Language-Independent Twitter Sentiment Analysis

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Abstract

Millions of tweets posted daily contain opinions and sentiment of users in a variety of languages. Sentiment classification can benefit companies by providing data for analyzing customer feedback for products or conducting market research. Sentiment classifiers need to be able to handle tweets in multiple languages to cover a larger portion of the available tweets. Traditional classifiers are however often language specific and require much work to be applied to a different language. We analyze the characterstics and feasibility of a language-independent, semi-supervised sentiment classification approach for tweets. We use emoticons as noisy labels to generate training data from a completely raw set of tweets. We train a Naïve Bayes classifier on our data and evaluate it on over 10000 tweets in 4 languages that were human annotated using the Mechanical Turk platform. As part of our contribution, we make the sentiment evaluation dataset publicly available. We present an evaluation of the performance of classifiers for each of the 4 languages and of the effects of using multilingual classifiers on tweets of mixed languages. Our experiments show that the classification approach can be applied effectively for multiple languages without requiring extra effort per additional language.

1 Introduction

Twitter is one of the biggest microblogging services on the internet. Microblogs are short text messages that people use to share all kinds of information with the world. On Twitter, these microblogs are called "tweets", and over 400 million[1] of them are posted every day. They can contain news, announcements, personal affairs, jokes, opinions and more.

In this paper we analyze methods of extracting people's opinions from tweets. A single piece of opinion from one person may not seem important, but among the billions of tweets the collection of opinions can form a comprehensive picture. People's opinions and sentiments about products, other people and events in large numbers are invaluable. Companies can use them to gain feedback on their products, to do market research and analyze customer demands, and for a wide variety of other applications.

There has been a large amount of research to find ways to automatically extract sentiment from text. Most research is conducted only on tweets of one language. However, Twitter is an internationally popular service and a large part of the tweets are authored in a wide variety of languages. Therefore analysing tweets in only one language covers only a part of the available content. Often, much work is put into hand-crafting features specific to that language. While using these features increases the quality of the sentiment classifications for that language, classifiers perform worse for other languages and readjusting the features requires much effort. Traditional multilingual sentiment classification approaches, like described by Mihalcea et al. [Mihalcea *et al.*, 2007] require resources like parallel corpora for every language that should be classified. Additionally, language specific classifiers require tweets to be sorted out by their language. Since tweets do not always have any explicit language information, their language needs to be detected, which is not a trivial task given their frequent brevity.

A classification approach that is not restricted to analyzing only one language would be able collect much more sentiment information from the hugely multilinugal twitterverse than a language-specific approach. Such an approach would ideally require as little effort as possible to be applied to additional languages. Multilinugal sentiment information can help companies get feedback from people of a variety of languages simultaneously. It can illuminate how a product is received around the world.

In this paper, we examine a language-independent sentiment classification aproach. We train a classifier to label the sentiment polarity specifically of tweets. We use a semi-supervised emoticon heuristic to generate labelled training data. For any language, our approach requires only raw tweets of that language for training and no additional adjustments or intervention.

We train classifiers on tweets of 4 different languages: English, German, French and Portuguese. For our evaluation, we collected thousands of human-annotated tweets in these 4 languages using Amazon's Mechanical Turk[2]. As part of our contribution, we make this evaluation dataset publicly available. We report on the differing outcomes between classifiers trained on different languages. We also report on our experiments on mixed-language sentiment classifiers.

Our approach assumes that any one tweet only contains one opinion at a time, so it can not separate between multiple sentiments in the same tweet. For our language-independent approach we assume that words are distinctly

[1] Source: http://news.cnet.com/8301-1023_3-57448388-93/twitter-hits-400-million-tweets-per-day-mostly-mobile/

[2] Amazon Mechanical Turk: http://mturk.com

separated. Thus, our approach can only be applied to languages that use spaces as word separators.

We find that our approach performs well on the sentiment classification task, especially given its independence of specific languages. Classification accuracies tend to vary significantly between different languages. We also find that using a mixed-language classifier decreases the classification performance only slightly, but can greatly increase the ease of application in a practical setting.

