Socially Driven News Recommendation

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Abstract

The question of how to recommend and manage information available in the Internet is an active area of research, namely concerning news recommendations. The methods used to produce news rankings by the most popular recommender systems are not public and it is unclear if they reflect the real importance assigned by the readers. Also, the latency period between the publication of a news item and acknowledging its importance prevents recent news from being quickly presented as relevant or otherwise. This paper presents an approach to news recommendation that is based on trying to anticipate the importance that will be assigned to each news item by the readers upon publication. To avoid the latency problem our approach uses models that predict this importance before we have feedback from readers. We use the number of tweets of a news as a proxy to the readers assigned importance. Through the improvement and extension of previous work, we describe an experimental comparison of different approaches to the task of forecasting the amount of future tweets of news items using resampling strategies, and we develop and evaluate approaches to translate the resulting predictions into concrete news rankings. The key distinguishing aspect of our work concerning this predictive task is the focus on accuracy concerning highly popular news, which are rare but are the more relevant for news recommendation. In this context, the main contribution of this work is a study and a proposal to the problem of predicting highly popular news upon their publication and their application in the context of news recommendation. Additionally, we developed an application of this work and present a comparison between our rankings and Google News.

1 Introduction

The possibility of each user making information publicly available, may it be an individual person or organization, provoked an explosion of accessible information and a growing demand concerning the computation capability to analyse, interpret and act upon this referred information. This is most visible concerning the users demand for information and the evolution of information retrieval (IR) systems. According to Baeza-Yates and Ribeiro-Neto these systems may be characterized by being responsible for dealing with the processes of storage, organization, representation and access to information documents in its various forms. Each of these processes is still under constant research in the quest to ensure better and more robust solutions.

The demand for information is clear when the high use of search engines is considered. The most known search engines serve as recommendation systems where a given user queries for a certain topic. First, the system gathers information, processes and stores it. Given a ranking algorithm, the documents are then classified according to importance or interest. Examples of these systems are the well-known search engines Google and Bing.

These search engines, factoring or not the influence of a given social network or other mediums, provide a ranked recommendation of resources containing what has been classified as most relevant

1http://www.google.com
2http://www.bing.com
to a given query. Therefore, these suggestions are based on data that ranges from a given point in the past to the present. This opens the issue dealt with this research.

For example purposes, time could consist of three parts: past, present and future. The suggestions provided by search engines are based on the analysis, computation and production of rankings given past data. To be precise, some of them provide a recommendation of resources that are very active in the present, such as Digg\(^3\). Digg provides news recommendations incorporating information provided by its own users in real-time. This process may also be done using social networks such as Twitter\(^4\) which provide a real-time medium to determine the evolution of attributed popularity or importance of the news articles through their respective number of publications. These publications are limited to 140 characters and are called tweets.

Blogs or micro-blog platforms such as Twitter are capable of providing a dynamic, multi-topic, real-time feed of world-wide opinion. Issues such as how to integrate that information, how to analyze it in real-time, how to correlate and/or recommend it to end-users and how to predict its development, are some questions which are still the object of research.

The news recommendation systems are a good example in order to explain the advantages of social networks data. Consider the following problem: When a given news article is published there is no available data concerning public opinion specific to that publication. Therefore, we have a latency problem related to its recency. When a given user uses these news recommendation systems such as Digg or the well-known Google News\(^5\) to query for a given subject or topic it receives a list of recommended articles. The most recent articles will take a certain period of time until they are considered. A notable difference between these two referred systems is the use of real-time social data in the case of Digg, that is factored in order to shorten the latency in helping the determination of its importance or interest.

A second point related with the use of data from social networks is also important: the difference between the recommendation made by these recommender systems and the importance attributed by the public. This is approached by DeChoudhury et al. \(^6\) where the issue of relevance to the end user is addressed. By applying some of the most popular algorithms (HITS and PageRank) the authors conclude that they would probably not point out the most relevant information comparing with the one recovered from Twitter.

From the considerations stated above, the issues of latency and recency are very important. Although it is possible to provide a recommendation with fair acceptance given the past and present data, as the referred systems do, the possibilities when considering the prediction of future data are scarce. The importance of this prediction is to minimize the referred latency and enable the treatment of recent news without a waiting period.

This paper describes a solution for a task that is part of a larger project that tries to merge the news recommendations provided by two types of sources: (i) official media that will be represented here by Google News; and (ii) the recommendations of Internet users as they emerge from their social network activity. Concerning this latter source, the idea is to use Twitter as the source of information for checking which news are being shared the most by users. We will use the number of tweets of a given news as a kind of proxy for its impact on consumers of news, on a given topic.\(^6\)

The workflow solved by the system we plan to develop within this project is the following:

1. At a time \(t\) a user asks for the most interesting news for topic \(X\)
2. The system returns a ranking of news (a recommendation) that results from aggregating two other rankings:
   - The ranking provided by the official media (represented by Google News)
   - The ranking of the consumers of news (represented by the number of times the news are tweeted)

This workflow requires that at any point in time we are able to anticipate how important a news will be in Twitter. If some time has already past since the news publication this can be estimated

\(^3\)http://www.digg.com  
\(^4\)http://www.twitter.com  
\(^5\)http://news.google.com  
\(^6\)We are aware that this may be a debatable assumption, still this is something objective that can be easily operationalised, whilst other alternatives would typically introduce some subjectivity that would also be questionable.
by looking at the observed number of times this news item was tweeted. However, when the news is very recent, the number of already observed tweets will potentially under-estimate the attributed importance of the news item. In this context, for very “fresh” news we need to be able to estimate their future relevance within Twitter, i.e. their future number of tweets. Moreover, given that we are interested in using this estimated number of tweets as a proxy for the news relevance, we are only interested in forecasting this number accurately for news with high impact, i.e. we are interested in being accurate at forecasting the news that will have a high number of tweets. This is the main goal of the work presented in this paper.

