Data Science Capstone - Tweet Classification System - Catastrophe or Not?

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Contents

1 Introduction

This document presents a machine learning model used to predict whether a particular tweet (message on Twitter.com) is related to a disaster/catastrophic event. This report is the last capstone assignment for HarvardX's Professional Certificate in Data Science, which can be taken at the edX platform. The program is available at https://www.edx.org/professional-certificate/harvardx-data-science.

This problem has been inspired in a Kaggle's beginner competition called Real or Not? NLP with Disaster Tweets. However, the data used in this data used in this exercise does not come from Kaggle. Instead, it has been downloaded directly from Kaggle's inspiration on figure-eight's "Data for Everyone" webpage.

Based on that aforementioned dataset, this report proposed an machine learning model that divides each tweet into four constituent components. A prediction for each of the component is made and an overall prediction is created based on those individual results. The four components or attributes are:

- The text/words of the tweet (natural language).
- The hashtags in the tweet, which should be meaningful labels for the content.
- The links included in the message. Since links are shared using the t.co shortening services, those will be "unshortened" and classified according their original URL domain.
- Any mention to other Twitter users ("handles" in Twitter's terminology).

This work is presented in the following sections: 1. This **Introduction**. 2. **Analysis**, which includes: 2.1 Initial data loading and cleaning into a workable format 2.2 Initial modelling, where the prediction algorithm is created. 2.3 Algorithm Finalisation, where it is tested and refined 2.4 Tuning of the most relevant parameters 3. Evaluation of **results** against validation dataset. 4. **Conclusions**.

The subsequent sections present the above points in further detail.

This file, and its associated R and csv files are available in Github.

2 Analysis

As mentioned in the Introduction, this report presents the attempt to build a machine learning model to classify Tweets in a binary model. In this particular case, the question to answer is whether those tweets correspond to a catastrophic event or not. The idea for this was taken of a Kaggle Competition for Starters (Real or Not? NLP with Disaster Tweets). Instead of using the data provided in Kaggle, in this report the original version in Data For Everyone is used.

To start, let's have look at sample data:

Table 1: Sample Data

id	target	text	keyword	location
1	1	Just happened a terrible car crash	NA	NA
6	1	All residents asked to 'shelter in place' are being notified by officers. No other evacuation or shelter in place orders are expected	NA	NA
33	0	London is cool ;)	NA	NA
49	1	@bbcmtd Wholesale Markets ablaze http://t.co/lHYXEOHY6C	ablaze	Birmingham
160	0	'The harder the conflict the more glorious the triumph.' Thomas Paine	aftershock	304
914	1	Uganda Seen as a Front Line in the Bioterrorism Fight	bioterrorism	Alaska
3 999	0	I forgot to bring chocolate with me. Major disaster.	disaster	Los Angeles, London, Kent
7 336	1	Finnish ministers: Fennovoima nuclear reactor will go ahead http://t.co/vB3VFm76ke #worldnews #news #breakingnews	nuclear%20reactor	World

As seen above, the dataset contains the following observations (to match Kaggle's format):

- **id** : unique sequential identifier.
- **target** : indicator of whether the tweet corresponds to a catastrophic event (**1**) or not (**0**).
- **text** : tweet, as extracted from Twitter.
- **keyword** : search term used in Twitter's search bar to retrieve the tweets.
- **location** : Name of the place where the tweet in question originated.

For this report, **keyword** and **location** will be ignored, choosing to focus on the text (tweet) only. After a brief observation of its content, in this analysis the text will be divided into four component:

- The text proper. i.e. the *natural language* sentence in the text. In the code, this will be called **words**. All the tweets in this file are written in English language, but they may contain non-English characters, emojis and emoticons.

- The **hashtags**, which are in user created categorisation. This is a meaningful component of the tweet and may help clarify whether the message is a real disaster. For example, in below tweet, the hashtag helps us to elucidate this is cricket commentary rather than a fire disaster:

Table 2: Tweet about cricket

id	text
1 674	Australia's Ashes disaster - how the collapse unfolded at Trent Bridge| cricket

- The **links** contained in the tweet - perhaps the respective Internet domain could help distinguish "quality" disaster sources (e.g. official announcement from relevant authority, The Red Cross/Crescent) from non-disaster ones (e.g. gossip magazine using hyperbolic language). To obtain meaningful content though, the links need to be "unshortened" from the t.co addresses provided by Twitter.
- Who is mentioned in the tweet (by their Twitter **handles**). Similarly to the previous points, it may be useful to distinguish between people reaching out to government/emergency service from *shock jocks* using florid language.

2.1 Processing and cleaning up the data

In order to obtain the data in the desired format for analysis, the function *prepare_data* has been created. Its code performs the below activities:

1. Extract hashtags, links and Twitter handles from the tweet.
2. Clean up the remaining text, removing links and handles, and performing transformation operations on emojis,emoticons and other special characters.
3. (Optional) Replace swear words and profane language with unique strings, in case seeing those wants to be avoided, yet retaining the words for analysis. Please note this report has been generated with the uncensored version, thus results may vary.
4. "Unshorten" link URLs to obtain domain names of linked sources.

The first step is similar for the three components - below is the code use to remove the hashtags:

```r
source_data$hashtag <- str_extract_all(source_data$text, "#\\S+")
 source_data <- source_data %>%
   mutate(hashtag = gsub(x=hashtag,
          pattern = "character\\(0)", replacement = "")) %>%
   mutate(hashtag = gsub(x=hashtag, pattern = "c\\(", replacement = "")) %>%
   mutate(hashtag = gsub(x=hashtag, pattern = "\"", replacement = "")) %>%
   mutate(hashtag = gsub(x=hashtag, pattern = ")", replacement = "")) %>%
   mutate(hashtag = gsub(x=hashtag, pattern = ",", replacement = ""))
```

In the following step, both links and mentions are removed, keeping the hashtags since they may also be part of the sentence in question. Then, leveraging the functions in the **textclean** package, the remaining data is further normalised, by replacing :

- contractions with full words,
- emojis and emoticons with equivalent word (e.g. :) with 'smile'),
- all non-ASCII characters wit equivalent,
- Internet slang with full words,
- html code,
- money symbols,
- numbers with full words,
- ordinals with full words replace_ordinal,
- timestamps.

The code that achieves this is shown below:

```
 #remove mentions and links from text, save original text in different observation

   source_data$original_text <- source_data$text
   source_data <- source_data %>%
    mutate( text = gsub(x = text, pattern = "#", replacement = ""))  %>%
    mutate( text = gsub(x = text, pattern = "@\\S+", replacement = "")) %>%
    mutate(text = gsub(x=text,
                       pattern = "(s?)(f|ht)tp(s?)://\\S+\\b",
                       replacement = ""))

#further clean text with textclean package

  source_data$text<-replace_contraction(source_data$text)
  source_data$text<- replace_emoji(source_data$text)
  source_data$text<- replace_emoticon(source_data$text)
  source_data$text<-replace_non_ascii(source_data$text,impart.meaning=TRUE)
  source_data$text<-replace_internet_slang(source_data$text)
  source_data$text<-replace_html(source_data$text)
  source_data$text<-replace_money(source_data$text)
  source_data$text<-replace_number(source_data$text)
  source_data$text<-replace_ordinal(source_data$text)
  source_data$text<-replace_time(source_data$text)
```

An optional step is to remove swear and profane vocabulary from the text, in case that is desired. This has been done through the below code:

```
  #profanity removal

  if(profanity_clean==1){

    #download profane words and prep for matching
    data(profanity_zac_anger)
    data(profanity_alvarez)
    data(profanity_arr_bad)
    data(profanity_banned)
```

```r
data(profanity_racist)
Sys.sleep(100)

special_chars <- as_tibble(c("\\!", "\\@",  "\\#","\\$", "\\&","\\(","\\)",
                             "\\-","\\‘","\\.","\\/","\\+",'\\"','\\"'))
special_chars$replacement <- paste0("st",
                                    stri_rand_strings(nrow(special_chars),
                                    3, '[a-zA-Z0-9]'))

profanity<-as_tibble(c(profanity_zac_anger,profanity_alvarez,
                       profanity_arr_bad,profanity_banned,
                       profanity_racist))
profanity<-unique(profanity)
profanity$replacement <- paste0("pr",
                                stri_rand_strings(nrow(profanity),
                                7, '[a-zA-Z0-9]'))

for(i in 1:nrow(special_chars)){
  profanity <- profanity %>%
    mutate(value=gsub(special_chars[i,]$value, special_chars[i,]$replacement,
                      value))
}
profanity <- profanity%>% mutate(value=paste0('\\b', value, '\\b'))

rm(profanity_zac_anger,profanity_alvarez,profanity_arr_bad,
   profanity_banned,profanity_racist)

#clean up profane words, replace by random string

for(i in 1:nrow(special_chars)){
  twitter_df <- twitter_df %>%
    mutate(text=gsub(special_chars[i,]$value,
                     special_chars[i,]$replacement,
                     text))
}

for(i in 1:nrow(profanity)){
  twitter_df <- twitter_df %>%
    mutate(text=gsub(profanity[i,]$value,
                     profanity[i,]$replacement,
                     text,ignore.case = TRUE))
}


twitter_df <- twitter_df %>%
  mutate(text=gsub("st[a-zA-Z0-9][a-zA-Z0-9][a-zA-Z0-9]",
                   "",text,ignore.case = TRUE))
    rm(profanity,special_chars)
  }
```

