Abstract

This work presents a novel approach for automatic creation of sentiment word lists. In this approach, words are first mapped into a continuous latent space, which serves as input to a multilayer perceptron (MLP) trained using sentiment-annotated words. When evaluated using manually annotated EmoLex corpus, our approach compares favourably with SentiWordNet 3.0, another automatically generated word list.

1 Introduction

Many of the state of the art sentiment analysis systems uses input features based on sentiment word lists (Mohammad et al., 2013). While such lists may be manually curated, automatic approaches are privileged if large lists need to be generated. SentiWordNet 3.0 (Baccianella et al., 2010) is an example of such an automatically generated sentiment word list.

In this work, we present a novel approach for automatic generation of sentiment word lists. In this approach, words are mapped into a continuous latent space using two embedding methods Word2Vec (Mikolov et al., 2013a)(Mikolov et al., 2013b) and GloVe (Pennington et al., 2014). The mappings are given as input to a MLP trained using sentiment annotated words, which outputs a sentiment class or score for each word. Results show that our method can create large sentiment lexicons with higher accuracy.

The method is based on a small annotated lexicon and large un-labeled corpora. Hence, it could be easily applied to domain-specific contexts or under-resourced languages.

2 Related Work

2.1 Word embeddings

In classical vector space representation of text, individual words directly correspond to dimensions in the feature vector. This approach does not take into account the semantic proximity between words. Recent advances have tried to overcome this limitation by representing words as points in continuous latent space, where proximity between points in space indicates semantic proximity e.g. Word2Vec. However, these systems based on word context do not necessarily encode word sentiment information. For example, based on word distances in a 300-dimensional latent space, the word “good” is closest to “bad” because “good” and “bad” are often found in similar contexts. In this work, we leverage the advantage of continuous latent spaces but add a MLP to infuse sentiment information.

2.2 Sentiment classification and word lists

Initially, sentiment classification was approached as a document classification problem. An early study of sentiment classification (Pang et al., 2002) compared Naive Bayes, Logistic Regression and Support Vector Machine (SVM) classifiers. An early example of sentiment analysis using microblogs is presented in (Pandey and Iyer, 2009). A comprehensive review of recent developments is presented in (Vinodhini and Chandrasekaran, 2012).

Recently, sentiment classification has seen increased use of word lists with associated sentiment
values, set either manually or automatically. Among automatic methods, (Turney and Littman, 2003) and (Esuli and Sebastiani, 2006) compute word sentiment based on context of known sentiment words using Pointwise Mutual Information. In (Mohammad et al., 2013), specific Twitter hashtags with positive or negative sentiment were exploited. In our experiments, we use SentiWordNet 3.0 (Baccianella et al., 2010). SentiWordNet was built in two steps, a first semi-supervised step and a second random walk step. Sentiment values of a set of seed words (Turney and Littman, 2003) were propagated using WordNet’s binary relations.\(^1\) Propagated labels were used to train a classifier which was applied on all words. The second step is a random walk on WordNet, where sentiment is propagated if most of the terms used to define a given term and the term itself are of a specific sentiment value. SentiWordNet is publicly available.

2.3 Word embeddings for sentiment

Works which use word embeddings for sentiment classification include (Amir et al., 2014) where the Word2Vec vector of all words present in the document are summed and used to detect sentiment. In (Irsoy and Cardie, 2014) Recursive Neural Networks are used with Word2Vec as input. In (Tang et al., 2014b) and (Tang et al., 2014a), tweets are represented using sentiment-specific word embeddings. Note that these approaches deal with sentiment classification of documents. In contrast, our work uses word embeddings with MLP for sentiment classification of words. Furthermore, (Tang et al., 2014b) requires sentiment-annotated corpora to learn latent space embeddings, while our approach uses unsupervised methods which may be trained using any suitable unannotated corpora.

3 Methodology

We created two MLP-based systems to estimate sentiment value of words. The first is a classifier system that predicts sentiment class (positive, negative, neutral). The second is a regressor system predicting a sentiment value for each word in a continuous range. The classifier and regressor systems use as inputs two different word representations in embedded continuous space: Word2Vec\(^2\) model trained with 100 billion tokens and GloVe\(^3\) trained with two corpora, one containing 42 billion tokens and second containing 840 billion tokens. The two represent each word in a 300-dimensional space.

