Sentiment analysis as reputational risk indicator

NFQ Solutions

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Abstract

Fundaments of classification lie on the interdependences between the features and the labels to classify. For social parameters, this relationships are difficult to model and measure. In this paper, a way of obtaining a social indicator using sentiment analysis in Twitter is explained. With the classification of opinions as good or bad, it can be formed a metric for reputation.

Naive Bayes classifier has been tested with a different construction of features, which lead us to a new classifier. The object to classify is not consider as a vector to features; instead, a union of them. This approximation avoid extreme scoring.

The motivation for this work is to find a way to measure reputational risk for financial institutions, in order to give instruments for a more technological, motivated by RegTech paradigm, which links the regulation with the innovation of technology.

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1 Introduction

1.1 Motivation

Regulation tends to follow the paths opened by technology. Usually, it comes afterwards a new technology is applied. The financial industry is one example. It has seen an incredible growth in its extension, due to the development of computers, internet and mathematical finances wilmott1995mathematics. The concept behind this growth is known as FinTech arner2016fintech. This have lead to a full sector of companies, such as Activehours, Fundbox or ZestFinance sharf$_2$016.

However, moving from technology to regulation might not be the only way to proceed. Financial regulators have moved into a more stricted regulation after the current financial crisis arner2016fintech. Regulation can provide frameworks where certain technology develops. The concept RegTech "describes the use of technology, particularly information technology, in the context of regulatory, monitoring, reporting and compliance" arner2016fintech. Certain sectors, such as the financial one, tends to do not implement metrics and valuations until regulators force them to. What if regulation moved faster than technology? Would it be an opportunity for change and developpement? RegTech deals with this.

Searching for a standarization of the measures methodologies, financial regulator tends to look for mathematical models in order to manage the use of the regulations applied. This is one of the reasons the mathematical finance increases in importance among the applied mathematics. For risk like credit risk or market risk, well-known models, deriving from Black-Scholes formulas, are applied johnson2010financial. One may argue that strict application of regulations becomes a nonsense if it cannot be specified in a technology or methodology. Although this conflict allows multiples approaches, European Banking Authority (EBA) seems to apply a recommendation. An example of this RegTech problem appears with reputational risk.

Reputational risk, according to the EBA, "means the current or prospective risk to the institution's earnings, own funds or liquidity arising from damages to the institution's reputation" eba2016regulation. Instead of adjusting exactly to a well-known methodology, EBA emphasizes reputation, giving a guide of good or bad reputations moves for banking, along as a list of examples. Some of these cases are the number of media campaigns from consumer associations against a bank, or the number and the evolution of customer complaints. EBA did not make this guide compulsory. However, EBA recommends if a bank has a measure of this reputation, which eventually affects to the reports EBA does. This kind of regulation motivates the search for a technology which attacks that problem.

Our goal is to define a reputation scheme, which contains a source opinion, an indicator and a metric. As other articles suggest pak2010twitter, microblogging is a useful opinion source. We choose Twitter as source opinion because it is a well known microblogging service and its API is really easy in order to download text messages and search specific queries. We trained some tweets following EBA's prescriptions to build a classifier, which is our indicator. The idea of using a text classifier lies on the concept of sentiment analysis and how subjectivity (though standarized by EBA's rules) plays an important role.

Eventually, we aggregate the results of our indicator to create a metric. Our approach of this problem tries to provide mathematical tools to control financial institution's reputation, and provide them with a framework to successfully fulfil EBA's recommendations.

1.2 Sentiment analysis and classifiers

Sentiment analysis can be defined as an automatic determination of the subjectivity, polarity and force of a text, without depending on it is written with objective or subjective intencionality. brooke2009cross.

With this definition in mind, classifing text with a certain subjectivity instead of classifying objects with numeric features makes a huge difference in the approximation of the problem. Existing approaches to sentiment analysis can be grouped into three main categories: knowledge-based techniques, statistical methods, and hybrid approaches cambria2013new.

Moreover, sentiment analysis tends to simplify and collapse a complex opinion into a polarity. For example, a hotel can have a convenient location, but mediocre food cataldi2013good. That is the main reason to keep on EBA's line thought about what influence in a reputation badly or goodly. In our case, we transform several 'good' and 'bad' opinions into a reputation, composing the sentiments of the opinions through a period (a week, a month, a year ...).