As a last step, the function *expand_urls* from the *longurl* package has been leveraged to unshorten the t.co URLs, to obtain the domains of the links. This is done trough the below code:

```
split<-200
value <- round(nrow(processed_source)/split,0)
segments <- tibble(start=integer(),end=integer())
segments <- add_row(segments, start=1,end=value)

for(i in 2:(split-1)){
   segments <- add_row(segments, start=value*(i-1)+1,end=i*value)
}

   segments <- add_row(segments, start=value*(split-1)+1,
                       end=nrow(processed_source))

# first segment
   segment <- processed_source[segments[1,]$start:segments[1,]$end,]
   domains<-get_domains(segment,anonimised = 0)
   iteration <- 1

for(i in 179:split){
  segment <- processed_source[segments[i,]$start:segments[i,]$end,]
   domains_i<-get_domains(segment,anonimised = 0)
   domains <- rbind(domains,domains_i)
   iteration <-segments[i,]$start
}

domains <-  domains %>%
    mutate(domain = gsub(x=expanded_url,
                         pattern = "(http|ftp|https)://",replacement = "")) %>%
    mutate(domain = gsub(x=domain,
                         pattern = "www.", replacement = "")) %>%
    mutate(domain = gsub(x=domain,
                         pattern = "ww[0-9].", replacement = "")) %>%
    mutate(domain = gsub(x = domain,
                         pattern = "/S+", replacement = ""))

domains$domain <- domain(domains$expanded_url)
domains <-  domains %>%
    mutate(domain = gsub(x=domain, pattern = "www.", replacement = "")) %>%
    mutate(domain = gsub(x=domain, pattern = "ww[0-9].", replacement = "")) %>%
    mutate(domain = gsub(x = domain, pattern = "m.", replacement = ""))

domains_list <- domains %>% select(domain) %>% unique(.)
```

```r
domains_list$domain_key <- paste0("domain_",seq.int(nrow(domains_list)))
domains <- domains %>% left_join(domains_list,by="domain")
```

As result of this processing, we have two data frames to use for further analysis: one with the processed tweets and another with a list of t.co URLs and domains. A sample of both is shown below:

Table 3: Sample Data

id	target	text	hashtag	link	mention
1	1	Just happened a terrible car crash	NA	NA	NA
6	1	All residents asked to 'shelter in place' are being notified by officers. No other evacuation or shelter in place orders are excuse me tongue sticking out ected	NA	NA	NA
33	0	London is cool wink	NA	NA	NA
49	1	Wholesale Markets ablaze	NA	http://t.co/lHYXEOHY6C	@bbcmtd
160	0	'The harder the conflict the more glorious the triumph.' Thomas Paine	NA	NA	NA
914	1	Uganda Seen as a Front Line in the Bioterrorism Fight	NA	NA	NA
3 999	0	I forgot to bring chocolate with me. Major disaster.	NA	NA	NA
7 336	1	Finnish ministers: Fennovoima nuclear reactor will go ahead worldnews news breakingnews	#worldnews #news #breakingnews	http://t.co/vB3VFm76ke	NA

Table 4: Sample Data

link	domain	domain_key
https://t.co/irWqCEZWEU	bbc.co.uk	domain_1
https://t.co/lHYXEOHY6C	twitter.com	domain_2
https://t.co/pmlOhZuRWR	sigalert.com	domain_17
https://t.co/GKYe6gjTk5	lawsociety.org.uk	domain_18
https://t.co/FaXDzI90dY	change.org	domain_61
https://t.co/SB5R7ShcCJ	change.org	domain_61
https://t.co/ZNTg2wndmJ	twitter.com	domain_2
https://t.co/JLRw0Oi9ee	twitter.com	domain_2

Both datasets in their "uncensored" and "sanitised" versions have been made available on GitHub.

Before proceeding, we will split this data into three datasets:

- a **training** dataset, to be used for further analysis, modelling and tuning.
- a **testing** dataset, to be used in tuning.
- a **validation** dataset, which will put aside and only use at the end to generate the last results.

Unless said otherwise all the below analysis has been done with the **training** dataset only!

2.2 Scoring each tweet.

In order to use a machine learning method that allows us to determine whether any relationship between the content of each tweet and its target status, we need to be able to generate a function that rates each piece of content. A way of do this is to generate a numeric value for each tweet, that then can be used for estimate whether it is "catastrophic" or not.

In the case with text, a simple way to achieve this is to assign each constituent word a score and then use those to calculate a sentence value (with a simple way of calculating such value being adding to individual scores). The following lines explain the way this was done in this particular exercise - please note that as a starting point, we are making them assumption this is a good method - how to determine the right formula is a problem by itself.

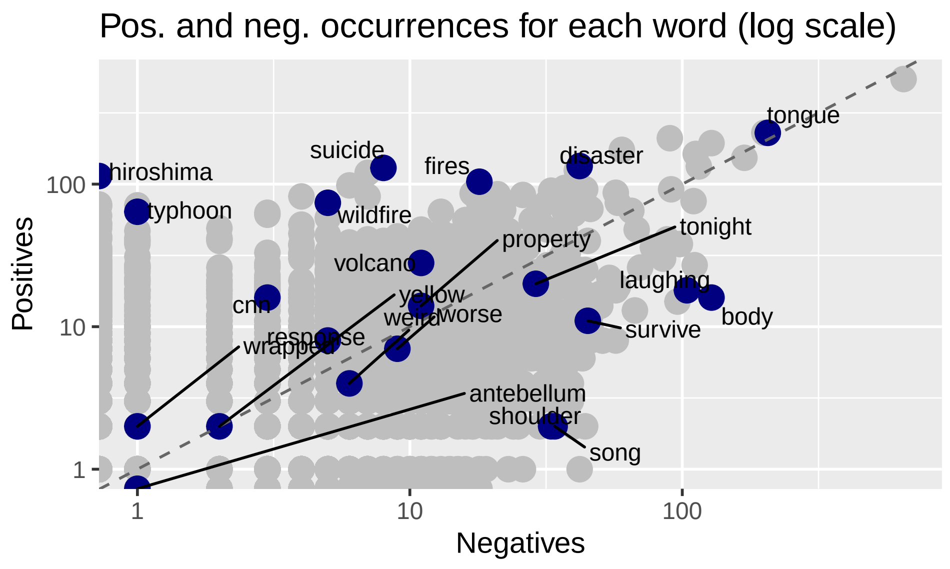
Taking the each tweets processed text, the first step is to "tokenise" this dataset, i.e. split it in its component words - for this the function *unnest_tokens* from the *tidytext* package has been used. Since we would like to know how this words are split between catastrophic ("positive") and non-catastrophic ("negative") entries and perhaps use this a scoring base, we will also remove "stop words" (common words such as "and" "or", basic verbs,etc..), we will filter them using the *stop_words* dataset available on *tidytext*.

The code to achieve this goes as follows:

```r
data("stop_words")
extra_stop_words$lexicon <- "EXTRA"
stop_words<-rbind(stop_words,extra_stop_words)
rm(extra_stop_words)


tokenised_words <- training_dataset %>% unnest_tokens(word,text)
tokenised_words <- output$tokenised_words %>%
                        anti_join(stop_words, by="word")
```

With the data, we can calculate how frequent each word is, in general and in both positive and negative tweets. The chart below shows this, highlighting some selected words for analysis:

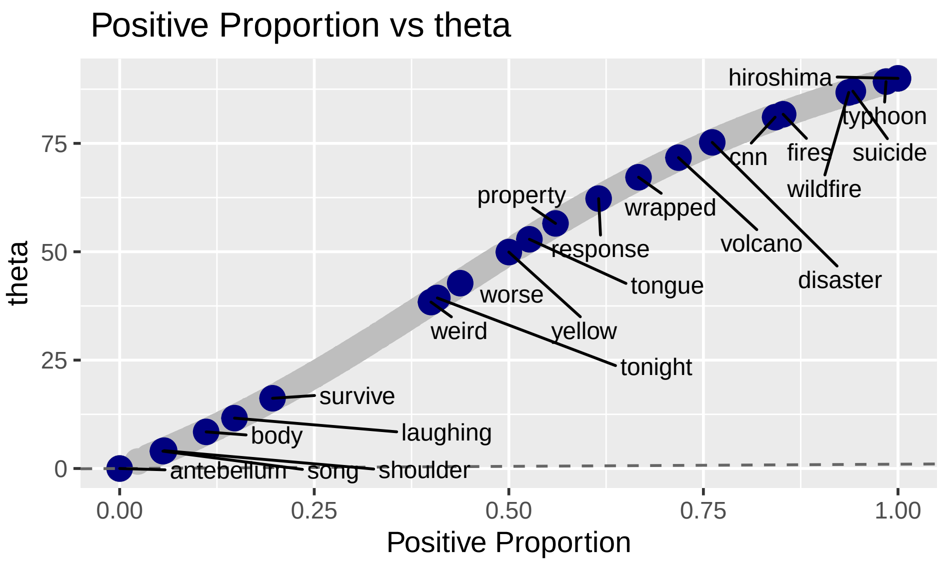


Since we are looking at the impact of the word for a tweet being positive, the above chart can be reduced to one indicator, the proportion each words appears positive tweets against its total number of appearances.