Our findings help explore the use of sentiment classifiers in a multilinugal setting. We give insight on how to create classifiers that function for different languages without additional overhead. Our evaluation dataset provides a basis for the evaluation of a wide range of multilingual sentiment classification approaches for microblogs.

2 Related Work

There has been a large amount of research to find ways to automatically extract sentiment from text. While traditional work [Pang *et al.*, 2002] focused on text sources like movie reviews, more recent research has explored microblogs for sentiment analysis. The methods involved differ somewhat since texts like tweets have a different purpose and a more colloquial linguistic style [Han and Baldwin, 2011]. Notable works have been Go et al. [Go *et al.*, 2009] wo have trained a sentiment classifier to label tweets' sentiment polarities as "positive" or "negative". Pak et al. [Pak and Paroubek, 2010] trained classifiers to also detect "neutral" tweets that do not contain sentiment.

Sentiment classifiers require a large amount of training data, but obtaining it by having humans annotate tweets is very costly. To gather training data, Go, Pak and others used a heuristic method introduced by Read [Read, 2005] to assign sentiment labels to tweets based on emoticons instead. Test data is usually hand-labelled and consists only of a small amount of data.

To train a sentiment classifier, the source texts first have to be converted into some type of features. The most prominent features are n-grams, values from sentiment lexicons, part-of-speech tags and special microblogging features [Barbosa and Feng, 2010; Kouloumpis *et al.*, 2011] that include among other emoticons, hashtags, punctuation and character repetitions and words in capital letters. Because the language used on Twitter is often informal and differs from traditional text types [Han and Baldwin, 2011], most approaches include a preprocessing step. Usually emoticons are detected, URLs removed, abbreviations expanded and twitter markup is removed or replaced by markers.

Go et al. [Go *et al.*, 2009] compared different machine learning methods, Naïve Bayes, Maximum Entropy and Support Vector Machines (SVM), with unigram, bigram and part-of-speech features. Their training data consisted of 1.6M tweets equally split between positive and negative classes. The evaluation was performed on 359 hand-annotated tweets (182 positive and 177 negative tweets). Pak and Paroubek [Pak and Paroubek, 2010] collected 300k tweets as training data and performed evaluation on 216 hand-annotated tweets. The explored features included unigrams, bigrams and trigrams. The group conducted experiments with multinomial Naïve Bayes, SVM and Conditional Random Field classifiers; multinomial Naïve Bayes using bigrams performed best.

While most groups used a single classifier, Barbosa and Feng [Barbosa and Feng, 2010] followed a two-step approach with a neutral/subjective classifier and a positive/negative classifier. Instead of n-gram features they used part-of-speech tags, lexical and microblogging features to build SVM classifiers. Zhang et al. [Zhang *et al.*, 2011] combined a lexicon-based classifier with an SVM to increase the recall of the classification.

Other research in sentiment classification focused beyond simple classification. Jiang et al. [Jiang *et al.*, 2011] tried to perform a more fine-grained classification and assigned values from 1 to 5 to reflect the strength of expressed sentiments. Thelwall et al. [Thelwall *et al.*, 2010] built a classifier that takes into account the targets of sentiment expressions and also considers related tweets.

Multilingual sentiment classification approaches often classify sentiment by using cross-lingual training [Wan, 2009; Mihalcea *et al.*, 2007] with classification approaches for English texts. This however requires resources, like parallel corpora, that bridge between English and every language that should be classified. Many other approaches rely on machine-translation to first translate texts into English, and applying English classification techniques [Denecke, 2008] to the translated texts. Others use language-specific features to accommodate different languages [Boiy and Moens, 2009].

Multilingual sentiment classification approaches on tweets have before made use of emoticons as noisy labels for text of varying languages. However to the best of our knowledge, no work has methodically compared classifications among several languages. Davies and Ghahramani [Davies and Ghahramani, 2011] analyze bayesian learning on a set of mixed-language tweets, but report only test error on their training data. Cui et al. [Cui *et al.*, 2011] use a graph propagation algorithm on a few seed tokens to build a multilingual sentiment lexicon, but do not report on outcomes between individual languages.