We describe an experimental comparison of a proposed approach to forecasting the future number of tweets of news, where the goal is predictive accuracy for highly popular news. This latter aspect is the key distinguishing aspect of our work when compared to existing related work, and it is motivated by the above-mentioned long-term project of news recommendation integrating different types of rankings. Furthermore, we develop and evaluate the translation of the resulting predictions into concrete rankings. In this context, the main contribution of this work is a study and proposal of an approach to the problem of predicting highly popular news upon their publication. Additionally we developed an application of this work and present a comparison of rankings between our solution and Google News ranking and the one produced by Twitter data.

This paper is structured as follows. In Section 2 previous work concerning recommender systems which combine official media and social recommendations as well as prediction approaches are presented. In Section 3 the data mining tasks are presented and the strategy to handle imbalanced distributions is outlined. Section 4 describes the used data, the regression methods used and the evaluation procedure. The results are described in Section 5 and conclusions are presented in Section 6.

2 Previous Work

Given a very astounding set of alternatives, recommender systems provide the ability to assist the users in suggesting what the best choices should be. It should be noted that the concrete process of rank production of the previously mentioned popular news recommender systems such as Google News and Digg is not public, although there are some clues available. For example, concerning Google News, official sources state that it is based on characteristics such as freshness, location, relevance and diversity. This process, based on the Page Rank algorithm explained by Page et al. [25] and generally described by Curtiss et al. [7], is of the most importance as it is responsible for presenting the best possible results for a user query on a set of given terms. However, some points have been questioned such as the type of documents that the algorithm gives preference to and its effects, and some authors conclude that it favours legacy media such as print or broadcast news “over pure players, aggregators or digital native organizations” [10]. Also, as it seems, this algorithm does not make use of the available information concerning the impact in or importance given by real-time users, such as Twitter, in an apparent strategy of deflecting attempts of using its capabilities in ones personal favour. Nonetheless, the large amount of data that Twitter enables everyone to access provides the necessary information for profiling and recommending processes. The following paragraphs depict examples of those possibilities related to our research scope.

Phelan et. al [27] describe an approach to news recommendation that includes harnessing real-time information from Twitter in order to promote news stories. For this endeavor, the authors achieve a basis for story recommendation by mining Twitter data, identifying emerging topics of interest and matching them with recent news coverage from RSS feeds. The approach adopts a content-based recommendation technique and it enables three recommendation strategies: public-rank, friends-rank and content-rank. The first uses a basic technique based on tf-idf scores to rank latest RSS and Twitter data using tweets from the public timeline available; the second, friends-rank, is as the first, but the data used from Twitter mines tweets from the user’s Twitter friends; and, finally, content-rank, which does not use Twitter, ranks articles based solely on term frequency. This work is extended [26] through the increase in comprehension and robustness of the recommendation framework, using different sources of recommendation knowledge and strategies.

Hannon et. al [13] applies and evaluates several profiling and recommendation strategies in order to recommend followers and/or followees, using Twitter data as a basis for both processes.
The authors describe a system capable of harnessing real-time information from Twitter and using it for followee recommendation. A variety of recommendation strategies are explored, such as content-based techniques, collaborative filtering style approaches and hybrid strategies. The system described by Hannon and colleagues provides two types of operation: user search and user recommendation. The former requires the user to provide query terms and the result is a ranked-list of relevant Twitter users. The latter uses the user’s information as a query, resulting in a list with a set of users whom the system judges to be relevant. The profiling strategies include representing users by their own tweets, tweets of the followers or followees and an identification of their followees or followers, but nonetheless these strategies can be combined.

Abrol and Khan [1] proposes TWinner, a tool capable of combining social media to improve quality of web search and predicting whether the user is looking for news or not. This is done through a process of mining Twitter messages in order to add terms to the search query, a query expansion approach, in order to point out to the search engine when the user is looking for news. This process includes the assigning of weights, measuring of semantic similarity and choosing the $k$ optimum keywords. The tool process starts with the introduction of a location by the user, which the system uses to compile information and then gather a proposed ratio by the users, the Frequency Population Ratio. Depending on the result being higher or lower than 1, the query is tagged as being news intended. If so, several other procedures are executed, as Twitter messages from the last 24 hours are extracted and weighted according to their likelihood, and after the analysis of the semantic similarity between keywords the weights are reassigned. The ones that are semantically dissimilar but gather the maximum weight are considered the best results.

The referred approaches are very similar to the one proposed in this paper. The main difference is that in every case, the issue of latency is not addressed any further. Nevertheless, the referred approaches present various options for discussion regarding the combination of official media and social recommendations.

Determining the importance of a given news article is a very interesting variable when referring to news-based recommender systems. This has been pursued by combining documents from legacy media sources such as newspapers, and the produced content in social media by their users. As referred formerly, a good example of this is the Digg platform which continuously provides this correlation between the news articles available and their respective attention. This process gathers enough information to ponder the recommended content according to its popularity or attributed importance. Nevertheless, it fails to provide a prediction of the future importance that the documents will have. Concerning this aspect, some work has been carried out.

In Yang and Leskovec [37] the authors suggest that popular news take about 4 days until their popularity stagnates. Early research of the data collected for the current paper suggests that the growth of the number of tweets of a news item very rarely exceeds a period of two days, and when it occurs, it is residual.

In the work of Asur and Huberman [2] the authors use Twitter to forecast the box-office revenues for movies by building linear regression models, as well as demonstrate the utility of sentiment analysis in the improvement of such objectives.

