective contact rate and it is calculated by solving the following equation at time $t = 0$:

$$\lambda(t) = \int_0^t \beta(s) I(s) ds \tag{10}$$

Therefore, the Effective Reproduction Number or Effective Copy Number is given by:

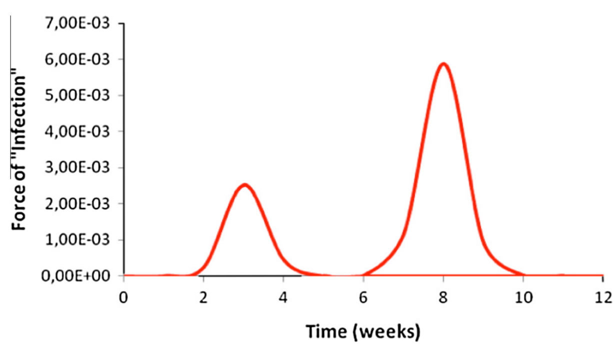


**Fig. 8** ''Force of Infection'' in meme spreading. According to Eq. (8), the figure shows the per capita number of new individuals joining the community in the two ''outbreaks''.

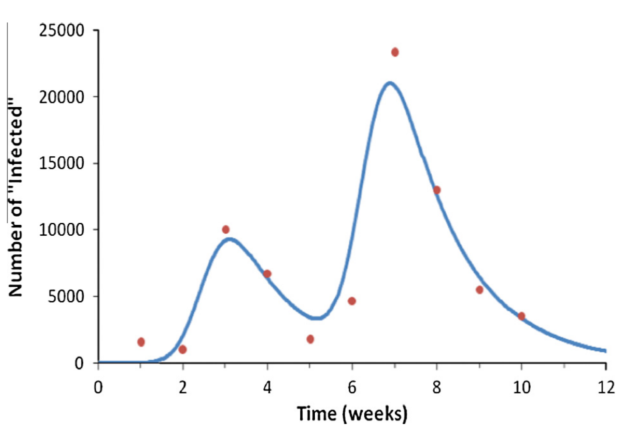


**Fig. 9** Comparing Theoretical Simulation and Real Data. The figure shows the model's performance to preview the number of individuals joining the community. The numerical simulation (blue line) is compared with actual data (red dots).

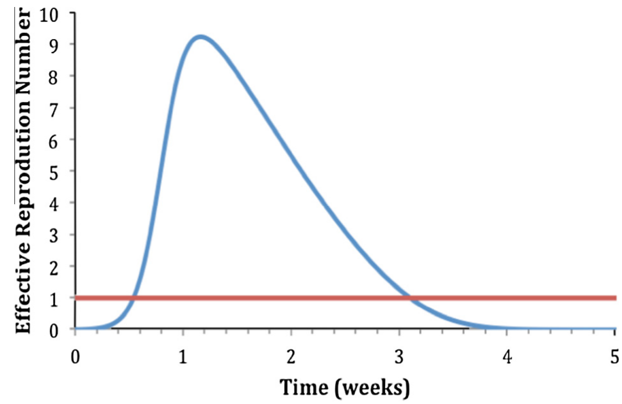


**Fig. 10** Time Evolution for the First Outbreak. The Effective Reproduction Number in each moment along the ''outbreaks''. The horizontal line indicates the threshold (equal to one). Below the threshold there is no case and above it the ''outbreaks'' are triggered.

$$R(t) = \frac{\beta N}{(\mu + \gamma + \alpha)} \frac{S(t)}{N(t)} \tag{11}$$

Fig. 10 shows the time evolution of $R(t)$ for the first outbreak (blue line). Note that the first outbreak begins when $R(t)$ crosses the threshold 1 (red line) around half week, when one case generates at least one new case.

## The risk of 'infection'

Let us assume a closed population of size $N$ and that in the absence of competitive risks, the risk of infection (in the sense of being a vector for the propagation of a meme) can be stochastically calculated by a two state model without recovery. A SI model is one in which **S** individuals are susceptible to the infection. Individuals who acquired the infection, remaining infected during the time of analysis, are called **I.**

Let us start by calculating the probability that x individuals are in the state $S$ and $y$ individuals are in the state $I$ at time $t + \Delta t$:

$$P_{x,y}(t + \Delta t) = P_{x,y}(t)(1 - \lambda x \Delta t) + P_{x+1,y-1}\lambda(x+1)\Delta t \tag{12}$$

The first term refers to the probability that there were $x$ and $y$ individuals at time $t$ in the $S$ and $I$ conditions respectively, and that no susceptible individuals $x$ acquired the infection in the period. The second term refers to the probability that there were $(x + 1)$ and $(y - 1)$ individuals at time $t$ in the $S$ and $I$ conditions respectively, and that one susceptible individual acquired the infection in the period.

From the previous equation it follows:

$$\frac{dP_{x,y}(t)}{dt} = -\lambda x P_{x,y}(t) + \lambda(x+1)P_{x+1,y-1}(t) \tag{13}$$

The general expression for the Probability Generation Function (PGF), $G(z, t)$, is given by:

$$G(u, v, t) = \sum_{y=0}^{N} u^x v^y P_{x,y}(t) \tag{14}$$

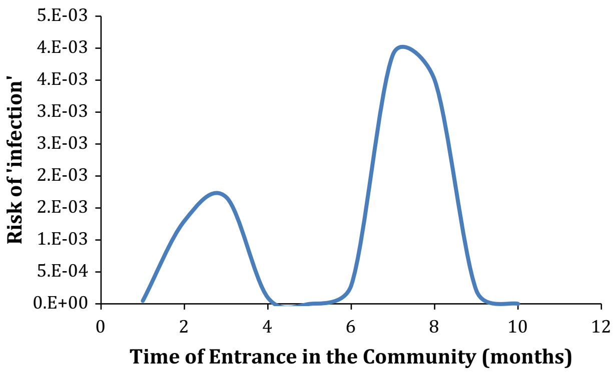


**Fig. 11** Risk of Infection. The risk since the time of entrance in the community. The figure shows the probability of being ''infected'', thus joining the community in the two ''outbreaks''.

