

RESEARCH ARTICLE

The rumour spectrum

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Abstract

Rumour is an old social phenomenon used in politics and other public spaces. It has been studied for only hundred years by sociologists and psychologists by qualitative means. Social media platforms open new opportunities to improve quantitative analyses. We scanned all scientific literature to find relevant features. We made a quantitative screening of some specific rumours (in French and in English). Firstly, we identified some sources of information to find them. Secondly, we compiled different reference, rumouring and event datasets. Thirdly, we considered two facets of a rumour: the way it can spread to other users, and the syntagmatic content that may or may not be specific for a rumour. We found 53 features, clustered into six categories, which are able to describe a rumour message. The spread of a rumour is multi-harmonic having different frequencies and spikes, and can survive several years. Combinations of words (n-grams and skip-grams) are not typical of expressivity between rumours and news but study of lexical transition from a time period to the next goes in the sense of transmission pattern as described by Allport theory of transmission. A rumour can be interpreted as a speech act but with transmission patterns.



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Data Availability Statement: Interested researchers can reproduce the data underlying this study by consulting the Supporting Information file titled "S2 Appendix," which contains both the API used to query Twitter and build a random corpus of Tweets, as well as the time frame, key words, and other search criteria used to collect Twitter data. Interested researchers may also contact the corresponding author for further clarification or to access data files at the following email address: nturenne@u-pem.fr.

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Introduction

Disinformation (or misinformation) is a human language phenomenon that has always existed based on a mechanism of spreading from mouth to ear [1, 2]. However, with regard to the Internet and recent quantitative methods, we can investigate it with an up-to-date analysis. In the past, the spread of rumours could only be by word of mouth. The rise of social media provides an even better platform for spreading rumours. As Metaxas [3] explains massive amounts of data are being created and circulated, and often there are individuals or bots trying to manipulate this data to promote their own agenda. But sharing information with others after an emotionally powerful event can be cathartic. Understanding various rumour discussions could help to design and develop technologies to identify and track rumours, or reduce their impact on society.

In psychology a rumour is a declaration that is generally plausible, associated with news, and is widespread without checking [2, 4]. Some famous rumours are the urban legend "rue des Marmousets" in Paris where a barber and a pastry chef made cake trade based on human flesh in XVth century, or the disappearance of young girls in fitting rooms inside Jewish shops in the town of Orleans (France) in 1969 [5]. According to Gaildraud [6], a rumour is an informal noise that exists, persists, becomes evanescent and disappears as fast as it appeared. The definition of rumour is vague, such as one or several pieces of information that move around

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by individuals and/or the Internet. In the social sciences, rumouring behaviour is analysed as a social process of collective sense-making through which individuals can understand situations characterised by high levels of uncertainty, anxiety and a lack of official news. Classical social science research proposed two important ways of understanding rumour prevalence: (1) in terms of the amount of rumour-related information present in the environment, and (2) in terms of the number of individuals who have encountered or heard a particular piece of information. However, much of this very early work suffers from a lack of empirical support.

Ongoing research on the spread of rumours online is roughly quantitative, including descriptive studies of trace data [7–9], theoretical research on network factors [10, 11], and prescriptive studies that experiment with machine learning methods to classify rumours as true or false [12, 13]. Kwon et al. [8] include a descriptive analysis of temporal characteristics; false rumours on Twitter have more spikes than true rumours. Quantitative understanding of rumours focuses on how people participated in the rumour discussions and how the rumour developed over time. For instance, it could lead to the extraction of patterns in the text content, or different user roles. Rumour analysis has gained from studies in the related fields of meme-tracking [14], diffusion [15, 16] and virality [17, 18] in social networks, measuring the influence in networks and information credibility estimation.

Yet few studies provide significant insight into *how* and *why* rumours spread, and classification research has been limited to distinguishing between true and false information. Current studies work like outlier detection of a specific database. Hence, they learn a local model that is specific to a social media, not applicable to another platform, and they speculate that a rumour is a negative message, like ‘spam’, which need to be rejected from the platform. One theory is nevertheless interesting in spreading rumor in a community [2]. They argue that transmission evolves in three steps: levelling, sharpening and assimilation. First step is deleting details, second step is keeping the main details, assimilation is transmission with noise. We can take advantage of social network datasets to test such theory. Taking the automatic content analysis and data mining processing of a message [19–21], we are interested in exploring the following research questions, summarised below:

Q1: Which features are relevant?

Q2: Can we model a rumourous event as a multi-spike event?

Q3: How is a rumourous text different from a non-rumourous text?

Q4: Can we observe levelling-sharpening-assimilation in datasets?

In our article, part 1 is dedicated to an extensive review of literature of 80 papers on rumours. Among them, 58, written after 2010, were about rumour studies, revealing recent interest in rumour/credibility/misinformation issues, and specifically with social media platforms. We made a synthesis of principal features used to describe rumours in these quantitative approaches. Feature selection is a key question in quantitative and modelling investigation. Part 2 presents the datasets we used for spread and content analysis. We used not only ad-hoc corpora for our studies, but also external databases, such as hoaxes/disinformation repositories and language corpora. Part 3 presents our modelling approach for rumour spreading and a comparison with a standard approach such as epidemiological models. Finally, part 4 shows a comparison of rumour corpora and event corpora with n-gram and skip-gram studies.

Material and methods

Related studies

Rumour theory. In psychology and sociology [1, 2, 22, 23] were first attempts to study rumor and showing increase errors across the retellings. Rumours can be hoaxes, jokes, little

stories or information leaks [24–26]. But it can be also early reports during breaking news lacking enough support or evidence. If we look at the classification proposed by [27], we observe seven categories of rumours: computer virus alerts, superstitious chains, solidarity chains, petitions, hoaxes, urban legends, fun stories and funny photos/pictures. But [28] imagined another classification with nine topics: urban legends, commercial disinformation, political attacks, commercial offer attacks, false commercial offers, financial disinformation, defamation, loss of credibility operations and panic alert to induce terror. Often a rumour is dedicated to disturb VIPs [6]. Recently, others [29] have suggested that rumours are a communication strategy similar to speech acts [30, 31].

Rumour detection. Recently, more computing studies have investigated the emergence of rumours, but they stay at the level of a specific rumour, as in Fig 1 [32–39].

Contrary to these studies, our goal is to analyse any kind of rumour and a corpus of rumours. Some systems claim to detect rumours but they are based on the similarity between an unknown message (i.e. email) and a well-known database of hoaxes or rumours [41–43]; other kinds of systems are more of a surveillance system for interesting message detection from the Internet (that are possibly rumours), and in this sense, they are more like an approximate recommendation system [44].

Formulation of the problem:

Microblog data can be modelled as a set of events = $\{E_i\}$, and each event E_i consists of relevant microblogs for which we can associate a value for being or not being a rumour $\{m_{ij}, y_i\}$. An event E_i can be described by a set of k features from l different categories $\{F_{kl}\}$. Hence, each

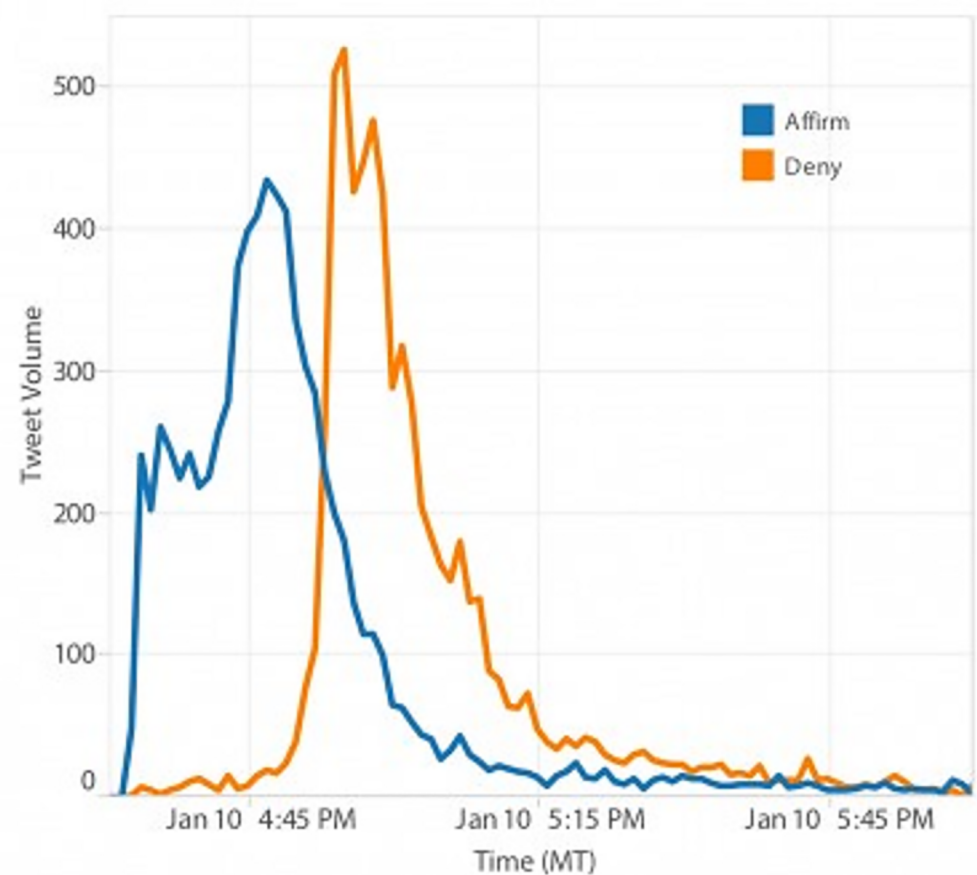


Fig 1. Propagation and denial of Westjet Hijacking rumor (tweets volume per minute, affirms versus denials)[40].

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message m_{ij} can be described by some values of these features. The most difficult case is to discover, in an unsupervised way, the value y_i for any message. In some cases we can know this value for a reduced amount of data from which we can learn a model (i.e. a profile), in a supervised way, and to detect similar messages.