Regression, classification and hybrid approaches are used by Gupta et. al [12] also to predict event popularity. However, in this work the authors use data from Twitter, such as the number of followers/followees. The objective is the same in the work of Hsieh et. al [15], but the authors approach the problem by improving crowd wisdom with the proposal of two strategies: combining crowd wisdom with expert wisdom and reducing the noise by removing ”overly talkative” users from the analysis.

Recently, a bayesian approach was proposed by Zaman et al. [38] where a probabilistic model for the evolution of the retweets was developed. This work differs from the others in a significant manner. This work is focused on the prediction of the popularity of a given tweet and its publications (retweets) which, concerning the focus of our work, has not the same objective. However, the authors conclude that it is possible to predict the popularity of a given tweet after 10 minutes of its publication by stating that after two hours of its publication the total number should achieve a fraction of the first, roughly 50%. The test cases include both famous and non-famous Twitter accounts. This work is preceded by others also using the retweet function as a predictor having as the objective result an interval [14] or the probability of being retweeted.

In the work of Bandari et. al [4] classification and regression algorithms are examined in order
to predict popularity, translated as the number of tweets, of articles in Twitter. The distinguishing factor of this work from others that attempt to predict popularity of events ([31], [19], [32], [17], [20]), is that it attempts to do this prior to the publication of the item. To this purpose, the authors used four features: source of the article, category, subjectivity in the language and named entities mentioned. Furthermore, the authors conclude that the source of a given article is one of the most significant predictors.

The interest of determining the future importance of a given real-time event is mainly related to the quality of recommendations made to the end-user. As stated in all the work made concerning news recommender systems and Twitter, the distribution of news articles in the referred social network and their number of tweets are described by a power-law distribution. This is an important detail as it shows that only a very small portion of the cases are in fact highly tweeted, and therefore important to the public. And although most of the referenced work obtains enthusiastic results they are not focused on these rare cases. Our interest should be to predict these cases in order to favour them concerning the social recommendation of news articles.

The current paper extends our previous work [23, 24] by addressing two main shortcomings. Namely, we have significantly extended the amount of data used in the previous experiments concerning the use of resampling methods to try to forecast the number of tweets of a news. Moreover, we have also extended this work by evaluating the usage of the predictions of our models to derive rankings of news that are to be given to the final user as a news recommendation.

3 Problem Description and Approach

This work addresses the issues of predicting the number of tweets of very recent news events with a focus on the predictive accuracy at news that are highly tweeted and of transforming that outcome into rankings.

The first issue is a numeric prediction task where we are trying to forecast this number based on some description of the news. However, this task has one particularity: we are only interested in prediction accuracy at a small sub-set of the news - the ones that are tweeted the most. These are the news that the public deems as highly relevant for a given topic and these are the ones we will place at the top of our news recommendation so we want to accurately predict their relevance for the readers. The fact that we are solely interested on being accurate at a low frequency range of the values of the target variable (the number of tweets) creates serious problems to standard numeric prediction methods that are focused on maximising average accuracy.

The second task consists on the production and evaluation of news rankings using the results of the approaches to the first task. This second task should confirm the possibility of reducing the latency issue related to the recency of news.

In this paper we describe and test several approaches that try to improve the predictive performance on the difficult task of predicting the importance of a news item. Additionally, we transform the resulting predictions into rankings and compare them with the Google News rankings, using as ground truth the ranking resulting from observing the number of effective tweets of users on Twitter.

3.1 Data Mining Tasks

Concerning the first task, our goal of forecasting the number of tweets of a given news is a numeric prediction task, usually known as a regression problem. This means that we assume that there is an unknown function that maps some characteristics of the news into the number of times this news is tweeted, i.e. \( Y = f(X_1, X_2, \ldots, X_p) \), where \( Y \) is the number of tweets in our case, \( X_1, X_2, \ldots, X_p \) are features describing the news and \( f() \) is the unknown function we want to approximate. In order to obtain an approximation (a model) of this unknown function we use a data set with examples of the function mapping (known as a training set), i.e. \( D = \{(x_i, y_i)\}_{i=1}^n \).

The standard regression tasks we have just formalised can be solved using many existing algorithms, and most of them try to find the model that optimises a standard error criterion like the mean squared error. What sets our specific task apart is the fact that we are solely interested in models that are accurate at forecasting the rare and high values of the target variable \( Y \), i.e. the
news that are highly tweeted. Only this small sub-set of news is relevant for our overall task of providing a ranking of the most important news for a given topic. In effect, predictive accuracy at the more common news that have a small number of tweets is completely irrelevant because only the top positions of the ranking of recommended news are really relevant for the user, and these top positions are supposed to be filled by the news that have a very high number of tweets.

Regarding the second task, rankings are produced using the outcome of the first task, the predicted number of tweets for each given news item in a certain batch of news. This means that, given these predicted numbers of tweets, this second task reduces to the trivial process of ranking the news by decreasing predicted number of tweets.

3.2 Handling the Imbalanced Distribution of the Number of Tweets

Previous work [29, 35, 36] has shown that standard regression tools fail dramatically on tasks where the goal is accuracy at the rare extreme values of the target variable. One of the goals of the current paper is to compare some of the proposed solutions to this type of imbalanced regression tasks in the particular problem of forecasting the number of tweets of news.

