Learning to Predict the Stock Market Dow Jones Index Detecting and Mining Relevant Tweets

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Abstract: Stock market analysis is a primary interest for finance and such a challenging task that has always attracted many researchers. Historically, this task was accomplished by means of trend analysis, but in the last years text mining is emerging as a promising way to predict the stock price movements. Indeed, previous works showed not only a strong correlation between financial news and their impacts to the movements of stock prices, but also that the analysis of social network posts can help to predict them. These latest methods are mainly based on complex techniques to extract the semantic content and/or the sentiment of the social network posts. Differently, in this paper we describe a method to predict the Dow Jones Industrial Average (DJIA) price movements based on simpler mining techniques and text similarity measures, in order to detect and characterise relevant tweets that lead to increments and decrements of DJIA. Considering the high level of noise in the social network data, we also introduce a noise detection method based on a two steps classification. We tested our method on 10 millions twitter posts spanning one year, achieving an accuracy of 88.9% in the Dow Jones daily prediction, that is, to the best our knowledge, the best result in the literature approaches based on social networks.

1 INTRODUCTION

The spread of social networks and micro blogging enables people to share opinions and moods, creating very large and constantly updated textual corpora. Sentiment Analysis techniques seek to extract emotional states or opinions expressed in each text document and create a collective social emotional state.

Can the trend of social emotional state predict the macroscopic evolution of global events such as some economic indicators? Recent studies have answered affirmatively to this question. In particular, (Liu et al., 2007) using a Probabilistic Latent Semantic Analysis (pLSA) model extracts sentiment indicators on blogs that predict future sales, (Mishne and de Rijke, 2006) shows how through assessments of blog sentiments can predict the movie sales; similarly (Asur and Huberman, 2010) shows how public sentiments on movies expressed on Twitter can actually predict box office receipts. (Gruhl et al., 2005) tests the predictability of books sales using online chat activities. But all that glitters ain't gold: (Gayo-Avello, 2012) criticises some literature on this topic, showing results that are in fact unpredictable, for instance the prediction of election. Of course analyses of tweets can help to understand the political popularity, but can not consistently predict the results so far.

In this work we experiment the prediction of the Dow Jones Industrial Average (DJIA) from Twitter messages. For obvious reasons, the ability to predict the stock market trends has historically attracted interest from shareholders as well as academia. Efficient Market Hypotesis (EHM) proposed in (Fama, 1965) states that prices of financial assets are managed by rational investors who rely on new information, i.e. *news*, and not by present or past prices; since news are not predictable, neither is the stock market, which, according to past studies (Kimoto et al., 1990; Fama, 1991), follows in general a random walk trend. However, (Malkiel, 2003) confutes the EMH, providing evidences that market prices reflect all the available information. Moreover, several studies show that the trend of the stock market does not follow a random walk model and can be predicted in some way (Lo and MacKinlay, 1988; Butler and Malaikah, 1992), including, for example, with mining techniques applied to market news (Gidófalvi and Elkan, 2001; Schu-

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maker and Chen, 2006) or to past prices (Li et al., 2011) or even to financial reports (Lin et al., 2008).

Recently several works have studied the correlation between sentiments extracted from Twitter and socio-cultural phenomena (Bollen et al., 2011a), such as the popularity of brands (Ghiassi et al., 2013), and also the correlation between public mood in Twitter and the DJIA trend (Bollen et al., 2011b).

Differently from previous works that predict DJIA by computing people sentiments or moods from their twitter opinions, we introduce a simpler method based on mining techniques and text similarity measures for the characterisation and detections of relevant tweets with respect to increments or decrements of DJIA. In particular, as far as the selection of tweets is concerned, our method includes a noise detection approach in short textual messages in order to filter out irrelevant tweets in predicting DJIA. As discusses in Section 2, there is a large literature regarding the detection of noise in data mining and especially in data clustering; various methods have also been applied to text mining, generally for the recognition of noisy features (Samant and Rao, 2011) or for novelty detection (Markou and Singh, 2003), i.e. the discovery of unknown data that a machine learning system has not been trained with.

In this work we employed the same set of ten millions tweets posted in 2008 used by (Bollen et al., 2011b), but with a much smaller training set in order to assess our method more reliably with a wider test set. Intuitively, our method is based on training an intermediate classifier on five millions tweets posted in the first seven months of the 2008. By analysing the results of this classification, we create a pruning scheme based on four goodness groups of tweets, namely true and false positives and true and false negatives, depending on the outcome of the classification. We subsequently transform the training set by removing irrelevant tweets considered noise. This technique has been applied at two level: both to individual tweets and to aggregations of them, which correspond to actual instances of the training set.