[45] makes a good survey in the field of rumor detection. Most of the existing research uses common supervised learning approaches such as a decision tree, random forest, Bayes networks and a support vector machine (SVM). [46] imagined of first rumour detection system for the Chinese language and the Weibo social network. Weibo has a service for collecting rumour microblogs [47]. Qazvinian et al. [13] used a tagged corpus of 10,000 tweets of about five rumours, five categories of features (1-grams, 2-grams, Part-of-speech, hashtags, URLs) to classify rumours using the log-likelihood approach with good results (95% of accuracy) but they cannot apply their method to new, incoming, emergent rumours.

Rumour propagation. We can see rumour messages as a bag of documents, but also as a timeline with occurring messages. In that way, the formulation of the problem is a little different because it concerns the description of a discrete time series evolving over time [48].

Some previous work [49, 50] focuses on rumour propagation through the social network. They try to use graph theory to detect rumours and find the source of rumours. Virality is a major concept in rumour propagation [51], using epidemiological models, and some current studies still try to improve the models [52]. Spiro et al. [9] also model the rate of posts over time in their exploration of rumouring during the Deepwater Horizon oil spill in 2011. [53] identified five kinds of rumour statements, coded posts accordingly, and presented a model of rumour progression with four stages characterised by different proportions of each statement type.

The website TwitterTrails [54, 55] is one of the rare tools that does not present only a database but also intelligent information exploration (timeline, propagators, negation, burst, originator, main actors) in 547 social media stories. [10] prove that minimising the spread of the misinformation (i.e. rumours) in social networks is an NP-hard problem and also provide a greedy approximate solution.

Kwon et al [8] promoted uses of both temporal features, structural features and linguistic features. Linguistic features are related to the most words used in messages and taken from a sentiment dictionary (4,500 words stem). Network features are properties about the largest connected component (LCC). Temporal features point out periodicity of rumour phenomenon and give importance to an external shock that may incur not one but multiple impacts over time; here, the main feature is periodicity of an external shock. Fang et al. [56] describe a quantitative analysis of tweets during the Ebola crisis, which reveals that lies, half-truths and rumours can spread just like true news. They used epidemiological models. Fang et al. [56], studying 10 rumours about the Ebola crisis in 2014, claim that rumours propagate like news but they encourage quantitative analytics to distinguish news from rumours.

Granovetter [57] explains with its seminal work about weak ties, that some nodes in social networks mediate between different communities. Acemoglu et al. [58] give importance to bridges in social networks to spread biased beliefs. Menczer [59], in a talk for a world-wide web conference, underlined the importance of misinformation detection and fact checking, with good results from machine learning techniques. Social media and traditional media work together to spread misinformation. Structural, temporal, content, and user features can be used to detect astroturf and social bots.

Rumour sources

Disinformation sources. We are focusing on digital data that may be grabbed from the Internet. Others sources allow free access to misinformation like the website Emergent [60]. It

monitors and evaluates the propagation of a rumour that has recently received a lot of attention. A new web service, emergent.info, developed by journalist Craig Silverman, is using journalists to evaluate online claims and deem them as true/false/unverified. They track the number of shares a rumour has on Facebook, Twitter and Google+ and report the numbers along with links to articles that support or counter the rumour.

We identified at least seven websites containing curated databases and serve as a reference to inform and to provide reassurance about rumours and disinformation on the web. These databases contain not only rumours but also hoaxes and jokes that may propagate on the Internet. ‘Snopes’ is the biggest, but with ‘hoaxkiller’, it is impossible to know how many articles it contains because the interface requires query function by keywords (Table 1).

‘Hoaxkiller’, ‘hoax-slayer’ and ‘dehoaxwijzersite’ are databases that display a list of hoaxes to show hoaxes and frauds. ‘Debunkersdehoax’ is a website that helps to invalidate rumours and disinformation from nationalists. ‘Hoaxes.org’ is a website that explores disinformation throughout history. ‘Snopes’ covers urban legends, rumours on the Internet and email, and other doubtful stories. We made a crawler (robot in perl language) to collect automatically the content of each website.

The famous and open encyclopaedia, Wikipedia, gives 220 as the number of existing social networks on Internet. These social media play as web 2.0 platforms with thousands till millions of active users where information as rumours can propagate quickly and easily. Twitter is one of them, and probably the most famous microblogging platform where 500 million tweets are published each day and 600 million users are registered, with 117 million active accounts publishing at least one tweet per month. Such a social platform is an ideal dissemination ‘relais’ for rumours. Two API (application programming interface) allows any computing programme to query the twitter database. Twitter Search API can index more than tweets but only from the previous seven days. Twitter Streaming API can retrieve more messages, but no more than 1% of the content per day.

From the database cited in Table 1, we compiled a corpus of 1,612 rumours (DIS-corpus) and disinformation texts among with 1,459 in English and 153 in French (81,216 tokens; 6,499 words).

Part 2 presents information sources and datasets. Part 3 is related to propagation. Part 4 addresses issues about information patterns in messages. We used R as the computing framework for modelling [61].

Text data collections: Social media corpora and reference corpora

From Table 1, it is possible to see a sample of texts that is more related to rumours and disinformation because texts from databases are classified with categories. Hence, we were able to grab 1,612 texts discussing rumours (1,010 texts) and disinformation (602 texts). The size of

Table 1. Disinformation web open databases.

| Source | Language | #articles |
|---|----------|-----------|
| hoaxbuster | French | 292 |
| hoaxkiller | French | ? |
| hoax-slayer | English | 2435 |
| debunkersdehoax | English | 340 |
| hoaxes.org | English | 4635 |
| sites.google.com/site/dehoaxwijzer | Flammish | 147 |
| snopes.com | English | 7289 |

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Table 2. Three groups of datasets: First, rumour corpora; second, random corpora; third, event corpora.

| Corpus | Language | #tweets | size (kb) | #tokens | #words |
|-------------|----------|---------|-----------|---------|--------|
| Holland | French | 371 | 82 | 7,592 | 1,586 |
| Lemon | French | 270 | 49 | 13,611 | 3,451 |
| Pin | English | 679 | 118 | 31,612 | 6,691 |
| Swine | English | 1024 | 159 | 54,056 | 10,511 |
| Random1_Fr | French | 1000 | 131 | 72,387 | 15,449 |
| Random2_Fr | French | 1000 | 131 | 90,998 | 19,596 |
| Random3_En | English | 1000 | 135 | 110,657 | 24,580 |
| Random4_En | English | 1000 | 135 | 130,113 | 28,757 |
| Rihanna_Fr | French | 543 | 131 | 149,102 | 30,431 |
| Rihanna_En | English | 1000 | 81 | 160,295 | 32,264 |
| Euro2016_Fr | French | 1000 | 131 | 166,929 | 31,807 |
| Euro2016_En | English | 1000 | 147 | 188,882 | 32,771 |

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the texts is relatively small, such as the news. But it is quite difficult to automatically select lexical information (by one or two words) that is typical from a given text. So we have manually chosen four texts and built a lexical query with two or three words to grab tweets from the Twitter social network (S2 Appendix).

From data collected in an open-access web database, we made a manual query to grab tweets from Twitter [62], and we built eight corpora to compare with the rumour corpora (Table 2).

The first rumour, ‘Hollande rumour’, is about the French political leader François Hollande. The rumour started in 2002 in private parties and in editorial offices. According to the rumour scenario, the president of France—at that time he was deputy of the Correze region and first secretary of the labour party—was the father of one of Anne Hidalgo’s children, at that time, the First Executive Assistant of the Paris governor. Wikipedia’s description of Anne Hidalgo highlights that she had two children from a previous relationship. A black hole of information is sufficient to excite the web. The following query induced the retrieval of data:

(hollande AND hidalgo AND fils) lang:fr

The ‘lemon rumour’ pointed out that a lemon could cure cancer, saying it exceeds the power of chemotherapy by 10,000. The origin of this rumour is a Reuters news article in 2003, ‘An Orange a Day May Keep Some Cancers Away’. The following query induced the retrieval of data:

(citron AND cancer) -femme-campagne-musique-arabes-punk-branché-limonade-Kickstarter-gato-Crowdfunding-Baptême-court-CM-tittytuesday-morito-nestea-bracelet-aluminium-déodorant-déodorants-agrumes-puce-poils-tropic-art-astrologie-bouteille-crame-coude-photo-tartes-bronzage-olive-horoscope-bonbons-google-jeu-hypocrisie-rose-malboro-Ananas-Bronzage-quantitatif-Tropiques-Téflon lang:fr

The ‘PIN rumour’ claimed that in New York, entering your personal identification number (PIN) backwards will automatically send a message to the police that you are in trouble and that they will respond to the machine. This rumour seems to have appeared in 2006. The reverse PIN system was first imagined in 1994 and patented in 1998 by Joseph Zingher but never adopted by the banking industry. The following query induced the retrieval of data:

(pin AND atm AND police) lang:en

‘Swine flu rumour’, related to the swine flu virus or officially called the H1N1 flu virus, mentioned that thousands of people were sent to the hospital during the soccer championship in 2009 in South Africa. The following query induced the retrieval of data:

Table 3. Content of reference corpora for French and English.

| Corpus | Language | #Files | Storage (Mb) | #Words | #tokens |
|---------------------------------|----------|--------|--------------|---------|-------------|
| Est Républicain Newspaper (ER) | French | 544 | 1,025 | 654.134 | 130,746,677 |
| Frantext literary database (FR) | French | 500 | 147 | 817.754 | 20,218,763 |
| Contemporary American (COCA) | English | 115 | 10 | 62.47 | 1,809,601 |
| British National Corpus (BNC) | English | 4.049 | 4,680 | 981.636 | 98,112,611 |

<https://doi.org/10.1371/journal.pone.0189080.t003>

("swine flu"AND "South Africa") lang:en

There are two kinds of reference corpora. The first group is random corpora made on Twitter with a stopword. We chose the first 1000 tweets for each operation, repeated two times and for both French and English. The second group is related to events, and we also collected data from Twitter in April 2016. First event is a concert in France in August 2016 by Rihanna. The second event is the UEFA Europe football championship in France in 2016. For both events, data was collected in French and English and we kept no more than 1000 tweets.

