NTNUSentEval at SemEval-2016 Task 4:
Combining General Classifiers for Fast Twitter Sentiment Analysis

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Abstract

The paper describes experiments on sentiment classification of microblog messages using an architecture allowing general machine learning classifiers to be combined either sequentially to form a multi-step classifier, or in parallel, creating an ensemble classifier. The system achieved very competitive results in the shared task on sentiment analysis in Twitter, in particular on non-Twitter social media data, that is, input it was not specifically tailored to.

1 Introduction

As a growing platform for people to express themselves on a global scale, Twitter has become exceedingly attractive as an information source. In addition to text, a tweet comes with metadata such as the sender’s location and language, and hashtags, making it possible to quickly gather vast amounts of data regarding a specific product, person or event. With a working Twitter Sentiment Analysis system, companies could get a feel of what consumers think of their products, or politicians could estimate their popularity amongst Twitter users in specific regions.

However, tweets and other informal texts on social media are quite different from texts elsewhere. They are short in length and contain a lot of abbreviations, misspellings, Internet slang, and creative syntax. Although the relative occurrence of non-standard English syntax is fairly constant among many types of social media (Baldwin et al., 2013), analysing such texts using traditional language processing systems can be problematic, primarily since the main common denominator of social media text is not that it is informal, but that it describes language in rapid change (Androutsopoulos, 2011; Eisenstein, 2013), so that resources targeted directly at social media language quickly become outdated.

Twitter Sentiment Analysis (TSA) has been a rapidly growing research area in recent years, and a typical approach to TSA has been identified, using a supervised machine learning strategy, consisting of three main steps: preprocessing, feature extraction and classifier training. Preprocessing is used in order to remove noise and standardize the tweet format, for example, by replacing or removing URLs. Desired features of the tweets are then extracted, such as sentiment scores using specific sentiment lexica or the occurrence of different emoticons. Finally, a classifier is trained on the extracted features.

Since the machine learning algorithms used commonly are supervised, sentiment-annotated data is a prerequisite for training — and the growth of the TSA research field can largely be attributed to the International Workshop on Semantic Evaluation (SemEval) having run shared tasks on this theme since 2013 (Wilson et al., 2013), annually producing new annotated data. The SemEval-2016 version (Task 4) of the TSA task and the data sets are described by Nakov et al. (2016). Here we will specifically address Subtask A, which is a 3-way sentiment polarity classification problem, attributing the labels ‘positive’, ‘negative’ or ‘neutral’ to tweets.

The rest of the paper is laid out as follows: Section 2 describes a general architecture for building
Twitter sentiment classifiers, drawing on the experiences of developing two previous TSA systems (Selmer et al., 2013; Reitan et al., 2015). Section 3 reports the application of such a system (‘NTNU-SentEval’) to the SemEval data sets, while Section 4 points to ways that the results could be improved.

2 Sentiment Classifier Architecture

To solve the three-way sentiment classification task, a general multi-class classifier, BaseClassifier, was created. Utilizing a general methodology enables the combination of several BaseClassifiers in various ways, either sequentially to create a multi-step classifier, or in parallel, as a classifier ensemble.

The BaseClassifier consists of three steps: preprocessing, feature extraction, and then either classification or training. These are handled by a Pipeline object built in the Scikit-Learn Python machine learning library (Pedregosa et al., 2011). Scikit-Learn Transformer objects are used to extract or generate feature representations of the data. Figure 1 illustrates the overall architecture of the system. When creating a BaseClassifier instance, a set of parameters is specified, including the classification algorithm, the preprocessing functions to use, and options for each of the transformers. The preprocessing methods invoked depend on the transformers and the features they aim to extract.

2.1 Preprocessing

The preprocessing step modifies the raw tweets before they are passed to feature extraction: noise is filtered out and negation scope is detected. The filtering consists of a chain of simple methods using regular expressions. There are ten basic filters that can be invoked, six of which replace various twitter-specific objects with the empty string: emoticons, username mentions, RT (retweet) tags, URLs, only hashtag signs (#), and hashtags (incl. the string following the sign). The other four filters transform uppercase characters to lowercase, remove non-alphabetic or space characters, limit the maximum repetitions of a single character to three, and perform tokenization using Pott’s tweet tokenizer (Potts, 2011).