The paper is organized as follows. Section 2 analyses literature about stock market prediction based on news, social network analyses and noise detection methods. Section 3 explains the data considered, the Vector Space Model construction and the noise detection technique. Section 4 describes and compares experiments with other works showing our results improves the best existing outcomes we found among social network based prediction approaches. Finally, Section 5 sums results up and outlines future work.

2 RELATED WORK

Stock market analysis and prediction has always received great interest by the academic world: several possible approaches have been proposed, from time series prediction to textual news analysis, until arriving to the social networks analysis. We start from classic stock market prediction approaches, then we summarize the most recent works using social network information to forecast the market prices. Finally, we analyze the most known noise detection methods proposed in literature.

Both academia and practitioners worked to the prediction of stock prices by analysing the underlying dynamics of financial markets. Initially, the scientific researches were based on the Efficient Market Hypothesis (EMH) (Fama, 1965) according to which prices of traded assets reflect all relevant information available at any time. In such financial market model, neither technical prediction analysis of future prices based on the study of past prices, nor fundamental analysis studying the evolution of the business value, allows an investor to achieve higher profits than those that another investor would get with a portfolio of stocks selected randomly, with the same degree of risk. However, in the last decades a great amount of works refused the unpredictability hypothesis (Malkiel, 2003; Qian and Rasheed, 2007) showing that stock price series follow the random walk theory only in a short period of time and consequently arguing that in general they could be predicted.

Two major approaches to stock market prediction exist: using features derived from technical analysis based on the history of stock index prices and using related news and textual information to predict trends. Surveys about the two approaches are given in (Atsalakis and Valavanis, 2009) and (Mittermayer and Knolmayer, 2006) respectively. Other researches employ blog posts to predict stock market behaviour by determining correlation between activities in Internet message boards and stock volatility and trading volumes (Antweiler and Frank, 2004). (Gilbert and Karahalios, 2010) create an index of the US national mood, called Anxiety Index, by exploiting over 20 million posts from the LiveJournal website: when this index increased significantly, the S&P 500 ended the day marginally lower than expected. A comparative survey of artificial intelligence applications in finance is reported in (Bahrammirzaee, 2010).

Twitter represents a huge knowledge base providing information about the most disparate topics. It can be argued that this knowledge base can provide an indication on the public mood. In fact the emotional state, as the prerogative of a single human be-

ing, propagates to social status as a feature of all of the individuals. This phenomenon is studied by (Bollen et al., 2011a): authors find that events in the social, political, cultural and economic sphere do have a significant, immediate and highly specific effect on the various dimensions of public mood extracted from Twitter. They speculate that large scale mood analysis can provide a solid platform to model collective emotive trends in terms of their predictive value with regards to existing social as well as economic indicators. This predictive feature of Twitter mood has been used for forecasting different phenomenons, like the sales of a movie (Asur and Huberman, 2010), the public opinion on a particular brand (Ghiassi et al., 2013) and so on.

Unlike the proposal of this paper, many of the approaches in literature apply *sentiment analysis* techniques to tweets to create forecast models. (Bollen et al., 2011b) measure collective mood states (positive, negative, calm, alert, sure, vital, kind and happy) through sentiment analysis applied to more than 9 million tweets posted in 2008. Tweets are filtered by some generic sentiment expressions (e.g. "I'm feeling") not directly related to stock market. They analyse tweets by two mood tracking tools: Opinion Finder (OF, (Wilson et al., 2005)) that classifies tweets as positive or negative, and Google-Profile of Mood States (GPOMS) that measure mood in the other 6 dimensions. They found that the *calm* mood profile yields the best prediction result for Dow Jones Industrial Average (DJIA) with an accuracy of 86.7% in the prediction of the daily directions in the month of December, moreover they also show how a tweet aggregation in a 3-day period ensures better prediction on the daily DJIA. Similarly, (Chyan and Lengerich, 2012) use the calm score of tweets extracts from June and December 2009, achieving an accuracy of 75% in 20-day test of prediction of Dow Diamonds ETF (DIA). They increase the accuracy up to 80% by adding a quantitative feature related to the previous value of the DIA.

