The USAGE review corpus for fine-grained, multi-lingual opinion analysis

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Abstract

Opinion mining has received wide attention in recent years. Models for this task are typically trained or evaluated with a manually annotated dataset. However, fine-grained annotation of sentiments including information about aspects and their evaluation is very labour-intensive. The data available so far is limited. Contributing to this situation, this paper describes the Bielefeld University Sentiment Analysis Corpus for German and English (USAGE), which we offer freely to the community and which contains the annotation of product reviews from Amazon with both aspects and subjective phrases. It provides information on segments in the text which denote an aspect or a subjective evaluative phrase which refers to the aspect. Relations and coreferences are explicitly annotated. This dataset contains 622 English and 611 German reviews, allowing to investigate how to port sentiment analysis systems across languages and domains. We describe the methodology how the corpus was created and provide statistics including inter-annotator agreement. We further provide figures for a baseline system and results for German and English as well as in a cross-domain setting. The results are encouraging in that they show that aspects and phrases can be extracted robustly without the need of tuning to a particular type of products.

Keywords: sentiment analysis, corpus, product reviews

1. Introduction

The task of analyzing sentiments and opinions of users about products, events, services etc. has generated wide interest not only in academia but also in industry due to its high commercial relevance. Approaches to develop sentiment analysis and opinion mining frameworks can be roughly divided into two categories. On the one hand, we find systems which rely on rules or dictionaries to extract evaluative phrases and the aspects they refer to. Such rule-based or dictionary-based methods typically exploit manually crafted or semi-automatically built resources like the subjectivity dictionary by Wilson et al. (2009) or the polarity dictionary by Ding et al. (2008). On the other hand, there are approaches that exploit machine learning techniques to induce a sentiment extraction model from training data, either in a fully supervised or weakly supervised fashion. Fully supervised systems that train on manually annotated data are commonly used to extract aspects and subjective phrases (Klinger and Cimiano, 2013a; Klinger and Cimiano, 2013b; Li et al., 2010) or in order to classify the polarity or subjectivity of text (Täckström and McDonald, 2011; Sayeed et al., 2012; Shi and Li, 2011; Pang and Lee, 2004; Wiebe, 2000). In contrast to these fully supervised systems, Turney (2002) for instance proposed a system that is in this sense weakly supervised in that it relies on the two seed words “excellent” and “poor” and textual similarity to induce other “similar” adjectives that express a positive or negative sentiment, respectively. Completely unsupervised approaches have also been applied to the task (Titov and McDonald, 2008).

In most of the above mentioned cases, annotated data is needed, e.g., to tune the parameters of a system in a supervised fashion or in order to evaluate the approach in question. However, creating annotated sentiment corpora is a labour-intensive task, so that the availability and size of such datasets is limited so far.

With this paper, we provide the Bielefeld University corpus for Sentiment Analysis in German and English (USAGE), a resource based on Amazon product reviews for a variety of product classes, both in German and English. The annotation is fine-grained in the sense that not only course classes are assigned to sentences or whole reviews but word or token-based semantic information is provided as well. The corpus is freely and publicly available for future research.

1.1. Previous Work

For sentiment analysis and opinion mining, several manually annotated corpora are available. An overview of the corpora mentioned in the following is given in Table 1. Examples include fine-grained annotations such as released by Hu and Liu (2004) and Ding et al. (2008), who have provided an annotated dataset consisting of Amazon reviews in which every sentence is annotated with an aspect and a polarity score. However, the actual offsets of phrases which denote the aspect or a subjective or evaluating phrase are not provided. The data set published in the context of the SemEval 2013 shared task provides annotations on Tweets (Nakov et al., 2013). These datasets focus on the task of extracting subjective phrases for given aspects and entities. Thus, aspects are pre-given and do not need to be extracted. The University review data set by Toprak et al. (2010) is annotated with opinion holders, targets, modifiers, anaphora as well as the relevance for a topic.

Restaurant reviews annotated on a sentence level with predefined aspects and polarities are made available by Ganu et al. (2009). Lakkaraju et al. (2011) have provided reviews for different product classes with predefined aspects and polarities

The corpus is available at http://dx.doi.org/10.4119/unibi/citec.2014.14. It will be further developed and future versions will be linked from that URL.
polarity annotations. The MPQA corpus consists of fine-grained annotations, focusing on debates and news articles (Ruppenhofer et al., 2008; Wiebe, 2000; Wiebe et al., 2005). The JDPA sentiment corpus consists of blog posts about cars and cameras and is annotated with a complex set of entities and relations, including aspects, subjective phrases, polarities, part-of relations, feature-of relations, opinion holders and others. The entities are provided on token level (Kessler et al., 2010). The Twitter data set by Spina et al. (2012) is annotated with offsets for aspect mentions (of given categories) and subjective phrases as well as overall subjectivity. Polarities are not given. Both corpora have been influential examples in the design of our annotation guidelines.

