# Expanding Subjective Lexicons for Social Media Mining with Embedding Subspaces

Silvio Amir, Rámon Astudillo, Wang Ling\*, Paula C. Carvalho, Mário J. Silva

INESC-ID Lisboa, Instituto Superior Técnico, Universidade de Lisboa \* Google DeepMind, London

samir@inesc-id.pt ramon@astudillo.com lingwang@google.com pcc@inesc-id.pt mjs@inesc.id.pt

#### Abstract

Recent approaches for sentiment lexicon induction have capitalized on pre-trained word embeddings that capture latent semantic properties. However, embeddings obtained by optimizing performance of a given task (e.g. predicting contextual words) are sub-optimal for other applications. In this paper, we address this problem by exploiting task-specific representations, induced via embedding sub-space projection. This allows us to expand lexicons describing multiple semantic properties. For each property, our model jointly learns suitable representations and the concomitant predictor. Experiments conducted over multiple subjective lexicons, show that our model outperforms previous work and other baselines; even in low training data regimes. Furthermore, lexiconbased sentiment classifiers built on top of our lexicons outperform similar resources and yield performances comparable to that of supervised models.

#### **1** Introduction

The rise of the social web brought about an unprecedented volume of data about human interactions, paving the way for a new, computational, approach to social sciences. Nowadays, scholars are able to study societal and behavioral dynamics through the analysis of large-scale social networks and vast amounts of social media. For example, natural language processing techniques have been applied to massive microblogging repositories to investigate a wide range of phenomena, such as population well-being (Mitchell et al. 2013), political participation (Tumasjan et al. 2010) and public opinion (O'Connor et al. 2010).

One of the key resources to support this kind of analyses are subjective lexicons—i.e., lists of words with semantic annotations. Particularly, **sentiment** lexicons, which categorize words according to the polarity of sentiment they convey; and **emotion** lexicons, which quantify the emotional states or responses evoked by a given word (e.g. *joy* or *arousal*). Typically, these resources are manually created by experts or via crowdsourcing campaigns; a process that can become expensive and time-consuming. Therefore, manually crafted lexicons are necessarily incomplete, thus failing to capture the use of non-conventional word spellings, slang and new expressions commonly found in social media. The automatic extraction of lexicons is a well-known and widely studied problem. Most proposed solutions are predicated on the idea that *similar* words should have similar labels. These solutions differ, essentially, along two axes. First, how the word similarities are captured, e.g. leveraging knowledge bases, such as WordNet (Hu and Liu 2004) or from word co-occurrence statistics derived from corpora analysis (Bestgen and Vincze 2012); and second, how the label assignment is operationalized, e.g. with supervised classifiers (Esuli and Sebastiani 2006) or using graph-based label propagation algorithms (Rao and Ravichandran 2009).

Recent work has also begun exploring neural word embebddings, due to their ability to capture word similarities and latent semantic properties. Tang et al. (2014) induced Twitter sentiment lexicons using sentiment-specific word embeddings, obtained via distant supervision, whereas Amir et al. (2015) proposed a predictive model, leveraging unsupervised embeddings as features. Using this approach, Amir et al. developed the top ranking submission of a lexicon expansion shared task organized by SemEval 2015 (Rosenthal et al. 2015). However, both these methods are inherently limited by their choice of word representations. On the one hand, Tang et al.'s approach uses embeddings tailored to capture sentiment information, but then it can only be used for polarity lexicons. Amir et al.'s method, on the other hand, can be used for other lexicon types, but it uses generic, unsupervised embeddings which are sub-optimal for specific downstream models (Astudillo et al. 2015; Labutov and Lipson 2013).

In this paper, we present an approach to overcome these limitations. Following Amir et al., we expand lexicons for social media mining with predictive models, leveraging unsupervised word embeddings features. This allows us to deal with lexicons describing different properties. Unlike their approach, however, we induce and exploit intermediate, *task-specific* representations via embedding subspace projection (Astudillo et al. 2015). The evaluation was conducted over seven lexicons describing 15 subjective properties. The results show that our models largely outperform the other baselines (with two exceptions). To assess the quality of our lexicons, we built and evaluated lexicon-based Twitter sentiment classifiers. We found that our lexicons: (i) outperform other similar resources; (ii) yield performances comparable to that of supervised models.