Negation detection uses a simple approach where \( n \) words appearing after a negation cue, but before the next punctuation mark, are marked as negated. The negation cues were adopted from Councill et al. (2010), supplemented by five common misspellings obtained by looking up each negation cue in TweetNLP’s Twitter word cluster (Owoputi et al., 2013): anit, couldn't, dnt, does'nt, and wont.

2.2 Feature Extraction

The feature extraction is implemented as a Scikit-Learn Feature Union, which is a collection of independent transformers (feature extractors), that build a feature matrix for the classifier. Each feature is represented by a transformer. Eight such transformers have been implemented: two extract the number of punctuations (repeated alphabetical and grammatical signs) and the number of happy and sad emoticons found in the tweet. Two other transformers extract TF–IDF values for word n-grams and character n-grams using a bag-of-words vectorizer implementation, which is an extension of Scikit-Learn’s default TfidfVectorizer.

A part-of-speech transformer uses the GATE TwitIE tagger (Derczynski et al., 2013) to assign part-of-speech tags to every token in the text; the tag occurrences are then counted and returned. A word cluster transformer counts the occurrences of different TweetNLP word clusters (Owoputi et al., 2013), that is, if a word in a tweet is a member of a cluster, a counter for that specific cluster is incremented.

The last two transformers are essentially lexical: the VADER transformer runs the lexicon-based social media sentiment analysis tool VADER (Hutto and Gilbert, 2014) and extracts its output. VADER (Valence Aware Dictionary and sEntiment Reasoner) goes beyond the bag-of-words model, taking into consideration word order and degree modifiers.

The lexicon transformer is a single transformer using a combination of six automatically and manually annotated prior polarity sentiment lexica. The
automatically annotated lexica used are NRC Senti-
ment140 and HashtagSentiment (Kiritchenko et al.,
2014), that contain sentiment scores for both uni-
grams and bigrams, where some are in a negated
context. Similarly, two manually annotated lexica,
AFINN (Nielsen, 2011) and NRC Emoticon (Mo-
hammad and Turney, 2010), give a sentiment score
for each word (AFINN) or each emoticon (NRC
Emoticon). However, two further manually anno-
tated lexica, MPQA (Wilson et al., 2005) and Bing
Liu (Ding et al., 2008), do not list sentiment scores
for words, but only whether a word contains positive
or negative sentiment. For those two lexica, nega-
tive and positive word sentiments were mapped to
the scores $-1$ or $+1$, respectively.

For all lexica, four different features were ex-
tracted from each tweet. Following Kiritchenko et
al. (2014), the four features for manually annotated
lexica are the sums of positive scores and of nega-
tive scores for words in both affirmative and negated
contexts, while the four features for automatically
annotated lexica comprise the number of unigrams
or bigrams with sentiment score $\neq 0$, the sum of all
sentiment scores, the highest sentiment score, and
the score of the last unigram or bigram in the tweet.

2.3 Classification

After all desired features have been extracted, a
BaseClassifier instance allows for the use of state-
of-the-art classification algorithms such as Support
Vector Machines (SVM), Naïve Bayes and Maxi-
mum Entropy (MaxEnt). Scikit-Learn includes a se-
ries of implementations of the SVM algorithm (Vap-
nik, 1995). The NTNUSentEval system uses the
SVC variant, also known as C-Support SVM classi-
fier since it is based on the idea of setting a constant
$C$ to penalize incorrectly classified instances. High
$C$ values create a narrower margin, enabling more
elements to be correctly classified. However, this
can lead to overfitting, so it is desirable to perform
some kind of parameter optimization to find the best
$C$ value. For multi-class classification, Scikit-Learn
uses a One-vs-One method with a run time com-
plexity more than quadratic to the number of ele-
ments; however, this is not a problem for our rela-
tively small (under 10,000 elements) datasets.