We used two reference corpora for comparison with common language and for each language (Table 3). FR-corpus is an open database that contains 500 literary works from the 18th to 20th century. It is a free sample of the Frantext online database containing 248 million words [63]. ER-corpus is a collection of news from the French local newspaper East-Republican ('L'Est Républicain') about 1999, 2002 and 2003 [64]. BNC-corpus is a collection of samples of written and spoken language of British English from the latter part of the 20th century. The written part consists of extracts from regional and national newspapers, specialist periodicals and journals for all ages and interests, academic books and popular fiction, published and unpublished letters and memoranda, school and university essays, among many other kinds of text. The spoken part (10%) consists of orthographic transcriptions of unscripted informal conversations and spoken language collected in different contexts, ranging from formal business or government meetings to radio shows and phone-ins [65]. The COCA-corpus contains spoken texts, fiction, popular magazines, newspapers, and academic texts produced between 1990 and 2015. It is a free sample of the 520 million word original corpus [66].

Information propagation

Classical epidemiological models. In the Internet era, many studies about rumours have shown that that rumours disseminate as a disease contagion like a Poisson distribution. We tried to confirm this hypothesis.

We made two displays of propagation with our four rumours corpora. First, visualisation is obvious, and we can plot the occurrence of tweets as on a timeline in a histogram plot. We do not know the IP number of senders of a tweet but we can know if a tweet is a retweet, hence, if a tweet has been transmitted. More generally, we can study the natural language content of each tweet. Hence, the second visualisation concerns tweet grouping by similarity to explore their distribution over time.

A rumour can be seen as a disease propagating over a population of sane individuals becoming infected over time. Several models are possible. Let be *S* the sensible population that is likely to be infected, *E* the population that is exposed, *I* the population that is infected and *R* the population that is cured. Eq (1) to Eq (18) summarise main models (Fig 2 shows the respective infected output for each model). The most simple is the SI (sensible-infected) model created by Hamer in 1906. In this model no individual can be cured. β Parameter is valued between 0 and 1. $\beta \sim P(S \leftrightarrow I) * P(S \rightarrow I)$, where $P(S \leftrightarrow I)$ is the probability that a sensible

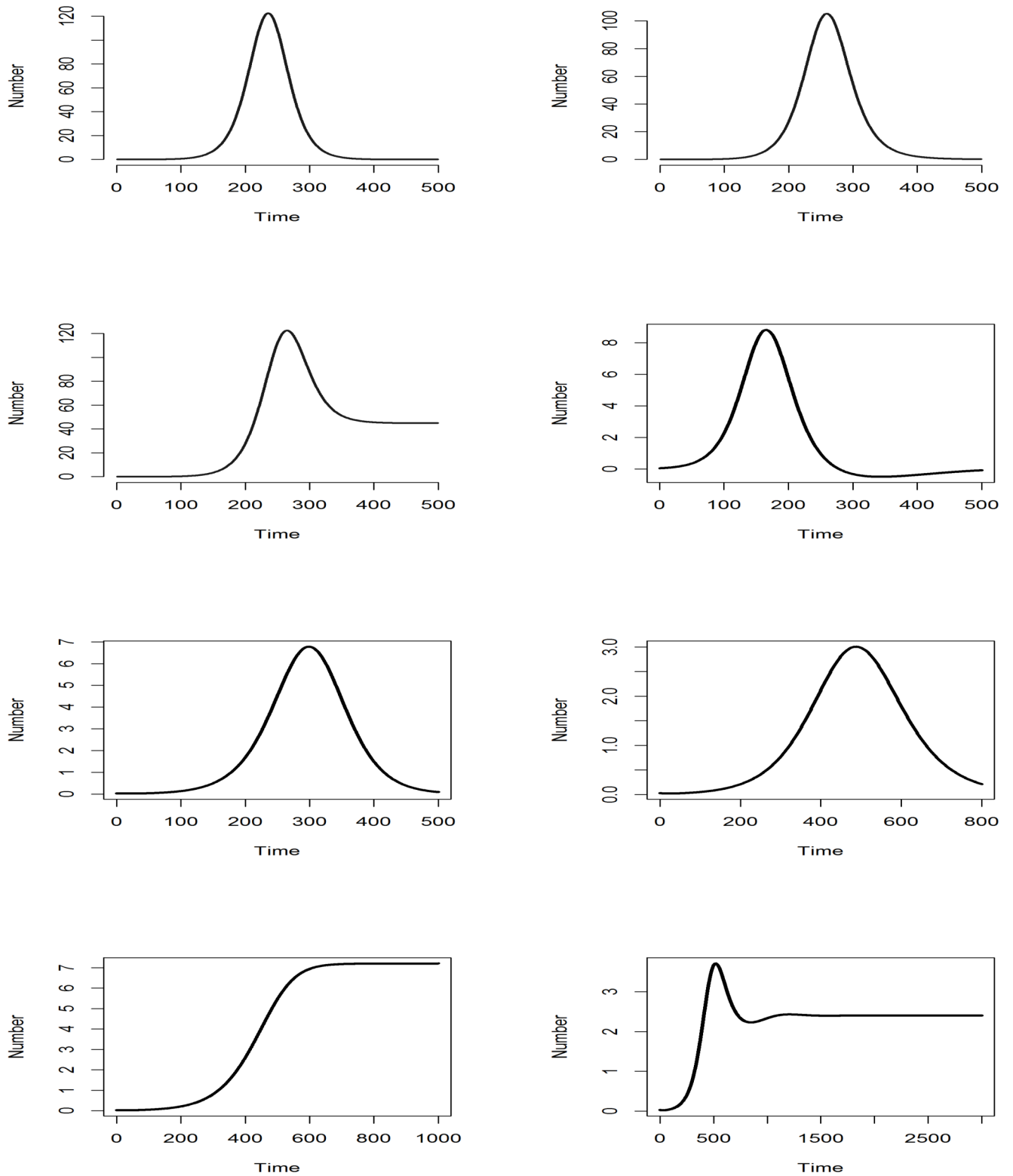


Fig 2. Displays of epidemiological model profiles (number of infected individuals over time). We can see at first line: SI model (left), SIR Model (right); at second line SIS model (left), SIRS model (right); at third line SEI model (left), SEIR model (right); at fourth line SEIS model (left), SEIRS model (right).

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individual will be in contact with an infected individual, and $P(S \rightarrow I)$ is the probability that a sensible individual becomes infected if they are in contact.

(a). SI model

$$\begin{aligned} & \frac{\beta SI}{N} \text{ new infected number per day} \\ \frac{dS}{dt} &= -\frac{\beta SI}{N} \\ \frac{dI}{dt} &= \frac{\beta SI}{N} \end{aligned} \tag{Eq(1)}$$

(b). SIR model

$$\begin{aligned} \frac{dS}{dt} &= -\frac{\beta SI}{N} \\ \frac{dI}{dt} &= \frac{\beta SI}{N} - \gamma I \\ \frac{dR}{dt} &= \gamma I \end{aligned} \tag{Eq(2)}$$

(c). SIS model

$$\begin{aligned} \frac{dS}{dt} &= -\frac{\beta SI}{N} + \gamma I \\ \frac{dI}{dt} &= \frac{\beta SI}{N} - \gamma I \end{aligned} \tag{Eq(3)}$$

(d). SIRS model

$$\begin{aligned} \frac{dS}{dt} &= -\frac{\beta SI}{N} + fR \\ \frac{dI}{dt} &= \frac{\beta SI}{N} - \gamma I \\ \frac{dR}{dt} &= \gamma I - fR \end{aligned} \tag{Eq(4)}$$

(e). SEI model

$$\begin{aligned} \frac{dS}{dt} &= -\frac{\beta SI}{N} \\ \frac{dE}{dt} &= \frac{\beta SI}{N} - \epsilon E \\ \frac{dI}{dt} &= \epsilon E \end{aligned} \tag{Eq(5)}$$

(f). SEIR model

$$\begin{aligned} \frac{dS}{dt} &= -\frac{\beta SI}{N} \\ \frac{dE}{dt} &= \frac{\beta SI}{N} - \epsilon E \\ \frac{dI}{dt} &= \epsilon E - \gamma I \\ \frac{dR}{dt} &= \gamma I \end{aligned} \tag{Eq(6)}$$

(g). SEIS model

$$\begin{aligned} \frac{dS}{dt} &= -\frac{\beta SI}{N} + \gamma I \\ \frac{dE}{dt} &= \frac{\beta SI}{N} - \epsilon E \\ \frac{dI}{dt} &= \epsilon E - \gamma I \end{aligned} \tag{Eq(7)}$$

(h). SEIRS model

$$\begin{aligned} \frac{dS}{dt} &= -\frac{\beta SI}{N} + fR \\ \frac{dE}{dt} &= \frac{\beta SI}{N} - \epsilon E \\ \frac{dI}{dt} &= \epsilon E - \gamma I \\ \frac{dR}{dt} &= \gamma I - fR \end{aligned} \tag{Eq(8)}$$

Harmonic modelling. A harmonic oscillator is an ideal oscillator that evolves over time by a sinusoid, with a frequency independent of the systems properties, and the amplitude is constant. Oscillations can be damped, and the equation is hence written as follows:

$$\frac{d^2s}{dt^2} + \frac{2}{\tau} \frac{ds}{dt} + \omega_0^2 x(t) = 0 \tag{Eq(9)}$$

If $\omega_0 > \frac{1}{\tau}$ state is sub-critical, solution is a damped oscillation with such pulsation:

$$\omega = 2\pi f = \omega_0 \cdot \sqrt{1 - \frac{1}{\tau^2 \omega_0^2}} \tag{Eq(10)}$$

$$s(t) = A \cdot e^{-\frac{t}{\tau}} \cdot \cos(\omega t + \varphi_0) \tag{Eq(11)}$$

where A is the amplitude, f is the frequency, φ_0 the phase to origin, ω the pulsation, τ the relation time.

Models implementation. Epidemiological model displays were done with R with the basic plot function. Experimental implementation of harmonic modelling was done by fast Fourier transform using `fft` function and least-square in R using function `nls` (stats package) [61].

Rumour lexical content

Frequent syntagmatic extraction. In this part we try to understand what kind of combinations can be typical of a rumour or a set of messages about a specific rumour.