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## 2 Related Work

The previous work on automatic lexicon induction, can be roughly divided into two classes: *knowledge-based* and *corpora-based*. These approaches assume that there is a small number of words, for which the labels are known (sometimes referred as the *seed set*). Knowledge-based approaches, then use lexical databases such as WordNet to, e.g., exploit word relations such as antonymy/synonymy or hyponymy/hypernymy between new words and words in the seed set (Hu and Liu 2004; Kim and Hovy 2006; Rao and Ravichandran 2009). Others, classify new words leveraging distances to known words in the synset graph (Kamps et al. 2004). However, these methods are unsuited for the social web since they rely on formal lexical resources that do not encompass the informal language and writing style typical of this domain.

Corpora-based approaches, implicitly exploit the distributional hypothesis, which works under the assumption that similar words tend to occur in similar *contexts* (Harris 1954). Based on this idea, word similarities can be computed from a term co-occurrence matrix, built from large corpora, using e.g. the *point-wise mutual information* (PMI) between terms (Turney and Littman 2003; Kiritchenko, Zhu, and Mohammad 2014) or with vector distance metrics, over the space induced by *Latent Semantic Analysis* (Bestgen and Vincze 2012; Yu et al. 2013).

In the last few years, efficient neural language models have been proposed to induce word embeddings (i.e. dense feature vectors) by learning to predict the surrounding contexts of words in large corpora(e.g. (Pennington, Socher, and Manning 2014)). Recent work on lexicon expansion has also explored these representations, due to their ability to capture word similarities and latent semantic properties (Tang et al. 2014; Amir et al. 2015; Rothe, Ebert, and Schütze 2016). Nevertheless, because these vectors are estimated by minimizing the prediction errors made on generic, unsupervised tasks, they can be sub-optimal for specific downstream models. In this work, we take this observation into account and demonstrate that better models can be induced, by jointly learning *task-specific* representations and predictors.

# 3 Learning Task-Specific Embeddings

Neural embeddings are *distributed representations*, i.e. each concept is described by multiple *features* (vector dimensions can be interpreted as abstract features) and each feature can be involved in describing multiple concepts (Hinton 1986)<sup>1</sup>. However, we hypothesize that not all features contribute equally to capture any given aspect of the input. Thus, if we knew exactly which subset of features describe a given property (e.g. sentiment), we could extract a more compact representation containing only the meaningful information. This would eliminate noise and irrelevant aspects of the data. But more importantly, predictors based on smaller representa-

tions require fewer free parameters, which makes them easier to train with small datasets without overfiting.

One common solution to extract compact representations from a large feature space, is to perform dimensionality reduction by Principal Component Analysis (PCA). But this is a generic linear transformation that does not take into account the prediction targets, hence it is sub-optimal<sup>2</sup>. Alternatively, we could use the full embeddings and fit a predictor with a sparsity inducing objective, e.g. using  $\ell_1$ -norm regularization (Tibshirani 1996). This regularizer tries to bring the weights associated to some input dimensions down to zero, essentially eliminating the contribution of some features. However, without any prior knowledge about the structure of the embeddings there is no guarantee that only the irrelevant dimensions would be eliminated. Moreover, given the distributed nature of word embeddings, simply ignoring arbitrary dimensions may degrade their expressiveness. Of course, we could just use vectors with fewer dimensions but small embeddings have less capacity and tend to be better suited to syntactic tasks than to semantic ones (Ling et al. 2015).