A single BaseClassifier acts as a one-step clas-
sifier, but by chaining BaseClassifiers sequentially,
a multi-step classifier can be created. Each classi-
fier can be trained independently on different data, thereby learning a different classification function. Figure 2 illustrates how chaining two BaseClassifiers can create a two-step classifier. The first Base-
Classifier is trained only on data labeled as subjec-
tive or objective, while the second BaseClassifier
is trained only on subjective data, labeled positive
or negative. When classifying, if the first Base-
Classifier classifies an instance as subjective, the in-
stance is forwarded to the second BaseClassifier to
determine if it is positive or negative. The results
from both classifiers are then combined and the final
classification is returned.

By combining BaseClassifiers in parallel, an en-
ssemble of classifiers can be created. Each of the
classifiers is independent of the others and all clas-
sify the same instances. In the end, the classifiers
vote to decide on the classification of an instance.
Since the BaseClassifiers are so general, it is pos-
sible to create BaseClassifiers that extract different
features, do different preprocessing, or use different
classification algorithms — and then combine these
to create an ensemble system.

2.4 Parameter Optimization

In order to find the optimal parameter values for
the NTNUSentEval system, an extensive grid search
was performed through the Scikit-Learn framework
over all subsets of the training set (shuffled), using
stratified 5-fold cross-validation and optimizing
on $F_1$-score. During development we were able
to find parameters that yielded better results on the
complete test set than the parameters from the grid
search. However, the optimal parameters are those
that perform best on average, and using the param-
eters identified through development when presented
with new data would most likely perform worse than
using the parameters identified through grid search.
As described in Section 2.2, a total of eight different feature extractors have been implemented, all of which can be enabled or disabled. Each feature extractor utilizes a specific preprocessor setting, as shown in Table 1. Further, there are three option settings for the SVM algorithm: type, kernel and \( C \), which after grid search were set to SVC, Linear, and 0.1, respectively. In addition to the preprocessor options, there are eleven more feature extractor options, whose grid-searched optimal values are displayed in Table 2, where \( n\text{-range} \) gives the lower and upper \( n \)-gram sizes, \( \text{use\_idf} \) enables Inverse Document Frequency weighting, \( \text{min\_df} \) and \( \text{max\_df} \) give the proportions of lowest resp. highest document frequency occurring terms to be excluded from the final vocabulary, and \( \text{negation\_length} \) the maximum number of tokens inside a negation scope.

### 3 Experimental Results

The NTNUSentEval TSA system was trained on the Twitter training set (8,748 tweets), using the optimal parameters identified through grid search, and tested on the SemEval Twitter test sets from 2013 and 2014. The complete results on these test sets are shown in Table 4 below, while Nakov et al. (2016) give the results on all test sets, including the unknown 2016 tweet set, in terms of the official evaluation metric, \( F_{1}^{1} \), which is the average of the F1-scores on the negative and the positive tweets.

Notably, our system performed extremely well on the out-of-domain test sets (i.e., the non-Twitter data), being the best of all 34 participating systems on the 2013-SMS set (with a 0.641 \( F_{1}^{1} \) score, compared to a 0.190 \( F_{1}^{1} \) baseline), the 3rd on the 2014-Live-journal set (\( F_{1}^{1} = 0.719 \), with a 0.272 baseline), and overall tied for first on the out-of-domain data, supporting our claim that the approach taken in itself is quite general. However, the lack of domain fine-tuning of the system showed in comparison to the best systems on Twitter data, with the NTNUSentEval system consistently placing 11–13 on the different test sets, including 11th on the 2016 set (\( F_{1}^{1} = 0.583 \), with baseline 0.255).

### 3.1 Ablation Study

In order to detect the overall importance or impact each feature has, a simple ablation study was conducted by removing each feature in turn and checking how the performance of the system was affected. The results of this study are shown in Table 3.