We can set two main kinds of combinations. The first ones are lexical n-grams. A lexical n-gram is a sequence of n contiguous words separated by a blank. If $n = 1$, it is a simple word (as we can see in any dictionary entries for instance) if $n > 1$, it is what it is named in linguistics ‘collocations’. Some collocations can be paradigmatic and then they are named ‘phrases’ (if they do not contain verbs, they are named ‘noun phrases’). The second kind of combination is a set of 1-gram separated by an n-gram not included in the combination. In case such a combination consists of two n-grams, it is named ‘co-occurrence’; in the cases where it is several n-grams, it is called a ‘frequent itemset’. We can also find the word ‘skipgram’, by analogy of n-gram.

Rare syntagmatic extraction. We tested the capacity of a rumour text to involve a non-standard combination of words. For such studies we used common languages corpora. The first experiment is an extraction of cleaned n-grams, and we checked presence/absence in reference corpora. The second experiment is a check of frequent skipgrams consisting of most frequent simple words.

In the first experiment we measured originality of a given corpus by the ratio MW_c of n-grams not included in a reference corpus by the number of total segments. We used 12 corpus among those four rumours corpus, but also randomly constituted corpora, and corpora based on recent real-world events in French and in English (in the present case: Rihanna concert in Europe in summer 2016, and UEFA Euro 2016). The measure MW_c is expressed as follows:

$$MW_c = \frac{NMW_c(no)}{NS_c} \quad \text{Eq(12)}$$

where $NMW_c = NMW_c(no) + NMW_c(yes)$ with NMW_c is the number of multiwords in the corpus c and $NMW_c(no)$ is the number of multiwords not contained in a language reference corpus (for instance COCA-corpus for English).

Syntagmatic combination analysis. Finally, the next step after analyzing lists of features of 2 or 3 words is to measure the incidence of content with vector of words. For that, we cannot use the DIS-corpus because each rumour is unique and a set of ten or twenty words could not show similarity with other rumours. But if we take the Twitter rumours, we can observe how people talk about a rumour and compare the specificity of rumour discourse with ordinary messages.

We would like now get an overview of words importance in the rumorous content over time. Recall that (Allport, and Postman, 51) specifies a rumor mechanisms in three different mechanisms applicable in any situation. The first mechanism is a selection of main features (leveling, or loss of details). The second mechanism is sharpening refers to is an emphasis of some details during the transmission. Finally the last mechanism, assimilation refers to a distortion in the transmission of information. Linguistic assimilation usually consisted of inserting the words "is," "is as," "as," or "it's" or noise. Let suppose a rumor starts with nine details and ends with three, they would say that six were leveled and three were sharpened.

Our empirical studies is done in four steps:

- first step is lexical preprocessing of the dataset—splitting data into elementary words.
- second step is time preprocessing of the dataset—splitting dataset into 7 timestamps (getting enough data in each chunk at least 50 messages).
- third step is subset preprocessing of the dataset—splitting word features into three box according Zipf law saying that lexical distribution is always distributed into a small set of high frequency, medium frequency set words, and big set of low frequency.
- fourth step is computation of transitions.
- fifth step is plotting transitions.

We implemented the scripting in R platform, using regular expression for lexical splitting, 'intersect' function for calculation of transitions and GMisc'package 'transitionplot' for display of transitions.

Another angle to capture association is machine learning algorithms. Why, because machine learning algorithms use features, often within non-linear techniques indirectly taking into account combination of features. In summary, it captures correlation of features to make a good prediction without specifying association between features. We used four famous algorithms to make prediction: 'Maxent', 'Random Forest' (regression tree), 'SVM' and 'SLDA' (topic model). The first question that arises, due to sensitivity of algorithms to the feature space, is to define the dimensionality of the feature space. We can take the whole set of words (between 3,000 and 4,000 words) but it can be time consuming for some techniques or noise generation. We make a documents x terms matrix using different samples, i.e. the 10, 50, 100, 150, 200 and 300 most frequent words. We consider that rumorous messages starting by the same 70 characters (half of the message) are the same and we delete them for building the dataset. Hence the dataset consists of 1,678 messages containing all the four rumors messages, the pool of message to predict. We mixed this subset with 9,818 non-rumor messages. As training dataset we chose all the rumor subset and 2,000 non-rumor messages. As test dataset we take the 1,648 rumorous messages (17%) and 8,170 non-rumorous messages (83%). As baseline for comparison of techniques we consider the random assignment. A message can be assigned randomly as rumorous or non-rumorous. So the success rate is 50% percent of accuracy. Let suppose we classify all messages as non-rumorous we get 83% of accuracy but we lost all rumorous prediction because accuracy for rumorous will be 0%. Hence for each classification method we compute two indicators that are the global accuracy that we want enough high better than random for a stream of both rumorous and non-rumorous messages, and accuracy specific for rumorous messages that we expect also close to random score.

In the next experiment we keep the same matrix as before with 100 most frequent feature space but we change the document space. We make three submatrix: the first submatrix is 100% of the document space (1,618 rumorous messages), the second submatrix is the first 30% over time (498 rumorous messages), the last 30% over time (524 rumorous messages). Amount of non-rumorous messages in test set is always about 8,000 messages, and for the train set we keep the same amount than the rumorous set (about 500 or 2,000 messages).

Models implementation. The experimental implementation was done in R. The syntagmatic extraction is a function using regular expression analysis with gsub function (base package), multi-word extraction with ngram function (ngram package), and data cleaning using a stopwords list. Classification models were created using train_model function (RTextTools package) [61].

Results

Spreading modelling

Fig 3 displays time distribution of tweets emission by users for each rumour. We can see that no plot really can fit with a 2-local maximum distribution, as shown on Fig 2.

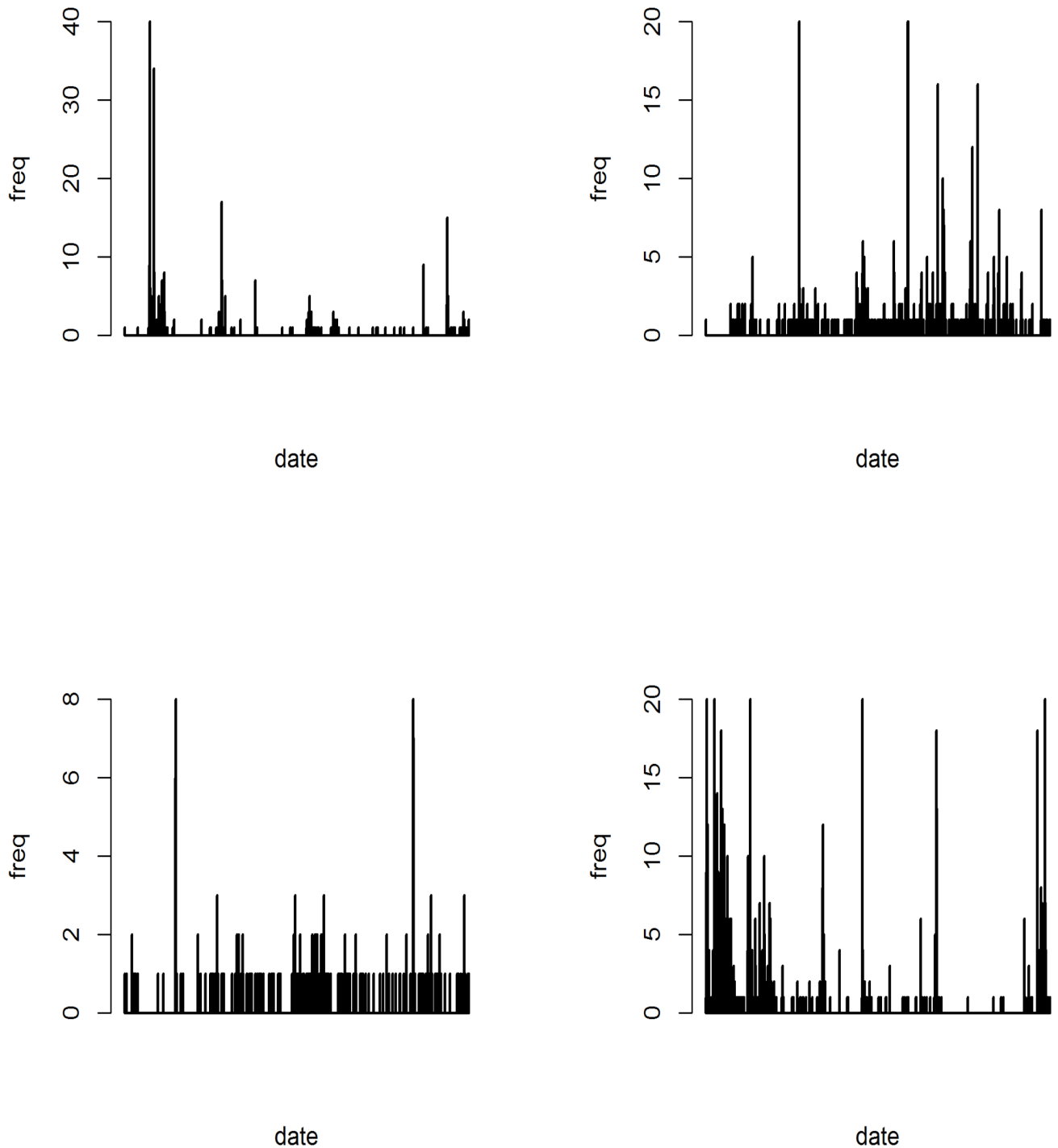


Fig 3. Displays of number of infected individuals over time for each epidemiological model (upper left: Hidalgo-corpus; upper right: PIN-corpus; bottom-left: Lemon-corpus; bottom-right: swine-corpus).

<https://doi.org/10.1371/journal.pone.0189080.g003>

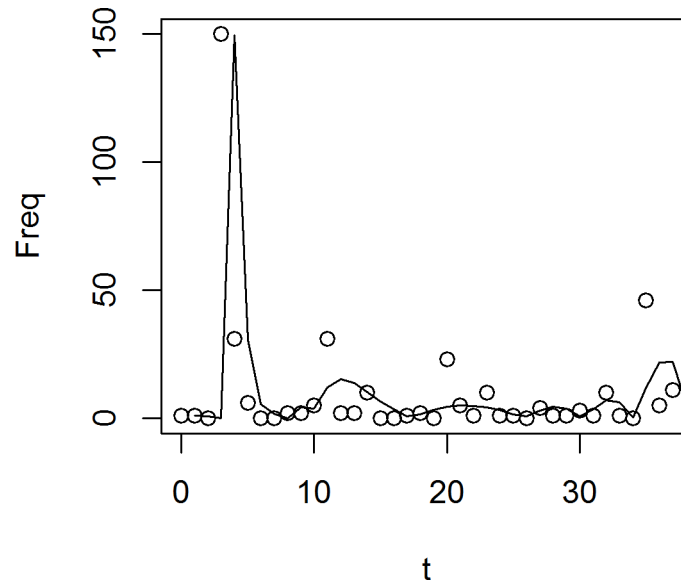


Fig 4. Fitting between a harmonic oscillator model and tweet distribution emission over time.