#### Word Embedding Sub-spaces

A simple, yet effective solution to this problem consists of estimating linear projections from generic embeddings to lower-dimensional *sub-spaces* (Astudillo et al. 2015). Given an embedding matrix  $\mathbf{E} \in \mathbb{R}^{d \times |\mathcal{V}|}$ , where the columns represent words from a vocabulary  $\mathcal{V}$  and d is the embedding size, one can induce new representations with a factorization of the input as  $\mathbf{S} \cdot \mathbf{E}$  where  $\mathbf{S} \in \mathbb{R}^{s \times d}$ , with  $s \ll d$ , is a (learned) linear projection matrix. This is similar to PCA, but here the projection is estimated to directly optimize the prediction of the target labels. Therefore, the transformation corresponds to adapting generic, unsupervised representations into task-specific ones. The intuition is that by aggressively reducing the representation space, the model is forced to learn only the most discriminative aspects of the input with respect to the prediction targets<sup>3</sup>.

#### 4 Proposed Approach

As we discussed above, lexicons can be expanded under the assumption that similar words should have similar labels. To operationalize this assumption, we capitalize on two fundamental properties of neural word embeddings: first, they encode functional (i.e., semantic and syntactic) similarities in terms of geometric locality. This will allow us to predict consistent labels to inflections, spelling variations and synonyms of a word; and second, they capture latent word aspects, some of which correspond to subjective properties, e.g. sentiment polarity.

<sup>&</sup>lt;sup>1</sup>On the other hand, *symbolic* representations associate each feature to only one concept—e.g. the *one-hot* encoding, represents word i as a zero vector with the value 1 on the *i*-th dimension.

<sup>&</sup>lt;sup>2</sup>Moreover, word embeddings can be seen as the result of a dimensionality reduction over a sparse word-context co-occurrence matrix (see (Baroni, Dinu, and Kruszewski 2014) and (Pennington, Socher, and Manning 2014)). Thus it is not clear how to interpret the result of a subsequent dimensionality reduction.

<sup>&</sup>lt;sup>3</sup>This is also related to the idea of learning representations with information bottlenecks, e.g with auto-encoders (Hinton and Salakhutdinov 2006)

Our approach to lexicon expansion consists of training models to predict the labels of pre-existing lexicons, leveraging unsupervised word embeddings as features. We further assume that different aspects captured by these embeddings are encoded in some (unknown) subset of features. Therefore, we adopted Astudillo et al. (2015) Non-Linear Subspace Embedding model (*NLSE*), to jointly learn embedding sub-space projections that better represent specific word properties, and the concomitant predictors.

The NLSE is essentially a feed-forward neural network, with a single hidden layer and a factorization of the input layer. Denoting a lexicon of n word/label pairs as  $\mathcal{D} = \{(w_1, y_1), \ldots, (w_n, y_n)\}$  where y is a categorical random variable over a set of classes  $\mathcal{Y}$ , the model estimates the probability of each possible category  $y = k \in \mathcal{Y}$  given a word  $w_i$  as

$$p(y = k | w_i; \theta) = \operatorname{softmax}(\mathbf{h}_i) = \frac{e^{\mathbf{W}_k \cdot \mathbf{h}_i}}{\sum_{j=1}^{\mathcal{Y}} e^{\mathbf{W}_j \cdot \mathbf{h}_i}} \qquad (1)$$
$$\mathbf{h}_i = \sigma \left( \mathbf{S} \cdot \mathbf{E}_{[i]} \right)$$

Here,  $\mathbf{E}_{[i]}$  selects the *i*-th column of the embedding matrix (corresponding to word  $w_i$ ),  $\mathbf{h}_i \in [0,1]^s$  is a vector of activations computed by the hidden layer and  $\sigma(\cdot)$  denotes an element-wise sigmoid non-linearity. The matrix  $\mathbf{W} \in \mathbb{R}^{|\mathcal{Y}| \times s}$  maps the embedding sub-space to the classification space. The parameters  $\theta = {\mathbf{W}, \mathbf{S}}$  are estimated to minimize the inverse log-likelihood of the training data

$$\theta \leftarrow \min_{\theta} - \sum_{(w_i, y_i) \in \mathcal{D}} \log p(y_i | w_i; \theta)$$
 (2)

The original embedding matrix is kept fixed, while the projection parameters are estimated jointly with the predictor, thus the model induce and exploit a compact, task-specific, representation that preserves the rich information captured by the embeddings.