From here, the question is how to take this into a score for each word that:

- Properly weighs "disaster" related words.
- Penalises "non disaster" words but without reducing the impact of more ambivalent terms.
- Allows to establish a clear division, so when compounded it clearly helps to distinguish positives from negatives.

After thinking how to achieve this objective, a score was defined taken angle of each point in the avoid chart, being this an effective measure of how "positive" or "negative" a word is. If we call this angle θ, we can generate an initial score that looks like the below chart:



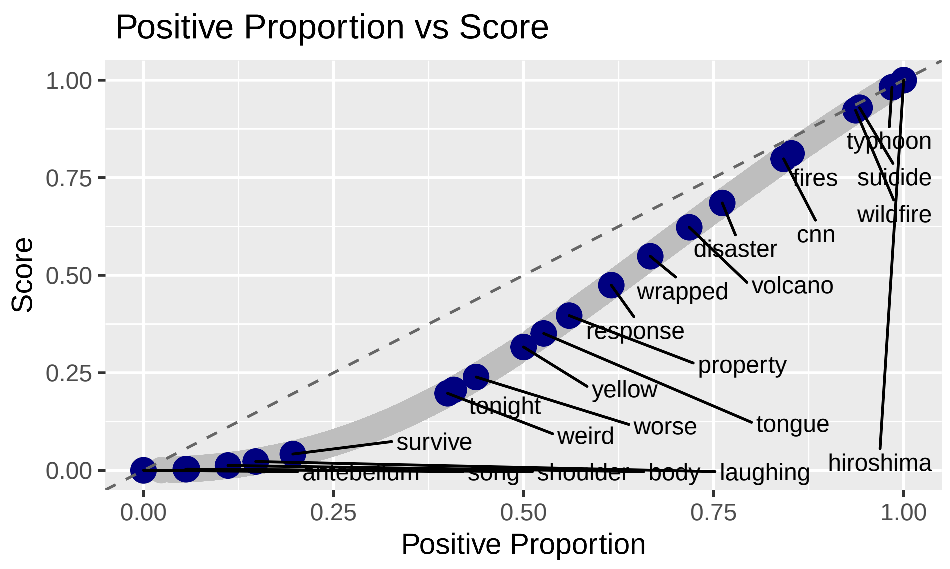
Although this is a good approach, after several iterations the following formula has been chosen instead:

$$pre\_score = sin(pos\_proportion)^{\lambda_1} * \frac{\theta}{90°}$$

$$score = \frac{pre\_score}{max(pre\_score)} - \lambda_2$$

where * $pos\_proportion$: Proportion of times where word was found in a "positive" tweet. This sinus of this parameter is used to help penalise less relevant words. * λ_1: Parameterisation parameter, used to modulate the effect of less relevant words. * θ: angle of vector $(positive\_proportion, negative\_proportion)$, as discussed previously. * λ_2: Offset to potentially give a negative value to less relevant words, in order to provide compensation - e.g. in case a "disaster" word is used in figurative context amongst many non relevant words. This will be treated as a tuning parameter.

Setting λ_1 to 1 and λ_2, we have a sample distribution, as follows:

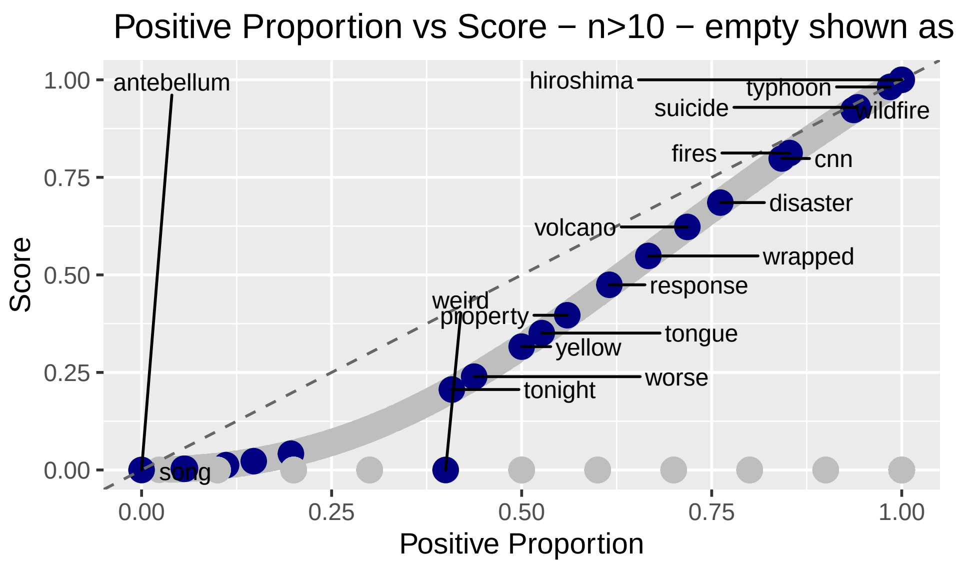


Looking at the chart above, we have achieve the objectives of giving distinct scores depending on the apparent "catastrophe" value of each word. This however, does not reflect the amount of times a word appears - it may be the case that a particular term appears just one and gets an extreme score which is not really a good indicator of its real "catastrophe value. Thus, a last modification of the formula is required:

$$score = \begin{cases} \emptyset & n \le \lambda_3 \\ \frac{pre\_score}{max(pre\_score)} - \lambda_2 & n > \lambda_3 \end{cases}$$

where * n : number of times the word is appears in the training set, * λ_3: arbitrary threshold to filter word with a low number of occurrences (and possibly biased). This is a tuning parameter.

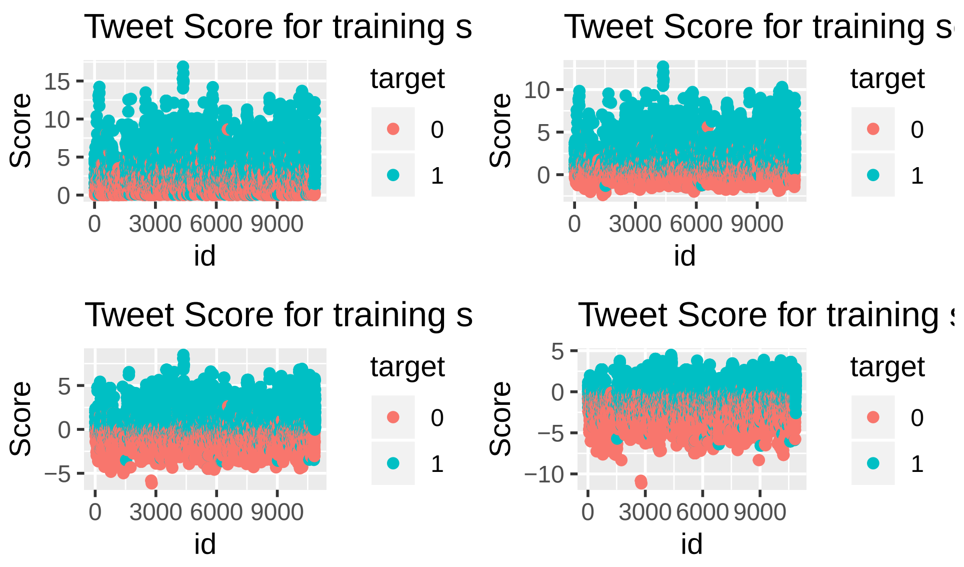
Using $\lambda_3 = 10$ for illustration purposes, we have the below chart:



With a set of scores, we would like to know if this produce a set of tweet scores that are a potential good input for a regression function. Due its simplicity, if we using a sum to calculate a score per tweet we can obtain those values with the below code:

```
tweet_score <- tokenised_words %>%
                  left_join(word_scores,by="word") %>% filter(!is.na(score)) %>%
                  group_by(id) %>% summarise(word_score=sum(score)) %>%
                  ungroup()
```

which, will produce results like the below graphs (for different offset values):



From the above, we can see that there is a diffuse division between positive and negative tweets. It is worth noticing this could potentially be improved with better modelling - however this could a problem but itself and the above - with tuning - is deemed acceptable for a first approximation.

A similar process has been done two create tweet scores for hashtags, links(or rather the domains of the unshorten URLs) and mentions. After try and error, a slightly different formula has been chosen for these three observations, represented below for hashtags:

$$pre\_score = \left(\frac{pos\_proportion}{\lambda_1}\right)^{\lambda_2} \cdot \frac{\theta}{90}$$

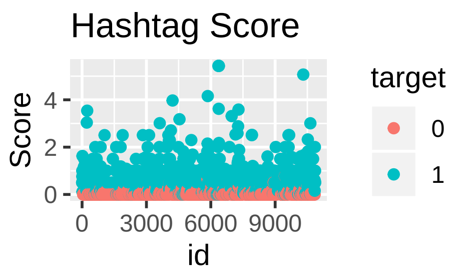
$$score = \begin{cases} \emptyset & n \leq \lambda_4 \\ \frac{pre\_score}{max(pre\_score)} - \lambda_3 & n > \lambda_4 \end{cases}$$

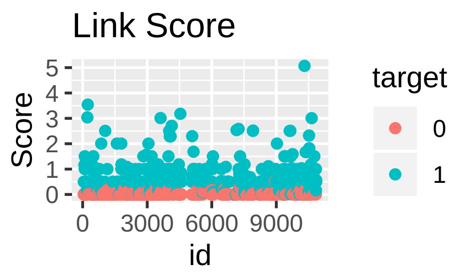
where

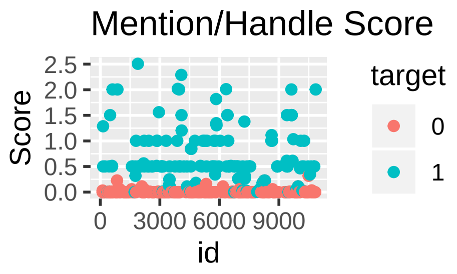
- $pos\_proportion$ is the proportion of the term in the entire corpus of positive hashtags/domains/mentions,
- λ_1 tuning parameter that re-scales - everything above the threshold is relevant, the rest not so much,

- λ_2 tuning parameter to weigh down irrelevant terms and weigh up relevant ones,
- θ angle of vector $(negatives, positives)$,
- λ_3, Offset to potentially give a negative value to less relevant term, in order to provide compensation - e.g. in case a "disaster" word is used in figurative context amongst many non relevant term This will be treated as a tuning parameter.
- λ_4, threshold of number of occurrences necessary to consider the score as valid.