There is only a comparatively small number of corpora available in other languages. For instance, the only fine-grained corpus in German we are aware of is the manually annotated corpus with subjectivity and polarity annotation on sentence, phrase, and word level by Clematide et al. (2012). Another German resource is the Amazon review corpus by Boland et al. (2013), which is annotated on sentence level, whereas aspects are not annotated.

We are not aware of any dataset which supports the development of multi-lingual and cross-lingual sentiment analysis methods that are applicable to different languages or can be trained in one language and applied to another one. Further, we are neither aware of a large German corpus consisting of reviews that are annotated with fine-grained aspects, evaluative (subjective) expressions and the relation between both. The work presented in this paper aims to close this gap.

1.2. Motivation

We are especially interested in the automated analysis of product reviews. Such textual data is for instance collected on websites like Amazon, by shopping portals like Google or Ciao. In detail, we are investigating the following research questions:

- How can we detect mentions of aspects and the corresponding evaluating phrases with their polarity?
- How can a model trained on the domain of a specific product be adapted to another domain with limited supervision?
- Can we exploit multilingual features to train sentiment analysis systems to improve performance?
- Can we train a model on one language and transfer that model automatically to another language?

To the best of our knowledge, no dataset is currently available to investigate such research questions.

2. The Bielefeld University Sentiment Analysis corpus for German and English (USAGE)

We present the USAGE corpus, the Bielefeld University Sentiment Analysis corpus for German and English, consisting of annotations of Amazon reviews in German and English for 8 product categories. The corpus is annotated with aspects, subjective evaluating phrases, polarities and their relation.

2.1. Corpus selection

We used the search functionality of Amazon.com and Amazon.de to retrieve lists of products for 8 classes of products. The search terms were “washing machine”, “coffee machine”, “trash can”, “microwave”, “vacuum cleaner”, “dish washer”, “toaster”, and “cutlery” for English and “Waschmaschine”, “Kaffeemaschine”, “Mülleimer”, “Mikrowelle”, “Staubsauger”, “Toaster”, and “Besteck”. For each search, we kept the top 60 results and downloaded up to 1000 reviews for each of the products for both English and German.

In order to provide the annotators with training material and to fine-tune the annotation guidelines provided to them, 5 sets of 16 English reviews (2 for each product) were selected. For the final corpus annotation, 800 English reviews and 800 German reviews were selected. Both annotators worked 10 hours a week for three months annotating as much reviews as possible within the given time.

2.2. Corpus annotation

The entity classes aspect and evaluative (subjective) expression are annotated in the corpus. Evaluative expressions are assigned a polarity (positive, negative, neutral) and a set of aspects they refer to. An aspect can be marked as “foreign” if a product or an aspect of a product is mentioned that is not an aspect of the main product discussed in the review. This is often the case in cross-product comparisons and mentions of envisioned or desired features of products. Co-references were to be annotated if the target is not in the same sentence as the evaluative expression.

The annotators were instructed to regard everything as an aspect that is part of a product or related to it and can influence the opinion about it, including the whole product itself. Evaluative phrases express an opinion. Negations are not separately annotated but are part of a phrase. Annotators were asked to avoid overlapping annotations if possible. The annotations should be as short as possible, as long as the meaning is understandable if only the annotations were given (without the sentence itself).

The annotators worked on the corpus for 3 months for about 10 hours a week. The training phase took 20 days. After the training phase, the annotators were instructed to work on as many reviews as possible while trying to keep the number of German and English reviews comparable. Towards the end of annotation, the annotators were coordinated to work on
the same reviews, such that the whole corpus is annotated twice. Some examples are given below, with aspects marked in blue and subjective phrases marked in red:

- I had **no problems** with the return. return is a target of **no problems**. no problems is positive.
- The **washer** itself is **great**, the included **hose** is **junk**.
- washer is a target of great, hose is a target of junk. great is positive, junk is negative.
- It **looks** very neat, like a **storage container**, and **using** it is very **simple** and **easy**.
- looks is a target of very neat, using is a target of simple and of easy.

