Characterizing the spread of exaggerated news content over social media

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Abstract

In this paper, we consider a dataset comprising press releases about health research from different universities in the UK along with a corresponding set of news articles. As a first step we perform an exploratory data analysis to understand how the basic information published in the scientific journals get exaggerated as they are reported in these press releases or news articles. This initial analysis shows that some news agencies exaggerate almost 60% of the articles they publish in the health domain; more than 50% of the press releases from certain universities are exaggerated; articles in topics like lifestyle and childhood are heavily exaggerated.

Motivated by the above observation we set the central objective of this paper to investigate how exaggerated news spreads over an online social network like Twitter. We observe that the fraction of tweets sharing exaggerated news articles is higher than the ones sharing non-exaggerated tweets almost a year after the publication date of the news. In these late arriving tweets, we observe that there is a weaker presence of words in certain LIWC categories like death words, sexual, sad and negative emotion relative to the tweets sharing non-exaggerated news; similarly, there is a stronger presence of words in the categories like assent, feel, religion and anxiety. The LIWC analysis finally points to a remarkable observation – these late tweets are essentially laden in words from opinion and realize categories which indicates that, given sufficient time, the wisdom of the crowd is actually able to tell apart the exaggerated news. As a second step we study the characteristics of the users who never or rarely post exaggerated news content and compare them with those who post exaggerated news content more frequently. We observe that the latter class of users have less retweets/mentions per tweet, have significantly more number of followers, use more slang words, less hyperbolic words and less word contractions. We also observe that the LIWC categories like ‘bio’, ‘health’, ‘body’ and ‘negative emotion’ are more pronounced in the tweets posted by the users in the latter class. As a final step we use these observations as features and automatically classify the two groups achieving an F1-score of 0.83.

Introduction

News media has a tremendous power in shaping people’s beliefs and opinions[1]. The Internet subculture is found to take increasing advantage of this current media ecosystem to manipulate news frames, set agendas, and propagate ideas[2]. Such media manipulation has significantly contributed to decreased trust of mainstream media, increased misinformation, and further radicalization[3]. Fake and unnecessarily exaggerated news has consequently captured worldwide interest, and the number of organized efforts dedicated solely to fact-checking has almost tripled since 2014[4].

Exaggeration in scientific news

Scientific news is no exception. This is especially a point of serious concern in the context of health and food related news since these are usually of wide general interest and therefore heavily consumed by the common mass[5]. Motivated by the above observation we set the central objective of this paper to investigate how exaggerated news spreads over an online social network like Twitter. We observe that the fraction of tweets sharing exaggerated news articles is higher than the ones sharing non-exaggerated tweets almost a year after the publication date of the news. In these late arriving tweets, we observe that there is a weaker presence of words in certain LIWC categories like death words, sexual, sad and negative emotion relative to the tweets sharing non-exaggerated news; similarly, there is a stronger presence of words in the categories like assent, feel, religion and anxiety. The LIWC analysis finally points to a remarkable observation – these late tweets are essentially laden in words from opinion and realize categories which indicates that, given sufficient time, the wisdom of the crowd is actually able to tell apart the exaggerated news. As a second step we study the characteristics of the users who never or rarely post exaggerated news content and compare them with those who post exaggerated news content more frequently. We observe that the latter class of users have less retweets/mentions per tweet, have significantly more number of followers, use more slang words, less hyperbolic words and less word contractions. We also observe that the LIWC categories like ‘bio’, ‘health’, ‘body’ and ‘negative emotion’ are more pronounced in the tweets posted by the users in the latter class. As a final step we use these observations as features and automatically classify the two groups achieving an F1-score of 0.83.

Forms of exaggeration

In health related news articles, exaggeration can take different forms, such as the transformation of correlational statements into causal statements, change in explicitness and directness of included advice or misrepresentation of important experimental facts. Exaggeration can be traced to two main sources - (i) press releases made by universities[6], the corresponding scientific journals and publications that appear before the news and are more complete, exhaustive and authentic account of the facts are hardly consulted by the common mass[7]. The reason for this is the very abstruse and esoteric language, and academic nomenclature employed in the scientific articles, which is comprehensible often only to the health research community. Journalists and reporters, in turn, summarize the research presented in such scientific journals into a much simpler and coherent news piece, that is easily understandable by the common people.