1.3 Mathematical methods

Because of automated classification, statistical classifiers become a main instrument to sentiment analysis turney2002thumbs. In language, not all the words has a reputational meaning. Some of them, like prepositions or conjunctions, are used for grammatical reasons. The way in a text for creating features to classify makes the different among different concepts of classifying: knowledge-based techniques, statistical methods, and hybrid approaches cambria2013new.

Methods which are based on the presence of certain unambiguous words, such as *happy* or *angry*, are in the first category (knowledge-based techniques). Statistical methods use machine learning get a statistical process of labelled turney2002thumbs. By combining those approaches, hybrid techniques allows keep the semantic information while grammar constructions cambria2012sentic.

For mathematical classifiers, algorithm such as naive Bayes or maximum entropy are used abbasi2008sentiment, specially naive Bayes because of its simplicity potts2011sentiment. The features used for each tweet are extracted from the text. Dealing with text, correct treatment is necessary for a proper classification. This treatment is about transform text into ngrams, and then applying stemmming.

Ngrams are a sequence of n words, which are considered all together in an certain order jurafsky2014speech. Stemming is a procedure to reduce all words with the same stem to a common form lovins1968development. Snowball's Spanish algorithm was used snowballstem. It has been used ngrams constructed with 1 word (*unigrams*), 2 words (*bigrams*) and 3 words (*trigrams*). Although in english literature using just unigrams are enough features for the classifier Pang2004$_ngramWang2012_ngram, duetoSpanishgrammar'scomplexity.$

2 Mathematical reasoning

For a mathematical classifier, an object to classify is equal to the features the classifier can measure.

$$object \sim features \tag{1}$$

In our paper, the object to classify is a tweet, and its features are extracted from the text. The labels are *positive* and *negative*, because naive Bayes works worse with more than 2 labels pak2010twitter. We consider *negative* as the opposite of *positive* so these labels are complementaries.

2.1 Naive Bayes classifier

For a naive Bayes classifier, (1) is:

$$object = (feature_1, feature_2, \dots, feature_n) = \bigcap_i f_i \equiv features \tag{2}$$

Bayes theorem tell us that, if we have two events, A y B, we can express probability of happening A if we know B have happened with the following equation

$$P(B|A) = P(A|B)\frac{P(B)}{P(A)} \tag{3}$$

Where:

$P(B)$: Probability B to happen.

$P(A|B)$: Probability A to happen knowing B have happened.

$P(B|A)$: Probability B to happen knowing A have happened.

$P(A)$: Probability A to happen, also it is understand as a normalization of probability due to evidence posterior2012porciani.

We can use (3) and (2) to get an probability of being the tweet positive.

$$P(pos|features) = \frac{P(pos)P(features|pos)}{P(features)} \tag{4}$$

Where:

$P(pos|features)$: Probability of the tweet (its *features*) is positive.

$P(pos)$: Probability, a priori, of a tweet for being positive. This is known as *prior positive*.

$P(features|pos)$: Probability of a set of *features* appears in the positive corpus.

$P(features|neg)$: Probability of a set of *features* appears in the negative corpus.

Reminding positive and negative are complementaries label and using the law of total probability and , $P(features)$ can be written as

$$P(features) = P((features \cap pos) \bigcup (features \cap neg)) = P(features \cap pos) + P(features \cap neg) \tag{5}$$

In general, prior positive is related with our training set, meaning that, if there are more positives features than negatives ones, the classifier, independentely from the tweet to classify, establishes a probability of labelling positive.

However, we try to avoid pushing the balance in favor of a label. We establish a uniform prior probability ($P(pos) = P(neg) = 1/2$), so no label is more relevant to capture than other.

Using (5), we get

$$P(features) = P(pos)P(features|pos) + P(neg)P(features|neg) \tag{6}$$

And (4) can be rewriting using (6)

$$P(pos|features) = \frac{P(pos)P(features|pos)}{P(pos)P(features|pos) + P(neg)P(features|neg)} \tag{7}$$

The key to achieve the naive Bayes classifier is to obtain the expression for $P(features|pos)$ and its complementary, $P(features|neg)$. This classifier assumes independence hypothesis among features.

$$P(f_i \cap f_j) = P(f_i|f_j)P(f_j) = P(f_i)P(f_j) \quad \forall_{i,j}\ i \neq j \tag{8}$$

With (8) and the chain rule, $P(features|pos)$ can be written as

$$P(features|pos) = \frac{P((\bigcap_i f_i) \cap pos)}{P(pos)} = \frac{P(f_1, f_2, \ldots, f_n, pos)}{P(pos)} = \frac{P(f_1|f_2, \ldots, f_n, pos) \cdots P(f_n|pos)}{P(pos)} = \frac{\prod_i P(f_i \cap pos)}{P(pos)} = \prod_i P(f_i|pos) \tag{9}$$

The probability of each feature, $P(fi|pos)$, is a Laplace smoothing, constructed using a corpus formed by positive labelled tweets and negative ones.