### 3. Analysis

The training of the annotators and optimization of the guidelines has been conducted in four iterations. In order to estimate the inter-annotator agreement, Cohen’s kappa was calculated (Cohen, 1960). In the first annotation round of 16 English reviews, the agreement between the annotators reached a \( \kappa \)-value of 0.524 (on token level). After discussion, the independent re-annotation of the same data lead to \( \kappa = 0.608 \). A further independent annotation round of new 16 reviews resulted in \( \kappa = 0.62 \), showing that the annotators converged in their understanding of the task. In the next step, the annotators were asked to annotate 16 reviews more in interaction with each other. In a subsequent independent annotation step involving 16 further reviews, an agreement of \( \kappa = 0.66 \) was reached, which can be regarded as a moderate agreement in comparison to agreement by chance. The agreement has been increased by several discussion and annotation rounds. The agreement in the full German corpus is 0.65 and in the English corpus 0.64.

Statistics of the German and the English full corpus as well as broken down by product domains are shown in Table 2. The German corpus consists of 611 annotated reviews describing 127 different products. The total number of annotated aspects is 6340 for Annotator 1 and 5055 for Annotator 2. There are 5086 (4881) subjective annotations in total, of which 3840 (3717) are positive and 1094 (1052) are negative. The number of subjective phrase-target relations is 4085 (4643). The most frequent ones are ‘gut’, ‘sehr zufrieden’, ‘sehr gut’, ‘super’, ‘leicht’, ‘gute’, ‘schnell’, ‘sehr leise’, ‘einfach’.

The English corpus consists of 622 annotated reviews describing 217 different products. The number of aspects is 8545 (6699) in total. There are 5321 (5518) subjective annotations from which 3426 (3600) are positive and 1799 (1792) are negative. The number of subjective phrase-target relations is 4481 (5180). The most frequent subjective phrases are ‘recommend’, ‘best’, ‘nice’, ‘love’, ‘like’, ‘well’, ‘perfect’, ‘easy’, ‘good’, ‘love’, ‘great’.

The average numbers of annotated aspect and subjective phrase mentions are comparable between the different domains and between the annotators. Annotator 1 tends to annotate more aspects than Annotator 2 (13.7 to 10.6 for English and 10.4 to 8.3 for German in the full corpora). The highest difference is between washing machines and cutlery with washing machines having the highest density of aspects and cutlery the lowest (9.9/7.5 versus 19.4/13 in English and 6.5/6.2 versus 17.4/10.7 in German). Examples for such differences are the inclusion of aspects by Annotator 1 like the product description itself (“the dishwasher”) or aspects which are not directly connected to the product but clearly related to it (“hard water”, “customer service”, “dishes”). Obviously, these cases are hard to decide.

The differences in the average number of subjective phrases
is lower. However, differences between the two annotators can be observed for this class of segments as well. The average length (measured in characters) of annotated subjective phrases is higher than the lengths of aspect annotations. In addition, a difference in length between the two annotators can be observed, especially for the German subjective phrases.

Not every aspect or subjective phrase is actually in relation with a counterpart. The average number of aspect-subjective phrase relations is observed to be slightly lower than the number of aspects or subjective phrases. Annotator 2 tends to have more such relations, but the difference is only marginal. However, the annotation of coreferences differs a lot, with 67 such relations annotated by Annotator 1 and 462 by Annotator 2 for the English dataset. This difference is not based on a different understanding, but just by annotating more terms like “it” and “they”. Annotator 1 annotated such terms only if a subjective phrase could not be linked to another aspect, while Annotator 2 annotated anaphora more frequently.

In order to be able to quantify the differences between the two annotators, the F1 measure between them has been calculated. This serves as an upper bound for automatic extraction tools as well: If the agreement between two humans is lower than the agreement between a machine and a human, the result should be interpreted critically. This measure takes into account phrase boundaries and does not normalize over the probability of agreement, as Cohen’s $\kappa$ does. Note that the F1 numbers in this table are all based on exact matches. Detection of aspects is generally better.
To provide a strong baseline for future systems to be developed based on the USAGE corpus, we perform experiments based on our previously published approach on aspect and subjective phrase-oriented fine-grained sentiment analysis (Klinger and Cimiano, 2013a; Klinger and Cimiano, 2013b). This method is based on an undirected probabilistic model with Markov Chain Monte Carlo inference which can perform prediction of aspects, subjective phrases and their relation in a joint manner or in a pipeline setting.