References

1. https://bit.ly/2IAC2pD
2. https://bit.ly/2tnfJFm
3. https://stanford.io/2H9kuDY
4. https://bit.ly/2qbWN1A
5. NBC Report: https://nbcnews.to/2uXjQoo

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novel and interesting discoveries, make exaggerated and far-fetched claims in the press releases following a scientific publication in order to improve the chances of visibility of the research and gain increased recognition. News agencies and media houses, in addition, often exaggerate the scientific news content and the headline to make their articles more sensational and compelling. An earlier study (Dumas-Mallet et al. 2017) has concluded that journalists preferentially cover initial findings, although they are often contradicted by meta-analyses and rarely inform the public when they are later disconfirmed. Both these origins of exaggeration need to be regulated to preserve the integrity of health research.

There have been many studies published on exaggeration (Walsh-Childers et al. 2016; Sumner et al. 2014; Hasse et al. 2005; Cullen 2014); however, an in-depth analysis of how these news items spread over social media is lacking. In this paper, we characterize for the first time the spread of exaggerated news items over Twitter. We also analyze the behaviour of users who never or rarely post exaggerated news content and compare them with those who post exaggerated news more frequently.

**Working definition of exaggeration**

In order to perform such a quantitative study we need to have a working definition of exaggeration. In the following we present such a definition and operationalize it later in the dataset section.

**Working definition**: In order to quantify the extent of exaggeration we measure the difference of the journal publication from the followup press release/news articles in terms of (i) the strength of the relation between the research variables, (ii) the explicitness and directness of the issued advice and (iii) the identity of the sample used in experiments.

**Key Contributions**

Based on the above working definition, we make the following contributions in this paper.

- **Operationalize the definition of exaggeration**: We identify a suitably annotated dataset released by (Sumner et al. 2014) and perform an exploratory analysis. This dataset comprises detailed annotations of 462 press releases and 668 news articles, issued in 2011 by the Russell Group of Universities (20 leading UK Research Universities) in health related topics. Based on these annotations, we operationalize the definition of exaggeration. In order to ascertain the robustness of our analysis we also club close by classes to have more coarse-grained annotations. Our results do not seem to differ due to such coarse graining of the classes.

- **Exaggeration across various dimensions**: Using the above dataset, we analyze the extent of exaggeration across various universities, media houses and health disciplines. We also demonstrate through appropriate visualizations how the strength of the causal relations and the samples used for the experiments are exaggerated in the press releases and the news articles.

- **Propagation of the exaggerated news in Twitter**: We extensively investigate how exaggerated articles propagate in Twitter compared to non-exaggerated articles. In particular we study the tweet arrival behavior and the change in the overall linguistic construct of the tweets over time.

- **Characterization of users spreading exaggerated news**: We compare the tweeting behaviour of users who never or rarely post exaggerated news with those posting such news content more frequently. Finally, we construct a model that can automatically classify these two groups of users using their tweet properties.

**Result highlights**

Some of the key results that we obtain from our analysis are as follows.

- From our exploratory analysis we observe the certain news agencies exaggerate up to 60% of their articles; however, there are certain news agencies where levels of exaggeration seem pretty low. We observe that more than 50% of press releases from certain universities are exaggerated. Finally, press releases and news articles in the lifestyle and the childhood disciplines are more exaggerated relative to the other sub-disciplines; on the other hand, exaggerations in the policy sub-discipline are the least.

- Tweets sharing exaggerated news, on average, are more popular than those sharing non-exaggerated news.

- The fraction of tweets sharing exaggerated news is higher compared to those sharing non-exaggerated news almost a year after the publication date of the news.

- If we compare the early and the late arriving tweets propagating exaggerated news, we observe stark differences in certain LIWC categories – while the proportion of words in categories like death words, sexual, sad and negative emotion show a weaker presence, a stronger presence is observed in categories like assent, feel, religion and anxiety relative to the tweets sharing non-exaggerated news.

- Late tweets spreading exaggerated news seem to have increased proportion of opinionated and realization tweets.

- Users who spread exaggerated news more frequently have less retweets/mentions on average, have significantly larger number of followers, use more slang words and less hyperbolic words and contractions in their tweets compared to those users who never or rarely post exaggerated news content. Further, the LIWC categories like ‘bio’, ‘health’, ‘body’ and ‘negative emotion’ dominate in tweets posted by users who more frequently post exaggerated news content. Finally, we automatically classify these two groups of users achieving an overall F1-score of 0.83. Such classification can act as the first step in containing the spread of exaggerated content in social media early on.

We stress that this is the first work that investigates how exaggerated news spread in social media and shows how, given sufficient time, the wisdom of the crowd can actually tell apart the exaggerated news (increase in realization and opinion words). Further, it is also the first work that characterizes the users based on how frequently they post exaggerated content. This has the potential to help in containing the spread of such content in social media.
Related work

Investigating sensationalism in scientific news has been an area of research interest for quite some time although rigorous quantitative measurement studies are missing. In the following, we present a brief summary of some of the existing studies.