Another similar analysis of (Bollen et al., 2011b) is made by (Mittal and Goel, 2012), where the same dataset of (Chyan and Lengerich, 2012) is used in a multi-class classification, considering only *calm*, *happy*, *alert* and *kind* mood dimensions. Furthermore, 4 different learning algorithms (i.e. Linear Regression, Logistic Regression, SVMs and SOFNN) are used to learn and exploit the actual predictions; SOFNN based model performed best among all other algorithms, giving nearly 76% of accuracy. A comparison of six different and popular sentiment analysis lexical resources (Harvard General Inquirer, Opinion Lexicon, Macquarie Semantic Orientation Lexicon, MPQA Subjectivity Lexicon, SentiWordNet, Emoticons) to evaluate the usefulness of each resource in stock prediction is done by (Oliveira et al., 2013). (Sprenger et al., 2013) used sentiment analysis on stock related tweets collected during a 6-month period. To reduce noise, they selected tweets containing *cashtags* ($) of S&P 100 companies. Each message was classified by a Naïve Bayes method trained with a set of 2500 tweets. Results showed that sentiment indicators are associated with abnormal returns and message volume is correlated to the trading volume. Similarly, (Rao and Srivastava, 2012) associate a polarity to each day considering the number of positive and negative tweets via *sentiment140*[1], testing the DJIA and NASDAQ-100 index in a 13-month period between 2010 and 2011. (Mao et al., 2011) surveyed a variety of web data sources (Twitter,news headlines and Google search queries) and tested two sentiment analysis methods used for the prediction of stock market behavior, finding that their Twitter sentiment indicator and the frequency of financial terms occurrence on Twitter are statistically significant predictors of daily market returns.

There are several approaches that do not use directly the sentiment analysis to make predictions. For example (Mao et al., 2012) analyse with linear regression model the correlation between the Twitter predictor and stock indicators at three levels (stock market, sector and single company level) and find that the daily number of tweets that mention S&P 500 stocks is significantly correlated with S&P 500 daily closing price. They obtain in a 19-day test an accuracy of 68% for Stock Market and sector level prediction and of 52% for company stock. (Porshnev et al., 2013) create different types of features: to a "basic" data set corresponding to the tweets BoW of the previous day, they add features regarding the number of tweets containing the words "worry", "hope" or "fear" (Basic&HWF), or the words "happy", "loving", "calm", "energetic", "fearful", "angry", "tired" and "sad"(Basic&8emo), training a SVM with these datasets relating at 7 months of 2013. They get a maximum baseline accuracy of 65.17% for the DJIA, 57% for the S&P 500 and 50.67% for NASDAQ. In a different way, (Ruiz et al., 2012) extract two types of features, one concerning the overall activity in twitter and one measure the properties of an induced interaction graph. They found a correlation between these features and changes in S&P 500 price and volume traded. (Zhang et al., 2011) found a high negative correlation (0.726, significant at level $p < 0.01$) between the Dow Jones index and the presence of the words "hope", "fear", and "worry" in tweets.

[1] http://help.sentiment140.com/

A quantitative analysis is made by (Mao et al., 2013): using Twitter volume spikes in a 15-month period (from February 2012 to May 2013) they train a Bayesian classifier to assist S&P 500 stock trading and they show that it can provide substantial profit. (Arias et al., 2014) through extensive testing shows that adding Twitter-related data (either in term of volume or public sentiment) to in non-linear time series (SVMs or neural networks) will improve the predictions of stocks or indexes.

Noise detection is a topic of interest since the dawn of information retrieval. In the Vector Space Model representation, the noise removal can be addressed at two levels. At *feature level* useless and non-informative words are removed: normally this problem is addressed with a lists of stopwords and feature selection schemes (Yang, 1995; Gabrilovich and Markovitch, 2004). At *instance level* are instead removed non-informative documents, which could be source of confusion for the classification model. Here can be ideally used the various noise detection techniques proposed in IR, without considering the textual nature of the single features. There exist in literature a large amount of proposed methods, for example using K-nearest neighbors approach, neural networks, decision trees, SVM or bayesian networks. In-depth descriptions of all of these techniques have been reported in surveys as (Chandola et al., 2009; Markou and Singh, 2003).