<https://doi.org/10.1371/journal.pone.0189080.g004>

Fig 4 shows fitting of the Hidalgo-rumour corpus and the oscillator model with the setting: $A = 10, \varphi_0 = 15, \tau = 23, f = 0.3$.

An advantage of the oscillator model is that it produces several local maxima (see Fig 5), whereas epidemiological models produce only one or two local maxima.

Fig 4 shows us a fit of Hidalgo-corpus with a damped oscillator model. It fits quite well, and better than any epidemiological model. But it seems that amplitude is not stable.

$$s(t) = \sum_{i=1}^n A_{1i} \cdot e^{-\frac{t}{A_{2i}}} \cdot \cos(A_{3i}t + A_{4i}) \tag{Eq(13)}$$

$$A_{11} = 48.9, A_{21} = 8.8, A_{31} = 0.36, A_{41} = 14.5,$$

$$A_{21} = 234.5, A_{22} = 2.37, A_{23} = 1.10, A_{24} = -0.11,$$

$$A_{31} = 501.9, A_{32} = 1.28, A_{33} = 3.83, A_{34} = -20.8,$$

$$A_{41} = -0.0036, A_{42} = -4.00, A_{43} = 51.0, A_{44} = -16.5$$

Frequent syntagmatic extraction

Table 4 shows us a list of frequent n-grams for each corpus of rumours: Hidalgo-corpus, Lemon-corpus, Pin-corpus and swine-corpus. ‘Counting’ is the number of occurrences in terms of documents about cleaned n-grams. We cleaned n-grams by subtracting the prefix or suffix matching with stopwords. Processing is done in both languages.

In Table 4 no information appears to make sense for a rumour in general. We mostly distinguish lexical patterns clearly related a given rumour like ‘flu death’, ‘h1n1’, ‘Africa swine’, ‘flu cases’ for swine corpus.

If we look at Table 4’s top four lexical strings, we see that only simple words appear; it is a general observation that stopwords are more frequent than simple words, and simple words are more frequent than multi-words. Next we tried to extract the most frequent simple words

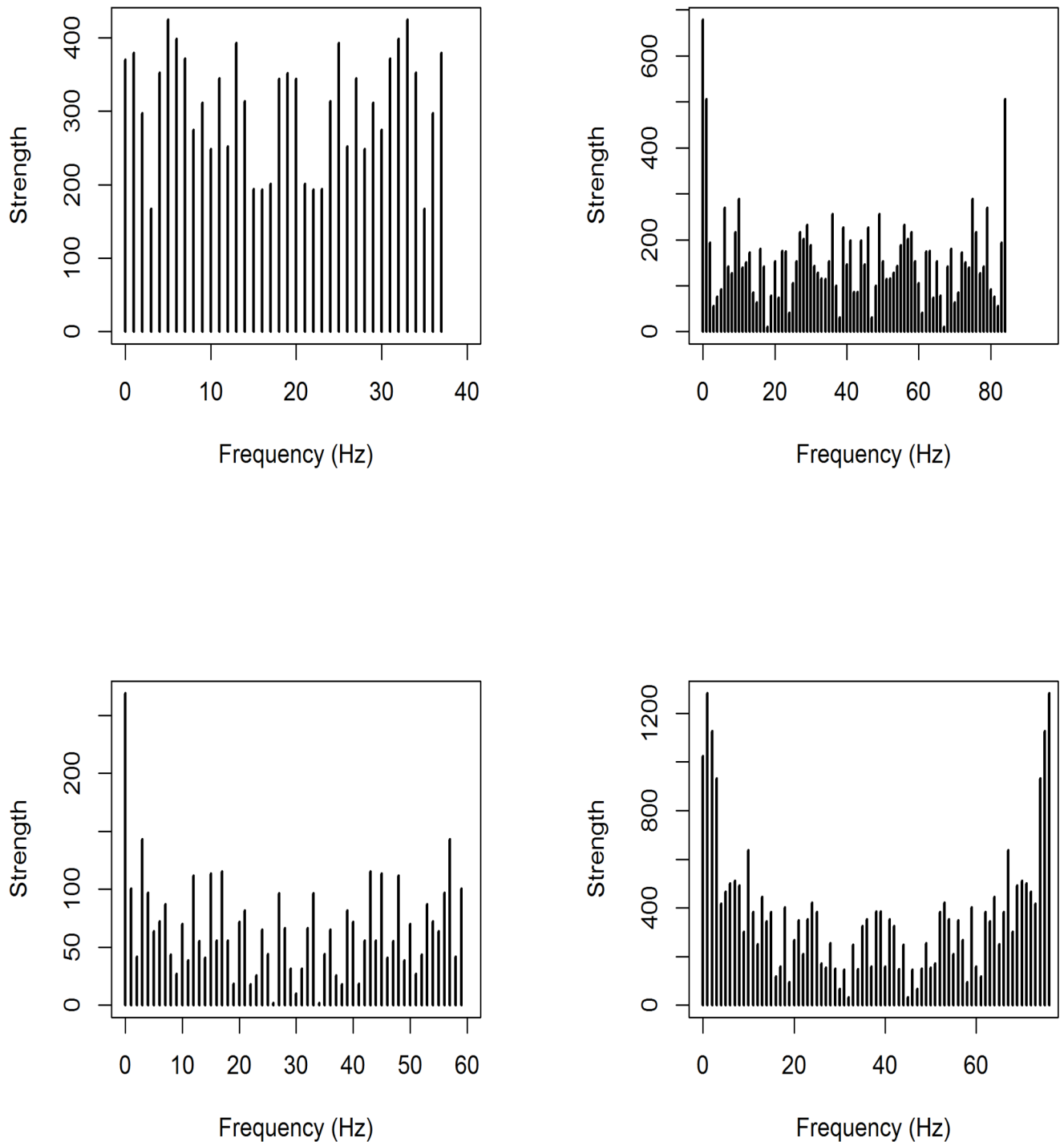


Fig 5. Displays of frequencies by fast Fourier transform for each corpus (upper left: Hidalgo-corpus; upper right: PIN-corpus; bottom-left: lemon-corpus; bottom-right: swine-corpus).

<https://doi.org/10.1371/journal.pone.0189080.g005>

over the 1,612 rumourous texts (1,459 in English, 153 in French). Table 5 shows the most frequent words in the database by decreasing order of occurrences or documents. If we set a threshold such as 10% of documents (146 in English, 15 in French) and if we consider the number of occurrences, we observe that only 20 simple words are significant. Among these

Table 4. List of 30 most frequent words and noun phrases in rumours corpora (Holland, lemon, Pin, swine).

| Hidalgo-corpus | frequency | Lemon-corpus | frequency | pin-corpus | frequency | swine-corpus | frequency |
|-------------------------|-----------|--------------------|-----------|-------------------------|-----------|------------------|-----------|
| hollande | 256 | cancer | 203 | police | 629 | flu | 807 |
| caché | 216 | citron | 200 | reverse | 626 | south | 801 |
| hidalgo | 184 | contre | 46 | atm | 624 | swine | 795 |
| fil | 161 | ennemi | 38 | pin | 622 | africa | 792 |
| françois | 128 | plus | 37 | pin reverse | 475 | south africa | 791 |
| censure | 123 | contre cancer | 37 | will | 289 | swine flu | 781 |
| enfant | 123 | n°1 | 31 | entering | 259 | cases | 141 |
| enfant caché | 121 | ennemi n°1 | 31 | call | 186 | #swineflu | 115 |
| caché censure | 120 | ennemi n°1 cancer | 30 | +alert | 166 | h1n1 | 115 |
| enfant caché censure | 120 | n°1 cancer | 30 | alert | 166 | news | 114 |
| françois hollande | 119 | citron ennemi | 29 | money | 159 | health | 107 |
| twitter | 116 | jus | 27 | entering your pin | 155 | world | 100 |
| hollande hidalgo | 114 | citron ennemi n°1 | 26 | atm pin | 138 | cup | 92 |
| caché censure twitter | 114 | fois | 25 | atm will | 131 | flu south | 91 |
| censure twitter | 114 | puissant | 25 | reverse any atm | 128 | flu south africa | 87 |
| hidalgo enfant | 111 | fois plus | 24 | enter | 112 | world cup | 87 |
| hidalgo enfant caché | 111 | jus citron | 23 | call the police | 108 | swine flu south | 84 |
| hollande hidalgo enfant | 109 | santé | 22 | will not call | 97 | confirmed | 81 |
| fil caché | 94 | thé | 22 | alert the police | 95 | #h1n1 | 76 |
| rumeurs | 84 | plus puissant | 21 | atm pin reverse | 91 | outbreak | 66 |
| non | 82 | #cancer | 20 | rumors | 87 | flu cases | 65 |
| compagne | 81 | cancer citron | 20 | contrary | 86 | swine flu cases | 65 |
| divorcée | 81 | 0 | 19 | rumors entering | 86 | death | 63 |
| compagne non | 81 | ovaire | 19 | popular | 85 | reported | 55 |
| compagne non divorcée | 81 | 000 fois | 19 | thief | 83 | news24 | 55 |
| non divorcée | 81 | 000 fois plus | 19 | contrary popular | 83 | flu death | 51 |
| caché compagne | 80 | fois plus puissant | 19 | contrary popular rumors | 82 | africa swine | 50 |
| caché compagne non | 80 | guérit | 16 | popular rumors | 82 | africa swine flu | 50 |
| fil caché compagne | 80 | cancer ovaire | 16 | popular rumors entering | 82 | swine flu death | 50 |

<https://doi.org/10.1371/journal.pone.0189080.t004>

words we can see only two words about a specific topic (cancer, Obama) and no word very typical for a rumourous alert. If we consider the number of documents, 160 words are relevant (64 in French, 96 in English). Most of words are very short (two or three characters). We cannot see any named entity in these lists (person’s name, organisation, product names). Many words seem to be tool words such as: *pro, ex, hey, side, app*, etc. Another big cluster of words are general verbs such as *go, use, eat, see*, etc. Some general meaning words seems recurrent too such as *men, one, day, king, war, ease*, etc. We cannot extract any global argumentative structure of a rumour that is redundant across a large set of documents.

