Subjectivity and Sentiment Analysis of Modern Standard Arabic

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Abstract

Although Subjectivity and Sentiment Analysis (SSA) has been witnessing a flurry of novel research, there are few attempts to build SSA systems for Morphologically-Rich Languages (MRL). In the current study, we report efforts to partially fill this gap. We present a newly developed manually annotated corpus of Modern Standard Arabic (MSA) together with a new polarity lexicon. The corpus is a collection of newswire documents annotated on the sentence level. We also describe an automatic SSA tagging system that exploits the annotated data. We investigate the impact of different levels of preprocessing settings on the SSA classification task. We show that by explicitly accounting for the rich morphology the system is able to achieve significantly higher levels of performance.

1 Introduction

Subjectivity and Sentiment Analysis (SSA) is an area that has been witnessing a flurry of novel research. In natural language, subjectivity refers to expression of opinions, evaluations, feelings, and speculations (Banfield, 1982; Wiebe, 1994) and thus incorporates sentiment. The process of subjectivity classification refers to the task of classifying texts into either objective (e.g., Mubarak stepped down) or subjective (e.g., Mubarak, the hateful dictator, stepped down). Subjective text is further classified with sentiment or polarity. For sentiment classification, the task refers to identifying whether the subjective text is positive (e.g., What an excellent camera!), negative (e.g., I hate this camera!), neutral (e.g., I believe there will be a meeting.), or, sometimes, mixed (e.g., It is good, but I hate it!) texts.

Most of the SSA literature has focused on English and other Indo-European languages. Very few studies have addressed the problem for morphologically rich languages (MRL) such as Arabic, Hebrew, Turkish, Czech, etc. (Tsarfaty et al., 2010). MRL pose significant challenges to NLP systems in general, and the SSA task is expected to be no exception. The problem is even more pronounced in some MRL due to the lack in annotated resources for SSA such as labeled corpora, and polarity lexica.

In the current paper, we investigate the task of sentence-level SSA on Modern Standard Arabic (MSA) texts from the newswire genre. We run experiments on three different pre-processing settings based on tokenized text from the Penn Arabic Treebank (PATB) (Maamouri et al., 2004) and employ both language-independent and Arabic-specific, morphology-based features. Our work shows that explicitly using morphology-based features in our models improves the system’s performance. We also measure the impact of using a wide coverage polarity lexicon and show that using a tailored resource results in significant improvement in classification performance.

2 Approach

To our knowledge, no SSA annotated MSA data exists. Hence we decided to create our own SSA annotated data.\textsuperscript{1}

2.1 Data set and Annotation

Corpus: Two college-educated native speakers of Arabic annotated 2855 sentences from Part 1 V 3.0 of the PATB. The sentences make up the first 400 documents of that part of PATB amounting to a total of 54.5% of the PATB Part 1 data set. For each sentence, the annotators assigned one of 4 possible labels: (1) OBJECTIVE (OBJ), (2) SUBJECTIVE-POSITIVE (S-POS), (3) SUBJECTIVE-NEGATIVE (S-NEG), and (4) SUBJECTIVE-NEUTRAL (S-NEUT). Following (Wiebe et al., 1999), if the primary goal

\textsuperscript{1}The data may be obtained by contacting the first author.
of a sentence is judged as the objective reporting
of information, it was labeled as OBJ. Otherwise, a
sentence would be a candidate for one of the three
SUBJ classes. Inter-annotator agreement reached
88.06%. The distribution of classes in our data set
was as follows: 1281 OBJ, a total of 1574 SUBJ,
where 491 were deemed S-POS, 689 S-NEG, and
394 S-NEUT. Moreover, each of the sentences in our
data set is manually labeled by a domain label. The
domain labels are from the newswire genre and are
adopted from (Abdul-Mageed, 2008).

**Polarity Lexicon:** We manually created a lexicon
of 3982 adjectives labeled with one of the follow-
ing tags {positive, negative, neutral}. The adjectives
pertain to the newswire domain.

