From Sentiment to Reputation: ILPS at RepLab 2012

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From Sentiment to Reputation
ILPS at RepLab 2012

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Abstract. We report on our participation in the profiling task of the first edition of the CLEF RepLab evaluation initiative. We assume that a statement—such as a tweet—that carries negative sentiment can have a positive impact on the reputation of the entity it talks about (and vice versa). Our model directly captures this impact by observing the reactions—such as replies—the statement solicits. We present the assumptions behind our model and the model itself. We find that given the current setting, results on the test set are strongly entity-dependent and that the test data is very different from the trial data. We conclude with a proposal on how to create a task that avoids such dataset dependent problems.

1 Introduction

The Reputation of an entity is an opinion about that entity, typically in a social context. Twitter as an opinion-conveying medium provides this social context: here, reputation is what Twitterers think of the entity.

The reputation task in RepLab was to identify if a tweet’s content has positive or negative implications on the reputation of a brand name. A tweet has mainly implications on opinions of people it reaches, directly or indirectly. Thus, an oracle or manual annotation would select all tweets uttered by Twitterers directly after they were read. One could then analyse manually if the original tweet had any implication on the opinion about the brands in those uttered tweets. Unfortunately, this is infeasible on many different levels. However, if we assume that tweets uttered in response to a tweet convey the implication on reputation of the entity mentioned in this tweet, we come to the first research question:

Can we bootstrap the implication on reputation from sentiment-annotated tweets in the replies and retweets to a source tweet?

This research question implies that our understanding of reputation is something very different to sentiment.

Additionally, tweets have a lot of metadata that may contain information as to how far a tweet can be considered polarized with respect to reputation.

Can we use machine learning to learn an appropriate combination of features to classify the polarity of a tweet?
Our work is organized as follows: We first describe our filtering methods in Section 2, we then continue with our polarity methods in Section 3. In Section 4, we describe how we use a machine learning approach to perform feature selection and classification. We then describe our experiments in Section 5. Results and analysis are presented in Section 6. We finish with a conclusion in Section 7.

2 Filtering Methods

The filtering task is to classify a tweet as relevant to a source entity or not. We were provided with the Wikipedia pages of a source entity. For the disambiguation of the source entities we semanticised the tweets with Wikipedia pages and disambiguated on the grounds of these pages. For each entity, we automatically assemble sets of Wikipedia pages that, if they are linked to in a tweet, this indicates the relevance of the tweet for a source entity.

In the baseline we assume all tweets to be relevant for a source entity. In the following, we lay out how the related Wikipedia pages for a tweet are found using semanticising (see Section 2.1) and how from this, sets of entities (as their Wikipedia page) that are related to the source entity are created (see Section 2.2). In Section 2.3, we shortly explain how relevant tweets are selected.

2.1 Semanticising

Each tweet can have possible semantic links to Wikipedia pages. Finding those links means disambiguating and finding concepts in a tweet. Following Meij et al. [2012], we use two features: the \textsc{LinkProbability} and the \textsc{Commonness} feature. The earlier is the probability that an \textit{n}-gram in a tweet is a link in Wikipedia: how many occurrences of this \textit{n}-gram are actually within hyperlinks to a page? The second feature \textsc{Commonness}, is the probability of an \textit{n}-gram to link to a certain concept. The product of the two features is the number of links to a concept if this \textit{n}-gram is a link to a Wikipedia page.

2.2 List Aggregation

\textbf{Top Entities} For each source entity, we aggregate the number of times Wikipedia pages are linked in tweets. The top \textit{N} most linked pages are the set \textsc{TopPages}.

\textbf{Entities in Wikipedia Page} Another group on entities is selected with the help of the provided Wikipedia pages of the source entities (\textsc{SourcePages}). Here, we select all outgoing links to internal Wikipedia pages. Those pages are called \textsc{WikiPages}.