Several methodologies were proposed for addressing this type of tasks. Resampling methods are among the simplest and most effective. Resampling strategies work by changing the distribution of the available training data in order to meet the preference bias of the users. Their main advantage is that they do not require any special algorithms to obtain the models - they work as a pre-processing method that creates a "new" training set upon which one can apply any learning algorithm. In this paper we will experiment with two of the most successful resampling strategies: (i) SMOTE [5] and (ii) under-sampling [18]. These methods were originally developed for classification tasks where the target variable is nominal. The basic idea of under-sampling is to decrease the number of observations with the most common target variable values with the goal of better balancing the ratio between these observations and the ones with the interesting target values that are less frequent. SMOTE works by combining under-sampling of the frequent classes with over-sampling of the minority class. Namely, new cases of the minority class are artificially generated by interpolating between existing cases. Recently, these methods were extended [36, 34] for regression tasks as it is the case of our problem. We have used the work of these authors to create two variants of each of our datasets. The first variant uses the SMOTEr algorithm [36] to create a new training set by over-sampling the cases with extremely large number of tweets, and under-sampling the most frequent cases, thus balancing the resulting distribution of the target variable. The second variant uses the under-sampling algorithm proposed by the same authors to decrease the number of cases with low number of tweets, hence the most common, once again resulting in a more balanced distribution. In our experiments we will apply and compare these methodologies in order to check which one provides better results in forecasting accurately the number of tweets of highly popular news items.

4 Data and Methods

4.1 The Used Data

The experiments are based on news concerning four specific topics: economy, microsoft, obama and palestine. These topics were chosen due to two factors: its actual use and because they report to different types of entities (sector, company, person and country). For each of the four topics we have constructed a dataset with news mentioned in Google News during a period of over four months, between 2014-May-01 and 2014-Sep-03, with queries of the top 100 news every 15 minutes. Figure 1 shows the total number of news per topic during this period (left) and a smoothed approximation of the amount of news per day for each topic (right).

For each news recommended by Google News the following information was collected: title, headline, publication date and its position in the ranking. For each of the four topics a dataset was built for solving the predictive task formalized in Section 3.1. These datasets were built using the following procedure. For obtaining the target variable value we have used the Twitter API [8] to

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7 The total number of news for all topics is 54,143.
8 Twitter API Documentation: https://dev.twitter.com/docs/api

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check the number of times the news was tweeted in the two days following its publication. These
two days limit was decided based on the work of Yang and Leskovec [37] which suggests that after
a few days the news stop being tweeted. Despite the results of this research which indicates that
this period could achieve four days, some initial tests on our data sets have shown that after a
period of two days the number of tweets is residual, and therefore we chose this time interval. In
terms of predictor variables used to describe each news we have selected the following. We have
applied a standard bag of words approach to the news headline to obtain a set of terms describing
it. Some initial experiments we have carried out have shown that the headline provides better
results than the title of the news item. We have not considered the use of the full news text as
this would require following the available link to the original news site and have a specific crawler
to grab this text. Given the wide diversity of news sites that are aggregated by Google News, this
would be an unfeasible task. To this set of predictors we have added two sentiment scores: one for
the title and the other for the headline. These two scores were obtained by applying the function
polarity() of the R package qdap [30] that is based on the sentiment dictionary described by Hu
and Liu [16]. Summarizing, our four datasets are built using the information described on Table 1
for each available news.

| Variable    | Description                                                                 |
|-------------|-----------------------------------------------------------------------------|
| NrTweets    | The number of times the news was tweeted in the two days following its publication. This is the target variable. |
| $T_1, T_2, \cdots$ | The term frequency of the terms selected through the bag of words approach when applied to all news headlines.          |
| SentTitle   | The sentiment score of the news title.                                      |
| SentHeadline| The sentiment score of the news headline.                                    |

As expected, the distribution of the values of the target variable for the four obtained datasets
is highly skewed. Moreover, as we have mentioned our goal is the accuracy at the low frequency
cases where the number of tweets is very high. We will apply the different methods described
in Section 3.2 to our collected data. This will lead to 12 different datasets, three for each of the
selected topics: (i) the original imbalanced dataset; (ii) the dataset balanced using SMOTEr; and
(iii) the dataset balanced using under-sampling. The hypothesis driving the current paper is that

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9We have used the infra-structure provided by the R package tm [9].
by using the re-sampled variants of the four original datasets we will gain predictive accuracy at the highly tweeted news, which are the most relevant for providing accurate news recommendations.

Since a news item may appear in more than one position in the Google News ranking, on different timestamps, additional datasets are built in order to harness that information. For each topic a dataset is constructed containing a news item identifier, the timestamp of the query and the respective position, as described on Table 2. This data is used in the second data mining task previously described.

Table 2: The ranking positions of the news items

| Variable       | Description                                           |
|----------------|-------------------------------------------------------|
| NewsIdentifier | An unique identifier for each news item.               |
| QueryTimeStamp | The timestamp of the query.                           |
| RankingPosition| The position in the ranking proposed by Google News.   |

4.2 Regression Algorithms

In order to test our hypothesis that using resampling methods will improve the predictive accuracy of the models on the cases that matter to our application, we have selected a diverse set of regression tools. Our goal here is to try to make sure our conclusions are not biased by the choice of a particular regression tool.

Table 3 shows the regression methods and tools that were used in our experiments. To make sure our work can be easily replicable we have used the implementations of these tools available in the free and open source R environment. All tools were applied using their default parameter values.

Table 3: Regression algorithms and respective R packages

| ID  | Method                 | R package   |
|-----|------------------------|-------------|
| RF  | Random forests         | randomForest [21] |
| LM  | Multiple linear regression | stats [28]   |
| SVM | Support vector machines | e1071 [22]  |
| MARS| Multivariate adaptive regression splines | earth [11] |

4.3 Evaluation Metrics

The metrics presented here are used to evaluate the performance of our approach in both their parts: (1) the prediction of rare events and (2) the production of news rankings using those predictions.