3 Methods

We use a two-class Naïve Bayes classifier with n-gram features for our sentiment classification. Training data is labeled by a semi-supervised approach that uses emoticons as noisy labels. Our training method is applicable as described for almost any language that uses spaces as word separators.

3.1 Tokenization and Features

We use a Naïve Bayes classifier on n-gram features to classify sentiment in tweets. To obtain n-gram features, we first have to tokenize the text input. Tweets pose a problem for standard tokenizers designed for formal and regular text. Tweet texts have unique characteristics like missing whitespaces, irregular spelling and special tokens such as hashtags ("#tag"), mentions of twitter users ("@username") and retweet markers ("RT"). Therefore the data is tokenized using an extended version of O'Connor's regular-expression-based tweet tokenizer [O'Connor *et al.*, 2010]. It employs rules to define strings that form a token, e.g. emoticons, urls and strings of punctuation, and splits the rest of the strings at whitespaces.

We extended O'Connor's tokenizer to match a great variety of emoticons used in different languages, including eastern style emoticons (e.g. `^_^`). In addition, emoticons can sometimes be attached directly to words, but they can also contain letters. Therefore it was important to account for cases where wrong tokenization would separate words (e.g. the emoticon `:D` should be found in "He finally asked:D", but not in "He asked:Did you see the new movie?"). A further extension handles emoticons with character repetitions, which usually expresses a stronger sentiment, e.g. :(((.

We used n-gram counts of tokens as basic features for training the classifier. We reduced the feature space by reducing multiple letter repetitions to at most 2 consecutive letters and lower-casing all tokens after tokenization. We replaced uninformative tokens, e.g. URLs, usernames, numbers and single non-letter characters, by placeholder tokens.

3.2 Emoticon Heuristic

To generate training data, we used a method similar to the one used by Pak and Paroubek [Pak and Paroubek, 2010]. We assign noisy polarity class labels to tweets based on the existence of positive or negative emoticons. If a tweet contains one or more happy emoticons, and no negative ones, we assign it to the positive class, and vice versa. Because of the shortness of tweets, we assume here that the sentiment of a smiley applies to the whole text of the tweet. Although this may be wrong in some cases, it simplifies the analysis significantly. We used a range of emoticons that are very distinctly positive or negative as noisy labels. Below are shown some examples of the emoticons we used:

Examples of positive emoticons used:
:)   :-)   =)   ;)   :]   :D   ^-^   ^_^   ...
Examples of negative emoticons used:
:(:-(:((-.-   >:-(D: :/   ...

3.3 Classifier

We employed the Naïve Bayes classifier from the NLTK natural language processing toolkit[3] for training. We modified the classifier with an extension that allowed us to continuously retrain the classifier by updating the observed feature frequency count with the new training data.

We classifiy tweets using the same features we used for the training data. Class probabilites for the polarities are calculated using logarithmic probabilites. The classifier then assigns the label of the most probable class to the tweet.

After the training, the classifier is optimized by removing some uninformative features. All n-grams with equal counts are removed as they do not influence the classification. Features with a count under a given threshold are also removed. These optimizations lead to a vast reduction of the classifier size and in our experiments resulted in no significant deterioration of classification performance.

4 Annotated Sentiment Dataset

Although there are several public datasets of tweets annotated with sentiment available, we were not able to find any that spanned mutliple languages. To be able to evaluate our classifiers, we therefore created our own human-annotated multilingual sentiment dataset from tweets of 4 different languages: English, German, French and Portuguese. We have made the evaluation dataset publicly available for research purposes[4]. See Table 1 for detailed statistics of the dataset.

We constructed the dataset by selecting a subset of tweets from a larger corpus (see Section 5.1) according to the following criteria: Half of the source tweets were selected randomly, the other half was constrained to contain a brand name from a small list of brands: *"sony", "audi", "nike", "hilton", "adidas", "microsoft", "samsung", "nintendo", "gucci", "bing"*. The tweets could either contain emoticons or not.

For each language, we let workers on Amazon's Mechanical Turk manually annotate whole tweets into different sentiment categories: "positive", "negative", "neutral" and "irrelevant". See Table 1 for a comparison of the number of obtained tweets.