In (2016), the authors defined two measures – scientific quality and sensationalism, and devised an entropy model to learn the same for news paper articles. The annotations were crowd sourced through a questionnaire. Schwartz et al. (2012) investigated whether the quality of the news articles can be influenced by the quality of press releases. Yavchitz et al. (2012) coined a term called “spin” as specific reporting strategies (intentional or unintentional) emphasizing the beneficial effect of the experimental treatment, and investigated the same for 498 press release articles. Woloshin et al. (2009) investigated the works of 10 medical centers at each extreme of U.S. News & World Report’s rankings for medical research, and concluded that press releases from academic medical centers often promote research that has uncertain relevance to human health and do not provide key facts or acknowledge important limitations. Selvaraj et al. (2014) studied which medical research was most likely to be covered in media, and concluded that observational studies had the highest frequency. Brechman et al. (2009) examined the presentation of genetic research relating to cancer outcomes and behaviors in both the press release and its subsequent news coverage. Adams et al. (2017) studied how people understand scientific expressions used in news headlines. In (2014), the authors study the association between exaggeration in health related science news and academic press releases. In this study, the authors report the overall levels of exaggeration in the claims made in the press releases, in the advice statements made and the samples used for the experiments. In this paper, we use the same dataset made public by the authors as well as the annotations that they use to mark exaggerated content. However, instead of analyzing the overall levels of exaggeration, we launch a more micro-scale study and observe levels of exaggeration university-wise, news agency-wise as well as sub-discipline-wise. We further investigate for the first time how the exaggerated content spreads in an online social network like Twitter.

Dataset

We use the publicly available dataset released by (Sumner et al. 2014) for our experiments. This dataset contains detailed annotations of 462 journals, corresponding 462 press releases and 668 news articles, issued in 2011 by the Russel Group of Universities (20 leading UK Research Universities) in health related topics, for three distinct categories - strength of statement, advice and sample. Every individual press release is a followup of a journal paper; we assume this journal paper to be the reference for our analysis (as has also been assumed in (Sumner et al. 2014)). Every press release in turn, can be discussed by some news reports. In our dataset, 230 out of 462 journals and press releases have at least one news article coverage. The data set primarily spans over eight disciplines. The number of press releases and articles in each of these disciplines are shown in Table 1.

In order to operationalize the definition of exaggeration one needs to be aware of the statements appearing in the different documents (journal papers, press releases or news articles). This is done as follows.

Strength of statement

Health related research experiments involve various compounds and quantities that are measured and controlled. Independent variables (IV) refer to those variables that are varied in the experiment while dependent variables (DV) refer to those variables that get affected and are measured. This could be thought of as analogous to the subject and the object in a natural language sentence. For example, consider the sentence Wine causes cancer. Here ‘wine’ is the IV and ‘cancer’ is the DV. We may have multiple IV’s and DV’s for a research study, and they can be determined by carefully reading through the journal article. The strength of statement is defined as a numerical measure of the strength of the causal relationship of the statement that relates an IV and a DV. In (Sumner et al. 2014), this strength has been quantized into seven different levels that are noted below.

1. No relationship mentioned - No relationship is mentioned, e.g., “wine and cancer”.
2. Statement of no relationship - Explicitly stating that there is no relationship, e.g., “wine does not cause cancer”.
3. Statement of correlation - IV and DV are associated, but causation cannot be explicitly asserted, e.g.“wine is associated with cancer”.
4. Ambiguous statement of relationship - It is unclear what the strength of relationship of this statement is, e.g., “wine is linked to cancer”. This could mean that “wine causes cancer”, or that “wine is associated with cancer” - either would be applicable.
5. Conditional statement of causation - Causal statements show that the IV directly changes the DV. Conditional causal statements carry an element of doubt in them, e.g., “wine might cause cancer”.
6. Statement of “can” - The word “can” is unique as a statement of relationship in that it implies that the IV has the potential to directly change the DV, e.g., “wine can cause cancer”. Therefore it is stronger than any conditional statement of causation.

| Discipline               | press releases | news articles |
|-------------------------|---------------|---------------|
| Life-style              | 70            | 121           |
| Mental Health           | 14            | 14            |
| Childhood               | 43            | 58            |
| Treatment               | 61            | 108           |
| Observational Identification | 203     | 282           |
| Policy                  | 29            | 30            |
| Ageing                  | 3             | 4             |
| Physical Disease        | 38            | 49            |
| Not Mentioned           | 1             | 2             |

Table 1: Number of press releases and articles in each discipline.
7. Statement of causation - The strongest are the statements of causation, e.g., “wine causes cancer”. This statement says that the IV definitely and directly alters the DV.