Formally, naive Bayes classifier is expressed like

$$P(pos|features) = \frac{P(pos)\prod_i P(f_i|pos)}{P(pos)\prod_i P(f_i|pos) + P(neg)\prod_i P(f_i|neg)} \tag{10}$$

Applying independence hypothesis, with the construction of the tweet over its *features* as (2), naive Bayes classifier is deduced. This independence hypothesis (8) is the main reason for being called *naive*. Grammatically and semantically interdependence among words (our features) exists, but this classifier neglect them, so it is clear naive Bayes classifier make a huge simplification hand2001idiots. Nevertheless, in practice this simplification works reasonably well murphy2006naive.

A problem this classifier presents is roughness. With roughness we mean that the classifier scores with extreme values. The rougher, the more extreme it scores. This effect is caused by how naive Bayes classifier combines the probabilities of the features (9) in order to obtain $P(pos|features)$. When the classifier labels, it tends to do it with a probability nearly 1 or 0, rarely with cautious probabilities such as 0.7 or 0.25.

We realised this was a huge problen when naive Bayes classifier assigned to a clearly negative tweet a probability of 0.99, just because few of its features were positives. This motivates us to search for a classifier which does not assign much significance to each feature separately.

2.2 Union classifier concept

Using the same hypothesis (7), other classifiers can be constructed. Looking for less rough classifier, we went back to (2). One can say that an object is defined by a set of its features, which are related as

$$object \sim \bigcup_i f_i \equiv features \tag{11}$$

So an object is an average or a union of its features. To this different construction has been named union classifier, because of (11) formulation.

Taking into account this object construction, we define the probability $P(features|pos)$ as:

$$P(features|pos) \equiv \frac{1}{n}\sum_i^n P(f_i|pos) \tag{12}$$

The construction of reputational probability $P(pos|features)$ from the average probability of the features, instead of the product of them

$$P(pos|features) = \frac{P(pos)\frac{1}{n}\sum_i P(f_i|pos)}{P(pos)\frac{1}{n}\sum_i P(f_i|pos) + P(neg)\frac{1}{n}\sum_i P(f_i|neg)} \tag{13}$$

Using the complementarity of our problem

$$P(pos) + P(neg) = 1 \tag{14}$$

$$P(f_i|pos) + P(f_i|neg) = 1,\ \forall i \tag{15}$$

We can simplified (13):

$$P(pos|features) = \frac{1}{n}\sum_i P(f_i|pos)\frac{P(pos)}{(2P(pos)-1)\frac{1}{n}\sum_i P(f_i|pos) + 1 - P(pos)} \tag{16}$$

We are aware of we must be cautious with adding elements to a probability because the final result is a probability. However, probabilities are already normalized (12). So we assure that probability in (13) is bounded to $[0,1]$.

2.3 A simple example

For an enlightening explanation, two examples are provided. Let's suppose we have a tweet to analize. We know, in advance, it is negative. This tweet is in the Appendix, page 11, as *tweet* 1. Stemmed ngrams are also in the appendix as *Ngrams* 1. Given a frequency dictionary *Classifier* 1, obtained by human trained data. We see for each ngram the probability of being positive. For the example, we used the additive smoothing probability schutze2008introduction.

We are going to show only probabilities of the tweet for being positive, due to the complementary of the labels (positive and negative). Our concept of indicator lies in collapsing those probabilities in positive label if $P(tweet|positive) \geq 0.5$ and negative label otherwise. In the table 2.3, it can be seen the probabilities of the tweet for being positive for naive Bayes classifier and for us union classifier, with different ngrams.