3 METHODOLOGY

3.1 Benchmark Text Set

To obtain a comparative evaluation than the well-known work of (Bollen et al., 2011b), we use the same collection of tweets: that is about 10 million tweets posted from January 1th to December 19th of 2008, by approximately 2.7M users. Following the pre-processing applied by Bollen et al., only tweets in english language that contain explicit statements of the author's mood state are taken into consideration, i.e. those that contains one of this expressions "i fell", "i am feeling", "i'm feeling", "i dont feel", "I'm", "Im", "I am", and "makes me". Tweets that contain links or that address the tweet content to another user are removed. All tweets are tokenized in single words and, as done by (Oliveira et al., 2013), also the emoticons are considered into our model using three different tokens.

Figure 1 shows the daily closing values of DJIA. To properly evaluate the models' ability in the prediction of DJIA prices, we split the benchmark set into i) a training set with the first seven months of the year (from January 2 to July 31) to create the prediction models; ii) a test set with two months, August and September, with which we tune the models and apply the noise detection; iii) finally a validation set with the latest three months, from October 1st to December 19th, larger than the work of Bollen et al, which refers to only 19 days of December and consequently to only 15 days of opening stock market.

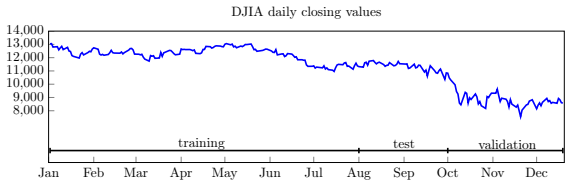


Figure 1: Daily closing values of the DJIA prices and split of the benchmark set.

3.2 Vector Space Model Construction

Tweets are grouped according to the publication date and will provide the information base to generate future predictions on the stock market. As shown by the experiments of Bollen et al, the higher correlation between social mood and the DJIA is obtained by grouping tweets of several days and shifting the prediction for a certain time lag. Thus it becomes interesting to evaluate the accuracy of the predictions considering these two parameters in the forecasting model:

- Lag (l): temporal translation from the forecast date, $l = 0$ means the day before the prediction.
- Aggregation (a): number of days to be aggregated to make a prediction, $a = 0$ means only one day.

As a simple example, assume that we consider $l = 1$ and $a = 2$, to make the prediction on day t will be considered tweets published in the days $t-2$, $t-3$ and $t-4$. The range of days considered for the prediction of day t will be: $[t-1-l-a, t-1-l]$.

According to the two previous parameters, all the tweets related to the prediction of a day (in the previous example, all tweets of $t-2$, $t-3$ and $t-4$) are collected in a single *Bag-of-Words*. Given the high number of tweets available, a dimensionality reduction is required. Once selected the tweets, stop-words are removed and a stemming process is performed, each term is then weighted using the common *tf.idf* (Domeniconi et al., 2016). Finally, a number n_f of them, with greater weight, are selected.

The proposed DJIA prediction process is summarized in Figure 2.

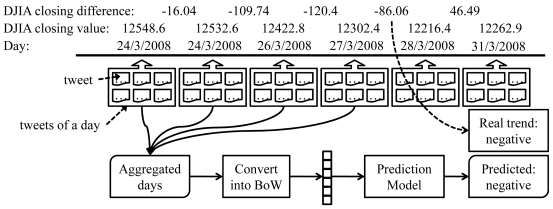


Figure 2: Diagram of the DJIA prediction process through tweets aggregation. In this example the system predicts the DJIA trend for 28/03/2008 using the aggregated tweets posted in the previous four days ($l = 0$ and $a = 3$).

3.3 Noise Detection

Twitter provides a great deal of information, but is necessary to understand what is useful for a given analysis and what is not. Considering this, we propose a noise detection method to define what tweets to use in the DJIA prediction model. Our idea can be summarised in few steps:

1. Once created the representation of the data, as described in the previous section, we train a classification model and we apply it on the test set.
2. We create four prototypes, one for each possible outcome of the classification, i.e. true positive (TP), predicted days, true negative (TN), false positive (FP) and false negative (FN). Each prototype is a BoW merging all the instances of the test set, i.e. all the tweets of the a days before each prediction.
3. We use prototypes to discover the noisy tweets in the dataset. We propose to apply this method at two different levels: i) a tweet level: removing from the dataset all the tweets with cosine similarity less than a threshold τ_g with respect to the good prototypes (TP and TN) or greater then a threshold τ_b with respect to the bad prototypes (FP and FN); ii) a instance level: removing from the training set instances similar to the bad prototypes.
4. With the cleaned data set we train a new prediction model using the training and test set and we use it to classify the validation set.