\textbf{Combination of List} For each source entity, \textsc{TopWikiPages} is the intersection of the sets \textsc{TopPages} and \textsc{WikiPages}. Additionally, every list contains the pages in \textsc{SourcePages}. 
2.3 Disambiguation

Finally, for the disambiguation, we assume that a tweet is relevant to a source entity if

1. there are links to Wikipedia pages found by the semanticiser, and
2. those links are in a set of related Wikipedia pages for the source entity: either
   TOPWIKIPAGES, TOPPAGES, WIKIPAGES, or SOURCEPAGES.

Our runs for the filtering task differ in the use of the set of related Wikipedia pages.

3 Polarity Methods

The polarity task asks to classify a tweet for a given entity into having an impact on the reputation of that entity or not. There are three classes of polarity, positive, negative, and neutral.

This section proposes two groups of models: sentiment models (see Section 3.1) and reputation models (see Section 3.2). The two sentiment models build upon another, where sentiment model 1 is the first iteration of the iterative sentiment model 2. All reputation models are iterative and based on sentiment terms. They differ in the way they split positive and negative polarity vectors and in their initialization.

3.1 Sentiment Baselines

In the following we introduce two sentiment models. Sentiment model 1 (see Section 3.1) estimates sentiment based on the sentiment value of terms in a tweet, whereas sentiment model 2 (see Section 3.1) uses this as an initialization for an iterative approach.

**Sentiment Model** A simple way of estimating sentiment is to define sentiment as the sum of the sentiment of terms in a tweet.

Manually annotated sentiment lists can be found in Hu and Liu [2004], Liu et al. [2005], and Pérez-Rosas et al. [2012]. We say \( S(w) \) is the sentiment for a term \( w \). The sentiment for a tweet \( t \) and its terms \( \text{terms}(t) \) is

\[
\text{sent}(t) = \frac{1}{|\text{terms}(t)|} \sum_{w \in \text{terms}(t)} S(w). \quad (1)
\]

We refer to this model as sentiment model 1.

**Iterative Sentiment Model** Language use in Twitter is very different from traditional texts. We use a more elaborate sentiment model where the sentiment terms are learnt on a Twitter corpus. For that, we use the sentiment vectors \( S(w) \) from Section 3.1 and learn Twitter specific sentiments in an iterative approach.

We estimate the sentiment of a tweet \( t \) in iteration \( i \) as

\[
\text{sent}_i(t) = \frac{1}{|\text{terms}(t)|} \sum_{w \in \text{terms}(t)} S_i(w), \quad (2)
\]
and update the sentiment vector $S_i(w)$ based on all tweets $T$

$$S_i(w) = \sum_{t \in T} \text{sent}_{i-1}(t).$$

(3)

We refer to this model as sentiment model 2. The initial sentiment $\text{sent}_0(t)$ is equivalent to the sentiment in sentiment model 1.

3.2 Unsupervised Reaction Models Bootstrapped with Sentiment

The goal of this method is to learn the polarity of words with respect to an entity. In the sentiment models, we simply use the general sentiment that words carry, irrespective of the entity that is talked about. From examples, we know that the baseline approach is too simplistic. Depending on the context—the entity in question—the polarity of a word can be completely opposite from the general sentiment it carries. The obvious example is: *R.I.P. Michael Jackson, we miss you*. In this example, words carry negative sentiment (sadness) while the statement itself has a positive impact on the reputation of Michael Jackson. In the context of another entity, however, these words can carry a negative impact on the reputation. In this model, we intend to learn this in an unsupervised manner.

In the following we lay out the assumptions underlying the models in Section 3.2 and introduce the different reaction models, Model 1 (see Section 3.2), Model 2 (see Section 3.2), and Model 3 (see 3.2).

**Assumptions** Based on interviews with experts we hypothesize the following:

1. The message in a tweet is not necessarily about the entity we are concerned with. But, as tweets are rather short, we assume it is about some entity as soon as we find a reference to it.
2. A tweet with positive (negative) sentiment from a user who tweets mainly negative (positive) tweets has more impact on the reputation.
3. Positive sentiment can cancel negative sentiment and vice versa; positive reputation can cancel negative reputation and vice versa.
4. The impact on the reputation of an entity as represented in a tweet is based on the sentiment the tweet causes in other users.