Tweet 1	3, 2 and 1 ngrams	2 and 1 ngrams	1 ngrams
Naive Bayes	0.0	$3 \cdot 10^{-15}$	$1 \cdot 10^{-4}$
Union classifier	0.40	0.41	0.42

Table 1: Probability of positive for *tweet* 1

From left to right, less information is provide. Looking at these probabilities, it could be thought that naive Bayes classifier is rougher than union classifier. Mathematically, this roughness comes from the multiplication that appears in (10). In the union classifier (13), this multiplication is replaced by an average, resulting in an effective probability smoothing. Conceptually, naive Bayes implies an intersection of the features, though union classifiers is an average of the probabilities for each feature.

The key point of those classifier is roughness. Our classifier tends to be more cautious (and, therefore, less rough) than naive Bayes classifier. Union classifier tends to score nearly the prior positive probability (in our case, 0.5), while naive Bayes classifier tends to score with extreme values. Eventually, they return the same results: when a tweet is classified positive by union classifier, generally naive Bayes classifier does the same. Main difference is roughness, so in our reputation scheme a metric which takes into account the roughness will be preferable to another which does not.

This non-roughness tendency comes from changing object concept (11), and this is the main characteristic about union classifier. Let's suppose the tweet 2 (Appendix), which is positive. The *ngrams* 2 are extracted from the tweet and stemmed.

Given a frequency dictionary *classifier* 2, obtained by human trained data, additive smoothing probability is constructed for each feature. Then, positive probability are calculated and showed in table 2.3

Tweet 2	3, 2 and 1 ngrams	2 and 1 ngrams	1 ngrams
Naive Bayes	$2 \cdot 10^{-6}$	$4 \cdot 10^{-5}$	0.04
Union classifier	0.70	0.64	0.63

Table 2: Probability of positive for *tweet* 2

In this second example, differences between naive Bayes classifier and union one are more highlighted. Naive Bayes indicator, also, fails at classify. This is due to a feature of the tweet (a ngram) is too negative, so in weight too much to negative label. Union classifier, however, assigns the positive label to this tweet.

3 A reputation metric

Having a classifier, next step is to evaluate opinions (in our case, tweets) from a source opinion (Twitter). With a considerable amount of opinions evaluated, a reputation metric, our initial goal, can be created from aggregating individual tweet classifications. We are going to considerate that a reputation metric is a methodology of taking evaluated opinions as inputs and giving an output numerically interpretable.

Before proposing any metric, it is necessary to discuss how opinions are going to be taken into account. One could take all the tweets referring to a financial institution in a period, evaluate them and aggregate the results in order to give a number. This would be a static metric, and could be normalized, for example, to the number of tweets aggregated.

However, a single number by itself gives no information to the institutions about what strategies they should implement to improve that number, or which particular events cause that good or bad reputation, without a time correlation. In contrast to this statical view, one could track tweets through a time period and aggregate the evaluations as a time series. This lead us to a dynamical view of the reputation metric. From this point of view, one can capture real time events, like news or complains, as tweets by Twitter's users.

Following the dynamical path, classifier's results should be transformed into a numeric, addable value. The simplest metric one could imagine is to attribute a value of $S(tweet) = +1$ to positive tweets and $S(tweet) = -1$ to negative ones.

$$S(tweet) = \begin{cases} +1 & \text{if } P(tweet|pos) \geq 0.5 \\ -1 & \text{otherwise} \end{cases} \tag{17}$$

We tracked from Twitter public messages talking about a certain Spanish bank. Composing by days, figure (1) is obtained. The negative event around 6th March 2016 is due to a negative tweet from a Spanish politician.

