Digital Tears, or the Impact of Terror Events on the Social Media Sphere

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Abstract

In this paper, we are describing our analysis of the reactions happening on the Social Media sphere following terror events around the world. By using a database of more than 17 billion tweets on a five years time interval, we first describe how we filtered the data, before matching it with a terror attacks database from Wikipedia. The concept of text filter is used on diverse part of the project, where we assign scores to different words in order to relate an attack with a reaction, along with other parameters such as the date. We complete our analysis with a more in-details look at terror attacks over the studied time period.

0 Introduction

Since the rise of the different Social Media giants in the end of the first decade of the millennial, our way of communicating, reacting to events has significantly changed. What was a decade ago not possible is now happening in a continuous way; everyone can inform itself on an event happening at the other side of the world with a simple connection to an app, and react to this particular event in a matter of seconds with a message that can also reach most of the connected places in the world. We are placing ourselves as spectators of this interconnected social web, with a strong desire to analyze those social reactions and their distribution, depending on the type of event that the people react to. What are the cities and countries most affected by terrorism ? Are those location correctly reflected by the Twitter population ? Are certain communities, locations, societies prone to receive more attention than others when they are hit by a tragic event ?

In Section 1, we will explain how we collect and filter our two main sources of data. The first one is a tweet database consisting of around 17 billion of tweets sent from January 2011 to January 2016, and stored in the EPFL IC Cluster. The second one is a collection of Wikipedia pages listing all terrorist attacks that happened worldwide. In Section 2, the process of matching the two sources of data is described, along with the formulas and hypothesis that we use. We detail in Section 3 our analysis of the the data previously cleaned and filtered, before showing our results and findings.

1 Data collection and filtering

1.1 Wikipedia scraping

The goal was to index all the terrorist attacks than happened from a date up until today. Wikipedia has a great list of articles than have such information. All the articles follow the same structure which means it is easy to scrape with tools such as BeautifulSoup. Thus, we scraped every page that listed terrorist attacks. We chose to get the data from January 2011. We only kept the information about the date, place and type of attack (e.g. suicide bombings, mass shootings, etc.), along with the damage each attack caused.

1.2 Twitter database

The database being in the cluster, we make good use of Spark first through our Jupyter Notebook file for preliminary testing, before sending longer

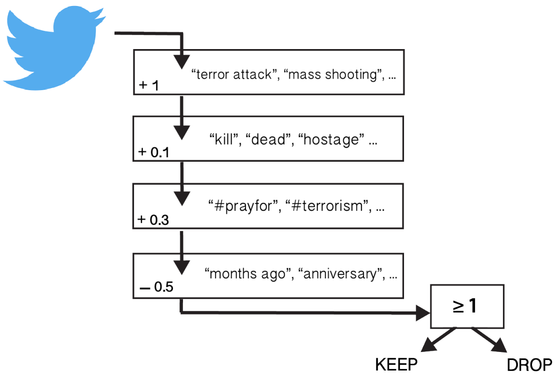

Figure 1: *First filter passed to Spark (simplified)*

processing jobs from the cluster. The strategy adopted is to compute a strict filter that would let through only the relevant content : tweet reactions to terrorist attacks. By doing so, we drastically increase the entropy of our data, passing from billions of tweets down to around half a million in our first filtering.

The filter (Figure 1) is composed of five list of words. The first three lists contain the most frequent words used in reactions to terrorist attacks, grouped by order of importance in three distinctive sets. The fourth list contains targeted hashtags, while the fifth is composed of words that should not be present in the tweets of our interests. Those lists are positively and negatively weighted, and a score is computed for every tweet passing through the filter, the tweet being accepted above a certain threshold.

2 Matching tweets with terrorist attacks

Even though, out of roughly 18 billions of tweets present in the cluster, we collected only 550 000 which gave us a ratio of $3 * 10^{-5}$ relevant tweets per tweet in the database not all of them are related to one particular attack. Which could be the case of this particular tweet:
Our task here is to build a filter, which we called the matched filter, that will match each tweets with at most one attack. We suppose that one tweet cannot refer to more than one attack. Even if it does, our filter will select the most relevant attack to match. The filter is quite different from the one described in Figure 1. Indeed, here we also need a score to validate a decision but in our case the decision is done over the whole set of attacks and not just on the tweet itself. We must therefore select the attack features that match the best with the selected tweet, and need to iterate over all attacks to pick the most related one. To do so, we defined for each relation between a tweet and an attack a score based on several criteria. At the end of iterating over all the attack set, we pick the attack that has the best score relating to one particular tweet, if we consider that the score is high enough (1 or more in our case). If it is not the case, we reject the tweet and classify it as none-matching.