In more detail, spans of aspects and subjective phrases are represented similarly to a semi-Markov conditional random field (Sarawagi and Cohen, 2005). Each span variable can have a list of other spans to be related with. In the case of aspects, this can be used to model coreferences. In the case of subjective phrases, a reference to the target of the phrase is kept. In addition, each subjective phrase can be positive, negative, or neutral.

In the pipeline setting, a classifier estimating if an aspect and a subjective phrase are in relation is trained. We report the results under the assumption of perfect knowledge about aspect and subjective phrases, estimating the difficulty and performance for relation extraction in isolation. In our previous work, we detected a higher performance for aspect detection in the joint inference setting and a higher result for subjective phrase detection in the pipeline setting. We report the best results over both learning settings (joint and pipeline), as a productive system would obviously use a hy-

### Table 3: $F_1$ measures serving as baselines for different experiments on the USAGE corpus. “10-fold cross-validation” refers to a cross-validation experiment on the full corpora or the product class specific subsets. “Cross-Domain” refers to a cross-domain experiment in which the model is trained on all data of the respective language except for the product class indicated in the table. This ‘left-out’ product class is used for testing, the results of which are included in the table.

| Aspect | Subjective | Asp-Subj | Approx. | Aspect | Subjective | Asp-Subj | Approx. |
|--------|------------|----------|---------|--------|------------|----------|---------|
| 0.56   | 0.43       | 0.49     | 0.57    | 0.75   | 0.41       | 0.41     | 0.58    |
| 0.49   | 0.39       | 0.47     | 0.48    | 0.43   | 0.41       | 0.41     | 0.49    |
| 0.50   | 0.47       | 0.47     | 0.50    | 0.56   | 0.43       | 0.43     | 0.50    |
| 0.50   | 0.39       | 0.47     | 0.50    | 0.56   | 0.43       | 0.43     | 0.50    |
| 0.50   | 0.39       | 0.47     | 0.50    | 0.56   | 0.43       | 0.43     | 0.50    |
| 0.50   | 0.39       | 0.47     | 0.50    | 0.56   | 0.43       | 0.43     | 0.50    |
| 0.50   | 0.39       | 0.47     | 0.50    | 0.56   | 0.43       | 0.43     | 0.50    |

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**English**

| coffee machine | cutlery | microwave | toaster | trash can | washing machine | dish washer |
|----------------|---------|-----------|---------|-----------|-----------------|-------------|
| 0.63            | 0.68    | 0.55      | 0.61    | 0.60      | 0.56            | 0.59        |

**German**

| Kaffeemaschine | Broteck | Mikrowelle | Toaster | Müllkorb | Staubsauger | Wäschmaschine |
|----------------|---------|------------|---------|----------|-------------|---------------|
| 0.63            | 0.68    | 0.55      | 0.61    | 0.60      | 0.56            | 0.59        |

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To provide a strong baseline for future systems to be developed based on the USAGE corpus, we perform experiments based on our previously published approach on aspect and subjective phrase-oriented fine-grained sentiment analysis (Klinger and Cimiano, 2013a; Klinger and Cimiano, 2013b). This method is based on an undirected probabilistic model with Markov Chain Monte Carlo inference which can compared to the detection of subjective phrases. German aspect detection has higher measures than for English (with 0.63 over 0.71 for the whole corpus), while there is no such big difference for subjective phrases (0.54 for English and 0.55 for German). The detection of relations yields comparable results for both languages (0.38 and 0.42). The results for coreferences are very low as the difference in annotation frequency between the two annotators already hints at. In order to exploit the coreference data, a deeper analysis of the annotation differences between the two annotators would be required.

### 4. Prediction Baseline

To provide a strong baseline for future systems to be developed based on the USAGE corpus, we perform experiments based on our previously published approach on aspect and subjective phrase-oriented fine-grained sentiment analysis (Klinger and Cimiano, 2013a; Klinger and Cimiano, 2013b). This method is based on an undirected probabilistic model with Markov Chain Monte Carlo inference which can compared to the detection of subjective phrases. German aspect detection has higher measures than for English (with 0.63 over 0.71 for the whole corpus), while there is no such big difference for subjective phrases (0.54 for English and 0.55 for German). The detection of relations yields comparable results for both languages (0.38 and 0.42). The results for coreferences are very low as the difference in annotation frequency between the two annotators already hints at. In order to exploit the coreference data, a deeper analysis of the annotation differences between the two annotators would be required.