Note that the model in Eq. 1 produces a probability distribution over the output classes, hence it is only suitable for categorical lexicons. Nonetheless, it can be easily adapted to continuous outputs by replacing the *softmax* classifier with a simple linear regressor:

$$\hat{y}_i = g(w_i; \theta') = \mathbf{w} \cdot \mathbf{h}_i + b \tag{3}$$

where  $\mathbf{w} \in \mathbb{R}^s$  and  $b \in \mathbb{R}$  are the regression weights and bias, respectively. The parameters  $\theta' = {\mathbf{w}, b, \mathbf{S}}$  are estimated by minimizing the Mean Squared Error over the training data

$$\theta' \leftarrow \min_{\theta'} \sum_{(w_i, y_i) \in \mathcal{D}} (y_i - \hat{y}_i)^2$$
 (4)

The loss functions in Eq. 2 and Eq. 4 can be minimized with standard gradient based optimization methods. After training, the models can be employed to extrapolate the labels of any word for which an embedding is available. Furthermore, by using embeddings induced from social media, we can adapt any pre-existing lexicon to include terms that are used in this domain.

#### **5** Predicting Lexicon Labels

In this section, we evaluate our method at inferring different subjective word properties, namely the **sentiment polarity**, **happiness level**, **affective responses** (specifically, the valence, arousal and dominance) and **emotion association** (concretely, Plutchik (1980)'s basic emotion set). We trained the models described in the previous section to predict the labels assigned by human judges to several well-known subjective lexicons. These are summarized in Table 1, and consist of two groups: categorical lexicons, associating words to specific classes e.g., *positive polarity* (on the top rows); and real-valued lexicons, assigning continuous values to words e.g., *valence* (bottom rows).

	# Words
Opinion Mining Lexicon (OML) (Hu and Liu 2004)	6,787
MPQA (Wilson, Wiebe, and Hoffmann 2005)	6,886
Emotion Lexicon (EmoLex) (Mohammad and Turney 2013)	14,174
ANEW (Bradley and Lang 1999)	1,040
SemEval (Sem-Lex) (Rosenthal et al. 2015)	1,515
LabMT (Dodds et al. 2011)	10,000
Ext-ANEW (Warriner, Kuperman, and Brysbaert 2013)	13,915

Table 1: Lexicons

#### **Experimental Setup**

Our approach requires an unlabeled corpus to support the induction of the word embedding matrix. Following Amir et al. (2015), we induced 600 dimensional Structured Skipgram word embeddings (Ling et al. 2015). We evaluated several baselines utilizing the same word embeddings as the input, but with predictors based on three variants of Support Vectors Machines (SVM) and Support Vectors Regression (SVR) (Vapnik 2000): (i) linear; (ii) with  $\ell_1$ -norm regularization; and (iii) with non-linear kernel. For the latter, we used a radial basis function (RBF) kernel of the form  $k(\mathbf{x}_i, \mathbf{x}_j) = e^{(-\gamma |\mathbf{x}_i - \mathbf{x}_j|^2)}$  with  $\gamma > 0$ , where  $\mathbf{x}$  denotes a feature vector. In this case, the models learn a linear function in the space induced by the kernel and the data, which corresponds to a non-linear function in the original space. This baseline corresponds to Amir et al. (2015) model. Finally, we considered the linear models but using compact representations obtained with PCA.

The experiments were performed by splitting the labeled data (i.e., the lexicons) in 80% for model training and the remaining 20% for evaluation. Then, for each experiment, 20% of the training data was reserved for hyper-parameter tuning via grid-search. We tuned the misclassification cost in the range  $C = [1e^{-2}, 1^{e-1}, 1, 10, 50, 100, 150]$  for all the SVM and SVR models. Furthermore, we searched over the following, model specific, hyper-parameters: kernel widths, in the range  $\gamma = [1e^{-3}, 1e^{-2}, 1^{e-1}, 1, 10]$  for the RBF kernel baselines; regularization constant in the range  $\lambda = [1e^{-4}, 1e^{-3}, 1e^{-2}, 1^{e-1}, 1, 10]$  for the regularized baselines; and the number of components to keep in the PCA baselines, in the range S = [3, 5, 10, 15, 20]. Regarding the NLSE model, we optimized the subspace size and