4.3.1 Prediction Evaluation Metrics

It is a well-known fact that when the interest of the user is a small proportion of rare events, the use of standard predictive performance metrics will lead to biased conclusions. In effect, standard prediction metrics focus on the "average" behaviour of the prediction models and for these tasks the user goal is a small and rare proportion of the cases. Most of the previous studies on this type of problems was carried out for classification tasks, however, Torgo and Ribeiro [35] and Ribeiro [29] have shown that the same problems arise on regression tasks when using standard metrics like for instance the Mean Squared Error. Moreover, these authors have shown that discretizing the target numeric variable into a nominal variable followed by the application of classification algorithms is also prone to problems and leads to sub-optimal results.

In this context, we will base our evaluation on the utility-based regression framework proposed in the work by Torgo and Ribeiro [35] and Ribeiro [29]. The metrics proposed by these authors assume that the user is able to specify what is the sub-range of the target variable values that is most relevant. This is done by specifying a relevance function that maps the values of the target
variable into a $[0, 1]$ scale of relevance. Using this mapping and a user-provided relevance threshold the authors defined a series of metrics that focus the evaluation of models on the cases that matter for the user. In our experiments we have used as relevance threshold the value of 0.9, which leads to having on average 7% to 10% of the cases tagged as rare (i.e. important in terms of number of tweets) depending on the topic.

In our prediction evaluation process we will mainly rely on one utility-based regression metric: F-Score. This is a composite measure that integrates the values of precision and recall according to their adaptation for regression described in the above mentioned evaluation framework. The F-Score measure is able to consider situations where the models forecast a high number of tweets for a news that ends up having a low number of tweets, i.e false positives.

4.3.2 Ranking Evaluation Metrics

Considering that, as referred before, the order of presentation is relevant to our endeavours, the metrics used to evaluate the production of rankings should be able to address that issue. In this context, we propose the use of several metrics including Precision at $k$ ($P@k$), Average Precision ($AP$), Mean Average Precision ($MAP$), R-Precision ($RP$), Mean R-Precision ($MRP$), Mean Reciprocal Rank ($MRR$) and Normalized Discounted Cumulative Gain ($NDCG@k$).

These metrics may be divided into two sets: (1) those focused on the global outcome, and (2) those that take into account the position of a given item in the ranking. The first set is formed by $P@k$, $AP$, $MAP$, $RP$ and $MRP$. The metrics $MRR$ and $NDCG@k$ form the second set.

Precision at $k$ measures the number of relevant items on the top-$k$ ranking positions.

$$P@k(q) = \frac{\text{# of relevant items up to rank } k \text{ in query } q}{k}$$

The metric Average Precision computes the average precision for all values of $k$ where $k$ is the rank, $n$ is the number of retrieved items and $Rel_k$ is a binary function evaluating the relevance of the $k$th ranked item, attributing 1 to the relevant items at rank $k$ and 0 otherwise. The Mean Average Precision is computed to determine the effectiveness of the ranking mechanism over all queries, where $|Q|$ is the number of queries.

$$AP(q) = \frac{\sum_{k=1}^{n} P@k(q) \times Rel_k}{\# \text{ of relevant items for query } q}$$

$$MAP = \frac{\sum_{q=1}^{|Q|} AP(q)}{|Q|}$$

In order to tackle the MAP issue concerning the effect of equally weighting each AP value, with disregard for the number of relevant documents found in each of the queries, the measure R-Precision is introduced. It measures the fraction of relevant items for the query $q$ that are successfully retrieved at the $R$th position in the ranking, where $R$ is the total number of relevant documents for the query. The Mean R-Precision corresponds to the arithmetic mean of all the R-Precision values for the set of all queries.

$$RP(q) = \frac{\# Rel_R}{R}$$

$$MRP(q) = \frac{\sum_{q=1}^{|Q|} RP(q)}{|Q|}$$

In our prediction evaluation process we will mainly rely on one utility-based regression metric: F-Score. This is a composite measure that integrates the values of precision and recall according to their adaptation for regression described in the above mentioned evaluation framework. The F-Score measure is able to consider situations where the models forecast a high number of tweets for a news that ends up having a low number of tweets, i.e false positives.

According to our objectives, we have established that the relevant items are those which belong to the top 10.
Finally, Normalized Discounted Cumulative Gain measures the search result quality of the ranking function by assigning high weights to documents in highly ranked positions and reducing the ones found in lower ranks. Its definition is presented as follows, where $\text{Rel}_{i,q} \in \{0, 1, 2, 3\}$ is the relevance judgment of the $i$th ranked item for query $q$. The normalization of Discounted Cumulative Gain (DCG) to a value between 0 and 1 is done by dividing the DCG value for the ideal ordering of DCG ($\text{idealDCG}$).

$$\text{DCG}@k(q) = \frac{1}{\log_2(1+i)} \sum_{i=1}^{k} 2^{\text{Rel}_{i,q}} - 1$$

$$\text{NDCG}@k = \sum_{q=1}^{Q} \frac{\text{DCG}@k(q)}{\text{idealDCG}@k(q)}$$

Concerning the concrete evaluation process we decided to use the metrics MAP, MRP, MRR and NDCG to enable a dual evaluation: a first that evaluates the global outcome and a second that takes into consideration the specific rank of each item.

5 Experimental Evaluation

This section presents the results on three sets of experiments. The first concerns the ability of models accurately predicting the rare high number of tweets of a news item. The second set of results relates to the application of the predicted number of tweets to create news rankings, and its evaluation. Finally, the third is a real world usage comparison between the recommendations by Google News and our approach, having as ground truth the news ranking from Twitter that is considered as a proxy for what people deem as more relevant.