The strength of statement level (1–7) of an entire document (e.g., a journal paper, a press release or a news article) is defined by the level of the strongest statement relating an IV and a DV appearing in that document. We shall refer to this strongest statement as the first statement throughout the rest of the paper. While (Sumner et al. 2014) provides the dataset already marked by one of the above seven quantization level for each journal, press release and news article, thus allowing for analysis of the exaggerated content, it is difficult to ascertain the robustness of the results obtained. This is primarily because some of the quantization levels seem to be too close. In order to test the robustness of the results that we present in the subsequent sections, we also club the above quantizations into more coarse-grained labels. Essentially, we consider a 4-class and a 2-class quantization. For the 4-class we map the above seven quantizations as follows: (1, 2) → 1, (3, 4) → 2, (5, 6) → 3 and 7 → 4. For the two class we map as follows: (1, 2, 3, 4, 5, 6) → 1 and 7 → 2.

Advice
Health related research often conclude with a statement of advice, given explicitly or implicitly, to the reader usually recommending what one should or should not do/ eat. Often such advice comes in the form of a quote from the lead researcher of the scientific article. Advice is quantized at four different levels based on the explicitness and directness in the lines of (Sumner et al. 2014). We enumerate these levels below in their ascending order of strength.

1. No advice - If no advice is given.
2. Implicit advice - If advice is implicit and hints that certain behavior needs to be changed, e.g., “Drinking wine is harmful because it causes cancer”. This implies that public should not drink wine but does not directly or explicitly state it.
3. Explicit and indirect advice - Advice is explicitly stated but is not directly addressed to the public, e.g., “Drinking wine causes cancer, therefore governments should advise their citizens not to drink wine”.
4. Explicit and direct advice - Advice is explicitly stated and is directly addressed to the public, e.g., “We should not drink wine because it causes cancer”.

Once again, the advice level (1–4) of a document corresponds to the level of the strongest advice statement appearing in the document. Note that these annotations are again already marked in the dataset made available by (Sumner et al. 2014) for each journal, press release and news article.

Sample
Research experiments can be conducted on humans, mice, bees, primates, rodents or even on diseased cells. In (Sumner et al. 2014) the authors make nine different classes of sample. However, an initial analysis indicated that the data becomes too sparse if one considers nine classes. Thus for our purpose, we simplify this classification by putting all human subject related research studies in the human class, and the rest non human subject based experiments into the non-human class. We assign the sample class human to a document if the research explicitly or implicitly states that human subjects were used or if the study was intended for humans. Otherwise, we assign the class non-human to the document.

In the next section, we operationalize the definition of exaggeration by comparing the level of the strength of statement, the level of the advice and the class of the sample.

Operational definition of exaggeration
We define three different variants for quantification of exaggeration by considering the journal paper as always the reference non-exaggerated document. These three variants differ based on how we quantize the strength of statement (7, 4 or 2). Suppose d is a document (a press release or a news article), with strength of statement level s_d, advice level a_d and sample class x_d. Also suppose j is the reference journal with strength of statement level s_j, advice level a_j and sample class x_j, where a_d, a_j ∈ {1, 2, 3, 4} and x_d, x_j ∈ {human, non-human}. The values of s_d, s_j are defined as per the following variants of quantization:

7-Class: Here we take strength levels as have been defined in (Sumner et al. 2014). So s_d, s_j ∈ {1, 2, 3, 4, 5, 6, 7}.

4-Class: As discussed earlier, here we shrink the seven classes to four classes. The mapping from the original seven class to the four class is as follows. (1, 2) → 1, (3, 4) → 2, (5, 6) → 3 and 7 → 4. So s_d, s_j ∈ {1, 2, 3, 4}.

2-Class: For the two class we map the original seven classes as follows: (1, 2, 3, 4, 5, 6) → 1 and 7 → 2. So s_d, s_j ∈ {1, 2}.

Exaggeration therefore is defined as
1. d is exaggerated in strength of statement if s_d > s_j.
2. d is exaggerated in advice if a_d > a_j.
3. d is exaggerated in sample if x_d = human and x_j = non-human.

Overall, the document d is exaggerated with respect to j if d is exaggerated in strength of statement or in advice or in sample.

Exploratory analysis
In this section we present an extensive measurement study of different forms of exaggeration in the strength of statement, advice and sample. In specific, we investigate the extent of exaggeration across various (i) news agencies, (ii) universities as well as (iii) disciplines.