The below charts show an example of score generated using this method:







In order to facilitate the next steps, the above process has been written into three functions, namely:

- **tokenise_data**, which takes the data in the pre-processed format and generates a data frames with the token words, hashtags, domains and Twitter handles.
- **calculate_scores**,which takes the output of the previous function (*tokenised* data) and calculate the scores for each word, hashtag, link and handle. All the previously discussed tuning parameter have been defined as inputs for this function.
- **score_tweets**, which will generate a score for each tweet for each of categories previously mentioned.

All these functions are written in the accompanying .R file, with in-line commentary explaining all the steps involved in the process.

2.3 Finalising the model and data quality.

From here, we can move to the next step and to generate the last part of the model - the one that will render a prediction.

Considering the work done so far, there are potentially many ways to use to the scores to create a model for prediction. After weighing the options, the following two-step approach will used:

1. First, a regression algorithm will be used to train a model for each attribute - i.e. 4 different predictions will be generated using each of the 4 scores previously created independently. The result of this process will be vector for each tweet, with the results of each prediction (1,0 or potentially N/A if there is no such attribute for a given tweet.)
2. Then this vector will be used again as a input of a second machine learning method , which will attempt to predict the target result based on the individual responses.

For this process, two functions have been written in this report .R file:

- **fit_model**, which is the training function. Its inputs are the scores plus relevant tuning parameters. It will output 5 machine learning models (for each attribute plus the aggregate one).
- **predict_values**, which will take the training score, the test data and the models previously generated. it will output the predictions and measure accuracy if the target value is provided.

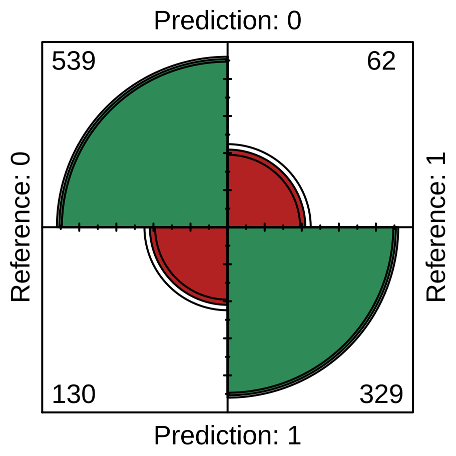
These functions leverage the caret package and they have been written to provide some flexibility - for example **fit_model** allows to be run using different machine learning models. For further details, please refer to the detailed commentary in the .R file.

For the initial run - that will help us establish and initial benchmark - the general linear model (glm) in caret is used for the individual predictions. For the aggregate prediction, we will use xgbBoost. For this the below code is used:

The accuracy for table and confusion matrix for this example are:

Table 5: Initial results

Method	Accuracy
word	0.8183538
hashtag	0.8148148
link	0.8108108
handle	0.8095238
aggregate	0.8188679



As observed, there are large number of false positives and false negatives. A sample of those is provided below:

Table 6: Initial results - False Positives

id	target	original_text
269	0	EMS1: NY EMTs petition for $17 per hour â€~minimum wageâ€™ http://t.co/4oa6SWlxmR #ems #paramedics #ambulance
1 026	0	Come and join us Tomorrow! August 7 2015 at Transcend:Blazing the Trail to the Diversified World of Marketing... http://t.co/Fd5od5PfCF
3 581	0	@mtnredneck It does when you are searching on a desolate part of the beach with no cell service and a mile away from your car.
9 779	0	#entertainment Hollywood movie about trapped miners released in Chile: SANTIAGO Chile (AP) â€” The Hollyw... http://t.co/C22ecVl4Hw #news
10 380	0	@Glosblue66 no idea what this means. Look at our violent crime rate without weapons. Ban guns we become like Mexico not Australia
10 402	0	NEW YORK: A whirlwind day of activities in New York. Breakfast at the Millennium Hotel United Nations Plaza. Lunch... http://t.co/laYZBA9y8h

Table 7: Initial results - False Negatives

id	target	original_text
3	1	Heard about #earthquake is different cities, stay safe everyone.
253	1	Anyone travelling Aberystwyth-Shrewsbury right now there's been an incident. Services at a halt just outside Shrews. Ambulance on scene.
1 172	1	#Detroit has made progress against blight but too many burned out shells of houses remain.
1 968	1	You picture buildings burning to the ground from the basement to the streetlight. I'm not your drinking problem a hole is in the sky.
6 571	1	@Sport_EN Just being linked to Arsenal causes injury.

A more detailed review of both sets, seems to indicated that the source file curation does seem to contain some errors : tweets that are seemingly not a catastrophe are tagged as such and vice-versa. One particular example of this are tweets allusive to the Hiroshima bombing in World War 2. Although those tweets a tragedy remembrance and do not carry the connotation of a current catastrophe, there are marked as "disaster" in the dataset.

Table 8: Initial results - Hiroshima Tweets

id	target	original_text
1 535	1	Hiroshima prepares to remember the day the bomb dropped http://t.co/oJHCGZXLSt
1 626	1	70 years ago today the United States of America bombed Hiroshima in Japan.
1 642	1	Just Happened in Asia: Japan marks 70th anniversary of Hiroshima atomic bombing http://t.co/E5dEmdScEh
1 652	1	70th Anniversary of Hiroshima bombing https://t.co/juwvomhGPd
3 995	1	I visited Hiroshima in 2006. It is an incredible place. This model shows devastation of the bomb. http://t.co/Gid6jqN8UG
5 032	1	How 'Little Boy' Affected the People In Hiroshima - Eyewitness Testimonials! - https://t.co/5x5hSV5sKO
5 041	1	On anniversary of Hiroshima bombing illustrated timeline of bombings. Eyewitness account particularly horrifying http://t.co/GZIb0mAwmn
5 523	1	70 years ago the first atomic attack flattened #Hiroshima 3 days later it was #Nagasaki both war crimes to put Moscow in its place
7 129	1	Courageous and honest analysis of need to use Atomic Bomb in 1945. #Hiroshima70 Japanese military refused surrender. https://t.co/VhmtyTptGR
7 441	1	The day Hiroshima through the eyes of the bomber crew and survivors http://t.co/AYEWJ8marn via @MailOnline
7 490	1	Here we are 70 years after the nuclear obliteration of Hiroshima and Nagasaki and Iâ€™m wondering iâ€_ http://t.co/fvkekft4Rs
7 520	1	Hannah: 'Hiroshima sounds like it could be a place in China. Isn't that where the oil spill was?'
9 397	1	Hiroshima survivors fight nuclear industry in Brazil Ã¢?? video http://t.co/GLZmGBM7w0
9 442	1	Remembrance http://t.co/ii4EwE1QIr #Hiroshima http://t.co/H3vUsqzyQo

The above reflects two important problems with machine learning and natural language:

1. This re-enforces that quality training data is essential. Bad data will probably result in bad results - even with a very sophisticated algorithm (It's called *Data* Science after all!).
2. Human language is complicated. Meaning of each word is highly contextual and changes depending on the register, dialect and over time. This can be difficult for a machine learning model to **grasp**.

To illustrate the second point, the above false positives and false negatives have been manually review and their new positive/negative result has been modified accordingly and added into the original data set. After feeding them back into the training dataset, selecting a new testing sample and running the machine learning model again, the below results are obtained:

Table 9: Initial results - corrected dataset

Component	Accuracy
word	0.7691580
hashtag	0.7968750
link	0.7101449
handle	0.7500000
aggregate	0.7688679

This illustrates that better training data can lead to better results. It is also worth noticing this may well reflect a real-life scenario, where a social media monitoring centre is constantly reviewing false negatives and false negatives with the purpose of keep re-training a model to adapt to changes language, emerging events, etc.

Of course, the other components in the model can also benefit of this *curated* approach. In this report, and for illustration purposes - the list of hashtags in the training set has been reviewed and then detected a couple of hashtags that most probably mean catastrophe (e.g. like #earthquake most like means one) and other most probably won't (like #ashes2017, which is unmistakable cricket, not matter how colourful and hyperbolic is the language).

Using a sample set of curated hashtag, it is possible to observe a small increment in accuracy. Handles and links will be left as a action to improve for the time being.