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In the pipeline setting, a classifier estimating if an aspect and a subjective phrase are in relation is trained. We report the results under the assumption of perfect knowledge about aspect and subjective phrases, estimating the difficulty and performance for relation extraction in isolation. In our previous work, we detected a higher performance for aspect detection in the joint inference setting and a higher result for subjective phrase detection in the pipeline setting. We report the best results over both learning settings (joint and pipeline), as a productive system would obviously use a hy-
brid approach combining the inferences of both the joint and the pipeline model. However, the configuration is the same as reported by Klinger and Cimiano (2013b) for English. An adaptation of the system to other languages would demand for inclusion of a language-specific dependency parser, which is still future work. Thus, the German sentiment analysis system does not make use of features computed on the basis of dependency parse information.

The experiments performed are the following, each for German and for English separately:

1. **10-fold cross-validation on the full corpus**:
   - including all product categories (denoted as ‘full’ in Table 2).
   - Cross-validation is performed on the document level such that no characteristics of one text are shared between the respective training and validation sets.

2. **10-fold cross-validation for each product category**: i.e., coffee machine, cutlery, microwave, toaster, trash can, vacuum cleaner, washing machine and dish washer for English, and Kaffeeemaschine, Besteck, Mikrowelle, Mülleimer, Staubsauger and Waschmaschine for German. Toaster is not taken into account for German due to the small number of reviews, not being suitable for a cross-validation setting. The aim of these experiments is to yield a class-specific baseline and in order to understand whether the difficulty of the task differs across product types.

3. **Cross-domain testing**: training on the reviews from all but one product class and test on the hold-out product class. These experiments are performed for each product category. The goal is to get insights about how easy a model trained on certain products can be transferred to a new product domain. It therefore allows for estimating if newly annotated corpora are actually needed when developing an opinion mining system for a specific product class.

The results of these experiments are summarized in Table 3. We report the $F_1$ measures with exact match between prediction and annotation and approximate (partial) match which regards an annotation which overlaps in at least one token with the gold standard annotation as a true positive. We report the results of these experiments are comparable to 10-fold cross-validation, e.g., for Annotator 1, cutlery’s aspects drop from 0.53 to 0.37. Most aspect performance rates drop in English and German but some remain stable. In contrast, for subjective phrase detection, $F_1$ measures increase in the cross-domain setting for all sub-domains. These results license the conclusion that there is a fraction of shared vocabulary between the domains that is used in similar contexts and grammatical structures.

5. **Availability and File Formats**

The corpus is made available via document object identifier 10.4119/unibi/citec.2014.11 and therefore accessible via http://dx.doi.org/10.4119/unibi/citec.2014.14 in a tabular separated file format which will be explained in the following. The annotation has been performed in Knowtator (Ogren, 2006), which is a plugin for the ontology building environment Protégé. The original files can be provided on request.

The corpus consists of a set of file quintuplets, each quintuple being a .txt file providing necessary information to be able to retrieve the reviews from Amazon, two files with the extension .csv storing the offsets and attributes of aspects and subjective phrases for each annotator, and two .rel files with the information about relations between phrases for each annotator, respectively.

In detail, the .txt needs to be the input for a crawling workflow which is also provided. The output of that workflow will be another .txt file consisting of an ID and the review title and text. The exact guidelines are available online. Note that we do not publish the Amazon reviews but only the (stand-off) annotations.

The .csv files consist of a column indicating whether the phrase represents an aspect or a subjective phrase, the ID to denote the correct entry in the .txt file, left and right offset, the string representation and an ID uniquely identifying this phrase. In addition, subjective phrases can have an unknown, positive, negative, or neutral polarity and aspects can have the label ‘foreign’, each in a separate column.

The .rel file stores target-subjective phrase relations and coreference relations. It specifies the kind of the relation, provides the .txt-ID and the two participating phrase IDs. In addition, the textual representations of the phrases are repeated, which simplifies error detection and statistical evaluations.

A more detailed explanation is available on the download website.

6. **Summary, Conclusion and Future Research Opportunities**

The corpus presented in this paper is, to the best of our knowledge, the largest manually annotated resource for fine-grained sentiment analysis with annotations of aspects, subjective evaluating phrases, their polarities and relations between them in two languages (German and English). We are sure that this dataset will motivate and enable an array of novel research questions to be investigated and foster the development of sentiment analysis methods which work on natural language processing.
multiple languages (multilingual mode), approaches which exploit multilingual features in one model (joint model), or methods that allow one to train a sentiment analysis system in one language and apply it to another language (cross-lingual transfer mode). In addition, the selection of reviews from different product categories will enable research in the areas of domain adaption for such fine-grained annotations.

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