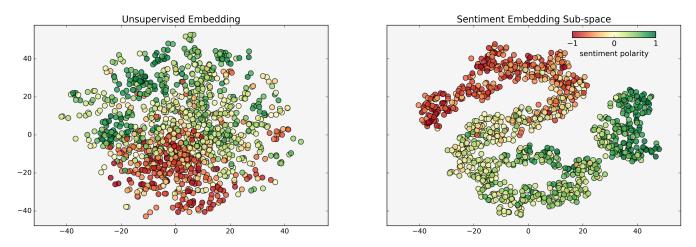


Figure 1: T-SNE projection of the embeddings associated to words from *Sem-Lex*, to two dimensions. The points are colored according to their sentiment polarity. The left plot, shows the words represented as 600-dimensional unsupervised embeddings. The right plot, shows the same words represented with *task-specific* embeddings induced with NLSE model.

the learning rate over the ranges S=[3,5,10,15,20] and  $\alpha=[1e^{-3},1^{e-2},5^{e-2},1^{e-1},5^{e-1}],$  respectively.

#### Results

The main experimental results are presented in Table 2, for the categorical lexicons, and Table 3, for the continuous ones. We can see that the NLSE largely outperforms all the other baselines, apart from two exceptions, where Amir et al. (2015)'s approach (RBF column) does slightly better. The results also show that the support vector models tend to perform better when used with non-linear kernels.

		NLSE	SVM			
			linear	$\ell_1$	RBF	PCA
OML	sentiment	0.882	0.868	0.686	0.872	0.852
MPQA	sentiment	0.691	0.691	0.221	0.669	0.555
	subjectivity	0.825	0.819	0.798	0.833	0.805
EmoLex	sentiment	0.676	0.630	0.404	0.640	0.468
	sadness	0.509	0.340	0.167	0.334	0.000
	fear	0.503	0.373	0.261	0.394	0.000
	anger	0.468	0.353	0.214	0.366	0.000
	disgust	0.446	0.343	0.180	0.352	0.000
	joy	0.440	0.333	0.148	0.329	0.000
	trust	0.403	0.201	0.190	0.167	0.000
	surprise	0.204	0.167	0.093	0.119	0.000
	anticipation	0.240	0.108	0.151	0.044	0.000

Table 2: Results for categorical lexicons in terms of Avg.  $F_1$ 

Regarding the baselines that try to uncover the relevant information from the embeddings (i.e., PCA and  $\ell_1$ ), we can see that they perform very poorly. This was expected, since the former induces a low-rank approximation of the original embedding, that (tries to) preserve most of the variance. However, since word embeddings are distributed representations, the values of individual dimensions are meaningless and should be regarded as coordinates in a high-dimensional space. The latter, on the other hand, tries to drop some of the input dimensions, but in doing so degrades the information contained in the word representations. These approaches are particularly inefficient in the more nuanced properties such as fine-grained emotions. Conversely, these are precisely the cases where our approach stands-out, which underlines the benefits of inducing task-specific representations.

		NLSE	SVR			
			linear	$\ell_1$	RBF	PCA
SemLex	sentiment	0.667	0.610	0.619	0.630	0.622
LabMT	happiness	0.640	0.576	0.573	0.622	0.464
ANEW	arousal	0.440	0.365	0.375	0.415	0.389
	valence	0.683	0.612	0.604	0.646	0.592
	dominance	0.546	0.477	0.456	0.494	0.475
Ext-ANEW	arousal	0.393	0.373	0.371	0.397	0.315
	valence	0.607	0.567	0.565	0.593	0.494
	dominance	0.480	0.445	0.443	0.464	0.405

Table 3: Results for continuous lexicons in terms of Kendall  $\tau$  rank correlation