Table 10: Initial results - Curated Hashtags

Component	Accuracy
word	0.7738884
hashtag	0.8181818
link	0.7101449
handle	0.7500000
aggregate	0.7735849

Looking at the work done so far, we have the below table showing the improvements obtained by improving and supplementing the data:

Table 11: Initial Comparison

attempt	accuracy
Initial training	0.7571429
Initial training - Data Correction	0.7688679
Curated hashtags	0.7735849

2.4 Tuning

With this new, *augmented* dataset the next step of the process is to tune the model. Looking at how the model it's constructed, there are *many* aspects to tune, namely:

- The parameters used to calculate the tweet, hashtag, link and mention scores.
- The selection of classification algorithms used.
- The tuning parameters of each selection algorithm.

Obviously, tuning every single parameter will result in quite a lengthy exercise. Instead, this report will focus on some of the key components in this model and discus what works and what else could be done.

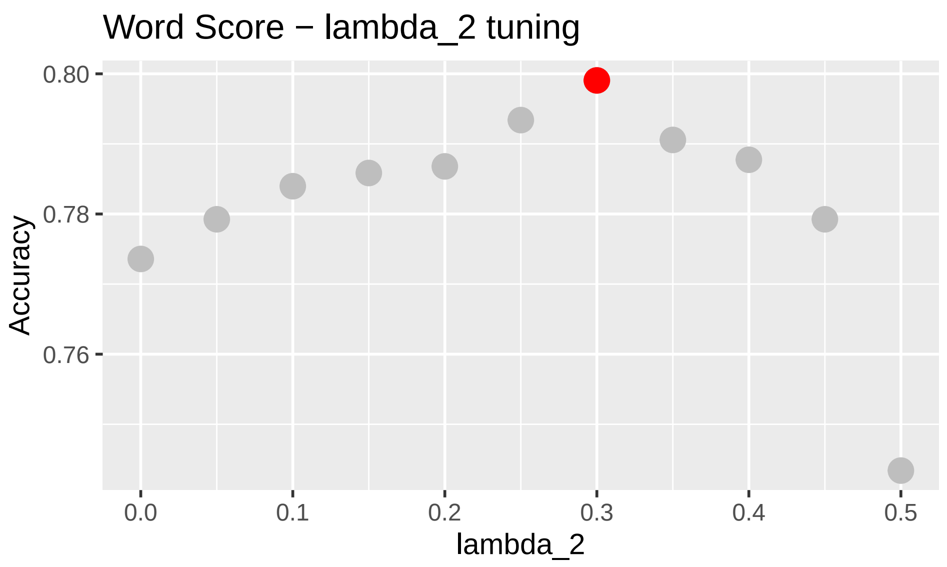
The first aspect to tune is the each word in the training corpus gets a individual score. This is perhaps the key component of the model. From the previous section, we have that this score is calculated through the below formulas:

$$pre\_score = sin(pos\_proportion)^{\lambda_1} * \frac{\theta}{90^\circ}$$

$$score = \begin{cases} \emptyset & n \leq \lambda_3 \\ \frac{pre\_score}{max(pre\_score)} - \lambda_2 & n > \lambda_3 \end{cases}$$

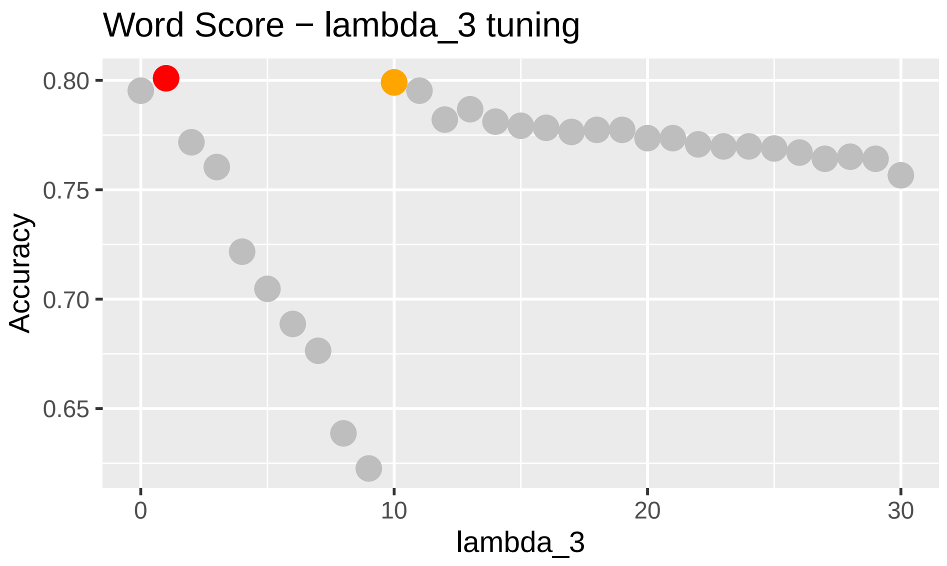
where * $pos\_proportion$: Proportion of times where word was found in a "positive" tweet. This sinus of this parameter is used to help penalise less relevant words. * λ_1: Parameterisation parameter, used to modulate the effect of less relevant words. * θ: angle of vector $(positive\_proportion, negative\_proportion)$, as discussed previously. * λ_2: Offset to potentially give a negative value to less relevant words, in order to provide compensation - e.g. in case a "disaster" word is used in figurative context amongst many non relevant words. This will be treated as a tuning parameter. * n : number of times the word is appears in the training set, * λ_3: arbitrary threshold to filter word with a low number of occurrences (and possibly biased). This is a tuning parameter.

In this report, λ_2 and λ_3 will be tuned, to see how the penalisation of irrelevant words and minimum number of occurrences affect the model. The results of tuning lambda_2 are shown below.



As shown above, the best result is obtained with $lambda_2$=0.3. It is also worth noticing that increasing this value won't necessarily result in better results, since it will then penalise "neutral" terms too.

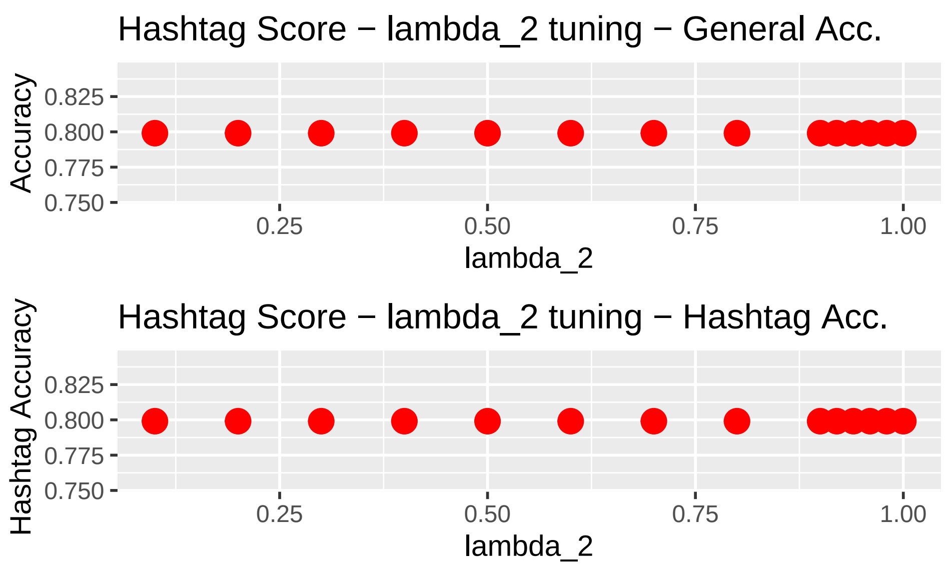
With this value, we will then also find if there is an optimal λ_3, i.e. to see if removing the words that rarely appear have an negative impact in the model. The results are shown below:



This result is a bit more interesting. As observed above, the first optimal λ_3 is quite a low value, however there is a relative bigger decrease in accuracy around its neighbours when compared against the second best λ_3. It is important to notice that the accuracy depends on the corpus of words in the test set and how they are combined into sentences. This is of course random and it will change from set to set. Even though we can do cross validation, perhaps it is not a bad a idea (as an initial step), choose a perhaps sub-optimal value for the sake of consistency - at least until more thorough tuning is possible. Therefore, to continue with this exercise, a value of $lambda_3$=10 has been chosen.

After the word scoring, perhaps the most relevant component in the model is the scoring function for hashtags (given that hashtag intend to be **meaningful** descriptors). Similarly to the word scoring, we will tune the equivalent parameters hashtag's $lamdba_2$ and $lamdba_3$.