Assumption 4 is the intuition that underlies our model. We hypothesize that the impact of a statement on reputation can be deduced from the sentiment of reactions.

**Reaction Model 1** We propose an iterative approach to estimate an entity $e$ specific term vector $W(e)$. The term vector is initialized with sentiment terms, similar to sentiment model 2 (see Section 3.1). We assume that the impact of reputation can be measured by the kind of replies and retweets it solicits. Thus, every iteration we estimate the polarity of a tweet based on the polarity contribution of the retweets and replies to a tweet. At the end of the iteration we update the term vectors $W_i$ based on this estimated polarity of a tweet and the previous term vector $W_{i-1}$. We assume that after $N$ iterations $W_N(e) \approx W(e)$ for all entities and we can estimate the polarity of every tweet, even if unseen.
**Reaction Model 2** The number of tweets with positive and negative sentiment is skewed in the dataset. This influences the estimation of the term vector $W$ — positive and negative influences do not cancel another out. We propose separate reputation vectors $W^+$ and $W^-$. The difference to Model 1 is the estimation of the polarity contribution and the iterative updating $W^+, W^-$: here we have different vectors for positive and negative polarities. As the reputation vectors are normalized at the end of each iteration and the influence of positive tweets is not overwhelming the negative tweets.

**Reaction Model 3** The third reaction model differs from Model 1 with respect to the initialization. In Model 1 (see Section 3.2), the initial vector $W_0(e)$ is the sentiment vector $S$, so $W_0(e, w) = S(w)$. In this model, Model 3, the vector of the original sentiment does not interpolate into $W_1$. That way, we have a stronger focus on the the actual reputation and have only terms in the sentiment lexicon that feature a strong polarity within Twitter.

### 4 Classification

We use a machine learning approach for classification the classification of polarity. We view all our models, described in Section 3.1 through Section 3.1, as features and train a classifier based on the trial data.

#### 4.1 Feature descriptions

For each tweet we collect 25 features. Those 25 features include the sentiment and reputation models, as well as metadata features.

- `reactionmodel1` as described in Section 3.2
- `reactionmodel2` as described in Section 3.2
- `reactionmodel3` as described in Section 3.2
- `sentimentmodel1` as described in Section 3.1
- `sentimentmodel2` as described in Section 3.1
- `scaledreactionmodel3` scaled—or, centered—version of the `reactionmodel3` feature
- `scaledsentimentmodel1` scaled—or, centered—version of the `sentimentmodel1` feature
- `entity` a reference to the entity as provided by the track organizers. Note that this feature can not be used in classifier that generalizes to the test collection.
- `lang` detected language
- `knownlang` whether `lang` is either `english` or `spanish`, the languages for which we have sentiment lexicons
- `nrrt` the number of retweets
- `nrrp` the number of replies
- `nrreact` the total number of reactions ($nrrt + nrrp$)
- `nrpos` the number of reactions with positive sentiment
- `nrneg` the number of reactions with negative sentiment
- `nrreactionfriends` the sum of the number of friends of the authors of all reaction tweets
fractionpos  the fraction of positive reactions (nrpos / nrreact)
fractionneg  the fraction of negative reactions (nrneg / nrreact)
reactpossum  the sum of sentiment of negative reactions
reactnegsum  the sum of sentiment of positive reactions
friends  the number of friends
favorite  whether a tweet was favorited
userreactionmodel3  the sum of the reactionmodel3 for this user
usercount  the number of thwarts from this user
useravgreactionmodel3  the average value of reactionmodel3 for this user

4.2 Classifier
We train a simple tree classifier\(^1\) using the above features and subsets of these features on the trial data. We select the subsets of features based on the information gain of individual features, as illustrated in Table 5.

5 Experimental setup
In this section we describe the experiments to answer the research questions mentioned in Section 1. We describe the official and external datasets as well as their preprocessing in Section 5.1. The runs and their evaluation are described in Section 5.2.