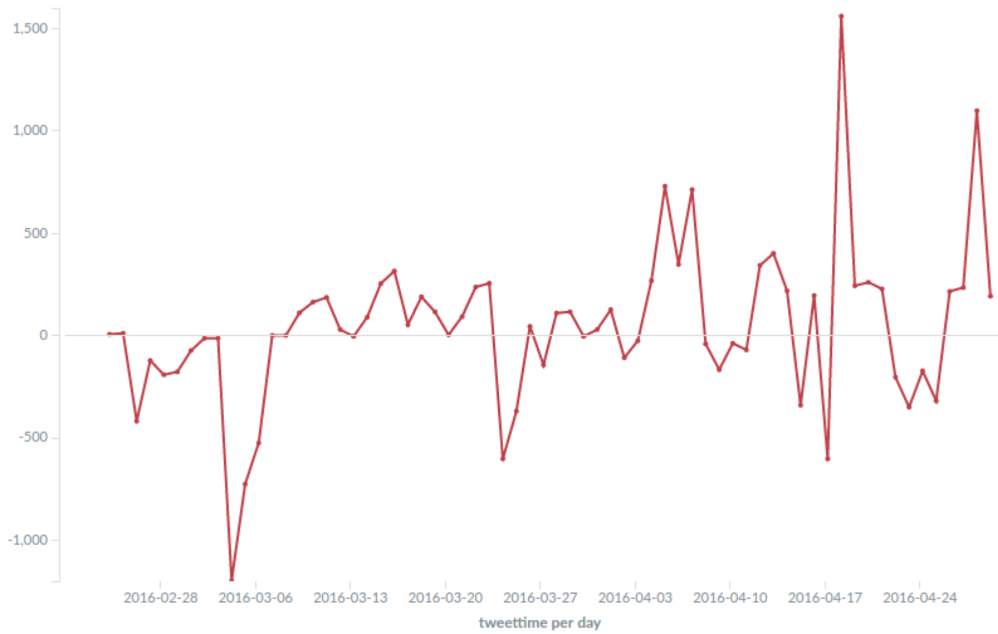

Figure 1: Value of metric S against the days

This graphic, together with some visualizations of most repeated words or most shared URLs, could be essential to extract operational information about what strategies are wrong or right from the reputational point of view.

However, this is just the simplest metric it can be obtained with our indicators. Naive Bayes and union classifiers give the same result, because they scores each tweet generally with the same tendency: when naive Bayes classifier assigns 'positive' to a tweet, union classifier usually does the same. This metric does not show the roughness of the classifier, because it does not operate with the probabilities of the evaluation. For instance, this metric does not distinguish among tweets assigned positive label with $P(tweet|pos) = 0.55$ or with $P(tweet|pos) = 0.95$; both lead to $S(tweet) = 1$. The same with negative labeled tweets.

As the main difference of both indicators lies in the roughness, metrics that include this property should be thought in order to catch indicator's uncertainty. Union classifier, as commented in section 2.3, scores each tweet depending the information it has. The larger the training data, the lesser indicator's uncertainty is.

The scoring of a single opinion by the indicator as $+1$ or -1 does not hold the information of indicator's uncertainty. In order to introduce that effect, we come to the idea of using the probability of positive and expand it to the interval $[+1, -1]$:

$$M(tweet) = 2P(tweet|pos) - 1 \tag{18}$$

We mean to that metric as *distance of positive*. When the classifier is sure the tweet is positive or negative, M takes values of $M(tweet) = +1$ or $M(tweet) = -1$, respectively. When the classifier is totally unsure, $M(tweet) = 0$. At this point, we would like to emphasise that M is continuous, opposite to S.

Aggregating over the same time interval that in figure (1), we get to figure (2). The variations among figures (1) and (2) bring us interesting information. The negative event we mentioned above is measured as 'more negative', which means the metric has given more importance relatively to the tweets from that event related to the average.