Table 6 represents another view of word frequency in the text database. It points out the distribution of lexical units (1-grams) over each database (French, English). We kept only words occurring in more than 10% of the documents, and we are displaying the list of words by decreasing order of coverage per cent. More French words are involved because 10% of a small sample covers only 15 documents. For English documents only three words cover more than 25% of the corpus: *one, people, know*. These words are not informative about a rumour’s general representation. We can also find prepositions or adverbs such as *like, now, us*. For French, 17 words cover 25% of documents, and among those, only two words are semantically significant—*France, pays*—but very general in any case. Other significant words are logical and

Table 5. Common words for English in DIS-corpus sorted by decreasing frequency order (right by occurrences count, right by document count).

| Word | Freq | Word | Freq | french | | | | english | | | | word | freq |
|-----------|------|----------|------|--------|------|----------|------|---------|------|------|------|--------|------|
| | | | | word | freq | word | freq | word | freq | word | freq | | |
| obama | 584 | american | 221 | word | freq | word | freq | word | freq | word | freq | word | freq |
| people | 437 | back | 183 | an | 152 | elles | 57 | er | 1393 | pa | 851 | sc | 471 |
| know | 419 | told | 183 | al | 142 | autre | 57 | re | 1383 | nc | 817 | king | 465 |
| just | 405 | world | 183 | si | 138 | lors | 57 | ed | 1350 | rd | 806 | day | 460 |
| said | 379 | take | 177 | or | 138 | avoir | 56 | ing | 1337 | ill | 790 | dr | 458 |
| president | 341 | years | 173 | el | 136 | rien | 56 | st | 1312 | eve | 765 | ran | 454 |
| please | 336 | country | 168 | no | 134 | personne | 56 | hi | 1281 | one | 762 | side | 450 |
| plus | 297 | think | 164 | ans | 132 | main | 56 | nt | 1274 | ear | 745 | know | 442 |
| like | 261 | cancer | 160 | ca | 127 | car | 55 | ve | 1238 | go | 671 | ring | 440 |
| time | 244 | make | 149 | com | 124 | puis | 55 | al | 1238 | use | 670 | old | 438 |
| | | | | lu | 123 | vers | 53 | ll | 1216 | ap | 670 | sin | 436 |
| | | | | va | 121 | toute | 52 | de | 1166 | com | 660 | son | 430 |
| | | | | ni | 121 | of | 52 | co | 1152 | ny | 654 | app | 429 |
| | | | | air | 118 | fois | 51 | ma | 1128 | men | 630 | rat | 429 |
| | | | | mme | 117 | pris | 51 | ca | 1123 | end | 618 | era | 426 |
| | | | | and | 111 | grand | 50 | us | 1121 | ga | 604 | lt | 421 |
| | | | | pu | 100 | met | 50 | ur | 1105 | ex | 596 | tim | 420 |
| | | | | dr | 100 | parti | 49 | hat | 1098 | pro | 583 | car | 419 |
| | | | | art | 100 | porte | 48 | ho | 1073 | man | 581 | ass | 416 |
| | | | | plus | 99 | autres | 47 | el | 1069 | hey | 581 | ms | 410 |
| | | | | tant | 99 | dire | 47 | la | 1037 | now | 579 | war | 406 |
| | | | | don | 91 | prend | 47 | wa | 1020 | ain | 579 | get | 402 |
| | | | | tout | 89 | cour | 47 | id | 1013 | ever | 575 | pen | 396 |
| | | | | ali | 89 | donc | 44 | un | 990 | red | 569 | ease | 394 |
| | | | | fait | 88 | loi | 44 | ad | 960 | ok | 564 | ten | 390 |
| | | | | vie | 82 | quelqu | 44 | lo | 941 | per | 526 | cause | 389 |
| | | | | cons | 82 | auto | 44 | em | 928 | ice | 513 | thing | 383 |
| | | | | voir | 81 | peut | 43 | rt | 896 | thin | 507 | low | 381 |
| | | | | jour | 81 | mal | 41 | sh | 887 | age | 489 | aid | 375 |
| | | | | comme | 79 | nation | 41 | ate | 875 | act | 488 | people | 373 |
| | | | | sent | 78 | vient | 40 | im | 864 | eat | 481 | inc | 366 |
| | | | | part | 76 | quelque | 40 | mo | 858 | led | 477 | see | 365 |
| | | | | eau | 74 | nouvel | 40 | ted | 853 | ally | 474 | way | 360 |

<https://doi.org/10.1371/journal.pone.0189080.t005>

argumentative such as: *si, donc*; but they still have a very global meaning for a consequence or condition. Other less frequent words deal with different topics such as people and domestic policy. An interesting fact is that the word *true* is often used in a message claiming a falsehood.

We would like now get an overview of words importance in the rumor content over time.

Rumorous datasets were initiated before creation of twitter platform except for ‘swine flu’ that emerged in 2009. About ‘lemon’, ‘hidalgo’, and ‘pin’ we can not observe the levelling step. About ‘swine flu’ we do not observe any loss of lexical information at beginning of the rumour propagation (see Fig 6).

Sharpening in a transition point of view can be seen as frequent words that can become more frequent. Assimilation can be seen as noise words that come in and out. Our transition diagram can differentiate growing in frequency details (transfer from low and medium boxes to high frequency box)—i.e. sharpening—and capturing noise (transfer from low to medium

Table 6. Common words for DIS-corpora (sorted by reverse frequency order).

| | french | | | | english | | | |
|-------------|--------|-----------|--------------|-----|-----------|-----------|-----|-----------|
| | doc | cov | | doc | cov | | doc | cov |
| plus | 92 | 60.130719 | mois | 24 | 15.686275 | one | 439 | 30.089102 |
| comme | 75 | 49.019608 | jusqu | 24 | 15.686275 | people | 376 | 25.771076 |
| si | 74 | 48.366013 | jours | 24 | 15.686275 | know | 341 | 23.372173 |
| fait | 61 | 39.869281 | islam | 24 | 15.686275 | please | 302 | 20.699109 |
| tous | 59 | 38.562092 | chaque | 24 | 15.686275 | said | 298 | 20.424949 |
| tout | 58 | 37.908497 | nombre | 23 | 15.032680 | now | 277 | 18.985607 |
| france | 55 | 35.947712 | gouvernement | 23 | 15.032680 | get | 272 | 18.642906 |
| faire | 54 | 35.294118 | vie | 22 | 14.379085 | new | 267 | 18.300206 |
| bien | 54 | 35.294118 | pourquoi | 22 | 14.379085 | time | 266 | 18.231666 |
| avoir | 45 | 29.411765 | paris | 22 | 14.379085 | like | 258 | 17.683345 |
| autres | 45 | 29.411765 | gens | 22 | 14.379085 | don | 243 | 16.655243 |
| donc | 42 | 27.450980 | pendant | 21 | 13.725490 | true | 239 | 16.381083 |
| fois | 41 | 26.797386 | loi | 21 | 13.725490 | obama | 224 | 15.352981 |
| entre | 41 | 26.797386 | hui | 21 | 13.725490 | us | 215 | 14.736121 |
| non | 37 | 24.183007 | elles | 21 | 13.725490 | president | 210 | 14.393420 |
| pays | 36 | 23.529412 | droit | 21 | 13.725490 | take | 205 | 14.050720 |
| ainsi | 36 | 23.529412 | ceux | 21 | 13.725490 | make | 205 | 14.050720 |
| encore | 34 | 22.222222 | aujourd | 21 | 13.725490 | also | 199 | 13.639479 |
| depuis | 34 | 22.222222 | femmes | 20 | 13.071895 | back | 197 | 13.502399 |
| alors | 34 | 22.222222 | dit | 20 | 13.071895 | many | 195 | 13.365319 |
| peut | 33 | 21.568627 | autre | 20 | 13.071895 | going | 192 | 13.159698 |
| monde | 33 | 21.568627 | toujours | 19 | 12.418301 | go | 191 | 13.091158 |
| deux | 33 | 21.568627 | seulement | 19 | 12.418301 | see | 190 | 13.022618 |
| rien | 32 | 20.915033 | partie | 19 | 12.418301 | two | 189 | 12.954078 |
| personnes | 32 | 20.915033 | parce | 19 | 12.418301 | even | 185 | 12.679918 |
| information | 32 | 20.915033 | musulmane | 19 | 12.418301 | way | 183 | 12.542838 |
| avant | 32 | 20.915033 | grande | 19 | 12.418301 | first | 177 | 12.131597 |
| aussi | 32 | 20.915033 | euros | 19 | 12.418301 | found | 176 | 12.063057 |
| ans | 32 | 20.915033 | etat | 19 | 12.418301 | years | 175 | 11.994517 |
| temps | 31 | 20.261438 | demande | 19 | 12.418301 | told | 175 | 11.994517 |
| quelques | 31 | 20.261438 | certains | 19 | 12.418301 | may | 175 | 11.994517 |
| toutes | 30 | 19.607843 | aucune | 19 | 12.418301 | think | 167 | 11.446196 |
| moins | 29 | 18.954248 | attention | 19 | 12.418301 | friends | 166 | 11.377656 |
| enfants | 29 | 18.954248 | vers | 18 | 11.764706 | well | 162 | 11.103496 |
| car | 29 | 18.954248 | trop | 18 | 11.764706 | everyone | 162 | 11.103496 |
| vient | 28 | 18.300654 | pourtant | 18 | 11.764706 | around | 158 | 10.829335 |
| sous | 28 | 18.300654 | plusieurs | 18 | 11.764706 | man | 157 | 10.760795 |
| nouvelle | 28 | 18.300654 | mieux | 18 | 11.764706 | day | 157 | 10.760795 |
| dont | 28 | 18.300654 | suite | 17 | 11.111111 | never | 155 | 10.623715 |
| contre | 28 | 18.300654 | ministre | 17 | 11.111111 | want | 150 | 10.281014 |
| jamais | 27 | 17.647059 | faites | 17 | 11.111111 | pass | 150 | 10.281014 |
| afin | 27 | 17.647059 | etc | 17 | 11.111111 | last | 150 | 10.281014 |
| toute | 26 | 16.993464 | dernier | 17 | 11.111111 | world | 146 | 10.006854 |
| quand | 26 | 16.993464 | savoir | 16 | 10.457516 | called | 146 | 10.006854 |
| musulmans | 26 | 16.993464 | quoi | 16 | 10.457516 | every | 145 | 9.938314 |
| effet | 26 | 16.993464 | message | 16 | 10.457516 | use | 143 | 9.801234 |