2.1 Characteristics of the matched filter

The matching of a particular tweet to one terrorist attack is done according to *7 criteria* listed and explained bellow

– *date criteria*
This criteria is used to highlight the tweets and the attacks that are close in time to each other. The score computed from this criteria is evaluated according to the following function:

$$f[x] = \begin{cases} 0.79 & \text{if } 0 \geq x \geq 4 \\ \frac{0.79}{0.55*(x-4)+1} & \text{if } 4 \geq x \end{cases}$$

Note that this function is discrete and takes as input the difference time between the attack date and the tweet date. Moreover, we make sure that the attack happened before the tweet creation time. The function is only defined positively. In addition, the constant 0.55 is chosen so that the slope is not too abrupt after a difference of 4 days between the attack and the tweet.

– *death number criteria*
If a particular attack contains the following subset of characters: "die", "death", "dead", "kill" and the exact number of death, we proceed to increase the score according to the following formula:

$$score = prevscore + 0.24 * d(\# \ of \ deaths)$$

where $d(x)$ is the number of digits that x contains: ex. $d(1282) = 4$. And $prevscore$ is the score gathered from the previous criteria. We define this variable because it is less likely to have mistakenly the same death number for large numbers than for small ones. The 0.24 constant is here so that a 4 exactly digits match is just not acceptable to directly classify the attack. This criteria is also fulfill if $\#death$ of the attack is equal to $\#death - 1$ contained in the tweet. Indeed, Wikipedia includes the death of the killer whereas most of the twitter users do not.

– *injured number criteria*
It is similar as the death criteria, but for the number of injured.

– *country criteria*
If a particular tweet contains the name where a particular attack happened, the score is increased by 0.6.

– *city criteria*
Similar than the country criteria except that since a city location is much more precise than a country one, we increase the score with 0.8 if the criteria is fulfilled.

– *type criteria*
If the tweet contains the particular attack type we increase the score by 0.5.

– *penalty word criteria*
The penalty words are the words that do not match the context of a terror attack. We acknowledge that if one or more of the penalty word are present in the tweet, we subtract 0.3 from the score. Example of those word : "great", " happy", " friend". The space before happy is to prevent that a tweet containing "unhappy" fulfill the criteria.

2.2 Efficiency vs Amount of collected tweets

To speed up the process of matching the tweets, we introduce the concept of sliding time window (STW). This time window represents the lapse of time from the attack to the tweet. We put an upper bound for the width of the STW to 31 days. It is a fair value according to us, since we noted that Twitter reactions are in large numbers in the first few days, before rapidly fading. This means that we no longer have to check whether a tweet is about an attack that happened more than a month ago. This process is saving us a lot of computational resources.

3 Description, analysis and results

3.1 Most dangerous places

We computed a dataset containing 4073 attacks up until December 19th, 2017. However, to match our Twitter data, we keep the data until January 31st, 2016, containing information about 1574 attacks. Based on the data retrieved from Wikipedia, we can find out about the most dangerous places in terms of number of attacks, or in terms of number of deaths. In both cases, the 2 countries where the most attacks happened are Iraq and Afghanistan. Another interesting fact is that attacks in Europe or in North America are less deadly than attacks in Africa or in the Middle East for example. We can see that when comparing the map with the number of attacks shown, and the one with the number of deaths per country. For example, the US has a ratio of around 4 deaths per attack (10 attacks, for a total of 41 deaths), while Iraq had had 278 attacks for 7923 deaths, which computes to around 29 deaths per attack.

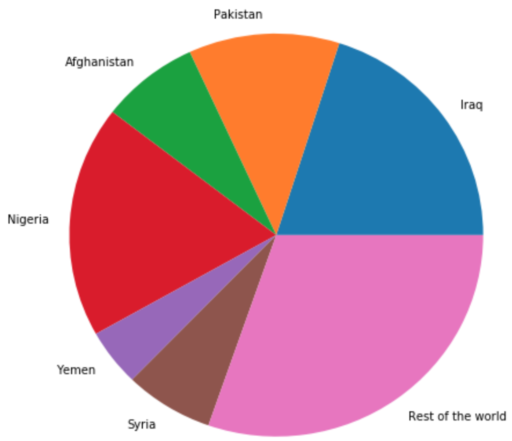

Figure 2: *Death toll distribution by country (%)*

Moreover, one very shocking result that can be obtained by aggregating the death toll by country (Figure 2) is that 6 countries are sharing almost **80% of all the deaths by terrorist attacks**, while all the other (almost 200) countries are accounting the the remaining 20%.