Evidently, the single most important feature is Sentiment Lexica. On the 2013-test set, system accuracy is reduced from 0.7227 to 0.6945 when the feature is removed, while the effect of removing it when testing on the 2014 set is not as apparent. A possible reason for this difference may be that most of the sentiment lexica used were created at the same time as the 2013-test set, and they might thus better reflect the language in that period of time. As noted in Section 1, the language of social media is rapidly changing, so that a lexicon created in 2013 might have reduced value already for data collected a year later. This effect is also noticeable when testing the system on the 2014-test set, where the VADER Sentiment feature is the most important one, reducing the accuracy from 0.6905 to 0.6793 when being removed. On the 2013-test set, the VADER Sentiment feature, which was created in 2014, does not have the same impact, again indicating a change in how the language is used and that VADER might better reflect the Twitter language of 2014.

The second most important contribution comes from the n-gram features. The removal of both char-
Table 3: Feature ablation study results ($F_1$-scores)

| Features                  | 2013-test | 2014-test |
|---------------------------|-----------|-----------|
| All                       | .7227     | .6905     |
| - Word $n$-grams          | .7136     | .6892     |
| - Character $n$-grams     | .7085     | .6885     |
| - Both $n$-grams          | .7017     | .6872     |
| - Automatic Lexica        | .7088     | .6799     |
| - Manual Lexica           | .7085     | .6938     |
| - All Sentiment Lexica    | .6945     | .6826     |
| - Word Clusters           | .7166     | .6872     |
| - Part-of-Speech tag counts | .7159    | .6865     |
| - Punctuation counts      | .7143     | .6932     |
| - Emoticons counts        | .7156     | .6918     |
| - All counts              | .7127     | .6925     |
| - VADER Sentiment         | .7114     | .6793     |

Another interesting result is the impact of the Emoticons and Punctuation count features. On the 2013-test set, removing them gives a slight reduction in performance, while on the 2014-test set we can observe a slight increase in performance. One possible reason for this could be that the way emoticons and punctuation are used in tweets changes over time, but the most likely cause is merely noise in the data. Although causing slightly increased or decreased performance, the individual count features do not significantly affect the overall results.

3.2 Architectural Experiments

Two instances of the BaseClassifier can be chained sequentially creating a 2-step classifier. Such a classifier was tested on the 2013 and 2014 test sets, as shown in Table 4. The 2-step classifier performs worse than the 1-step classifier on the 2013 set, while their performances on the 2014 set are comparable, so based on these results it is not clear that 1-step classification is better than 2-step.

The GATE TwitIE part-of-speech tagger uses an underlying model when tagging tweets. In addition to the standard best performing model, another high-speed model trading 2.5% token accuracy for half the tagging speed is available, and the results from testing BaseClassifier using the high-speed tagger model are also shown in Table 4. Although a slight reduction in performance can be observed compared to using the best tagger model, the high-speed model significantly reduced the total execution time, from 107 to 80 seconds on the 2013-test set and from 53 to 41 seconds on the 2014-test set.

4 Conclusion and Future Work

Drawing on the experiences from two previous Twitter Sentiment Analysis systems (Selmer et al., 2013; Reitan et al., 2015), a new TSA system was created using a simplified and generalised architecture, allowing for accurate and fast tweet classification.

As seen in the ablation study of Section 3.1, the Sentiment Lexica is the single most important feature, while also being one of the simplest: our implementation is based only on summing up the sentiment value of each word. A possible improvement would thus be to extract more information by considering the order of the words, part-of-speech tags, and degree modifiers, such as ‘very’, ‘really’ and ‘somewhat’, that can affect the sentiment value of the following word. These modifiers are currently not handled by the Sentiment Lexica extractor, yet they clearly carry a lot of sentiment weight.

Another interesting feature of lexicon-based systems is their good run-time performance, which is also confirmed in our system, where the lexicon feature extractor is one of the fastest feature extractors. This is a particularly important property for a TSA system to be useful in a real world setting, as the opinion mining accuracy confidence depends on the number of opinions examined.
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