5.1 Prediction Models Evaluation

Our data (news items) have a temporal order. In this context, one needs to be careful in terms of the process used to obtain reliable estimates of the selected evaluation metrics. This means that the experimental methodology should make sure that the original order of the news is kept so that models are trained on past data and tested on future data to avoid over-optimistic estimates of their scores. In this context, we have used Monte Carlo simulation as the experimental methodology to obtain reliable estimates of the selected evaluation metrics for each of the alternative methodologies. This methodology randomly selects a set of points in time within the available data, and then for each of these points selects a certain past window as training data and a subsequent window as test data, with the overall train+test process repeated for each point. All alternative approaches are compared using the same train and test sets to ensure fair pairwise comparisons of the obtained estimates. Our results are obtained through 50 repetitions of a Monte Carlo estimation process with 50% of the cases used as training set and the subsequent 25% used as test set. This process is carried out in R using the infra-structure provided by the R package performanceEstimation.

Our results contemplate four topics, as referred before: economy, microsoft, obama and palestine. Table 4 presents a summary of the estimated metric scores for the different setups that were considered. These three metrics (precision, recall and F1) are the most interesting from the perspective of our application with emphasis in the F1 measure because it penalises false positives (i.e. predicting a very high number of tweets for a news that is not highly tweeted). For each regression algorithm the best estimated scores are denoted in italics, whilst the best overall score is in bold.

These results clearly show that in all setups every algorithm is able to take advantage of resampling strategies to clearly boost its performance. The results obtained with Random Forest,
MARS and SVMs are remarkable, moreover taking into account that all methods were applied with their default parameter settings. With precision scores over 60% we can have more confidence that if we use the predictions of these models for ranking news items by their predicted number of tweets, the resulting rank will match reasonably well the reading preferences of the users.

Overall, the main conclusion from our comparisons is that resampling methods are very effective in improving the predictive accuracy of different models for the specific task of forecasting the number of tweets of highly popular news. These methods are able to overcome the difficulty of these news being infrequent. This is particularly important within our application goal that requires us to be able to accurately identify the news that are more relevant for the users in order to be able to improve the performance of news recommender systems.

### 5.2 Rankings Evaluation

The goal of the evaluation presented in this section is to check how effective are the news recommendation rankings produced using our predicted number of tweets. Therefore, we will want to compare the rankings produced by our method against the ground truth. The ground truth rank is based on the observed number of tweets of each news item within the period of two days following its publication timestamp. Based on these comparisons we will calculate two of the metrics described in Section 4.3.2, Mean Reciprocal Rank (MRR) and Normalized Discounted Cumulative Gain (NDCG@$k$), which both take into consideration the position in the rank. With that goal in mind we have designed the following experiment to compare the two news recommendations.

Concerning the prediction models and their train and test sets for this evaluation, we obtained our results through 50 repetitions of a Monte Carlo estimation process with 30% of the cases used as training set ($Tr$) and the following 1000 cases ($Ts$) used as test set.

Each time window ($Tr+Ts$) used in a Monte Carlo iteration is split in 15 minutes time intervals and we obtain the top 100 news recommendations at each of these steps from Google News. This leads to a data set as shown in Table 5, where, contrary to the previous evaluation where the cases were the news items, the rows (top 100 news items recommended by Google News) represent the cases referred. Each time $Q_i \in Ts$ forms our test set where we want to compare "our" ranking against the ground truth. This comparison is carried out as follows.

The starting point of our method is a news pool ($NP_1$) of the news items ranked by Google News in a time period that spans from $Q_i$ to two days back. This set can be decomposed into the set of news with publication date in the training period ($NP_1^{odd}$) and the set of news for which we still do not know the number of tweets ($NP_1^{new}$) because two days have not yet passed since their publication date. To our endeavour in this evaluation we will only use the news items of $NP_1^{new}$ as our objective is to ascertain the ability of our prediction models to produce correct rankings. It

| Topic       | Economy | Microsoft | Obama | Palestine |
|-------------|---------|-----------|-------|-----------|
| Prec        | Rec     | F1        | Prec  | Rec       | F1        | Prec  | Rec       | F1        |
| lm          | 0.23    | 0.05      | 0.08  | 0.09      | 0.03      | 0.04  | 0.15      | 0.00      | 0.00      | 0.18      | 0.09      | 0.12      |
| lm_SMOTE    | 0.64    | 0.36      | 0.37  | 0.49      | 0.23      | 0.31  | 0.55      | 0.39      | 0.45      | 0.54      | 0.14      | 0.22      |
| svm         | 0.46    | 0.00      | 0.01  | 0.00      | 0.00      | 0.00  | 0.00      | 0.00      | 0.00      | 0.04      | 0.00      | 0.01      |
| svm_SMOTE   | 0.67    | 0.52      | 0.58  | 0.66      | 0.59      | 0.62  | 0.68      | 0.71      | 0.69      | 0.83      | 0.54      | 0.65      |
| svm_UNDER   | 0.70    | 0.55      | 0.62  | 0.64      | 0.59      | 0.62  | 0.65      | 0.70      | 0.68      | 0.80      | 0.54      | 0.65      |
| mars        | 0.18    | 0.02      | 0.04  | 0.05      | 0.01      | 0.02  | 0.31      | 0.01      | 0.01      | 0.16      | 0.07      | 0.10      |
| mars_SMOTE  | 0.67    | 0.39      | 0.49  | 0.51      | 0.34      | 0.41  | 0.54      | 0.50      | 0.52      | 0.53      | 0.23      | 0.32      |
| mars_UNDER  | 0.76    | 0.52      | 0.61  | 0.67      | 0.47      | 0.55  | 0.62      | 0.61      | 0.63      | 0.75      | 0.41      | 0.52      |
| rf          | 0.28    | 0.04      | 0.06  | 0.13      | 0.02      | 0.03  | 0.31      | 0.01      | 0.02      | 0.00      | 0.03      | 0.04      |
| rf_SMOTE    | 0.67    | 0.51      | 0.58  | 0.50      | 0.48      | 0.49  | 0.53      | 0.61      | 0.57      | 0.62      | 0.43      | 0.51      |
| rf_UNDER    | 0.73    | 0.46      | 0.57  | 0.64      | 0.51      | 0.56  | 0.63      | 0.65      | 0.64      | 0.76      | 0.43      | 0.54      |

Table 4: Precision, Recall and F1-Score estimated scores for all topics.