Exaggeration by news agencies
Our dataset comprises news articles from 21 different media outlets including some of the leaders like BBC, Reuters, Guardian, Telegraph and Daily Mail. In Figure we report the overall as well as the category level exaggeration values for some of the top media outlets. For strength of statement,
we show the 7-class and 2-class variants only (the results of the 4-class variant are very similar and therefore not shown). We note some of the key observations below.

- Certain media outlets seem to overall exaggerate in more than 60% (50%) of the articles they publish considering 7-class (2-class) variants in the strength of statement. Nevertheless, there are some outlets that keep the exaggeration level very low.
- An interesting observation is that the news agencies exhibiting higher overall levels of exaggeration as per the 7-class as well as the 2-class variants are very similar. For the 4-class too, this trend prevails.
- Most media outlets exaggerate heavily in their strength of statements. However, for certain media houses one also finds exaggerations in advice and sample levels.

Exaggeration by universities

We have 20 research universities in our dataset. In Figure 2, we report the overall and the category level exaggeration percentages among the press releases made by these universities considering the 7-class and the 2-class variants of strength of statement. The trends for the 4-class variant are again very similar and therefore not shown. We enumerate some of the important observations below.

- Like media houses, certain universities seem to exaggerate their press releases heavily. However, there are certain universities that rarely exaggerate their press releases.
- Some universities exaggerate mostly in the sample category. This means that results on non-human subjects are reported as being done on human subjects.
- Many universities tend to exaggerate in the advice category. There are also some universities that exaggerate in the strength of statements in all the six press releases present in our dataset.
- For both the 7-class and the 2-class classification of the strength of statements, similar universities come at the top in overall levels of exaggeration.

Exaggeration across disciplines

Each journal article can be categorized into a discipline. There are, in all, eight disciplines - childhood, lifestyle, treatment, policy, observational identification, ageing, mental health and physical disease. This categorization also extends to the followup press release and the news articles. We examine the extent of exaggeration in each of these disciplines in Figure 3. Some of the important observations here are provided below.

- The maximum overall exaggeration appears in the childhood and the lifestyle disciplines. This is true for the 7-class, the 4-class as well as the 2-class variants of strength of statements used in the definition of overall exaggeration.
- In general, exaggeration percentages are more in news articles than in the press releases. However, in some disciplines like mental health the exaggeration percentage in press releases is double or less compared to the percentage in news articles.

Spread of news articles in Twitter

In this section, we investigate how social media discussion of the news articles in our dataset propagates on Twitter. We believe that this a unique, important and novel contribution of our paper. In this context, we shall denote tweets discussing exaggerated news articles by tweet\_EN, and those discussing non-exaggerated news articles by tweet\_N\_EN.

Collection process: We collect the headline of each news article, and use it to search for the corresponding webpage. From the webpage we record the headline, url, text and links displayed when we click on the ‘tweet share’ button (if it exists), date, time and the name of the author. We might not find any online version of our news article sometimes, especially if the news article originally appeared in the print media. In this case, we exclude the news article from further investigation. With the aforementioned metadata for each news article, we search and collect tweets. To this purpose, we use the python library GetOldTweetsfrom
From the tweets collected, we retain only those that were posted after the news article was published. To avoid spam, we further remove tweets that do not contain any url that link to the news article’s webpage. The total number of tweets that we finally collect is 14,686; the number of tweets in the tweet EN and tweet NEN considering the three class variants of strength of statement are shown in Table 2. As the table shows, the tweet distribution is roughly balanced across the tweet EN and tweet NEN categories for all the three variants.

| classification | tweet EN | tweet NEN |
|----------------|---------|-----------|
| 7 class        | 7,689   | 6,997     |
| 4 class        | 7,255   | 7,431     |
| 2 class        | 6,952   | 7,734     |

Table 2: Number of tweets in our dataset as per the three variants.

The official Twitter python API tweepy could not meet our requirement because our news articles date from 2011.

In Table 3 we note some of the basic properties of these two types of tweets for all the three class variants. Fraction of likes, retweets and mentions for the tweet EN category seem to indicate that the tweets that propagate exaggerated news are usually more popular.