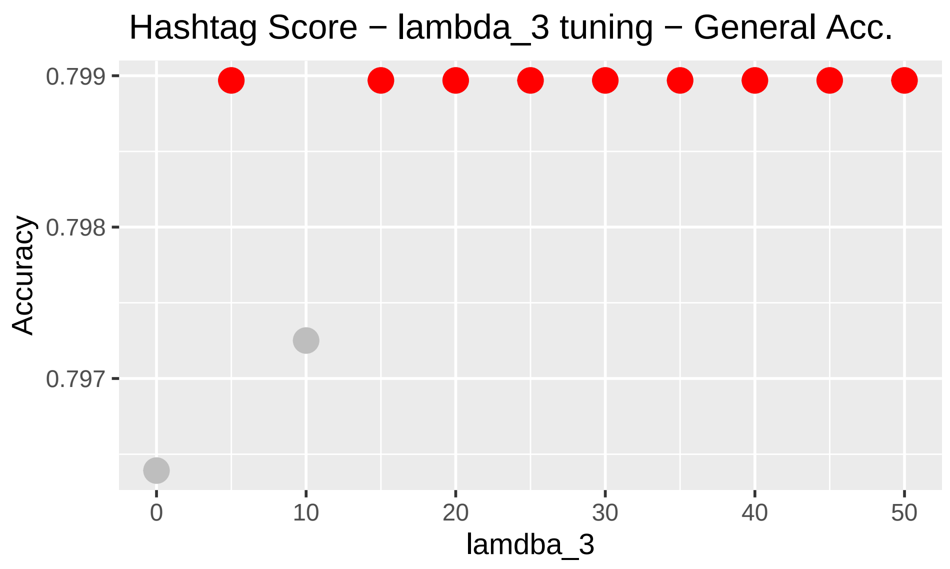
The results for the tuning of $lamdba_2$ are shown below:



The first graph shows the overall accuracy results (comparable to the word tuning), while the second graph shows the results where there is a hashtag. From them, the following points can be made:

- Smaller variations in the overall score can be explained to the fact that not all tweets have hashtags, thus the effect of tuning this part of the model will obviously have a limited effect on the general result.
- Taking the above point, it looks like its contribution to general score it is mostly when hashtags do indicate a catastrophe (and therefore have a bigger score). It is worth noticing that many of the high-score hashtag were not ranked by the algorithm but manually added - which is perhaps and indication that manual curation is not necessarily a bad idea - especially when data is poor quality or insufficient.

With this mind, the tuning of $lamdba_3$ will help to determine the overall effect of hashtag occurrence. The results are shown in the below chart.



This result seems similar in nature to the tuning for quantity cut-off for the word scoring.

Looking at the results so far (table below), this tuning process has only resulted in small gains when compared with the initial data corrections. Taking that the effect of hashtag tuning is small, in this report the tuning of the links and handle scoring functions will not be conducted. This doesn't mean they may bring an improved accuracy but perhaps are not worth the effort given the existing training dataset.

Table 12: Initial Comparison

attempt	accuracy
Initial training	0.7571429
Initial training - Data Correction	0.7688679
Curated hashtags	0.7735849
Optimised word score - lambda_2	0.7990566
Optimised word score - lambda_3	0.7990566
Optimised hashtag score - lambda_3	0.7989691

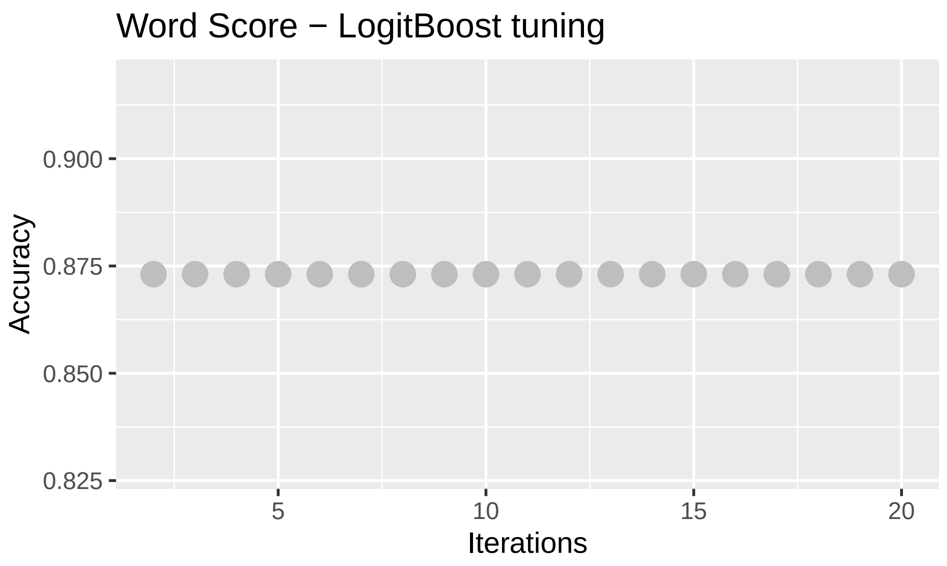
Instead, the decision is to focus on the tuning of the classification functions. At this point, the model uses the caret package to leverage to known machine learning algorithms, namely:

- *glm* (as in generalised linear model) in its logistic regression mode to turn word, hashtag, link and mention to make a prediction on those components independently.
- *xgbTree* (extreme gradient boosting) to predict an "overall" positive or negative based on the previous predictions.

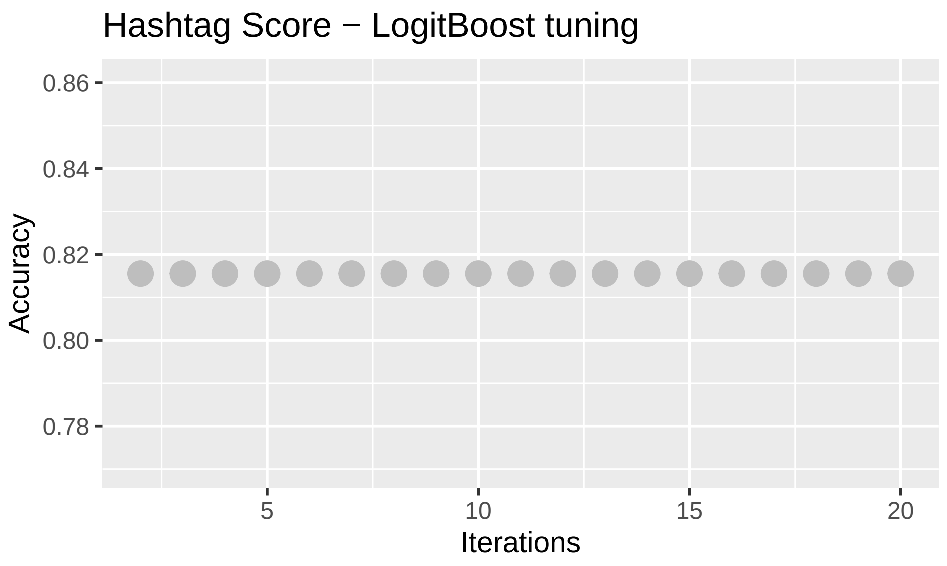
Considering that the assignment instructions state **"For this project, you will be applying machine learning techniques that go beyond standard linear regression"**, the next stage will be to asses if there is any model that produces better results than glm. (Although so far this is not a **standard** linear regression model any more.)

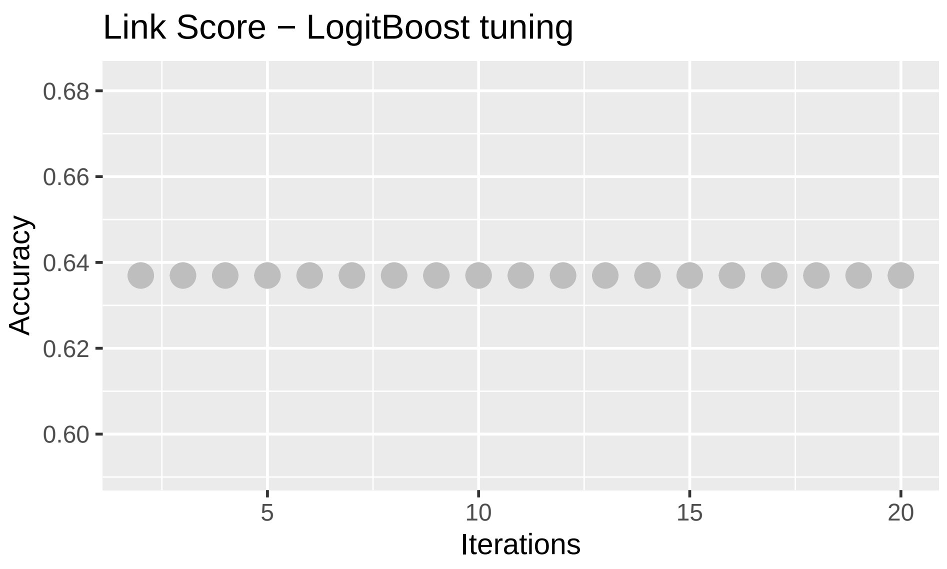
After investigating a number of possible algorithms, the **LogitBoost** will use as comparison. This algorithm is available in R through the **caTools** package.

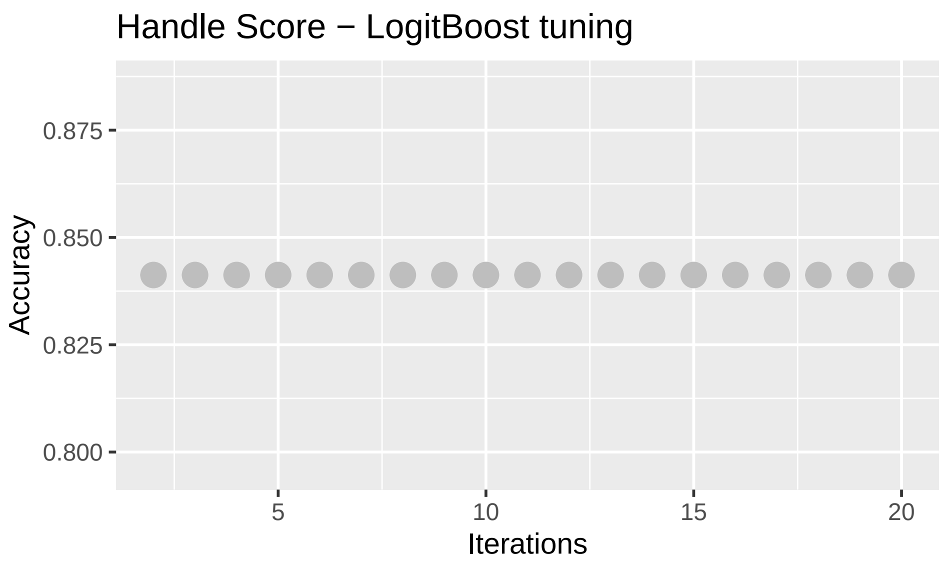
As a starting point, we will try this algorithm for the word score classification function. The below results show the best result after tuning its only parameter, which is the number of iterations.