For the particular model expressed in the equation it is possible to deduce that the PGF is:

$$G(xu, v, t) = [(u - v)e^{-\lambda t} + v]^N \tag{15}$$

Now the average number of $y$ individuals at time $t$ can be calculated by taking the first partial derivative of the PGF with respect to $v$ at $u$, $v = 1$:

$$\left.\frac{\partial G(u, v, t)}{\partial z}\right|_{u,v=1} = N(1 - e^{-\lambda t}) \tag{16}$$

Hence, the average per capita risk of infection, $\pi$ is given by:

$$\pi = 1 - e^{-\lambda t} \tag{17}$$

The variance of the probability distribution for the number of infected individuals at time $t$ is given by:

$$var[y] = \left.\frac{\partial^2 G(u,v,t)}{\partial v^2}\right|_{u,v=1} + \left.\frac{\partial G(u,v,t)}{\partial v}\right|_{u,v=1} - \left[\left.\frac{\partial G(u,v,t)}{\partial v}\right|_{u,v=1}\right]^2 \tag{18}$$

which results in:

$$var[y] = Ne^{(-\lambda t)}[1 - e^{(-\lambda t)}] \tag{19}$$

Fig. 11 shows the risk of getting the 'infection' by the meme to individuals who entered the community at various moments along the year and remain for one month.

## Discussion

Evolution has provided humans with many neural circuits to evaluate the intentions of other persons (Frith & Frith, 2007, 2010) and to calculate the fairness of such intentions (Fehr & Gächte, 2002; Güroğlu, Van den Bos, Rombouts, & Crone, 2010a, 2010b) to guide cooperative or competitive behaviours (Rocha et al., 2009) in social groups. Tension created by these antagonistic behaviours is a determinant of social cohesion and has to be maintained within boundaries. Political satire plays an important role in this process, and its Internet versions have became very popular nowadays.

The neurosciences have pointed dopaminergic circuits as involved in assessing of expected or experienced reward (e.g., Rocha et al., 2009) and recent studies showed that pleasure is determined by the difference between these two evaluations (Hollerman & Schultz, 1998). In our proposed model, reward ($\beta(\mathbf{d}(\mathbf{s_o^m}, \mathbf{s_t}))$ or $\beta(\mathbf{d}(\mathbf{s_o^n}, \mathbf{s_t}))$) for a given sentence $\mathbf{s_o^n}$, $\mathbf{s_t}$ or $\mathbf{s_o^m}$, $\mathbf{s_t}$ is inversely correlated with its possibility of being accepted as a sentence in a given language $\mathbf{L(G \mid H, C)}$ (Rocha et al., 2009). The most usual interpretation ($\mathbf{s_o^n}$) in the usual context $\mathbf{H_t}$ is associated with a small expected reward, whereas reward to the sentence ($\mathbf{s_o^n}$ or $\mathbf{s_o^m}$) proved to be the correct interpretation in the actual (joke) context $\mathbf{H_r}$. In this line of reasoning, political satire resolution triggers pleasure that is proportional to $\beta(\mathbf{d}(\mathbf{s_o^n}, \mathbf{s_t})) - \beta(\mathbf{d}(\mathbf{s_o^m}, \mathbf{s_t}))$.

Activity of neural circuits in charge of calculating rewards is modulated by motivation and preferences (e.g., Fellows & Farah, 2007; Krawczyk, Gazzaley, & D'Esposito, 2007; Tremblay & Schultz, 1999). This means that the pleasure triggered by a joke is under influence of social motivations and preferences created by economic and political events. Motivation increasing and preference focusing by means of political satire promotes social cohesion. This is the case of FHC memes. Brazilian economy is not doing well in the last years and economic strategies adopted by the President in her first government are blamed for presenting bad results. She was forced to adopt unpopular economic decisions. The Workers' Party corruption was acknowledged by Brazilian courts. All of this has resulted in large popular demonstrations of unsatisfaction since 2014 and increased the popularity of Internet sites directed to political questioning. In this context, the amusement promoted by FHC (and President Dilma Rousseff) memes is greatly amplified.

## Concluding remarks

- The theory of memes was formalized in a model used to describe human information processing in social media. On the one hand, this approach is complementary to current strategies in the cognitive neurosciences, approaching *social brain circuits* (Adolphs, 2009; Frith & Frith, 2007, 2010; Rocha et al., 2009). This is achieved by assuming that human individuals share similar neurobiological machineries for processing and encoding information, which support meme transmission from one to another individual. On the other hand, our approach is different from the study of brain mechanisms of cognition (as for instance Stepanyuk, 2015), since we focus on the *functions* of the living brain in the social environment, instead of investigating the neural mechanisms responsible for them.
- Today, online social networks are a major medium for meme spreading, with economic and political impact. Models of meme spreading in this medium — as we have developed here - can be of great interest for public organisations, private corporations and people in general.

— A word of caution is needed related to the use of dynamical models to validate hypotheses of interest. It is likely that a wide range of models might reproduce the observed phenomenon with equal accuracy. The limitation of modeling should be considered when interpreting data about any dynamical phenomenon. Models, therefore, should not be viewed as automatically validating scientific hypotheses, but simply as a way to test plausible conjectures.

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