### 2.2 Automatic Classification

**Tokenization scheme and settings:** We run experi-
ments on gold-tokenized text from PATB. We adopt
the PATB+Al tokenization scheme, where procli-
tics and enclitics as well as Al are segmented out
from the stem words. We experiment with three dif-
ferent pre-processing lemmatization configurations
that specifically target the stem words: (1) *Surface*,
where the stem words are left as is with no further
processing of the morpho-tactics that result from the
segmentation of clitics; (2) *Lemma*, where the stem
words are reduced to their lemma citation forms, for
instance in case of verbs it is the 3rd person mas-
culine singular perfective form; and (3) *Stem*, which
is the surface form minus inflectional morphemes, it
should be noted that this configuration may result in
non proper Arabic words (a la IR stemming). Ta-
ble 1 illustrates examples of the three configuration
schemes, with each underlined.

**Features:** The features we employed are of two
main types: Language-independent features and Mor-
phological features.

**Language-Independent Features:** This group of
features has been employed in various SSA studies.

*Domain:* Following (Wilson et al., 2009), we ap-
ply a feature indicating the *domain* of the document
to which a sentence belongs. As mentioned earlier,
each sentence has a document domain label manu-
ally associated with it.

**UNIQUE:** Following Wiebe et al. (2004) we ap-
ply a *unique* feature. Namely words that occur in our
corpus with an absolute frequency < 5, are replaced
with the token "UNIQUE".

**N-GRAM:** We run experiments with *N*-grams ≤ 4
and all possible combinations of them.

**ADJ:** For subjectivity classification, we follow
Bruce & Wiebe’s (1999) in adding a binary
*has_adjective* feature indicating whether or not any
of the adjectives in our manually created polarity
lexicon exists in a sentence. For sentiment classi-

cification, we apply two features, *has_POS_adjective*
and *has_NEG_adjective*, each of these binary fea-
tures indicate whether a POS or NEG adjective oc-
curs in a sentence.

**MSA-Morphological Features:** MSA exhibits a
very rich morphological system that is templatic,
and agglutinative and it is based on both derivational
and inflectional features. We explicitly model mor-
phological features of *person*, *state*, *gender*, *tense*,
*aspect*, and *number*. We do not use POS informa-
tion. We assume undiacritized text in our models.

### 2.3 Method: Two-stage Classification Process

In the current study, we adopt a two-stage classifica-
tion approach. In the first stage (i.e., Subjectivity),
we build a binary classifier to sort out OBJ from
SUBJ cases. For the second stage (i.e., Sentiment)
we apply binary classification that distinguishes S-
POS from S-NEG cases. We disregard the neutral
class of S-NEUT for this round of experimentation.
We use an SVM classifier, the SVM-light package
(Joachims, 2008). We experimented with various
kernels and parameter settings and found that linear
kernels yield the best performance. We ran experi-
ments with *presence* vectors: In each sentence vec-
tor, the value of each dimension is binary either a 1
(regardless of how many times a feature occurs) or
0.

**Experimental Conditions:** We first run ex-
periments using each of the three lemmatization
settings *Surface*, *Lemma*, *Stem* using various *N-
grams* and *N*-gram combinations and then iter-
atively add other features. The morphological fea-
tures (i.e., *Morph*) are added only to the *Stem*
setting. Language-independent features (i.e., from the
following set {DOMAIN, ADJ, UNIQUE}) are added
to the *Lemma* and *Stem+Morph* settings. With all

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2 A detailed account of issues related to the annotation task will appear in a separate publication.
the three settings, clitics that are split off words are kept as separate features in the sentence vectors.

3 Results and Evaluation

We divide our data into 80% for 5-fold cross-validation and 20% for test. For experiments on the test data, the 80% are used as training data. We have two settings, a development setting (DEV) and a test setting (TEST). In the development setting, we run the typical 5 fold cross validation where we train on 4 folds and test on the 5th and then average the results. In the test setting, we only ran with the best configurations yielded from the DEV conditions. In TEST mode, we still train with 4 folds but we test on the test data exclusively, averaging across the different training rounds.

It is worth noting that the test data is larger than any given dev data (20% of the overall data set for test, vs. 16% for any DEV fold). We report results using $F$-measure ($F$). Moreover, for TEST we report only experiments on the Stem+Morph setting and Stem+Morph+ADJ, Stem+Morph+DOMAIN, and Stem+Morph+UNIQUE. Below, we only report the best-performing results across the N-GRAM features and their combinations. In each case, our baseline is the majority class in the training set.