We let each tweet be annotated by three different Mechanical Turk workers. To ensure the quality of annotations, we required the workers to have completed a number of previous tasks with positive feedback (over 90%). We also randomly added "fake" tweets, such as *"The new speakers are mindblowing! Glad I decided to get them."* to each task that we prepared, and accepted only submissions with the correct sentiment labeled for these tweets. We implemented this as a verification method to ensure workers actually spoke the language they were annotating and were not just randomly labeling tweets.

We obtained an overall inter-annotator agreement of 0.407 Fleiss' kappa [Fleiss, 1981], an interrater agreement measure for more than two annotators. This level of agreement is quite low. One possible reason for this is that sentiment classification is generally very ambiguous and human agreement is often quite low [Wiebe *et al.*, 2005]. The fact that tweets give no further context other than their already short texts adds even more to the difficulty of the classification task.

5 Experiments

To determine if our sentiment classifier was applicable language-independently, we tested its performance on tweets of several languages. We also ran tests to compare differences in performances of classifiers for a single language versus one mixed-language classifier.

5.1 Training Dataset

For our experiments, we used a training dataset of over 800M tweets, containing tweets of the 4 languages of our evaluation dataset[5]. Tweets were collected from timelines of randomly selected Twitter users. Using the Chromium Compact Language Detector[6] we detected each tweet's language. To generate language-specific datasets, we compared the detected language to the tweet's metadata supplied by the Twitter API. To reduce the number of falsely identified tweets, we only added tweets to a language's dataset if both of these languages matched.

We used the semi-supervised heuristic described earlier (see Section 3.2) to label the tweets from our dataset. The distribution of the resulting labeled training set is described in Table 2. It is worth noting how much more positive than negative emoticons can be found in tweets.

Because they were used as selection criteria for the data, we removed all emoticons from the samples before training. This prevents the classifier from developing an adverse

[3] http://nltk.googlecode.com/

[4] The dataset can be found under http://www.dai-lab.de/%7Enarr/sentimentdataset

[5] The dataset was provided by SearchMetrics GmbH, http://www.searchmetrics.com.

[6] The language detector was extracted from the open-sourced code of the Google Chrome browser. See http://code.google.com/p/chromium-compact-language-detector/

Language	Total annotated	Fleiss’ kappa agreement	Sentiment class	Agreement >= 2	Agreement = 3
en	7200	0.430	pos	1595	739
			neut	4238	2536
			neg	998	488
			total	6831	3763
de	1800	0.419	pos	353	143
			neut	1096	711
			neg	239	95
			total	1688	949
fr	1797	0.244	pos	341	159
			neut	814	360
			neg	321	160
			total	1476	679
pt	1800	0.408	pos	626	297
			neut	583	262
			neg	414	213
			total	1623	772
fr+en+de+pt	12597	0.407	pos	2915	1338
			neut	6731	3869
			neg	1972	956
			total	11618	6163

Table 1: Our sentiment evaluation dataset: tweets annotated using Amazon Mechanical Turk. Each tweet was labeled by 3 human annotators. Shown are the total number of tweets for each language, the Fleiss’ kappa inter-annotator agreement, and the number of tweets for each sentiment class whose label 2 or more, as well as all 3 annotators agreed on.

Language	Tweets	Positive	Negative
en	148.6M	7.1% (10.6M)	1.7% (2.5M)
pt	50.6M	6.6% (3.3M)	3.2% (1.6M)
fr	2.9M	13.2% (385k)	1.4% (40k)
de	2.1M	15.8% (330k)	2.4% (49k)

Table 2: Overview of the training dataset: raw tweets and the number of tweets labeled as containing sentiment by our semi-supervised emoticon heuristic.

bias on these emoticons. Note that therefore the trained classifier will not be influenced by these emoticons during classification.