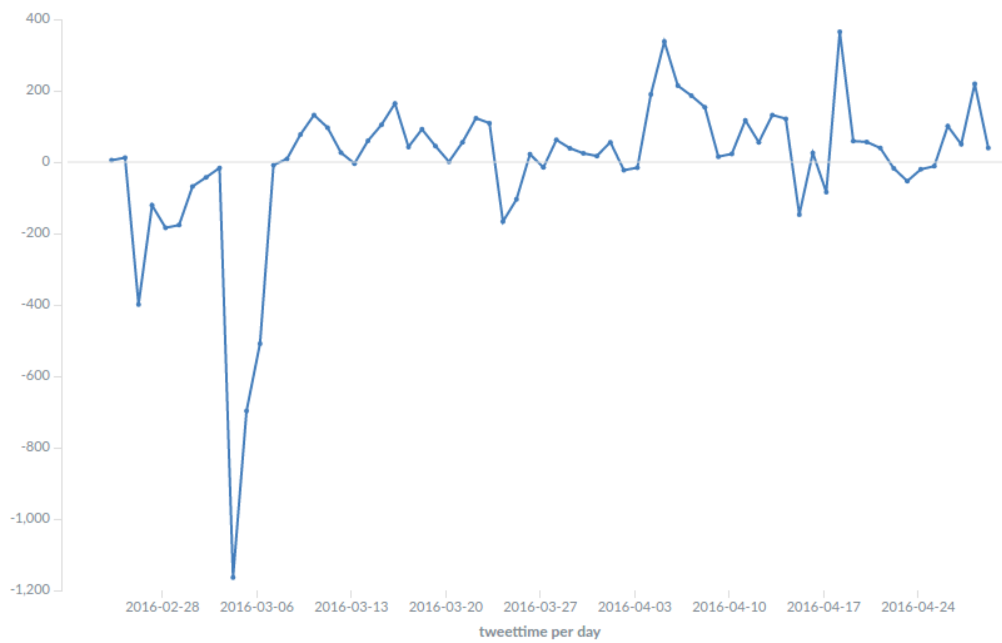

Figure 2: Value of metric M against the days

The metric M gives more relevance to tweets labelled certainly that uncertainly ones. If the training set is well-formed, clearly positive negative tweets will be weighted more than unsure labelled tweets. This effect is also possible due to union classifier does not present roughness.

4 Conclusions

Bearing in mind, the main aim of our work is to give a quantitative reputational scheme for financial institutions. We have adapted the sentiment analysis by three changes: to use more ngrams (because of Spanish language), to change the concept of the object to classify (leading to the definition of a new indicator) and two aggregable reputational metrics (distance of positive), that generate a reputational time series.

In order to avoid roughness, and using same assumptions as in naive Bayes classifier, we created another classifier, a union classifier, based on a different concept of object to classify, from (2) to (11). If we aggregate this values by time, we have a time series. Searching for tweets of a banking institution and comparing not the absolute values but the variations between days or weeks lead us to evaluate how the reputation of this institution evolves. This variation can be associated to direct actions this institution does, so an strategy to avoid bad reputation and look for good reputation can be advised.

Those time series can be correlated with financial series. This information could be useful in order to measure economic impact due to reputation. Keeping in mind, the latest goal of reputational analysis is to quantify reputational risk and this cannot be fulfilled without a measure of the money that is in risk.

Finally, we have followed a RegTech approach. Indeed, from EBA's recommendations and a foreseeable regulation (Reg), we have developed a reputational scheme which fulfils that future regulation (Tech).

References

[Abbasi et al.(2008)Abbasi, Chen, and Salem] Ahmed Abbasi, Hsinchun Chen, and Arab Salem. Sentiment analysis in multiple languages: Feature selection for opinion classification in web forums. *ACM Transactions on Information Systems (TOIS)*, 26(3):12, 2008.

[Arner et al.(2016)Arner, Barberis, and Buckley] Douglas W Arner, Janos Nathan Barberis, and Ross P Buckley. Fintech, regtech and the reconceptualization of financial regulation. *Northwestern Journal of International Law & Business, Forthcoming*, 2016.

[Brooke et al.(2009)Brooke, Tofiloski, and Taboada] Julian Brooke, Milan Tofiloski, and Maite Taboada. Cross-linguistic sentiment analysis: From english to spanish. 2009.

[Cambria and Hussain(2012)] Erik Cambria and Amir Hussain. *Sentic computing: Techniques, tools, and applications*, volume 2. Springer Science & Business Media, 2012.

[Cambria et al.(2013)Cambria, Schuller, Xia, and Havasi] Erik Cambria, Bjorn Schuller, Yunqing Xia, and Catherine Havasi. New avenues in opinion mining and sentiment analysis. *IEEE Intelligent Systems*, 28(2):15–21, 2013.

[Cataldi et al.(2013)Cataldi, Ballatore, Tiddi, and Aufaure] Mario Cataldi, Andrea Ballatore, Ilaria Tiddi, and Marie-Aude Aufaure. Good location, terrible food: detecting feature sentiment in user-generated reviews. *Social Network Analysis and Mining*, 3(4):1149–1163, 2013.

[European Banking Authority(2014)] European Banking Authority. Article 107 (3) of directive 2013/36/eu council regulation (EU) no 269/2014, 2014. URL `https://www.eba.europa.eu/documents/10180/748829/EBA-CP-2014-14+(CP+on+draft+SREP+Guidelines).pdf`.

[Hand and Yu(2001)] D. J. Hand and K. Yu. Idiot's bayes – not so stupid after all? *International Statistical Review*, 69(3):385–399, 2001.

[Johnson(2010)] Tim Johnson. What is financial mathematics? *The Best Writing on Mathematics*, pages 43–46, 2010.

[Jurafsky and Martin(2014)] Dan Jurafsky and James H Martin. *Speech and language processing*. Pearson, 2014.