To further illustrate the latter point, we wanted to visualize the effect of the sub-space projection on the word representation space. Therefore, we used Maaten and Hinton (2008) T-SNE algorithm to project the embeddings into twodimensions and plotted the words from Sem-Lex, colored according to their sentiment score. We first used the unsupervised embeddings and then, leveraging a sub-space projection (trained on Sem-Lex), induced and plotted new embeddings for the same words. These two plots are shown in Figure 1. On the left, we can see that unsupervised embeddings can naturally capture sentiment information-words with similar sentiment scores tend to be closer to each other. On the right, we see that in the space induced by the subspace projection, not only are similar words (w.r.t to sentiment) drawn even closer but also, quite interestingly, the words become arranged in what seems to be a continuum from the most negative to the most positive sentiment polarity.

The overall results show that pre-trained word embed-

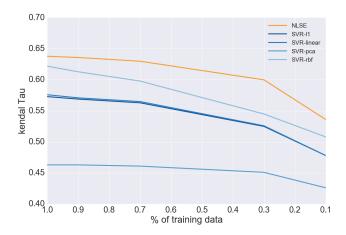


Figure 2: Performance of the different baselines in predicting the *happiness score* of words, as a function of the size of the training data.

dings can indeed capture a wide range of semantic properties, and be leveraged to induce subjective lexicons. Furthermore, the simplicity of our method suggests that it could be used to derive specific lexicons for different domains or demographics, to reflect the fact that some words are used with different connotations by different groups of people (Yang and Eisenstein 2015). However, this would require creating multiple 'training' lexicons, which raises the question of how much data is required to induce high-quality lexicons. To investigate this question, we plotted the performance of the different models, as a function of the training data size (Figure 2). As expected, the performance of all the models monotonically decreases with less training data. Nevertheless, we observe that the performance of our model decays slower than the RBF baseline (the second best method). Notably, when trained with 30% of the data, our model attains the same performance of the RBF baseline trained with 70% of the data.

# 6 Lexicon Based Twitter Sentiment Analysis

We now report on a set of experiments designed to assess the quality of our lexicons in downstream applications. To this end, we induced a large-scale sentiment lexicon, henceforth denoted as *NLSE-Lex*, with a model trained on the *Sem-Lex* lexicon. Then, we developed lexicon-based sentiment classifiers that infer the polarity of messages by aggregating the *sentiment scores* of individual words. More formally, given a message  $m = \{w_1, \ldots, w_n\}$  with n words, the overall sentiment is:

sentiment(m;t) = 
$$\begin{cases} positive, & \text{if score}(m) \ge t \\ negative, & \text{otherwise} \end{cases}$$
(5)

$$\operatorname{score}(m) = \frac{1}{n} \sum_{w_i \in m} y_i \tag{6}$$

where,  $y_i$  is the sentiment score associated to word  $w_i$  in a given lexicon and t is the threshold that separates the positive and negative classes.

We compared the performance of lexicon-based classifiers built on top of the following Twitter lexicons:

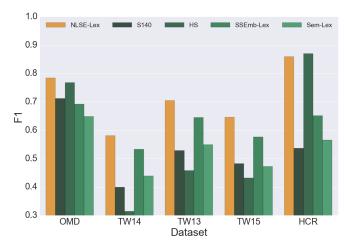
- *Sem-Lex*, a small manually labeled lexicon. This will provide a baseline performance;
- NLSE-Lex, induced with our method;
- Sentiment140 (S140) and Hashtag Sentiment (HL), created using term co-occurrence statistics collected from large corpora (Kiritchenko, Zhu, and Mohammad 2014);
- SSEmb-Lex, obtained using sentiment-specific embeddings (Tang et al. 2014).