5.2 Evaluation Dataset

Dataset	Language	Positive	Negative	Total
agree-2	en	1595	998	2593
	de	353	239	592
	fr	341	321	662
	pt	626	414	1040
	combined	2915	1972	4887
agree-3	en	739	488	1227
	de	143	95	238
	fr	159	160	319
	pt	297	213	510
	combined	1338	956	2294

Table 3: Datasets used to evaluate our experiments: The agree-3 set contains tweets all three annotators agreed on, agree-2 contains also tweets agreed upon by two.

We evaluated the classifier on a subset of tweets taken from our evaluation dataset of manually annotated tweets (see Section 4).

For our evaluation, we used the tweets from the Mechanical Turk set that had been classified as “positive” or “negative”. We ignored tweets annotated as “neutral”. We split the data into two evaluation sets. In the **agree-3** set, we only used tweets that all 3 annotators had agreed on to belong to the same sentiment class. In the **agree-2** set, we used tweets that *at least* 2 annotators had agreed on, thus including the agree-3 set. Each evaluation set contains tweets of the 4 languages: English (“en”), German (“de”), French (“fr”) and Portuguese (“pt”), and a set of the combined tweets of languages fr, en, de, pt. Table 3 gives details about the different evaluation set sizes.

5.3 Experimental Setup

We trained one classifier per language using an equal amount of tweets for both polarity classes from our training dataset. We trained a Naïve Bayes classifier separately, each using 1-grams, 2-grams and combined 1-grams and 2-grams.

We optimized each classifier using the process described in Section 3, with a threshold for infrequent n-grams of 2 or less. We also trained a fifth classifier on the combined tweets of a mixture of the 4 languages. Here we used an equal number of tweets for each language, as many as available for the smallest language set.

We trained the classifiers in multiple steps to gain insight on the effects of the amount of training data on the classification performance. We had fewer German and French training tweets available than for the other languages. Therefore we could only evaluate those two languages on about 100k training tweets. During experimenting, we used 10-fold cross-validation testing on the training data for validation and parameter tuning.

We ran experiments on our 5 classifiers using the 2 different evaluation datasets detailed in Section 5.2. Each classifier was evaluated using the tweets of the appropriate language. The mixed-language classifier was evaluated on the combined language sets (“frendept”).

5.4 Results & Discussion

The results of our experiments for the different classifier variations, grouped by each of the 4 languages, are displayed in Figures 1a through 1d. Figure 1e displays the results for the mixed classifier of all 4 languages. An overview of the performance of only the unigram classifier on a single evaluation set, compared between all languages, is shown in Figure 1f.

As a reference point for the classifiers, we added as a baseline the accuracy of a mock-classifier that always guesses a "positive" sentiment. The baseline accuracies were calcuated individually for each language, using the number of positive and negative tweets in the agree-3 evaluation set as shown in Table 3. Because we had more positive than negative test tweets in all but one evaluation set, we decided to use the positive guess as a baseline instead of discarding tweets to balance the test sets.

Unigrams

The unigram Naïve Bayes classifier provides a simple and very lightweight classification method. The best results we obtained were 81.3% accuracy for the English agree-3 test set. Generally, the classifiers' performance improves with an increased number of tweets used for training. Using too few training tweets leads to a lower accuracy because less of the highly diverse topics present in tweets can be captured by the classifier.

For the maximum number of available training tweets, the performance of all classifiers is significantly better than the best-guess baseline "baseline-all-pos". Even though the results are not directly comparable because of the different training and evaluation datasets, they are close in range to the performance of similar approaches [Jiang *et al.*, 2011]. We find that especially considering the applicability to a variety of languages, our observed results are very satisfactory.

Unigrams + Bigrams

The 1+2-gram classifier adds bigram features to the classification. Bigram features tend to be very sparse, even more so for datasets with more, irregular word tokens as found in tweets. Therefore the 1+2-gram classifier requires both more runtime memory and more training time than the unigram classifier. In our evaluations we could not observe a stable increase in performance for the 1+2-gram classifier across languages. While it tended to outperform the unigram classifier for both test sets in English and Portuguese, it performed worse than the unigram classifier for German and French.