### Table 1: Classification lexicon size

| Lexicon   | Training Data | Evaluation Data |
|-----------|---------------|-----------------|
|           | Neg  | Neu | Pos | Neg | Neu | Pos |
| SynthesioLex | 3544 | 2204 | 1500 | 880 | 552 | 375 |
| EmoLex     | 2591 | 6146| 1845 | 648 | 1537| 462 |
| MxDiff     | 260  | 431 | 62  | 109 |     |     |

3.1 Lexicons

For classification experiments, we use two lexicons. First one is curated by us over time and denoted in this work by SynthesioLex. It contains positive, negative or neutral sentiment class for each word. The second, EmoLex (Mohammad and Turney, 2013), is a publicly available lexicon\(^4\). For each word it contains a combination of sentiment tonality (positive, negative) and one of eight possible emotion classes (anger, anticipation, disgust, fear, joy, sadness, surprise, trust) for each word. In case of neutral words, all labels for tonality and emotion are 0. We keep only words that have sentiment tonality value and neutral ones. For regression, we use publicly available MaxDiff lexicon (Kiritchenko et al., 2014)\(^5\). It contains words with sentiment value in a continuous range from -1 to 1 and from 0 to 1 obtained manually by crowdsourcing (Orme, 2009). Table 1 gives more details about each lexicon. Note that EmoLex is bigger, and biased towards neutral class. SynthesioLex is slightly biased towards negative class. For each lexicon, we used 80% of the data for training and 20% for evaluation, uniformly sampled.

3.2 Test Setup

At its core, the system has a MLP with 3 layers: (1) input layer with linear activation function and 300 units, the same as the word representation space. (2) hidden layer with a tanh activation function and number of units varying from 20 to 500. (3) output layer with softmax activation function with

\(^1\)http://wordnet.princeton.edu
\(^2\)https://code.google.com/p/Word2Vec
\(^3\)http://nlp.stanford.edu/projects/glove/
\(^4\)http://saifmohammad.com/Lexicons/NRC-Emotion-Lexicon-v0.92.zip
\(^5\)http://saifmohammad.com/WebDocs/MaxDiff-Twitter-Lexicon.zip
2 or 3 units for classification, and linear function with single unit for regression. MLP training is done with mean square error as cost function using Keras library, a Python package built on top of Theano (Bergstra et al., 2010).

4 Results

Evaluation metric for classification is Macro-F1 between negative and positive classes. F1 measure of Neutral class is not considered, following the SemEval evaluations on twitter sentiment classification (Rosenthal et al., 2014). For regression, we use mean square error as evaluation metric.

4.1 Classification

In figure 1 and 2, we present Macro-F1 on evaluation data for each training epoch. All models converged quickly, and towards similar results. In subfigures 1(a) and 2(a) we see that convergence results are similar, independent of number of hidden units. With 20 units, model took longer to converge but it is evident that the model was able to train even with small number of units. Based on this, we used 100 hidden units for subsequent evaluations. In figures 1(b) and 2(b) we compare results for different word embedding spaces and again all converge to similar values, with Word2Vec taking longer time to stabilise. Classification results for the two lexicons are shown in Table 2. The binary cases represent binary classification where only positive and negative data were retained and all neutral data removed. The system performs better on SynthesioLex than on EmoLex, possibly due to higher number of neutral words in EmoLex. Results for the two lexicons are similar if we only use positive and negative sentiment classes (binary case, last two rows). This can be seen also in the confusion matrices in Tables 3.