5.1 Data

Twitter Dataset  We used the dataset provided by the organizers of RepLab@CLEF. The dataset was split in labeled (unlabeled of the test set) and background datasets. In particular, the background dataset contains 238,000 and 1.2 million tweets for trial and test set, respectively. This means 40,000 and 38,000 tweets per entity, respectively. The set of labeled tweets in the trial dataset contains 1649 tweets, of which we managed to download 1553 tweets (94.1%). The set of unlabeled tweets for the test data contains 12400 tweets, of which we managed to download 11432 tweets (92%).

Replies and Retweets to Tweets  The reputation models are based on the reactions to the tweets. For us, a reaction is a tweet that is either a reply or a retweet. We extracted \(\sim 434,000\) (17,000 per entity) reactions from the test background dataset and \(\sim 50,000\) (8,000 per entity) from the trial background dataset. These are supplemented with all \(\sim 228,000,000\) reactions from an (external) Twitter spritzer stream after the earliest date of a tweet in either trial or test data (25 October 2011). Those reactions were not necessarily reaction to tweets in the background and (un)-labeled corpora. Consider Table 1 for the number of reactions to tweets in the background dataset.

Sentiment Lexicons  We use publicly available sentiment word lexicons in English \[Hu and Liu, 2004, Liu et al., 2005\] and Spanish \[Pérez-Rosas et al., 2012\] as the vast majority of tweets are in either of these languages.

\(^1\) We use the WEKA \[Hall et al., 2009\] implementation of C4.5 by Quinlan \[1993\]
Table 1. Mean reactions per entity, statistics per dataset. The min, max and standard deviation are shown as well. Note that the number of replies is very different for the test data.

<table>
<thead>
<tr>
<th></th>
<th>trial data</th>
<th></th>
<th>test data</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>min</td>
<td>max</td>
<td>mean</td>
</tr>
<tr>
<td>#retweets</td>
<td>4767</td>
<td>2620</td>
<td>8982</td>
<td>2131</td>
</tr>
<tr>
<td>#replies</td>
<td>72</td>
<td>28</td>
<td>151</td>
<td>39</td>
</tr>
<tr>
<td>#reactions</td>
<td>4839</td>
<td>2648</td>
<td>9066</td>
<td>39</td>
</tr>
</tbody>
</table>

**Preprocessing** We preprocess all tweets using the following procedure:

1. separate punctuation characters from word characters but:
2. keep mentions, hashtags and smilies intact;
3. casefolding;
4. tokenize by splitting on whitespace.

Additionally, we perform language identification on tweets using the method described in Carter et al. [2013].

5.2 Evaluation

We participated with 5 runs, see Table 2 for a description of these runs. The sentiment models were trained on the entire background corpora, entity unrelated. The reputation models were trained on the reactions as explained in Section 5.1. We estimated the performance of each run on the trial data for polarity and filtering separately and paired the best polarity run with the best filtering run, the second best polarity run with the second best filtering run, etc.

The evaluation measures we use are accuracy for the polarity and F-score for the relevance filtering.

6 Results and Analysis

In this section we answer the research questions mentioned in Section 1. We first analyze the official results of the runs in Section 6.1. Section 6.2 analyses how a different approach to set up the experiments is likely to be more realistic and successful in estimating polarity and relevance for tweets given an entity.

6.1 Results of the Runs

Table 3 shows the results of our runs on the trial data and the test data. We can see that the performance with respect to the evaluation measures of the test runs are roughly inversely proportional to the performance with respect to the evaluation measures of the trial runs for the polarity task as well as the filtering task.
Table 2. Run descriptions, sorted in descending performance on the trial set (see Table 3) for polarity and filtering independently. The first 5 runs were submitted, the others serve as baselines for comparison in our analysis.