Performances Between Evaluation Sets

Figure 1a shows significant discrepancies in the quality of classifications between the agree-3 and the agree-2 evaluation dataset. Similar observations can be made for the other languages in Figures 1b, 1c and 1d. This is likely the case because the tweets in the agree-2 set were already evidently harder to classify accurately for the human annotators. Since there is less agreement between humans, the data poses a higher difficulty for a classification and thus leads to lower classifier performance.

Language-Specific Differences

Overall, the best accuracy performances measured on the agree-3 set were 81.3% for English, 64.9% for Portuguese, 79.8% for German and 74.9% for French. All of these best performances were achieved using the unigram classifier[7]. There is quite a large difference in classification performance between the 4 languages (as distinctly visible in Figure 1f). However, this does not seem to correlate to the amount of tweets containing emoticons in each language (see Table 2).

It is unsure if there is a discrepancy because of differences in the emoticon heuristic for different languages or in the classifier itself. It would be possible that the heuristic would label tweets with a smaller set of sentiment-containing words because of different styles in expressing sentiment in some languages. For example, in Brazilian Portuguese a positive sentiment is often conveyed by writing "kkkkk" or "rsrsrsrs" (much like the English "ha ha ha"), instead of a happy emoticon.

It is also possible that the Naïve Bayes classifier using word-level token features is less fit to classifiy some languages because of their structural differences. Further research would be needed to explore the unique impacts of different languages for our classifier.

The Multilingual Classifier

The mixed 4-language unigram Naïve Bayes classifier, trained on 300k tweets (75k per language), reaches an accuracy of 71.5% across the combined agree-3 sets. It performs distinctly better than the best-guess baseline (see Figure 1e). This is a reasonable performance, although it is slightly worse than the combined averaged accuracies of the 4 language classifiers for 75k tweets, normalized by the languages' evaluation set size (73.9%).

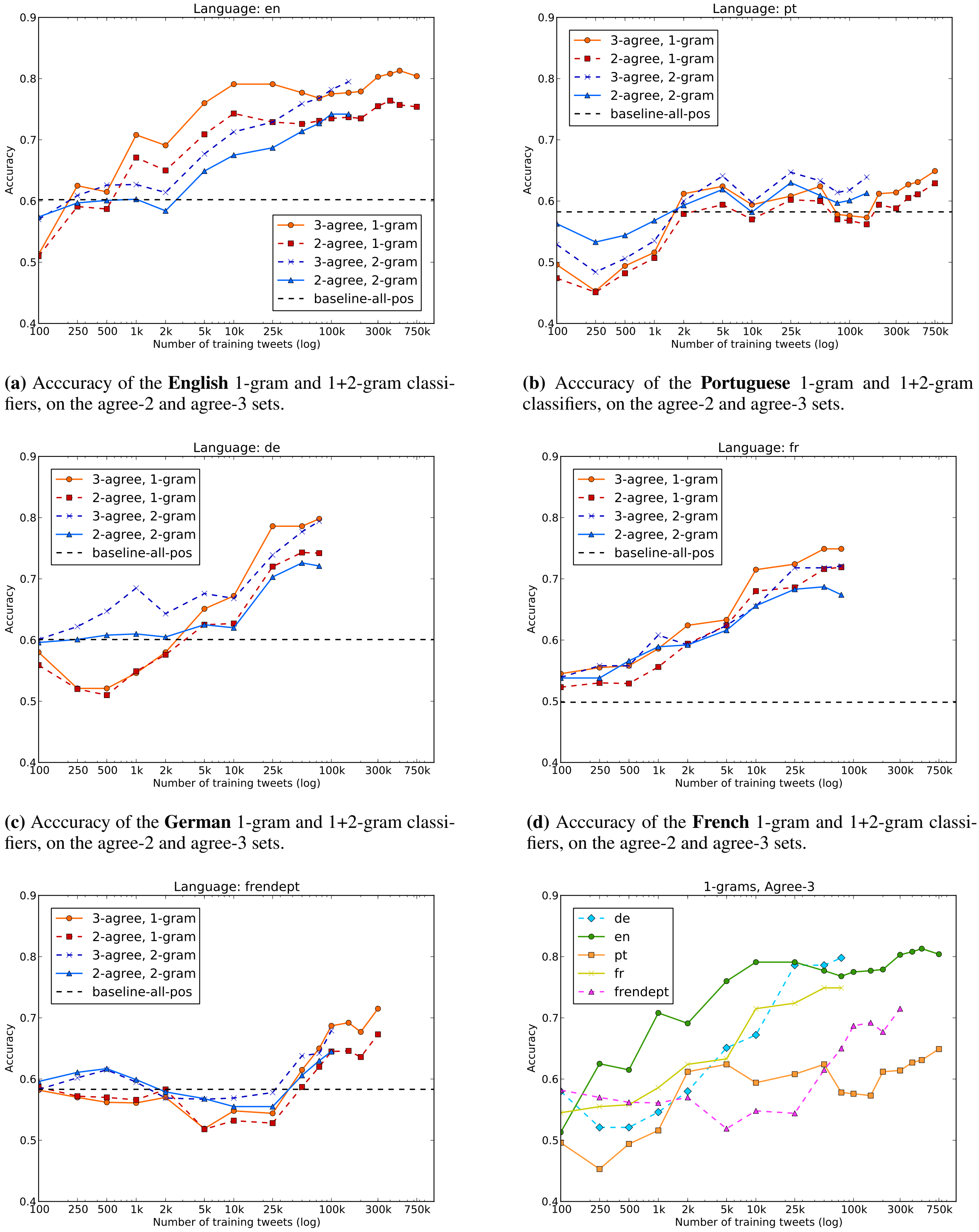
Nevertheless, these experiments show that it is indeed feasible to train a classifier on the combination of multiple languages. Though the perfomance degrades slightly, it can still be useful to employ such a combined classifier. If for example the tweets that should be classified come from a set of several possible languages, the degradation in performance could be acceptable, as a combined classifier saves the need to detect the tweets' language beforehand. Knowing that a combined classifier performs only slightly worse is valuable, as English is a ubiquitous language in microtexts, and tweets of any language are often intermingled with English ones.