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6http://keras.io/
7http://deeplearning.net/software/theano/
and 4 for SynthesioLex and EmoLex lexicons. For EmoLex, many sentiment words were classified as neutral, reducing recall. Also, when compared with SynthesioLex results, many neutral words are seen as having a sentiment, reducing precision.

| Lexicon     | Word rep | Macro-f1 | Best iter |
|-------------|----------|----------|-----------|
| SynthesioLex | Word2Vec | 90.23    | 6         |
|             | glove_42B | 89.05    | 4         |
|             | glove_840B | 90.96    | 7         |
| EmoLex      | Word2Vec | 75.85    | 18        |
|             | glove_42B | 74.33    | 2         |
|             | glove_840B | 74.78    | 6         |
| SynthesioLex | Word2Vec | 93.91    | 2         |
|             | glove_42B | 93.42    | 2         |
|             | glove_840B | 94.76    | 6         |
| EmoLex      | Word2Vec | 91.16    | 5         |
|             | glove_42B | 90.31    | 4         |
|             | glove_840B | 92.02    | 5         |

Table 2: Results for classification problem.

|          | Neg | Neu | Pos |
|----------|-----|-----|-----|
| Neg      | 835 | 29  | 16  |
| Neu      | 29  | 510 | 13  |
| Pos      | 32  | 23  | 320 |

Table 3: SynthesioLex confusion matrix, row: groundtruth, column: predicted.

|          | Neg | Neu | Pos |
|----------|-----|-----|-----|
| Neg      | 431 | 211 | 6   |
| Neu      | 91  | 1317| 129 |
| Pos      | 14  | 203 | 245 |

Table 4: EmoLex confusion matrix, row: groundtruth, column: predicted.

In Section 1, we mentioned that the current method can be used for automatic generation of sentiment word list. To test this proposition, we trained the MLP using SynthesioLex and compared it with another semi-supervised method, SentiWordNet 3.0. We used EmoLex lexicon for evaluation. For SentiWordNet, the sentiment value for each word was computed as average sentiment value over all possible synsets. Confusion matrix for the two methods can be seen in 5 and 6. SentiWordNet achieves very low recall for positive and negative emotion classes, predicting most words as neutral. Macro-F1 results are 44.85% for our method and 6.31% for SentiWordNet.

|          | Neg | Neu | Pos |
|----------|-----|-----|-----|
| Neg      | 1120| 311 | 68  |
| Neu      | 1826| 3445| 1220|
| Pos      | 186 | 558 | 680 |

Table 5: Confusion matrix between EmoLex (row) and SentiWordNet (column)

|          | Neg | Neu | Pos |
|----------|-----|-----|-----|
| Neg      | 1120| 311 | 68  |
| Neu      | 1826| 3445| 1220|
| Pos      | 186 | 558 | 680 |

Table 6: Confusion matrix between EmoLex (row) and current method (column)

4.2 Regression

For regression, we used same method for training as for classification. Optimal results were obtained with 100 hidden units. Best word representation is GloVe trained with 840 billion tokens. Lowest mean square error is 0.014. Regression results are shown in Figure 3. There is strong correlation of sentiment value between reference and result (correlation coefficient 0.85). One way to test this is to transform regressor to classifier by setting all words with sentiment value below 0.5 as negative and all with value above 0.5 as positive, keeping same training and evaluation splits. Figure 4 shows performance of such a classifier. Errors are associated with words close to decision boundary. For those whose sentiment is strongly positive or negative, there are few mistakes. This suggests setting to neutral all words whose regression values are close to decision boundary.
4.3 Discussion

Word embeddings like Word2Vec and GLoVE map “good” as closest to “bad” in latent space (ref. Section 1). MLP succeeds in mapping such opposite sentiment words far from each other at the hidden layer output space (ref. Section 3.2). In terms of cosine distance using the hidden layer of our MLP output, “good” was closest to “dignified”, “compassionate”, while “bad” was closest to “embarrassment”, “contemptuous”, “good” and “bad” were not part of the training data for this study.

5 Conclusion

Although the presented mappings do not consider sentiment information in word context, good results were obtained for word sentiment classification using these mappings as input to a MLP classifier trained and tested on two lexicons, SynthesioLex and EmoLex. When trained on SynthesioLex and tested on EmoLex, proposed approach performed better than SentiWordNet 3.0. We also studied a regression system which can be used to create features in a continuous sentiment space. This is a work in progress focusing on sentiment word list creation. In future, it is planned to integrated this approach in a complete document sentiment classification system.

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