<table>
<thead>
<tr>
<th>run</th>
<th>polarity name</th>
<th>description</th>
<th>filtering name</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ilps_1</td>
<td>best</td>
<td>J4.8, allrel feature selection with: reactionmodel1, reactionmodel2, reactionmodel3, sentimentmodel1, sentimentmodel2, reactionmodel1, lang, sentimentmodel1, knownlang</td>
<td>allrel</td>
<td>all tweets are relevant</td>
</tr>
<tr>
<td>ilps_2</td>
<td>model1</td>
<td>best excluding reactionmodel2 top30-0.2- and reactionmodel3 outlinks-origin</td>
<td>origin</td>
<td>tweets where one linked Wikipedia page is in TOP-WIKIPAGES, with ( N = 30 )</td>
</tr>
<tr>
<td>ilps_3</td>
<td>model2</td>
<td>best excluding reactionmodel1 top30-0.2- and reactionmodel3 origin</td>
<td>origin</td>
<td>tweets where one linked Wikipedia page is in TOP-WIKIPAGES, with ( N = 30 )</td>
</tr>
<tr>
<td>ilps_4</td>
<td>model3</td>
<td>best excluding reactionmodel1 outlinks-origin and reactionmodel2 origin</td>
<td>origin</td>
<td>tweets where one linked Wikipedia page is in WIKIPAGES</td>
</tr>
<tr>
<td>ilps_5</td>
<td>non-sent</td>
<td>all features excluding sentiment or reactions models and the entity feature</td>
<td></td>
<td>tweets where one linked Wikipedia page is SOURCEPAGES</td>
</tr>
</tbody>
</table>

base_6 random assigns classes randomly
base_7 zero picks the majority class
base_8 all J4.8 using all features
base_9 all+ent J4.8 on all features plus entity information
base_10 best+ent J4.8 on the best features plus entity information

In particular, for the polarity task our best runs on the trial data are using all reputation and sentiment models and the language feature, while on the test data, this performs worst with respect to accuracy: the run with the highest accuracy uses no reputation models at all.

Table 1 shows the number of reactions and replies for the trial and test data. We can see that for the test data we used significantly more replies than the trial data, while the number of retweets remains about the same. We suspect that with a higher number of replies comes more noise that misguides the bootstrapping approach. In this respect, the trial and test data are very different and it is only natural that this is reflected in the quantitative evaluation.

For filtering, the highest F-score on the trial set was using all tweets. All more informed attempts to disambiguate could never reach the F-score of 96%: We found that the bigger
Table 3. Results on the trial and test data for both the polarity and filtering. For most baseline runs, no test data is available.

Table: Results on the trial and test data for both the polarity and filtering. For most baseline runs, no test data is available.

<table>
<thead>
<tr>
<th>run</th>
<th>polarity accuracy</th>
<th>filtering F-score</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>trial</td>
<td>test trial</td>
</tr>
<tr>
<td>ilps_1</td>
<td>0.77</td>
<td>0.36</td>
</tr>
<tr>
<td>ilps_2</td>
<td>0.69</td>
<td>0.38</td>
</tr>
<tr>
<td>ilps_3</td>
<td>0.71</td>
<td>0.41</td>
</tr>
<tr>
<td>ilps_4</td>
<td>0.74</td>
<td>0.40</td>
</tr>
<tr>
<td>ilps_5</td>
<td>0.61</td>
<td>0.43</td>
</tr>
<tr>
<td>base_6</td>
<td>0.33</td>
<td>0.33</td>
</tr>
<tr>
<td>base_7</td>
<td>0.55</td>
<td>0.44</td>
</tr>
<tr>
<td>base_8</td>
<td>0.74</td>
<td>-</td>
</tr>
<tr>
<td>base_9</td>
<td>0.81</td>
<td>-</td>
</tr>
<tr>
<td>base_10</td>
<td>0.82</td>
<td>-</td>
</tr>
</tbody>
</table>

On an entity-level we can see that for 13 out of the 31 tweets the baseline assigning all of the relevance performs best. However, it does hurt the filtering performance with respect to F-score for other entities so much that F-score drops to be the worst. The run ilps_2, even though it performs best with respect to the overall F-score, only has higher F-scores than ilps_2 for 8 entities, but the difference in F-score is on average 0.55, with the F-score for ilps_1 being zero or near zero in 5 out of the eight cases.