4 RESULTS

We tested the effectiveness of the prediction varying i) the classification algorithm, we tested two different supervised models using the *Weka*[2] implementation: *Decision tree* (the J48 C4.5) and *SVM* (the SMO algorithm), ii) the number n_f of features (i.e. words) selected in the dataset, iii) the aggregation a and iv) the lag l parameters on the data cited above.

[2]www.cs.waikato.ac.nz/ml/weka/

Table 1: Results obtained in tuning the Decision Tree algorithm.

Aggr	Lag	n_f feat	fMeasure
3	0	500	0.799
3	1	2000	0.736
3	0	1000	0.700
0	2	500	0.668
0	2	2000	0.660
2	2	500	0.657
3	2	2000	0.653

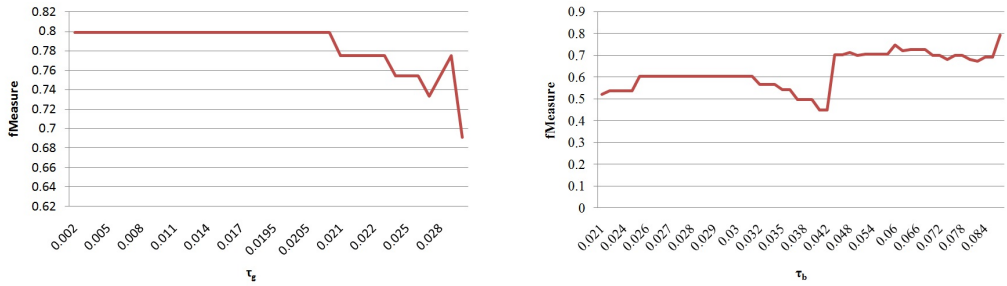
Table 2: Results obtained in tuning the SVM algorithm.

Aggr	Lag	n_f feat	fMeasure
2	1	1000	0.682
1	2	2000	0.668
3	2	1000	0.649
2	1	2000	0.649
1	3	2000	0.643
0	2	2000	0.642
2	1	500	0.642

Before the application of the noise detection method, we tested a simple prediction model based on the VSM built as described in Section 3.2, varying the parameters in order to discover the best tuning of them. Tables 1 and 2 show the best results obtained by the two supervised algorithms with the related parameters combination. A first noteworthy aspect is the aggregation parameter, that gives best results with three days gathered, this confirms the analysis done by Bollen at al. in their work, in which authors obtain the same consideration. This means that there is a strong correlation between the information extracted in a couple of days before and the outcome of a market trading day. In other words, the stock market seems to be affected to the information, and thus event or moods and so on, of the previous days. Moreover, it is evident the best accuracy obtained by the Decision tree model, that with few features required (just 500), achieves a f-Measure almost of 80%. From now on, every test is performed using the best combination of parameters shown in Table 1 and 2.

Once defined the best model, we applied the noise detection method in order to clean the dataset. The idea is to analyze the predictions made on the test set in order to define four groups of predictions and use those to find only the useful tweets, or aggregations of tweets, in the dataset.

First, we divided the test set instances based on the outcome of the predictions. Among all the tested instances, we selected only the predictions with the probability given by the classifier greater than 90%, in



(a) Mantaining tweets similar to the *good* prototypes. (b) Discarding tweets similar to the *bad* prototypes.

Figure 3: Tweets level noise detection experiments.

Table 3: Comparison with cosine similarities between instances (aggregated tweets) belonging to the different four groups. Each cell of the table is calculated as average value of the comparison of all the related couples of instances.

	TP	TN	FP	FN
TP	0.819	0.828	0.779	0.772
TP	0.823	0.914	0.776	0.738
FP	0.779	0.776	0.848	0.770
FN	0.772	0.738	0.77	0.912

order to pull out only the *surest* among them. These selected instances are then grouped based on the outcome (i.e. TP, TN, FP, FN). In order to assess the assumptions and the quality of the groupings made, we calculated the cosine similarity between both instances of the same group and belonging to different groups; we expected that the instances belonging to the same group should have a high similarity, while should appear dissimilarities comparing instances of different groups. These comparisons are shown in the Table 3; the main diagonal contains the comparisons between instances belonging to the same group, noteworthy is that these similarities are significantly greater than the other comparisons and this supports our hypothesis underlying the noise detection method.