(Continued)

Table 6. (Continued)

| | french | | | | english | | | |
|----------|--------|-----------|-----------|-----|-----------|----------|-----|----------|
| | doc | cov | | doc | cov | | doc | cov |
| dire | 26 | 16.993464 | islamique | 16 | 10.457516 | read | 142 | 9.732694 |
| voir | 25 | 16.339869 | comment | 16 | 10.457516 | really | 141 | 9.664154 |
| selon | 25 | 16.339869 | bonne | 16 | 10.457516 | right | 140 | 9.595613 |
| personne | 25 | 16.339869 | aucun | 16 | 10.457516 | news | 140 | 9.595613 |
| grand | 25 | 16.339869 | article | 16 | 10.457516 | made | 140 | 9.595613 |
| cas | 25 | 16.339869 | | | | come | 140 | 9.595613 |
| va | 24 | 15.686275 | | | | say | 138 | 9.458533 |
| peu | 24 | 15.686275 | | | | american | 138 | 9.458533 |

<https://doi.org/10.1371/journal.pone.0189080.t006>

boxes)—i.e. assimilation. We could see a sharpening in Fig 6 if the size of the arrow in our diagram increases, but it is not the case in any rumor.

On Fig 6 we can observe streams of words come in and out from low frequency box to medium frequency box in all rumorous transmission.

Rare syntagmatic extraction

Table 7. Shows the results about measure MW_c .

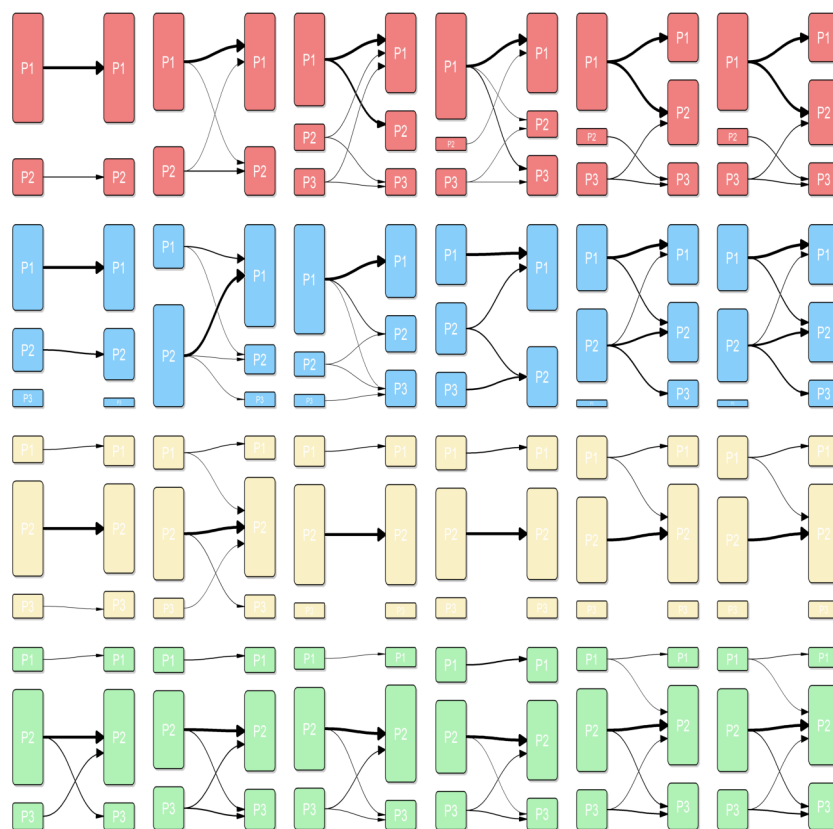


Fig 6. Lexical transfer from a period of time to the next for each rumorous datasets. Each line means a rumorous dataset (in red lemon, in blue: hidalgo, in yellow: pin, in green: swine-flu). Horizontal axis is the timeline. Each dataset is divided into 7 boxplot, generating 6 transitions. Each boxplot contains three frequency boxes. Top frequency box represent high frequency (around 10 words), the bottom frequency box represent 60% of lowest frequency words. The medium frequency box contain the remaining words.

<https://doi.org/10.1371/journal.pone.0189080.g006>

Table 7. MW_c measure for each tweets corpus.

| | random1 | random2 | random3 | random4 |
|--------|-------------|-------------|-------------|-------------|
| MW_c | 0.366500829 | 0.341423948 | 0.235514019 | 0.265442404 |
| | H | Lemon | Pin | swine |
| MW_c | 0.7090301 | 0.585551331 | 0.697626419 | 0.641923436 |
| | RiFr | RiEn | EuroFr | EuroEn |
| MW_c | 0.519650655 | 0.75060241 | 0.736717828 | 0.798293251 |

<https://doi.org/10.1371/journal.pone.0189080.t007>

The second experiment is based on simple words shown in Tables 5 and 6 from which we made a file of 144 simple English words; we computed all combinations between two words (2-skipgrams) and three words (3-skipgrams). Hence, we checked the presence or absence of each skipgram in the corpora of common language in English (COCA-corpus).

In Table 8 we see that only five 3-skipgrams are not inside the common language corpus:

- obama please thing
- alert obama sh
- number obama please
- alert info obama
- don obama please

Specificity of these combinations is clearly related to the Obama name and cannot provide information about rumour structure in general.

Syntagmatic combination analysis

On Fig 6 we can see different groups of similar messages for Hidalgo-corpus over time. At the beginning are two distinct groups of messages in bright blue and red, and at the end, a cluster in green. This figure shows us that during a flow of messages for a specific rumour, groups of similar messages can emerge in the same time window.

Fig 7 shows that bursts of similar messages occur over time, and leads us to think that indeed the content of rumour discourse is not heterogeneous.

We can suppose that a rumour discourse consists of local grammar and typical vocabulary in Twitter but also in the primitive short text. We plotted a timeline occurrence of rumours sorted (y-axis) by message similarity.

Another angle to capture association is machine learning algorithms that use features, often within non-linear techniques taking into account combination of indirectly correlated features.

Fig 8 shows four plot for each classification methods. On each plot we have three curves: random (in black), rumor accuracy (in red), global accuracy (in blue). We see that scores

Table 8. Skipgrams of DIS-corpora included or not included in the COCA corpus.

| | yes | no | total |
|-------------|--------|----|--------|
| 2-skipgrams | 10296 | 0 | 10296 |
| 3-skipgrams | 487339 | 5 | 487344 |
| total | | | 497640 |

<https://doi.org/10.1371/journal.pone.0189080.t008>

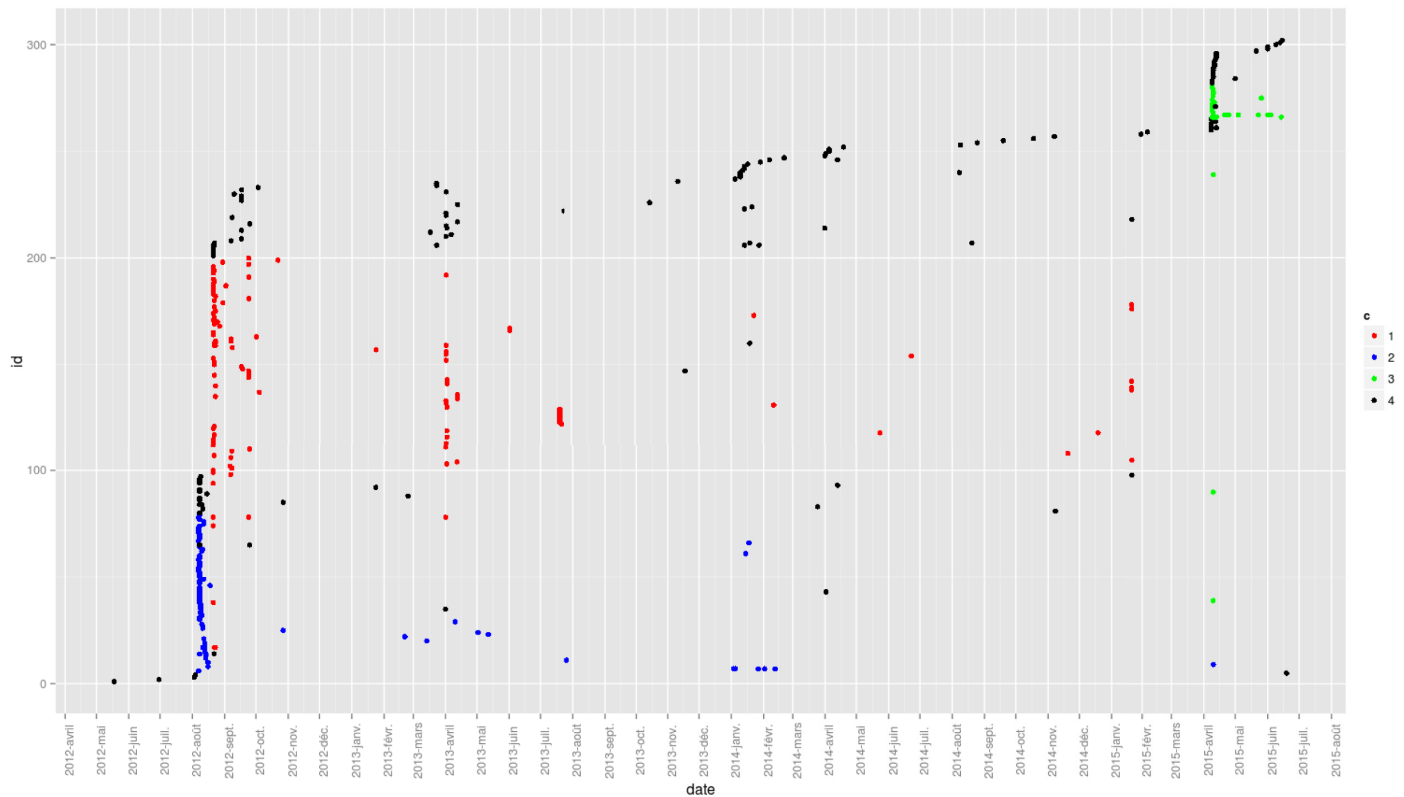


Fig 7. Clustering of messages according to similarity of message for Hollande-corpus.