**Arrival time**

In order to understand the dynamics of the propagation we study the arrival time distributions of the tweets as follows. In particular, in Figure 4, we plot the fraction of tweets in each of the exaggerated and non-exaggerated groups as well as the overall fraction that arrive within one day, between one day and one year and after one year from the date of publication of the news. We compute these fractions for all the three class variants of the strength of statement (results shown for only the 7-class and the 4-class in Figure 4). An intriguing observation is that, across all the class variants of the strength of statement, the fraction of tweets in the tweet EN category is higher after one year compared to the fraction of tweets in the tweet NEN category. Motivated by this observation, in the following, we analyze the linguistic
Table 3: Fraction of important attributes (per tweet) for the two types of tweets in various classes of exaggeration. L: Likes, R: Retweets, H: Hashtags and M: Mentions, structure of the late tweets (that arrive after one year) and compare them with the early tweets (that arrive within one day).

| Exagg. class | Tweet type   | L   | R   | H   | M   |
|--------------|--------------|-----|-----|-----|-----|
| 7 class      | tweet$_{EN}$ | 0.06| 0.21| 0.23| 0.23|
|              | tweet$_{NEN}$| 0.05| 0.17| 0.26| 0.14|
| 4 class      | tweet$_{EN}$ | 0.06| 0.20| 0.23| 0.23|
|              | tweet$_{NEN}$| 0.05| 0.18| 0.26| 0.15|
| 2 class      | tweet$_{EN}$ | 0.06| 0.20| 0.23| 0.23|
|              | tweet$_{NEN}$| 0.05| 0.18| 0.25| 0.15|

Analysis of the tweets
To obtain a non-trivial set of tweets for the analysis, we filter the tweet text by removing the news headline from the text if it exists, any domain words like news, bbc, telegraph and user mentions (@). Next we perform LIWC (http://www.liwc.net/comparison.php) analysis on the tweet text separately on the early and the late tweets for both the classes. The LIWC dictionary has 64 pre-defined categories (e.g., pronouns, verbs, adverbs, social, family, friends etc.). For each category $c$, we find the number of words per tweet belonging to that category separately from the early and the late tweets of the tweet$_{EN}$ and the tweet$_{NEN}$ groups. Let $eEarly_c$ and $eLate_c$ denote the respective fractions for the early and the late tweets of the tweet$_{EN}$ group in the LIWC category $c$. Similarly, let $nEarly_c$ and $nLate_c$ denote the respective fractions for the early and the late tweets of the tweet$_{NEN}$ group in the LIWC category $c$. We now compute two ratios $r^c_{EN} = \frac{eLate_c}{nEarly_c}$ and $r^c_{NEN} = \frac{nLate_c}{nEarly_c}$.

If $r^c_{EN} > 1$, it means that the fraction of words of category $c$ has increased in the tweet$_{EN}$ group over time. Similarly, if $r^c_{NEN} > 1$ then it means that the fraction of words of category $c$ has increased in the tweet$_{NEN}$ group over time.

Finally, we compute the ratio of these two ratios $r^c = \frac{r^c_{EN}}{r^c_{NEN}}$.

If $r^c > 1$ then the increase, over time, in the fraction of words in category $c$ is more pronounced in the tweet$_{EN}$ group than in the tweet$_{NEN}$ class. We now consider the two extreme ends of this ratio, i.e., cases where either $r^c >> 1$ or $r^c << 1$. The former signifies stronger presence of the fraction of words in a category $c$ in the late tweets spreading exaggerated news relative to the late tweets spreading non-exaggerated news. The latter, on the other hand, indicates a weaker presence the fraction of words in a category $c$ in the late tweets spreading exaggerated news relative to the late tweets spreading non-exaggerated news. The LIWC categories having extreme low and high values of $r^c$ across all the class variants of the strength of statement are shown in Figures 5 and 6 respectively. Some immediate observations are as follows. The late tweets spreading exaggerated news (i.e., the tweet$_{EN}$ class) show stark differences in certain LIWC categories – while the words in categories like death words, sexual, sad and negative emotion indicate a weaker presence, a stronger presence is observed in categories like assert, future, and feel.

At this point we would like to point out that distinguishing LIWC categories (both $r^c << 1$ and $r^c >> 1$) noted above are consistent across the definitions of exaggeration assuming the 7-class, the 4-class and the 2-class variants of the strength of statement. There are certain categories like anxiety, religion, personal pronouns etc. for which we observed distinctions for the 7-class and the 4-class but not for the 2-class. Deeper investigation revealed that for the 7-class and the 4-class, the number of tweets featuring such words were just one or two thus (falsely) signaling a distinction. This disappears when we consider the 2-class. These words therefore are not actually distinctive and get correctly flagged so because we consider the three class variants instead of a single one.

Important insights from the analysis of tweets
Two key insights that we obtain in the course of the LIWC analysis are the following.

Opinion tweets: The late tweets that spread exaggerated news show an increase in the proportion of opinionated tweets. Some illustrative examples are

- something to think about. from news -
- anyone noticed benefits of ?
- should #midwives undertake this test?
- no genetic testing needed, i know i have this gene!

this is great news if it really works.