6 Conclusion

In this paper we presented a language-independent classification approach to detect the sentiment polarity in tweets. Our approach uses a semi-supervised heuristic labeling scheme to acquire large amounts training data in a variety of languages, and content-based features that work well across languages. In our experiments, we trained a Naïve Bayes classifier on source sets of millions of tweets in English, German, French and Portuguese. We compared the results between languages using tweets that were human-annotated using the Amazon Mechanical Turk service. We make this multilingual evaluation dataset publicly available.

We showed that the used algorithm achieves a good performance for tweets of multiple languages, especially given its efficient applicability to new languages. The classifier can be trained effortlessly on new languages, given only raw training data. We have not dealt with classifying sub-

[7] We provide a detailed list of the classification performances for each classifier, language and training set size on our website. See http://www.dai-lab.de/%7Enarr/paper-sentiment



(a) Acccuracy of the **English** 1-gram and 1+2-gram classifiers, on the agree-2 and agree-3 sets.

(b) Acccuracy of the **Portuguese** 1-gram and 1+2-gram classifiers, on the agree-2 and agree-3 sets.

(c) Acccuracy of the **German** 1-gram and 1+2-gram classifiers, on the agree-2 and agree-3 sets.

(d) Acccuracy of the **French** 1-gram and 1+2-gram classifiers, on the agree-2 and agree-3 sets.

(e) Acccuracy of the **4-language mixed** 1-gram and 1+2-gram classifiers, on the agree-2 and agree-3 sets **combined for the 4 languages**.

(f) Overview of classifier accuracies for **each language**, using a unigram classifier on the agree-3 set.

Figure 1: Classification accuracies for different Naïve Bayes sentiment polarity classifiers. We compare the classifier performance for each of 5 different languages using an increasing number of heuristically labeled training tweets. Test data are human annotated tweets; one set of at least 2 and one set of 3 mutual annotator agreements (test set size varies with language). The **"baseline-all-pos"** baseline indicates the best-guess performance of a mock classifier for each language that always guesses a positive sentiment (the majority class in the evaluation dataset).

jectivity in tweets in this work. This is something we hope to be able to accomplish in future work.

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