6.2 Entity-specific annotation

Table 5 shows the ranks of the features used for polarity of trial data when sorted by information gain. The feature entity encodes for which entity the datapoint (tweet) is supposed to be classified. Of course, this feature can not be used in a classifier trained for the test set. We can see that knowing the entity in beforehand has the greatest information gain. The accuracy of base_9 and base_10 on the trial set feature is 0.82, 25% better than the runs without this prior information. The trial set is too small for elaborate analysis, but we conclude that for the entities used in the trial set, a manual entity-specific seed annotation is more useful than an entity-ignorant annotation. As the number of entities is limited, we propose to manually annotate tweets for every entity and train classifiers on those tweets for future incoming tweets. To ensure that changes in the use of language in the tweets over time are captured, an adaptive interactive interface for the reputation manager seems most convenient.
Table 4. Runs on the test data with distribution of the 11432 instances over classes. If a value for the relevance was missing it was assumed to be relevant.

<table>
<thead>
<tr>
<th>run</th>
<th>polarity</th>
<th>relevance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>neutral</td>
<td>positive</td>
</tr>
<tr>
<td>ilps_1</td>
<td>7433</td>
<td>3562</td>
</tr>
<tr>
<td>ilps_2</td>
<td>7032</td>
<td>4191</td>
</tr>
<tr>
<td>ilps_3</td>
<td>5841</td>
<td>5036</td>
</tr>
<tr>
<td>ilps_4</td>
<td>6589</td>
<td>4638</td>
</tr>
<tr>
<td>ilps_5</td>
<td>5643</td>
<td>5700</td>
</tr>
</tbody>
</table>

7 Conclusions

In general, we found that the trial and test set were very different. For the polarity task we are able to say that reputation models work well for all trial entities, but not for the test entities. Additionally, we also found that for the filtering task the best performing run strongly varied per entity.

Therefore, for future reputation management tasks we propose a more natural setting, where training entities and evaluation entities are the same. Entities are very different, and given the manpower of reputation management companies, it seems feasible to annotate a batch of tweets for each new entity that needs to be monitored. Results are likely to be more reliable and useful.

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8 References


Table 5. Attribute ranker that uses information gain, produced with WEKA.

<table>
<thead>
<tr>
<th>Information Gain Feature</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.29387 entity</td>
</tr>
<tr>
<td>0.193489 reactionmodel3</td>
</tr>
<tr>
<td>0.107189 reactionmodel2</td>
</tr>
<tr>
<td>0.106144 sentimentmodel2</td>
</tr>
<tr>
<td>0.099352 useravgreactionmodel3</td>
</tr>
<tr>
<td>0.077697 userreactionmodel3</td>
</tr>
<tr>
<td>0.063932 lang</td>
</tr>
<tr>
<td>0.035735 reactionmodel1</td>
</tr>
<tr>
<td>0.012383 sentimentmodel1</td>
</tr>
<tr>
<td>0.000788 knownlang</td>
</tr>
<tr>
<td>0 nrrt</td>
</tr>
<tr>
<td>0 friends</td>
</tr>
<tr>
<td>0 favorite</td>
</tr>
<tr>
<td>0 scaledreactionmodel3</td>
</tr>
<tr>
<td>0 fractionneg</td>
</tr>
<tr>
<td>0 usercount</td>
</tr>
<tr>
<td>0 reactnegsum</td>
</tr>
<tr>
<td>0 scaledsentimentmodel1</td>
</tr>
<tr>
<td>0 reactpossum</td>
</tr>
<tr>
<td>0 nrpos</td>
</tr>
<tr>
<td>0 nrrp</td>
</tr>
<tr>
<td>0 nrreact</td>
</tr>
<tr>
<td>0 fractionpos</td>
</tr>
<tr>
<td>0 nneg</td>
</tr>
<tr>
<td>0 nrreactionfriends</td>
</tr>
</tbody>
</table>