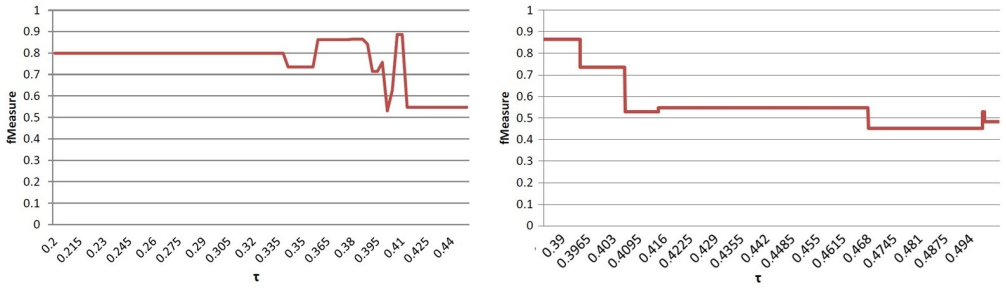
The first noise detection experiment has been made comparing all the single tweets in the dataset (both training and validation sets) with the four prototypes created aggregating the instances of the four groups of predictions analyzed above. We conducted a double experiment: i) keeping only the tweets similar to the two *good* prototypes, i.e. tweets whose cosine similarity with respect to TP or TN overcomes a threshold τ_g ; ii) discarding all the tweets similar to the *bad* prototypes, i.e. tweets whose cosine similarity with respect to FP or FN overcomes a threshold τ_b. Figure 3 shows the obtained results in both experiments, varying the thresholds. Unfortunately, the results do not show an improving trend by using this noise detection technique.

A further proposal to detect and remove noise is based on idea of that some training instances could compromise the accuracy of the prediction model, as outliers or simply containing noisy tweets. In this experiment, we remove in the training set of the final classification model all the instances that are similar to the bad prototypes and thus could negatively affect the model. Figure 4 shows the results obtained with the best tuning using both a decision tree and a SVM algorithm, varying the threshold τ in the noise detection algorithm. Results show a noteworthy improvement using the noise detection method. In particular, using the Decision tree algorithm, we achieve a $fMeasure = 0.889$ that is an improvement of 10% with respect to the results obtained in tests without the training set cleaning techniques. Similar considerations can be done when using a SVM classifier; in this case the improvement is even greater, since we started from a $fMeasure = 0.682$ and, with an improvement of 27%, we obtain a maximum of $fMeasure = 0.867$ when using the noise detection algorithm. By analyzing the results obtained by the best model, we found a $fMeasure$ related to the prediction of the positive market day of 0.848 and to the negative day of 0.912. The precision of the predictions in the validation set is 88.9%, that is higher than the precision obtained by Bollen at al. in their work, i.e. 86.7%.

A real comparison with the work of Bollen et al. can be done considering the same testset of their works, i.e. considering the 19 trading days in December 2008. Using this test set and training our method with the first 11 months of the year, we obtain a perfect classification (100%) of the 19 trading days, showing a sharp improvement with respect to the 86.7% obtained by Bollen et al.

5 CONCLUSION

In this paper, we have investigated whether the DJIA trend in a trading day is affected by the contents of tweets posted in the previous days. This correlation



(a) Decision tree supervised model.

(b) SVM supervised model.

Figure 4: Instance level noise detection experiments.

was already shown in some works in literature that use complex techniques to try to understand the semantic content of the textual documents in order to predict the stock market trends.

The aim of our work was to use a simple method, based on the well-known Vector Space Model representation and a supervised classifier. We have also introduced a noise detection technique, both at tweets and instances (i.e. aggregation of tweets) level, used to filter out from the data the large irrelevant corpus of tweets retrieved. We have tested and compared the method on the same tweets dataset and DJIA trends in the whole 2008 used by (Bollen et al., 2011b). Results shows that even a simple classification model based on the VSM achieves a good accuracy very close to 80%. This work have also demonstrated that our noise detection technique is able to distinguish the irrelevant tweets and instances, thus noise, in the training data, leading the accuracy to 88.9%, outperforming both our base classifier and the best prediction method based on social network posts illustrated in (Bollen et al., 2011b).

As future works we plan to further investigate possible correlations among different market indexes and stock options expanding the analysis to other sources of unstructured text streams.

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