Please note graph above shows the accuracy results for the LogitBoost regression only, not for the entire model. However, it shows that in this case the tuning has not effect. In this case, the overall accuracy equals *0.795.*These result is no better than the one using the a simple logistic regression. Similar results are obtained when the same comparison is repeated for the other scoring components.







In this case, the accuracy value equals **0.795**, which is no better than the classification using a logistic regression.

This results shouldn't be confusing - a more "sophisticated" method does not necessarily mean a better result the important thing is to find the model that better represents the problem at hand (when possible). Simpler models may also have an advantage in terms of processing time - which may be a key factor to consider even if other models perform marginally better.

Completed the above steps, there is one aspect left to tune : the XGBoost algorithm. This method has several parameters, for which a good explanation of them can be found here.

Given the number of parameters, a full sweep of all them could take very, very long. However, the caret packages already does some tuning by default. We will use the results from the previous iteration as a starting point.

Table 13: XGBoost - Best Tune

	nrounds	max_depth	eta	gamma	colsample_bytree	min_child_weight	subsample
13	50	1	0.3	0	0.8	1	0.75

Below is the code used for tuning:

```
training_tokenised <- tokenise_data(training,extra_stop_words,
                                    domains_data,training_flag=TRUE)
scores<- calculate_scores(training_tokenised,
                             word_parameters=c("sin",1,0,
                                                word_lambda_3,word_lambda_2),
                             hashtag_parameters=c("exp",4,
                                                   hashtag_lambda_2,hashtag_lambda_3),
                             handle_parameters=c("exp",4,0.8,4),
                             link_parameters=c("exp",4,0.9,4),
                              manual_scores = manual_scores)
training_vector <- score_tweets(training,training_tokenised,scores)

aggregate_tuning_grid <- expand.grid(nrounds = seq(45,55,1),
                                     max_depth = 1:3,
                                     eta = seq(0.2,0.4,0.1),
                                     gamma =seq(0,1,0.1),
                                     colsample_bytree = seq(0.7,0.9,0.1),
                                     min_child_weight = 1:3,
                                     subsample = 0.75)

fitting_model <- fit_model(training_vector,method_word="glm",
                      method_hashtag="glm",
                      method_link="glm",
                      method_handle="glm",
                      method_aggregate="xgbTree",
                      tuneGrid_aggregate = aggregate_tuning_grid)

results<-predict_values(test,fitting_model,scores,extra_stop_words,domains_data)

aggregate_model_3 <- fitting_model$aggregate
stats_7 <- results$eval
```

The optimised solution results in an accuracy of **0.799**. The optimised XGBoost parameters are:

Table 14: XGBoost - Best Tune

	nrounds	max_depth	eta	gamma	colsample_bytree	min_child_weight	subsample
254	45	1	0.2	0.2	0.8	3	0.75

When compared with all the previous results, we have the below chart

Table 15: Initial Comparison

attempt	accuracy
Initial training	0.7571429
Initial training - Data Correction	0.7688679
Curated hashtags	0.7735849
Optimised word score - lambda_2	0.7990566
Optimised word score - lambda_3	0.7990566
Optimised hashtag score - lambda_3	0.7989691
Word score - LogitBoost	0.7952830
Other scores - LogitBoost	0.7989691
Optimised XGBoost	0.7990566

As shown above, the greatest gains in accuracy are due to the data correction and the tuning of the word scoring formula. Further tuning only produces worse or marginally better results (from hashtag optimisation to optimised XGBoost, for example). Furthermore, the first impression is that perhaps there is a ceiling that has been reached, perhaps due to the limitation of the model or quality of the training data (bad inputs -> bad results).

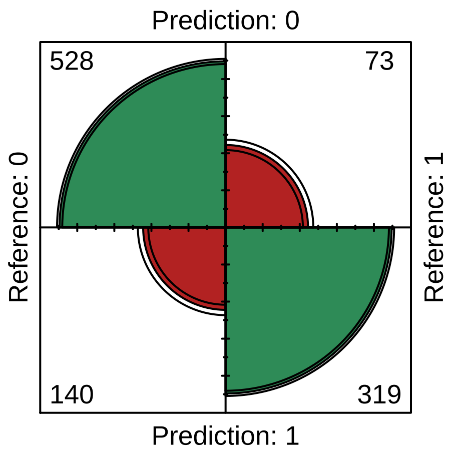
Nevertheless, up to this point we have try touched all the relevant aspects of the model. Therefore (for the purpose of the this assignment), the only step left is to assess against the validation data and then comment based on those results.

3 Results

As the last step of this report, the model has been assessed against the **validation** dataset that was set aside a the beginning of this exercise. In order to accomplish this, the below steps have been followed:

1. **Training** and **test** set have been merged into one dataset.
2. The model has been trained against this new dataset.
3. The newly-trained model has been used to generate prediction for the **validation** dataset

The confusion matrix for this result is shown below:



Looking at those results, it looks like we have reached some sort of ceiling for the model. As mentioned before, possible culprits are the model or the data. Considering that at the start of the this report data issues were flagged, it wouldn't be unreasonable to suspect that is a main contributor. To confirm this, both false positives and false negatives were inspected - below are a sample of both groups:

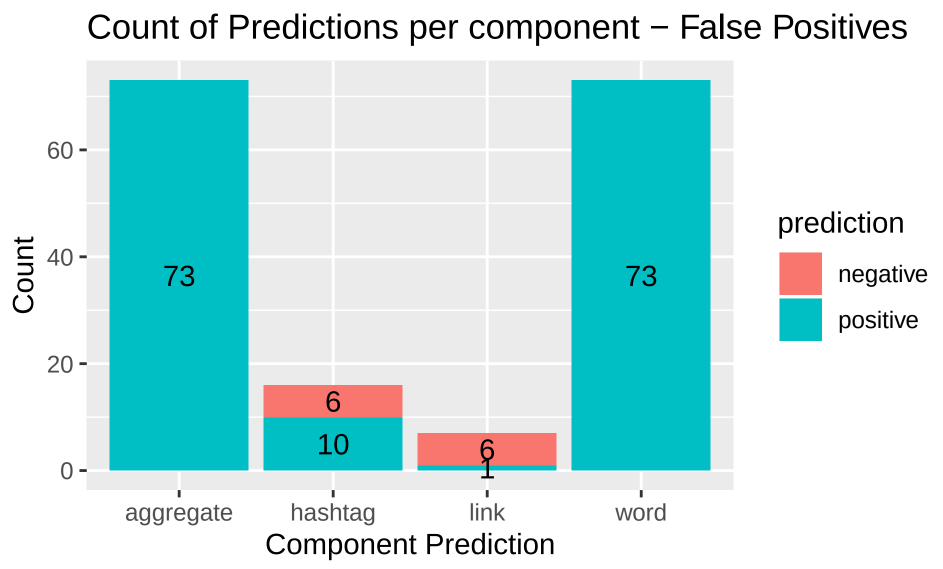
Table 16: Validation Results - False Positives

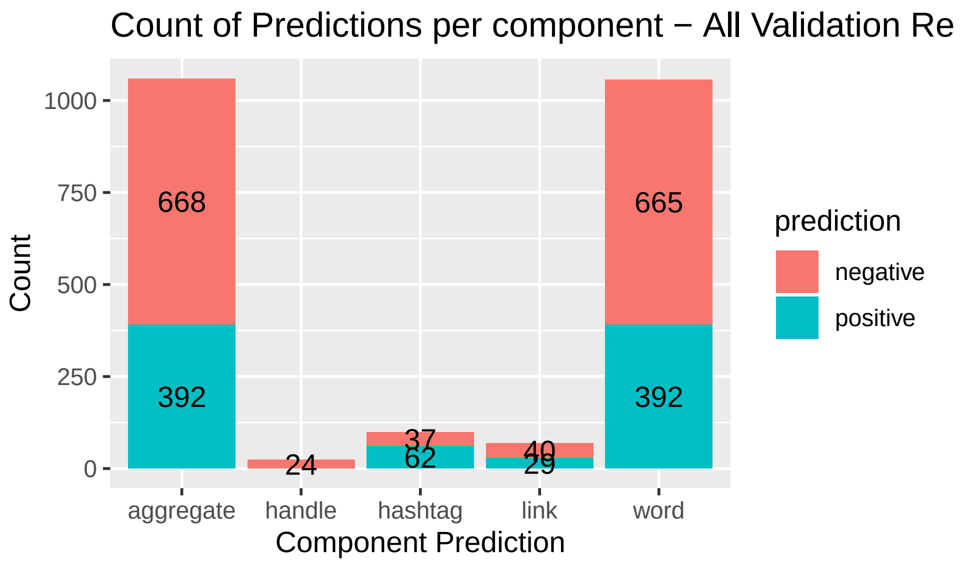
id	target	original_text
490	0	9 Charts Prove Financial Crisis Part 2 Has BEGUN!: The Financial Armageddon Economic Collapse Blog tracks tren... http://t.co/vHCXTvCINr
650	0	Credit to @pfannebeckers for inspiring me to rediscover this fantabulous #tbt http://t.co/wMHy47xkiL
2 153	0	@BarackObama hello Mr. President there is a really big problem in Puerto Rico regarding the water situation no more like a catastrophe...
5 434	0	Attention Service Members Veterans Educators First Responders in Jacksonville FL http://t.co/4UrtBEAcE5
9 600	0	Raise your words not your voice. It is rain that grows flowers not thunder.
10 402	0	NEW YORK: A whirlwind day of activities in New York. Breakfast at the Millennium Hotel United Nations Plaza. Lunch... http://t.co/laYZBA9y8h
10 492	0	11:57am Wildfire by The Mynabirds from Lovers Know