3.1 Subjectivity

Among all the lemmatization settings, the Stem was found to perform best with 73.17% $F$ (with 1g+2g), compared to 71.97% $F$ (with 1g+2g+3g) for Surface and 72.74% $F$ (with 1g+2g) for Lemma. In addition, adding the inflectional morphology features improves classification (and hence the Stem+Morph setting, when run under the same 1g+2g condition as the Stem, is better by 0.15% $F$ than the Stem condition alone). As for the language-independent features, we found that whereas the ADJ feature does not help neither the Lemma nor Stem+Morph setting, the DOMAIN feature improves the results slightly with the two settings. In addition, the UNIQUE feature helps classification with the Lemma, but it hurts with the Stem+Morph.

Table 2 shows that although performance on the test set drops with all settings on Stem+Morph, results are still at least 10% higher than the baseline. With the Stem+Morph setting, the best performance on the TEST set is 71.54% $F$ and is 16.44% higher than the baseline.

3.2 Sentiment

Similar to the subjectivity results, the Stem setting performs better than the other two lemmatization scheme settings, with 56.87% $F$ compared to 52.53% $F$ for the Surface and 55.01% $F$ for the Lemma. These best results for the three lemmatization schemes are all acquired with 1g. Again, adding the morphology-based features helps improve the classification: The Stem+Morph outperforms Stem by about 1.00% $F$. We also found that whereas adding the DOMAIN feature to both the Lemma and the Stem+Morph settings improves the classification slightly, the UNIQUE feature only improves classification with the Stem+Morph.

Adding the ADJ feature improves performance significantly: An improvement of 20.88% $F$ for the Lemma setting and 33.09% $F$ for the Stem+Morph is achieved. As Table 3 shows, performance on test data drops with applying all features except ADJ; the latter helping improve performance by 4.60% $F$. The best results we thus acquire on the 80% training data with 5-fold cross validation is 90.93% $F$ with 1g, and the best performance of the system on the test data is 95.52% $F$ also with 1g.

4 Related Work

Several sentence- and phrase-level SSA systems have been built, e.g., (Yi et al. 2003; Hu and Liu., 2004; Kim and Hovy., 2004; Mullen and Collier 2004; Pang and Lee 2004; Wilson et al. 2005; Yu and Hatzivassiloglou, 2003). Yi et al. (2003) present an NLP-based system that detects all ref-
erences to a given subject, and determines sentiment in each of the references. Similar to (2003), Kim & Hovy (2004) present a sentence-level system that, given a topic detects sentiment towards it. Our approach differs from both (2003) and Kim & Hovy (2004) in that we do not detect sentiment toward specific topics. Also, we make use of N-gram features beyond unigrams and employ elaborate N-gram combinations.

Yu & Hatzivassiloglou (2003) build a document- and sentence-level subjectivity classification system using various N-gram-based features and a polarity lexicon. They report about 97% F-measure on documents and about 91% F-measure on sentences from the Wall Street Journal (WSJ) corpus. Some of our features are similar to those used by Yu & Hatzivassiloglou, but we exploit additional features. Wiebe et al. (1999) train a sentence-level probabilistic classifier on data from the WSJ to identify subjectivity in these sentences. They use POS features, lexical features, and a paragraph feature and obtain an average accuracy on subjectivity tagging of 72.17%. Again, our feature set is richer than Wiebe et al. (1999).

The only work on Arabic SSA we are aware of is that of Abbasi et al. (2008). They use an entropy weighted genetic algorithm for both English and Arabic Web forums at the document level. They exploit both syntactic and stylistic features. Abbasi et al. use a root extraction algorithm and do not use morphological features. They report 93.6% accuracy. Their system is not directly comparable to ours due to the difference in data sets and tagging granularity.

5 Conclusion

In this paper, we build a sentence-level SSA system for MSA contrasting language independent only features vs. combining language independent and language-specific feature sets, namely morphological features specific to Arabic. We also investigate the level of stemming required for the task. We show that the Stem lemmatization setting outperforms both Surface and Lemma settings for the SSA task. We illustrate empirically that adding language specific features for MRL yields improved performance. Similar to previous studies of SSA for other languages, we show that exploiting a polarity lexicon has the largest impact on performance. Finally, as part of the contribution of this investigation, we present a novel MSA data set annotated for SSA layered on top of the PATB data annotations that will be made available to the community at large, in addition to a large scale polarity lexicon.

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