11Corresponds to a time span of about two days

12In effect, we remove from the training set the news whose publication date is greater than the end of the training period less 2 days. These news are too recent and thus we still do not know their number of tweets (we count it after 2 days) and thus are useless for training our models.

13For these we already know their observed number of tweets as two days have already passed since their publication date.
is for these news that we want effective predictions of the number of Tweets so that we are able to correctly rank these news items.

Using the observed number of tweets of each of the items in $NP_{i_{new}}$, a ground truth ranking is obtained ($TR_i$). The predicted ranking ($PR_i$) is built using our models to predict the number of tweets of each news item in $NP_{i_{new}}$ and rank the news according to these predicted numbers. Finally, these comparisons are carried out for all time steps $i \in Ts$, and in the end we calculate the ranking evaluation metrics. Namely, the top 10 and 50 of the predicted rank ($PR_i$) is evaluated using the ground truth rank ($TR_i$). In Table 6 the evaluation of the rankings proposed by the prediction models is presented.

Results show that our approach is capable of producing news rankings which obtain excellent results specially concerning the top 10 of the predicted rank. Additionally, results also show that the regression algorithm SVM presents the best results, confirming the outcome of the evaluation in the previous section. The results obtained show that it is possible to reduce the latency period related to the news items for a considerable amount of cases.

### 5.3 Real World Usage Comparison

In this section we present an evaluation of a real world case scenario using our predicted rank ($PR_i$) and the rank proposed by Google News ($GN_i$) against the ground truth. Our evaluation is focused on the top 10 news items as our objective is to check the ability to anticipate the users’ reading preference on highly tweeted news items.

The design of this experiment is very similar to the previous one. However, since our objective is to compare our proposal and Google News with the ground truth Twitter rank, some changes were effects. They are described as follows.

For this experiment, the starting point of our method is the top 100 news obtained from Google News for time step $Q_i$, $GN_i$. This set can be decomposed into $GN_{i_{old}}$ and $GN_{i_{new}}$, such as the previous experiment. We build our predicted rank ($PR_i$) by obtaining the number of tweets for all news in $GN_i$. For those belonging to $GN_{i_{old}}$ we use the known number of tweets, whilst for those in $GN_{i_{new}}$ we use our models to predict this number of tweets. Both $PR_i$ and $GN_i$ are then compared against the ground truth that is obtained using the observed number of tweets of all

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**Table 5: Illustration of the dataset used in rankings evaluation**

| Timestamp | $R_1$ | $R_2$ | ... | $R_{100}$ |
|-----------|-------|-------|-----|-----------|
| $Q_1$     | $N_{14}$ | $N_{43}$ | ... | $N_{73}$ |
| $Q_2$     | $N_{43}$ | $N_{14}$ | ... | $N_{85}$ |
| $Q_3$     | $N_{43}$ | $N_{23}$ | ... | $N_{85}$ |
| $Q_t$     | ... | ... | ... | ... |

**Table 6: MRR, NDCG@50 and NDCG@10 scores for all topics**

|            | MRR | NDCG@50 | NDCG@10 | MRR | NDCG@50 | NDCG@10 |
|------------|-----|---------|---------|-----|---------|---------|
| economy    |     |         |         |     |         |         |
| svmSMOTE   | 0.61| 0.71    | 0.75    | 0.59| 0.73    | 0.74    |
| svmUNDER   | **0.63**| **0.71**| **0.76**| 0.59| 0.73    | 0.74    |
| marsSMOTE  | 0.26| 0.52    | 0.56    | 0.28| 0.55    | 0.59    |
| marsUNDER  | 0.23| 0.49    | 0.50    | 0.26| 0.52    | 0.52    |
| rfSMOTE    | 0.22| 0.49    | 0.50    | 0.25| 0.52    | 0.53    |
| rfUNDER    |     |         |         |     |         |         |
| microsft   |     |         |         |     |         |         |
| svmSMOTE   | 0.29| 0.53    | 0.52    | 0.46| 0.69    | 0.69    |
| svmUNDER   | **0.30**| **0.53**| **0.52**| 0.46| 0.69    | 0.69    |
| marsSMOTE  | 0.18| 0.43    | 0.42    | 0.38| 0.64    | 0.65    |
| marsUNDER  | 0.18| 0.43    | 0.42    | 0.38| 0.64    | 0.66    |
| rfSMOTE    | 0.22| 0.45    | 0.45    | 0.31| 0.62    | 0.63    |
| rfUNDER    | 0.19| 0.43    | 0.43    | 0.32| 0.62    | 0.63    |

|          | obama | palestine |
|----------|-------|-----------|
| svmSMOTE | 0.29  | 0.53      |
| svmUNDER | **0.30**| **0.53**  |
| marsSMOTE| 0.18  | 0.43      |
| marsUNDER| 0.18  | 0.43      |
| rfSMOTE  | 0.22  | 0.45      |
| rfUNDER  | 0.19  | 0.43      |
news in the top 10 of time step $i$. A concrete illustration of this process is shown in Table 7 where news items belonging to $G^\text{old}_i$ are shown in italic.