This shows that the crowd is not just absorbing and spreading the news blindly but is forming a strong opinion about the same. Tracking these opinions over time therefore can help in developing a completely crowd-sourced mechanism to identify exaggerated news. To validate this further, we create a dictionary of opinion phrases and calculate the number of opinion phrases occurring on average in the early and late tweets of the tweet$_{EN}$ and the tweet$_{NEN}$ classes. As shown in Figure 7a, the number of opinion phrases increases drastically for the late tweets in the tweet$_{EN}$ class (results are shown when the definition of exaggeration assumes the 7-class variant of the strength of statement; for
Figure 5: LIWC categories having \( r^c << 1 \).

Figure 6: LIWC categories having \( r^c >> 1 \).

the 4-class and the 2-class variants the trends are very similar).

Figure 7: Fraction of opinion and realize words per tweet over time in the \( \text{tweet}_{EN} \) and \( \text{tweet}_{NEN} \) classes.

Realization tweets: Another very interesting insight that we gain is that the late tweets that spread exaggerated news also show an increase in the proportion of “realization” among the crowd. Some illustrative examples are noted in Table 4 along with the source news headline. This immediately shows that the crowd does not behave like a dumb box; instead the wisdom of the crowd is fully functional and becomes even stronger when exposed for longer time periods. This growing wisdom can be once again leveraged to confirm the authenticity of news articles. To strengthen our point we calculate the fraction of ‘realize’ words per tweet in the early and late tweets of both the \( \text{tweet}_{EN} \) and \( \text{tweet}_{NEN} \) classes. We use Pwerthesaurus’ realization lexicon\(^\text{10}\) with a minimum similarity rating of 5 for this purpose. As shown in Figure 7b the fraction of realization words increases in tweets of the \( \text{tweet}_{EN} \) class over the time, whereas for the \( \text{tweet}_{NEN} \) class, this fraction remains the same (results are once again shown when the definition of exaggeration assumes the 7-class variant of the strength of statement; the trends remain very similar for the 4-class and the 2-class variants).

Users spreading exaggerated news

In this section we compare the tweeting behavior of the users who post exaggerated news content more frequently with those who never or rarely post exaggerated content.

Dataset: For this purpose we crawl the timelines of all the users posting the \( \text{tweet}_{EN} \) and \( \text{tweet}_{NEN} \) tweets. This results in 8060 unique users and 21,029,228 timeline tweets. Based on the number of exaggerated news in our dataset a user has tweeted about, we divide the users into four categories (i) \( \text{users}_{NEX} \): set of users who never tweet about any exaggerated news, (ii) \( \text{users}_{EX1} \): set of users who tweet about exactly one exaggerated news (i.e., rarely), (iii) \( \text{users}_{EX2} \): set of users who tweet about two exaggerated news, and (iv) \( \text{users}_{EX3} \): set of users who tweet about three or more exaggerated news. The distribution of the number of users and the volume of timeline tweets across the different user categories are shown in Table 5.

Key results: Figure 8 shows the average number of retweets and mentions that a user gets per tweet in each category. Users who post exaggerated news more frequently tend to get less retweets/mentions. The average number of follow-
Table 4: Tweets demonstrating realization of the crowd.

| News headline | Tweet body |
|---------------|------------|
| Violent homes have the ‘same effect on brains of children as combat does on soldiers’ | did you know? can same impact that has a soldier? |
| Violent homes have the ‘same effect on brains of children as combat does on soldiers’ | i might but it depends person who sees it and what happened in your childhood #appcar |
| Poor diets may lower children’s IQ | iq. this is child abuse. #childism |
| Why the deaf see better than those who can hear | well, for me, i use my glasses just because of my vision doesn’t mean i get blind. |
| Why the deaf see better than those who can hear | do you agreed with scientists discovered that have vision hearing?? |

| User type | [Users] | [Timeline Tweets] |
|-----------|---------|-------------------|
| users\_NEX | 3,019 | 7,870,784 |
| users\_EX1 | 4,024 | 10,191,495 |
| users\_EX2 | 584 | 1,634,397 |
| users\_EX3 | 433 | 1,332,552 |

Table 5: Distribution of number of users and time-line tweets across user types.

ers of the users who post more exaggerated content is significantly higher (see Figure 9). Users who post exaggerated content more frequently use more slang words, less hyperbolic words, and less word contractions in their tweets (see Figure 10). Further LIWC analysis of the time-line tweets shows that the categories like ‘bio’, ‘health’, ‘body’ and ‘negative emotion’ are dominant in case of users who post exaggerated news more frequently.