3.2 Mixing the data : real impact vs social impact

As expected, the social impact is greater when the attacks happen in an European country (especially France) or in the US. France is the most 'tweeted' country after attacks, containing around 44000 tweets, while other countries - that have a more important impact in terms of number of deaths - receive a much weaker social reaction.

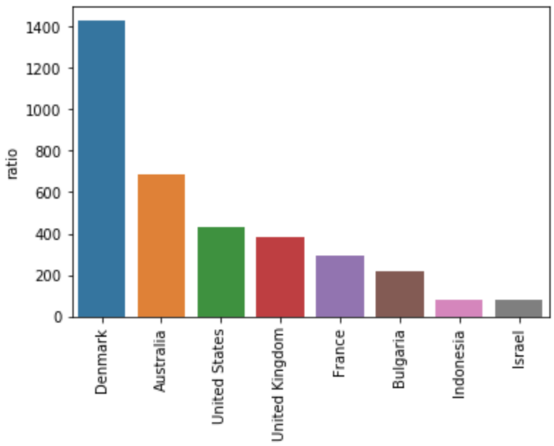

Figure 3: *Ratio of Tweet per victim of terrorism, by country*

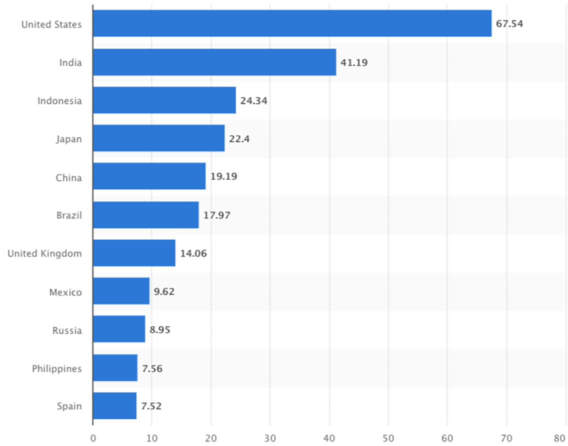

Figure 4: *Number of active Twitter users in million, 2017 (Statista DMO, 2017)*

One good way to see the difference between countries is to compute the number of tweets per victim of terrorism. By doing so, we can highlight the disparity of the reactions, with countries like Denmark having a ratio of more than 1400, compared to a ratio of 2.5 for the country most affected by the terrorist group *Boko Haram*, Nigeria. Finally, we observe that none of the six countries most hit by terror attacks in Figure 2 are present in the Figure 3.

3.3 Reflexion on results

The results obtained with the help of the Twitter database are representative of the content and more importantly the authors of the Tweets. Twitter being an company accessible through the Internet that first expanded in the USA, the distribution of the users will reflect the number and the content of the reaction. We can see on Figure 4 that the market is dominated by a few countries like the USA and India, and as a consequence the number of users in an area highly hit by terrorist events like the Middle East is marginal. An other important consideration is that Social Media users are reacting to the news that they are aware of. This principle allows the Media to have an important impact on the reaction distribution, by selecting and highlighting some terror events more than others (Nesrine Malik, 2015).

As we saw in the previous sections, the most famous Western capitals and cities are getting more attention through the reactions of the general public on Twitter. However, this difference has to be taken with care. The cities under the spots are already the ones that receive the most general attention: fewer people can name Peshawar, Pakistan as opposed to Paris, New York, Cairo. This lack of precision is pushing the reacting population to be less precise by omitting crucial and precise information about the attack, even though they were precisely reacting to this attack. Moreover, our approach being largely empirical, we don't expect the efficiency of a highly-trained Machine Learning Algorithm. We introduced some bias by designing the filter according to what we judged relevant and objective. Our procedure is nevertheless a good approach on the understanding of the difference of flow of massive reaction around the world.

4 Conclusion

A complete data analysis has been presented, with collection, filtering, merging and description steps. In our case, the filtering and matching of the data was the most important, as the link between real impact and social impact was the center of the project. Moreover, false positives are the elements that we want to avoid as much as possible with the help of a good filtering and matching. Plotting and ranking terrorist attacks were a first step towards the highlighting of Twitter reaction disparity, and the conclusions that we obtained are making us questioning our society and our information system, and can be a first step towards more equal recognition of lives of human beings, no matter where they come from.

References

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