These comparisons are carried out for all time steps $i \in T_s$ and in the end we calculate the ranking evaluation metrics. This process is repeated 50 times with Monte Carlo estimations and the metrics scores are presented in Table 8.

### Table 7: Prepared evaluation data example (top 10 of 100) for a given 15 minutes query.

| GroundTruthRank | RealNTweets | GN.rankPosition | Pred.NTweets | PR.rankPosition |
|-----------------|-------------|-----------------|--------------|-----------------|
| 1               | 474         | 18              | 127.45       | 49              |
| 2               | 398         | 97              | 398          | 1               |
| 3               | 299         | 57              | 299          | 2               |
| 4               | 283         | 58              | 136.21       | 38              |
| 5               | 278         | 24              | 125.52       | 52              |
| 6               | 271         | 35              | 298.59       | 3               |
| 7               | 270         | 1               | 244.09       | 9               |
| 8               | 245         | 17              | 102.24       | 74              |
| 9               | 198         | 6               | 157.89       | 29              |
| 10              | 179         | 15              | 115.33       | 67              |

### Table 8: MAP, MRP, MRR and NDCG@10 scores for all topics

| economy         | MAP | MRP | MRR | NDCG@10 | MAP | MRP | MRR | NDCG@10 |
|-----------------|-----|-----|-----|---------|-----|-----|-----|---------|
| Google          | 0.32| 0.33| 0.50| 0.63    | 0.28| 0.29| 0.49| 0.59    |
| svmSMOTE        | 0.68| 0.69| 0.79| 0.86    | 0.74| 0.72| 0.84| 0.88    |
| svmUNDER        | 0.68| 0.69| 0.79| 0.86    | 0.74| 0.72| 0.84| 0.88    |
| marsSMOTE       | 0.52| 0.42| 0.78| 0.85    | 0.54| 0.36| 0.88| 0.88    |
| marsUNDER       | 0.55| 0.41| 0.79| 0.87    | 0.54| 0.36| 0.86| 0.88    |
| rfSMOTE         | 0.65| 0.56| 0.79| 0.86    | 0.72| 0.63| 0.85| 0.89    |
| rfUNDER         | 0.63| 0.52| 0.79| 0.87    | 0.70| 0.57| 0.85| 0.89    |

| palestine       | MAP | MRP | MRR | NDCG@10 | MAP | MRP | MRR | NDCG@10 |
|-----------------|-----|-----|-----|---------|-----|-----|-----|---------|
| Google          | 0.14| 0.12| 0.51| 0.57    | 0.36| 0.36| 0.55| 0.67    |
| svmSMOTE        | 0.50| 0.47| 0.72| 0.78    | 0.72| 0.70| 0.80| 0.87    |
| svmUNDER        | 0.50| 0.48| 0.72| 0.78    | 0.72| 0.71| 0.80| 0.87    |
| marsSMOTE       | 0.26| 0.18| 0.78| 0.77    | 0.50| 0.36| 0.80| 0.87    |
| marsUNDER       | 0.32| 0.20| 0.80| 0.80    | 0.52| 0.38| 0.80| 0.87    |
| rfSMOTE         | 0.48| 0.40| 0.74| 0.79    | 0.67| 0.56| 0.80| 0.88    |
| rfUNDER         | 0.44| 0.34| 0.74| 0.79    | 0.63| 0.50| 0.81| 0.88    |

Results show that our approach is capable of producing news rankings which significantly improve Google News results. This improvement as shown, considering all the metrics used, ranges from 30% to around 300%.

From the results we may also draw two final considerations. First, it should be noted that although the regression algorithm SVM in combination with the resampling strategy SMOTE obtained the best results in the prediction models evaluation, it did not produce the most accurate rankings. Instead, we observe that the combination SVM and the under-sampling strategy did in fact produce the best overall results. Secondly, we observe that in three of the topics there is an important difference concerning the results of metrics MAP and MRP, and the metrics MRR and NDCG@10. The first set does not take into consideration the position of the news items in the rankings and the second set does consider it. We observe that the regression algorithm Random Forest produces the best overall results when considering the position in the ranking, whereas the regression algorithm SVM is best when this is not considered.
6 Conclusions

We have presented an approach to news recommendation that aims at anticipating the reading interests of users of these services. This approach uses the number of times a news is tweeted as a proxy for its relevance for users and, in this context, tries to predict this number for very recent news items. Given that these predictions will be used to rank news the models should focus on decreasing the prediction error for highly tweeted news, which are rare. This fact leads to one of the main contributions of our work: the study and comparison of modeling techniques that are able to accurately forecast the rare and high number tweets of news items. The importance of this prediction is to minimize the referred latency and enable the treatment and recommendation of recent news without a waiting period. To this endeavour, we used two data sources: (1) Google News and (2) Twitter. Regarding the first data source, the top-100 news rank of four different topics (economy, microsoft, obama and palestine) were obtained for a period of over four months with a 15 minutes step. Data on several aspects of the news were also obtained, such as title, subtitle and publication date. The data obtained from Google News provides the necessary information for the development of the prediction models and for the comparative evaluation of its news ranking and the one proposed by our approach. Concerning the second data source, Twitter, it provides the information regarding the target variable of our prediction models: the number of tweets a given news item received over the period of two days upon its publication date. It also provides the necessary information to produce a ground truth news rank of the interest of users for a given set of news items, such as the referenced queries of Google News. In our evaluation processes of both prediction models and rankings, it was demonstrated that it is possible to successfully approach and tackle the issue of latency related to the recency of news items, producing more robust solutions that are capable of taking into consideration the users’ reading interests. Finally, concerning future work, it is our intention to broaden the basis of analysis in order to include information from other news recommender systems.

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