[Lovins(1968)] Julie B Lovins. *Development of a stemming algorithm*. MIT Information Processing Group, Electronic Systems Laboratory Cambridge, 1968.

[Murphy(2006)] Kevin P Murphy. Naive bayes classifiers. *University of British Columbia*, 2006.

[Pak and Paroubek(2010)] Alexander Pak and Patrick Paroubek. Twitter as a corpus for sentiment analysis and opinion mining. In *LREc*, volume 10, 2010.

[Pang and Lee(2004)] Bo Pang and Lillian Lee. A sentimental education: Sentiment analysis using subjectivity summarization based on minimum cuts. In *Proceedings of the 42Nd Annual Meeting on Association for Computational Linguistics*, ACL '04, Stroudsburg, PA, USA, 2004. Association for Computational Linguistics. doi: 10.3115/1218955.1218990. URL `http://dx.doi.org/10.3115/1218955.1218990`.

[Porciani(2012)] C. Porciani. Posterior probability. University Lecture, 7 2012. URL `https://astro.uni-bonn.de/~kbasu/ObsCosmo/Slides2012/Lecture3_2012.pdf`.

[Porter(2015)] M. F. Porter. Snowball, Sep 2015. URL `http://snowballstem.org/`.

[Potts(2011)] Christopher Potts. Sentiment analysis symposium, san francisco, november 8-9, 2011. In *Sentiment Symposium Tutorial*, 2011. URL `http://sentiment.christopherpotts.net/`.

[Schütze(2008)] Hinrich Schütze. Introduction to information retrieval. In *Proceedings of the international communication of association for computing machinery conference*, 2008.

[Sharf(2016)] Samantha Sharf. The fintech 50: The complete list 2016, Nov 2016. URL https://www.forbes.com/sites/samanthasharf/2016/11/07/the-fintech-50-the-complete-list-2016/.

[Turney(2002)] Peter D Turney. Thumbs up or thumbs down?: semantic orientation applied to unsupervised classification of reviews. In *Proceedings of the 40th annual meeting on association for computational linguistics*, pages 417–424. Association for Computational Linguistics, 2002.

[Wang et al.(2012)Wang, Can, Kazemzadeh, Bar, and Narayanan] Hao Wang, Dogan Can, Abe Kazemzadeh, François Bar, and Shrikanth Narayanan. A system for real-time twitter sentiment analysis of 2012 u.s. presidential election cycle. In *Proceedings of the ACL 2012 System Demonstrations*, ACL '12, pages 115–120, Stroudsburg, PA, USA, 2012. Association for Computational Linguistics. URL http://dl.acm.org/citation.cfm?id=2390470.2390490.

[Wilmott et al.(1995)Wilmott, Howison, and Dewynne] P. Wilmott, S. Howison, and J. Dewynne. *The Mathematics of Financial Derivatives: A Student Introduction*. Cambridge University Press, 1995. ISBN 9780521497893. URL https://books.google.es/books?id=VYVhnC3fIVEC.

Appendix

Tweet 1:

Fui a un cajero y no pude sacar dinero. ¿Para qué quiero tener mi cuenta en este banco?

Translated into English:

I went to an ATM and I can't take my money. Why do I want to have my bank account in this bank?

Ngrams 1:

cajer, pud, sac, diner, par, quier, ten, cuent, banc, fui a, a un, un cajer, cajer y, y no, no pud, pud sac, sac diner, diner par, par que, que quier, quier ten, ten mi, mi cuent, cuent en, en este, este banc, fui a un, a un cajer, un cajer y, cajer y no, y no pud, no pud sac, pud sac diner, sac diner par, diner par que, par que quier, que quier ten, quier ten mi, ten mi cuent, mi cuent en, cuent en este, en este banc

Classifier 1:

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Tweet 2:

Este banco destina dinero a la caridad, así que voy a pedir el préstamo ahí

Translated into English:

This banks donates money to the charity, so I'm going to ask a loan there

Ngrams 2:

banc, destin, diner, carid, voy, ped, prestam, este banc, banc destin, destin diner, diner a, a la, la carid, carid asi, asi que, que voy, voy a, a ped, ped el, el prestam, prestam ahi, este banc destin, banc destin diner, destin diner a, diner a la, a la carid, la carid asi, carid asi que, asi que voy, que voy a, voy a ped, a ped el, ped el prestam, el prestam ahi

Classifier 2:

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