For simplicity, we converted the labels of all the lexicons to the range [-1,1] and discarded words with scores between [-0.2, 0.2] to keep only terms that strongly convey sentiment, as suggested by Dodds et al. (2011). The classification threshold was set with a simple heuristic: we assume that most Twitter posts do not convey any particular sentiment, thus we set the threshold to  $t = \mathbb{E}[\text{score}(m)]$ . In other words, if the score of a message is above the expected sentiment score, then it is considered positive, otherwise it is negative. Finally, we compared the performance of the lexicon-based classifier to that of supervised approaches. For each test set, we trained two SVM models. One using only bag-of-words (SVM-BOW) features; and another, combining BOW features with a set of features extracted from the manually created lexicon: the mean, sum, maximum, minimum and standard deviation of the word sentiment scores (SVM-BOW + Lexicon).

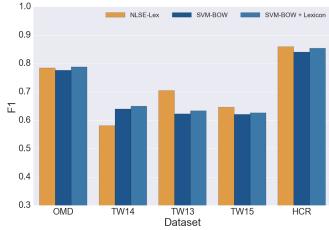
	# Training Tweets	<b>#</b> Test Tweets
TW-train	6,013	-
TW13	-	2,173
TW14	-	1,183
TW15	-	1,402
OMD	1,306	598
HCR	1,257	665

Table 4: Summary of the datasets used in the sentiment classification experiments. The top rows correspond to the test sets from SemEval's Twitter Sentiment Analysis competition; the *TW-train* dataset was only used as training data. The bottom rows, correspond to the datasets introduced by Speriosu et al. (2011).

The classifiers were evaluated on the following five datasets, summarized in Table 4. Three datasets compiled by SemEval for their well-known Twitter sentiment analysis challenge (Rosenthal et al. 2015) (TW-13, TW-14 and TW-15) (top rows); and two datasets introduced by Speriosu et al. (2011)—OMD, with reactions to the 2008 USA presidential debate opposing the democrat candidate Barack Obama and republican candidate Jonh Mccain; and HCR, with tweets discussing the 2010 health care reform in the USA. It should be noted that, Speriosu et al. datasets have standard splits for training, development and testing, hence for ease of comparison, our classifiers were evaluated on the



(a) Performance of lexicon-based classifiers built on top of different lexicons



(b) Comparison of lexicon-based classifiers against supervised models.

Figure 3: Results of the sentiment classification experiments

test sets. Furthermore, all the aforementioned datasets are labeled in terms of three classes—positive, negative and neutral, but in these experiments we excluded the neutral class and focused on binary classification.

#### **Results**

The results of the sentiment classification experiments are presented in Figure 3. In Figure 3a, we compare the performance of the different lexicons over the test data. We observe that our lexicon outperform the others in nearly all cases, with the exception of the *HCR* dataset where the *HL* lexicon performs marginally better. However, note that this same lexicon obtains the worst performance on *TW14*. In Figure 3b, we compare the *NLSE-Lex* with the supervised models. We found that our lexicon-based classifier is extremely competitive and, somewhat surprisingly, even outperforms the supervised baselines in almost all of the datasets.

### 7 Conclusions

This paper presented a novel approach to induce large-scale subjective lexicons suitable for social media analysis. We exploit the fact that unsupervised word embeddings capture semantic properties of words, and can be used as features for lexicon expansion models. However, instead of using the embeddings directly, we induce and exploit taskspecific representations, via sub-space projection. To this end, we leverage the Astudillo et al. (2015) NLSE model to jointly learn the adapted representations and respective predictor. The experimental results show that our approach outperforms previous work and other related baselines, across multiple lexicons and subjective properties. Working with lower-dimensional representations also allows us to induce predictors with less training data. Indeed, the results demonstrate that, compared to the other baselines, our method can make better use of limited amounts of training data. Finally, we empirically showed how the sub-space projections learned by the NLSE, transform the embedding space to better capture task-specific information.

To assess the quality of our lexicons, first, we compared the performance of lexicon-based sentiment classifiers built on top of ours, and other large-scale Twitter lexicons. We observed that the classifiers built with our lexicons largely outperform the other baselines. Second, we compared our lexicon-based classifier with supervised models and, surprisingly, we found that our lexicon-based model outperforms the more sophisticated models. These results demonstrate the quality of our lexicon and suggest that, with the appropriate lexicons, simple studies (e.g., involving binary sentiment classification) can be performed without the hassle of creating labeled data.

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