<https://doi.org/10.1371/journal.pone.0189080.g007>

are not so good for a small amount of features (less than 50,) and scores degrade when they are more than 200 features. So we decide to keep the solution of 100 features.

Fig 9 shows the results. We can observe that the behaviour of predication is almost the same for Random Forest, SVM and SLDA and we see that there is a change between the overall dataset prediction behavior and the first 30% dataset, and the overall dataset keep the same behaviour as the 30% last dataset but with a degradation of performance in prediction.

It means an impact of the lexical composition over time that changed. Maxent seems to have a bad behavior with low score of prediction. If we filter the number of prediction with more than 60% of certainty, we get only about 3,727 values, when other methods have about 9,500 values. When using the whole set of features (3,336, instead of 100 most frequent), the amount of values with high confidence raises to 7,351 but we still get only 9,2% for accuracy about the rumours set when other methods get more than 33%. Maxent seems to work better with a highest dimensional space, but keeping a lower performance.

Discussion

Our results show the complexity of rumour description and tracking in its diverse facets. Rumour analysis, being a psycho-social phenomenon, has regained interest because of social media platforms that relay news efficiently and widely, as well as events and information about important persons or organisations. Relevant studies have proven that the integration of specific features for automatic detection gives interesting results for case studies. Globally, there is no comparison of the difference between news and rumours. Furthermore, relevant features involved in models reveal that some misinformation lacks specific features or have more

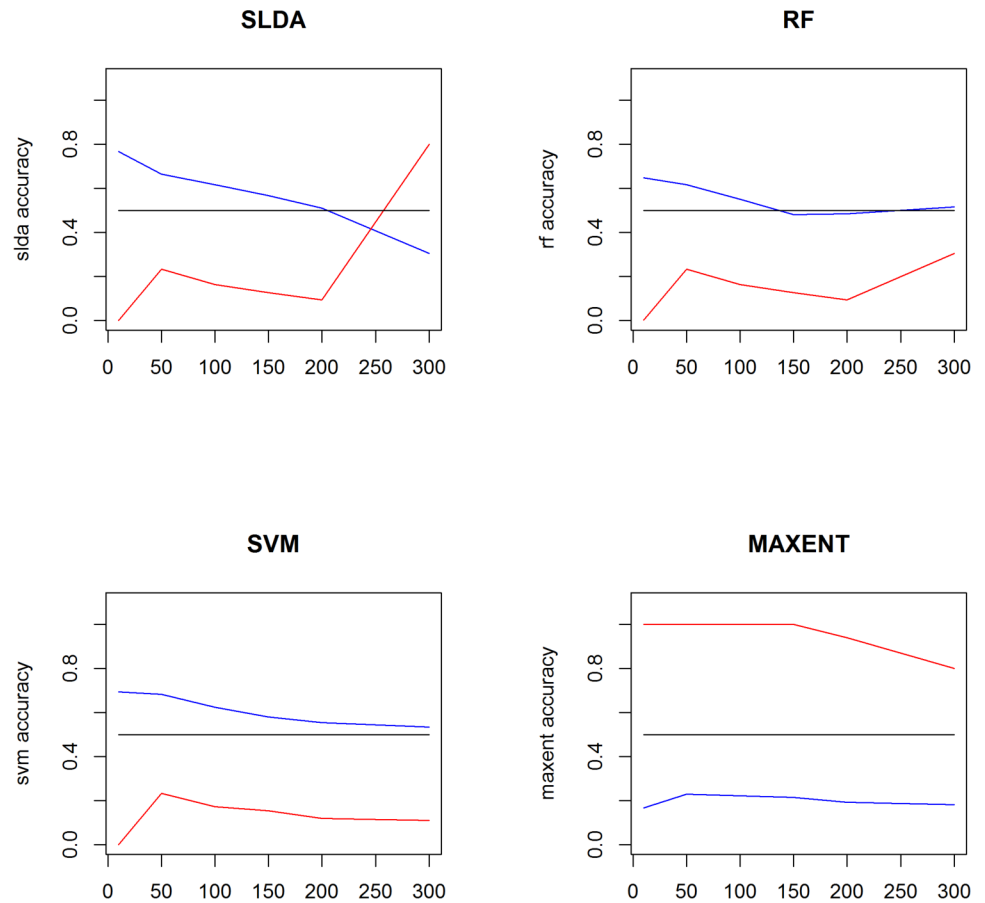


Fig 8. Classification performance (global accuracy rumorous/non-rumorous in blue; rumorous accuracy in red using following techniques: ‘SLDA’ (top left), ‘Random Forest’ (top right), ‘SVM’ (bottom left), ‘MAXENT’ (bottom right).

<https://doi.org/10.1371/journal.pone.0189080.g008>

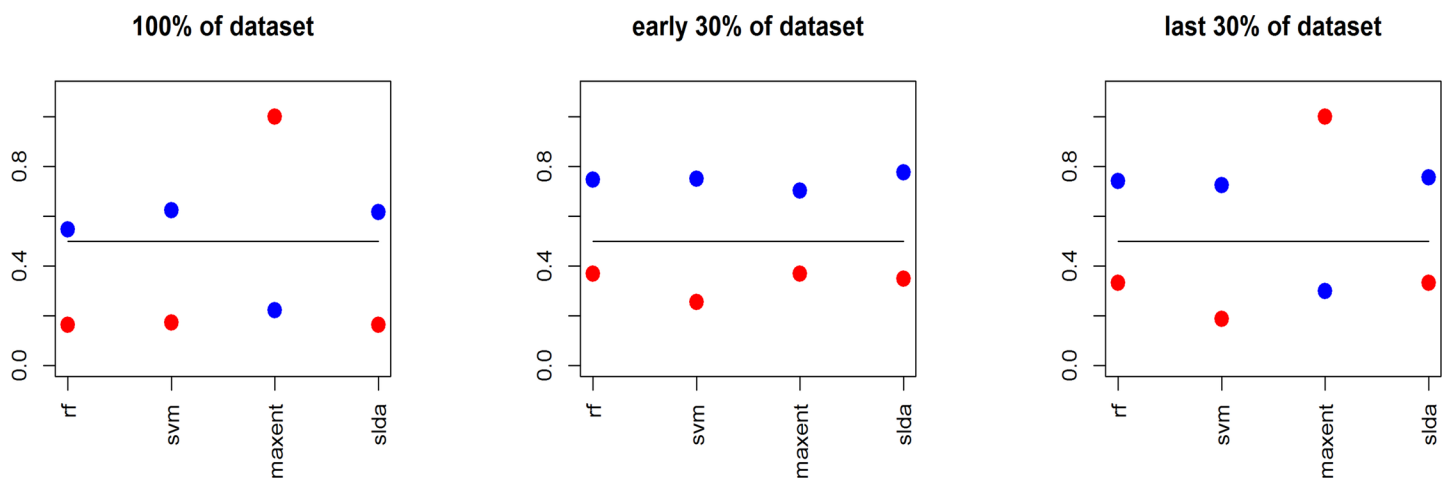


Fig 9. Classification techniques (Rf for ‘Random Forest’, ‘SVM’, ‘Maxent’, ‘SLDA’) applied on three samples: Whole rumorous dataset (left), the 30% first rumorous dataset in the range time (middle), the last 30% rumorous dataset in the range time (right). In blue the global accuracy (rumorous+non-rumorous), in red the rumors accuracy (only rumorous), in black the random baseline.

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specific features, but each social media space can generate its own properties and because of this, rumours can spread with a combination of features that are not found in existing platforms (like Weibo or Wikipedia). Indeed we observed 53 features involved in models, but the combination of these features is high and it is not realistic to imagine a unique set of features to anticipate the shape of a rumour in a given digital context. Globally detecting rumours can be implemented locally in the context in which it is spread for a specific category of users. Can we imagine a connected world without rumours? Language evolves in any social world, and a rumour is in itself a marker of the language at a rhetorical level. So rumours can evolve in the same way that language evolves. For instance, a series of hashtags in a microblog can be a new kind of message, but in the same way a new kind of rumour construction. A rumour lifecycle evolves naturally like a scientific hypothesis, requiring confirmation or denial by other publications; in this sense, the majority of people socially accept this rhetorical process.

Conclusion

To complete rumour and disinformation studies widely explored by qualitative means, we decided to investigate quantitative issues across any data sources. We studied several rumour datasets leading to a disinformation corpus of 1,612 rumourous texts (in French and English) from which we chose four rumours (French Hidalgo politician, lemon and cancer, ATM PIN code and swine flu in South Africa). We manually built two or three keyword queries to get tweets data about these four corpora. About the propagation of each rumour over time, we highlighted different profiles that may be either epidemiological-based but multi-harmonic-based. Focusing on the disinformation corpus we found that the intrinsic lexical content of rumours themselves has no specific content in term of lexical patterns when we compared them with reference corpora for the English or French common language, or to the corpora of event-based tweets. We tried also to highlight some previous theory of rumor arguing a transmission in three steps: levelling-sharpening-assimilation. Taken this as a basis, we consider social network data as an empirical framework to provide data for validation of such theory. We can only confirm the assimilation part; we guess that levelling and sharpening occur enough early in dissemination and we do not observed it under the scope of 4 given rumors. So we distinguish two properties of rumors, largely disseminated in natural language (as a speech act) whereby they seem to have lexically no specific genre, and have a propagation with a certain resilience and assimilation process.

Supporting information

S1 Appendix.

(DOCX)

S2 Appendix.

(DOCX)

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