Abstract

This paper describes our submission to SemEval 2014 Task 4\(^1\) (aspect based sentiment analysis). The current work is based on the assumption that it could be advantageous to connect the subtasks into one workflow, not necessarily following their given order. We took part in all four subtasks (aspect term extraction, aspect term polarity, aspect category detection, aspect category polarity), using polarity items detection via various subjectivity lexicons and employing a rule-based system applied on dependency data. To determine aspect categories, we simply look up their WordNet hypernyms. For such a basic method using no machine learning techniques, we consider the results rather satisfactory.

\(^1\)http://alt.qcri.org/semeval2014/task4/

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The food was great. The coconut juice is the MUST! The pizza tastes so good. Nice value. Their wine sucks. I liked the beer selection.

Table 1: Syntactic rules.

| Pattern | Example sentence |
|---------|------------------|
| Subaspect | Pred<sub>copula</sub> | PAdj |
| Subaspect | Pred<sub>copula</sub> | PNoun |
| Subaspect | Pred<sub>Adv_eval</sub> |
| Attr<sub>eval</sub> | Noun<sub>aspect</sub> |
| Subaspect | Pred<sub>eval</sub> |
| Subsource | Pred<sub>eval</sub> | Obj<sub>aspect</sub> |

1. Run Aspell\(^2\) to detect typos and obtain suggestions for them.
2. Select the appropriate suggestions using a language model (LM).

We trained a trigram LM from the English side of CzEng 1.0 (Bojar et al., 2012) using SRILM (Stolcke, 2002). We binarized the LM and use the Lazy decoder (Heafield et al., 2013) for selecting the suggestions that best fit the current context. Our script is freely available for download.\(^3\)

We created a list of exceptions (domain-specific words, such as “netbook”, are unknown to Aspell’s dictionary) which should not be corrected and also skip named entities in spell-checking.

3.3 Marking Known Aspects

Before any linguistic processing, we mark all words (and multiword expressions) which are marked as aspects in the training data. For our final submission, the list also includes aspects from the provided development sets.

3.4 Morphological Analysis and Parsing

Further, we lemmatize the data and parse it using Treex (Popel and Žabokrtský, 2010), a modular framework for natural language processing (NLP). Treex is focused primarily on dependency syntax and includes blocks (wrappers) for taggers, parsers and other NLP tools. Within Treex, we used the Morčie tagger (Hajič et al., 2007) and the MST dependency parser (McDonald et al., 2005).

3.5 Finding Evaluative Words

In the obtained dependency data, we detect polarity items using MPQA subjectivity lexicon (Wiebe et al., 2005) and Bing Liu’s subjectivity clues.\(^4\)

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\(^2\)http://aspell.net/
\(^3\)https://redmine.ms.mff.cuni.cz/projects/staspell
\(^4\)http://www.cs.uic.edu/~liub/FBS/sentiment-analysis.html#lexicon
We lemmatize both lexicons and look first for matching surface forms, then for matching lemmas. (English lemmas as output by Morče are sometimes too coarse, eliminating e.g. negation – we can mostly avoid their matching by looking at surface forms first.)

### 3.6 Syntactic Rules

Further, we created six basic rules for finding aspects in sentences containing evaluative items from the lexicons, e.g. “If you find an adjective which is a part of a verbonominal predicate, the subject of its governing verb should be an aspect.”, see Table 1. Situational functions are marked with subscript, PAdj and PNoun stand for adjectival and nominal predicative expressions.

Moreover, we applied three more rules concerning coordinations. We suppose that if we find an aspect, every member of a given coordination must be an aspect too.

The excellent mussels, puff pastry, goat cheese and salad.

Concerning but-clauses, we expect that if there is no other aspect in the second part of the sentence, we assign the conflict value to the identified aspect.

The food was pretty good, but a little flavorless.

If there are two aspects identified in the but-coordination, they should be marked with opposite polarity.

The place is cramped, but the food is fantastic!

### 3.7 Aspect Categories

We collect a list of aspects from the training data and find all their hypernyms in WordNet (Fellbaum, 1998). We hand-craft a list of typical hypernyms for each category (such as “cooking” or “consumption” for the category “food”). Moreover, we look at the most frequent aspects in the training data and add as exceptions those for which our list would fail.

We rely on the output of aspect identification for this subtask. For each aspect marked in the sentence, we look up all its hypernyms in WordNet and compare them to our list. When we find a known hypernym, we assign its category to the aspect. Otherwise, we put the aspect in the “anecdotes/miscellaneous” category. For category polarity assignment, we combine the polarities of all aspects in that category in the following way:

- all positive → positive
- all negative → negative
- all neutral → neutral
- otherwise → conflict

### 4 Results and Discussion

Table 2 and Table 3 summarize the results of our submission. We do not achieve the best performance in any particular task, our system overall ranked in the middle.

We tend to do better in terms of recall than precision. This effect is mainly caused by our decision to also automatically mark all aspects seen in the training data.

### 4.1 Effect of the Spell-checker

We evaluated the performance of our system with and without the spell-checker. Overall, the impact
is very small (f-measure stays within 2-decimal rounding error). In some cases its corrections are useful (“convienent” → “convenient parking”), sometimes its limited vocabulary harms our system (“fettucino alfredo” → “fitting Alfred”). This issue could be mitigated by providing a custom lexicon to Aspell.

4.2 Sources of Errors

As we always extract aspects that were observed in the training data, our system often marks them in non-evaluative contexts, leading to a considerable number of false positives. However, using this approach improves our f-measure score due to the limited recall of the syntactic rules.

The usefulness of our rules is mainly limited by the (i) sentiment lexicons and (ii) parsing errors.

(i) Since we used the lexicons directly without domain adaptation, many domain-specific terms are missed (“flavorless”, “crowded”) and some are matched incorrectly.

(ii) Parsing errors often confuse the rules and negatively impact both recall and precision. Often, they prevented the system from taking negation into account, so some of the negated polarity items were assigned incorrectly.

The “conflict” polarity value was rarely correct – all aspects and their polarity values need to be correctly discovered to assign this value. However, this type of polarity is infrequent in the data, so the overall impact is small.

Having participated in all four tasks, our system can be readily deployed as a complete solution which covers the whole process from plain text to aspects and aspect categories annotated with polarity. Considering the number of tasks covered and the fact that our system is entirely rule-based, the achieved results seem satisfactory.

5 Conclusion and Future Work

In our work, we developed a purely rule-based system for aspect based sentiment analysis which can both detect aspect terms (and categories) and assign polarity values to them. We have shown that even such a simple approach can achieve relatively good results.

In the future, our main plan is to involve machine learning in our system. We expect that outputs of our rules can serve as useful indicator features for a discriminative learning model, along with standard features such as bag-of-words (lemmas) or n-grams.

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