Table 17: Validation Results - False Negatives

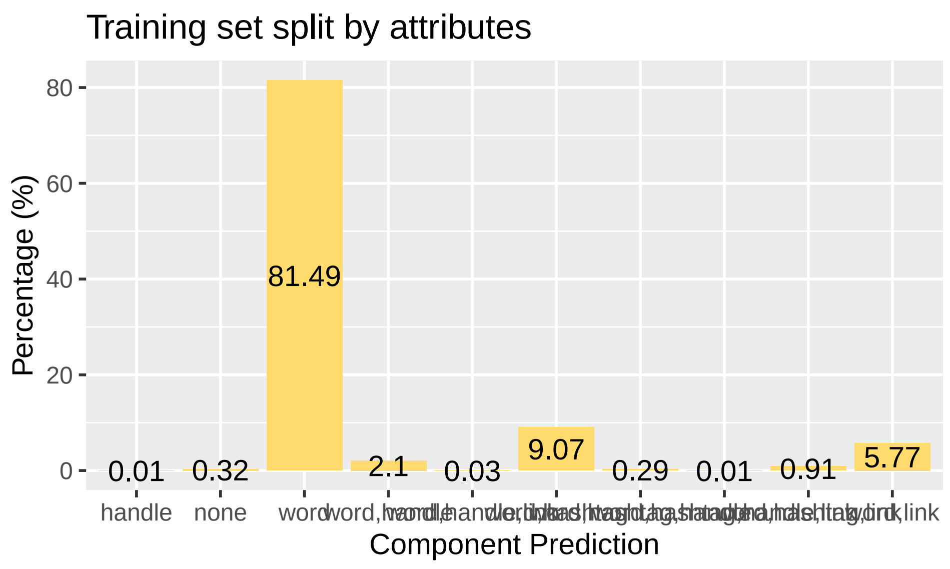
id	target	original_text
283	1	New Nanotech Device Will Be Able To Target And Destroy Blood Clots http://t.co/MnmyJXQ9go #science
391	1	World Annihilation vs Self Transformation http://t.co/pyehwodWun Aliens Attack to Exterminate Humans http://t.co/8jxqL8Cv8Z
1 172	1	#Detroit has made progress against blight but too many burned out shells of houses remain.
1 772	1	Fire hazard associated with installation of non-compliant external cladding on http://t.co/bTPQdehl3p - By @www.cbplawyers
2 341	1	Why did I come to work today.. Literally wanna collapse of exhaustion
3 259	1	Salvation Army bid to demolish cottages http://t.co/3kuXonOchl #Southend http://t.co/enQaSCGFyw
4 310	1	Dust Storm 'en route' from Alice Springs to Uluru http://t.co/4ilt6FXU45
9 781	1	Literally trapped in my room Cuz my bathroom being remodeled. The only exit is through a window
9 795	1	Hollywood Movie About Trapped Miners Released in Chile: 'The 33' Hollywood movie about trapped miners starring... http://t.co/tyyfG4qQvM

After inspecting for set, it looks like there is a problem of misclassification with the false negatives. In this case the model *correctly* predicts most of them as not a disaster tweet. However, upon inspection it seems the model is clearly *incorrectly* classifying most of all false positives. It is worth noticing though that all of them contain "catastrophe" words. A possible reason of this that the model is mostly driven by the words rather than the other attributes and its limited lexicon results in wrong scores for those tweets. Fortunately, it is possible to see for those tweets whether a prediction for each component was generated of not, which is shown in the below charts, for false positives and all validation tweets.

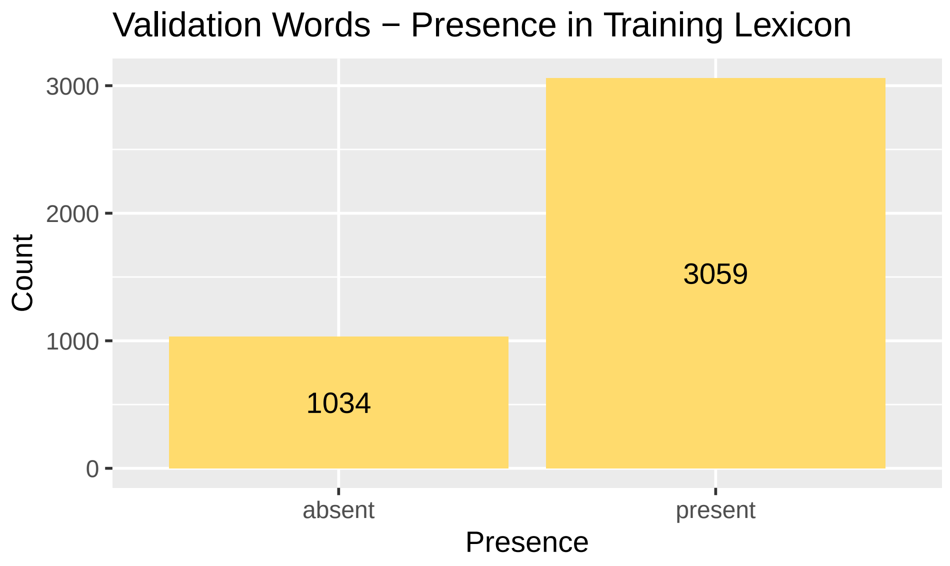




Both results show - interestingly that the overall results is almost entirely driven by the word scoring model. In fact, this model is basically ignoring the other attributes. This can be explained by the attribute distribution in the training data. As shown in below graph, the tweets that only have words exceed by far any other combination, which probably results in the XGBoost algorithm ignoring all other components. Although in theory hashtags, links and handles make sense, the existing data is making them irrelevant.



This probably only compounds another problem previously mentioned: the absence of several words in the lexicon created by the training data. This is summarised by the below chart.



The consequence of this will be incorrect or incomplete scoring - this is one probable reason for the high number of false negatives. Again, the conclusion seems to be that good quality training data, in reasonable quantities is critical for a good machine learning model.

4 Conclusion

In this report, we have attempted to create a machine learning model that correctly predicts whether a tweet correspond to a *disaster* or *catastrophic* event. A model to achieve this has been proposed, which combines individual predictions for each of the key available attributes of each tweet into a combined score, using the XGBoost algorithm. Through, successive data corrections and tuning the model the results were incrementally improved. Tested against the validation set, an accuracy of **0.799**.

Clearly, the presented is far from perfect. However through its flaws it was possible to draw a number of valuable conclusions which reflect relevant challenges applicable both in this particular case and in general practice. These main take aways are:

- A good quality training dataset is essential. Poorly curated training data will probably result in substandard predictions (the discipline is called **Data** Science after all!)
- Like in problem in Science/Engineering, coming up with a model that properly fits the problem is also essential. There aren't universal solutions and more *sophisticated* and popular models are not silver bullets. Sometimes, simpler linear models will be the best available fit - considering both accuracy, computing resources and the intention behind solving the problem.
- Tuning can be an enormous undertaking. Again, it is important to understand the purpose of behind the problem and be practical.
- In relation to this problem, natural language can be especially challenging. A simple model like this cannot really interpret meaning the same way a human does. The dictionary is always growing and changing - even one word can mean different things.

If someone would like to continue this work, there are multiple paths to keep exploring, namely:

- First, seek for a better dataset and run again to see the effects. Better dataset not only means the right classification but also: ** a greater proportion of hashtags, links and handles to see how they can better supplement the words in the tweet. ** a more diverse vocabulary to have a better collection of disaster and non-disaster words.
- In addition, a dataset with other property would be able also help to improve this model, for instance: ** rate tweets based on user ids (e.g. identify MMORPG players, shock jocks, emergency institutions, earthquake watchers,etc.). ** add a time and location function, which can be cross-referenced with other sources for catastrophic events (e.g. give a higher rating to all tweets from a particular city when a natural disaster strikes)
- Also, it would be interesting to see how this model rates against other natural language classification problems, like the Onion or Not dataset in Kaggle.

Last but definitely not least, this model needs better a mathematical justification behind the scoring functions. Those functions were defined to fit the expected results, but a better statistical understanding is required. This may be a big task but perhaps a necessary one to produce a "production" quality model.