**Prediction model:** We attempt to build a classifier that can automatically distinguish between the two classes of users – (class I: users\_NEX, users\_EX1), i.e., those who never or rarely post exaggerated content and (class II: users\_EX2, users\_EX3), i.e., those who post exaggerated content more frequently. We use the features described above like the retweet and mention count, count of slang, hyperbolic and contraction words and LIWC features. In addition, we also use simple features like the tweet count, the word count, the total word length, the number of stop words and the number of common phrases (commonly used catchphrases adapted from (Chakraborty et al. 2016)). We do a stratified ten fold cross validation for the evaluation. The precision, recall and F1-scores for different classifiers are presented in Table 6. Note that we use appropriate class weighting for both classification as well as precision/recall/F1-score calculation since our classes are unbalanced (number of users in class I is much larger than the number of users in class II).

**Conclusion**

In this paper we observe that tweets spreading exaggerated news items show distinctive increase in proportions at later times. While fraction of words in certain LIWC categories like *assent, future* etc. show a stronger presence in such tweets, for certain others like *anger and negative emotion* there is a weaker presence. A deeper digging into the text further reveals that such tweets are more opinionated and portray larger realization by the crowd. Users posting exaggerated content more frequently are distinct in their tweeting behavior.

One of the most crucial future steps would be to study the cascading properties of exaggerated content in social media. For instance, it might be interesting to estimate and be able to predict the depth of the spread of exaggerated content over the social network. Another direction would be to develop a framework to automatically detect if a statement is an exaggerated version of the other.

**References**

[Adams et al. 2017] Adams, R. C.; Sumner, P.; Vivian-Griffiths, S.; Barrington, A.; Williams, A.; Boivin, J.; Cham-
Figure 10: Various linguistic properties of the timeline tweets for various user categories.

| Classifier   | Precision | Recall | F1 Score |
|--------------|-----------|--------|----------|
| Naive Bayes  | 0.83      | 0.69   | 0.74     |
| Random Forest| 0.85      | 0.87   | 0.92     |
| SGD Classifier| 0.72      | 0.43   | 0.64     |
| XGBoost      | 0.83      | 0.87   | 0.93     |
| SVC          | 0.76      | 0.87   | 0.81     |

Table 6: Class weighted precision, recall and F1-score for classification of users into class I and class II.

[Schwartz et al. 2012] Schwartz, L. M.; Woloshin, S.; Andrews, A.; and Stukel, T. A. 2012. Influence of medical journal press releases on the quality of associated newspaper coverage: retrospective cohort study. *BMJ* 344:d8164.

[Selvaraj, Borkar, and Prasad 2014] Selvaraj, S.; Borkar, D. S.; and Prasad, V. 2014. Media coverage of medical journals: do the best articles make the news? *PloS One* 9(1):e85355.

[Sumner et al. 2014] Sumner, P.; Vivian-Griffiths, S.; Boivin, J.; Williams, A.; Venetis, C. A.; Davies, A.; Ogden, J.; Wheelan, L.; Hughes, B.; Dalton, B.; et al. 2014. The association between exaggeration in health related science news and academic press releases: retrospective observational study. *Bmj* 349:g7015.

[Sumner et al. 2016] Sumner, P.; Vivian-Griffiths, S.; Boivin, J.; Williams, A.; Bott, L.; Adams, R.; Venetis, C. A.; Wheelan, L.; Hughes, B.; and Chambers, C. D. 2016. Exaggerations and caveats in press releases and health-related science news. *PloS One* 11(12):e0168217.

[Taylor et al. 2015] Taylor, J. W.; Long, M.; Ashley, E.; Denning, A.; Gout, B.; Hansen, K.; Huws, T.; Jennings, L.; Quinn, S.; Sarkies, P.; et al. 2015. When medical news comes from press releases a case study of pancreatic cancer and processed meat. *PloS One* 10(6):e0127848.

[Woloshin et al. 2009] Woloshin, S.; Schwartz, L. M.; Casella, S. L.; Kennedy, A. T.; and Larson, R. J. 2009. Press releases by academic medical centers: Not so academic? *press releases by academic medical centers. Annals of Int. Med.* 150(9):613–618.

[Yavchitz et al. 2012] Yavchitz, A.; Boutron, I.; Bufeta, A.; Marroun, I.; Charles, P.; Mantz, J.; and Ravaud, P. 2012. Misrepresentation of randomized controlled trials in press releases and news coverage: a cohort study. *PLoS Medicine* 9(9):e1001308.