

Adversarial Deep Averaging Networks for Cross-Lingual Sentiment Classification

Xilun Chen[†]

xlchen@cs.cornell.edu ys646@cornell.edu

Yu Sun[†]

Ben Athiwaratkun[‡]

pa338@cornell.edu

Claire Cardie[†]

cardie@cs.cornell.edu

Kilian Weinberger[†]

kqw4@cornell.edu

[†]Dept. of Computer Science, Cornell University, Ithaca NY, USA

[‡]Dept. of Statistical Science, Cornell University, Ithaca NY, USA

Abstract

In recent years deep neural networks have achieved great success in sentiment classification for English, thanks in part to the availability of copious annotated resources. Unfortunately, most other languages do not enjoy such an abundance of annotated data for sentiment analysis. To combat this problem, we propose the Adversarial Deep Averaging Network (ADAN) to transfer sentiment knowledge learned from labeled English data to low-resource languages where only *unlabeled* data exists. ADAN is a “Y-shaped” network with two discriminative branches: a *sentiment classifier* and an adversarial *language predictor*. Both branches take input from a *feature extractor* that aims to learn hidden representations that capture the underlying sentiment of the text and are *invariant* across languages by competing with the adversary. Experiments on Chinese sentiment classification demonstrate that ADAN significantly outperforms several baselines, including a strong pipeline approach that relies on Google Translate, the state-of-the-art commercial machine translation system.

1 Introduction

There has been significant progress on English sentence- and document-level sentiment classification in recent years using models based on neural networks (Socher et al., 2013; İrsoy and Cardie, 2014a; Le and Mikolov, 2014; Tai et al., 2015; Iyyer et al., 2015). Most of these, however, rely on a massive amount of labeled training data or fine-grained annotations such as the Stanford Sentiment Treebank (Socher et al., 2013),

which provides sentiment annotations for each phrase in the parse tree of every sentence. On the other hand, such luxury is not available to many other languages, for which only a limited number of sentence- or document-level sentiment annotations exist. To aid the creation of sentiment classification systems in such low-resource languages, we propose the ADAN model that uses the abundant resources for a *source* language (here, English) to produce sentiment analysis models for a *target* language with (little or) no available labeled data. Our system is unsupervised in the sense that it does not require annotations in the target language. In this paper, we use Chinese sentiment classification as a motivating example, but our method can be readily applied to other languages as we only require *unlabeled* text in the target language, which is fairly accessible for most languages.

In particular, Chinese sentiment analysis remains much less explored compared to English, mostly due to the lack of large-scale labeled training corpora. Previous methods perform Chinese sentiment classification by training linear classifiers on small domain-specific datasets with hundreds to a few thousand instances. Training modern deep neural networks is impossible on such small datasets, and consequently a lot of research effort goes into hand-crafting better features that do not necessarily generalize well (Tan and Zhang, 2008; Lee and Renganathan, 2011). Although some prior work tries to alleviate the scarcity of sentiment annotations by leveraging labeled English data (Wan, 2008; Wan, 2009; Lu et al., 2011), these methods rely on extra external knowledge such as bilingual lexicons or machine translation (MT) systems, both of which are expensive to obtain.

In this work, we propose an end-to-end neural network model that only requires labeled English

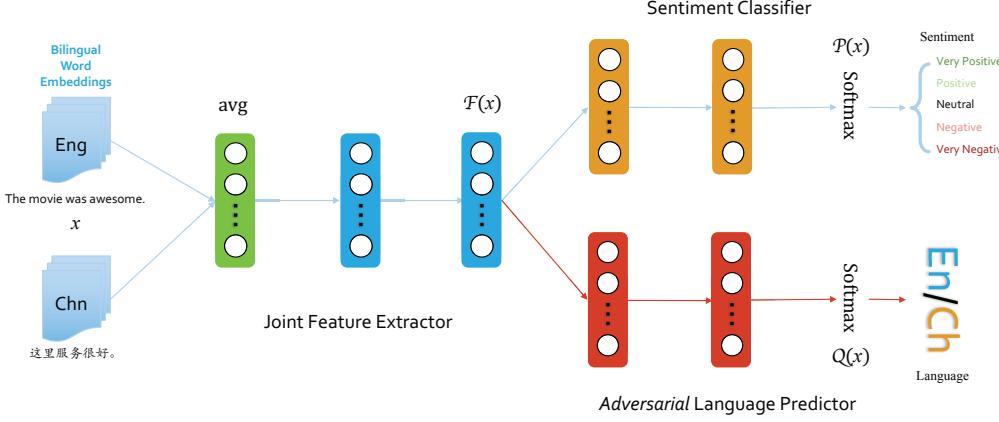


Figure 1: Adversarial Deep Averaging Network. The sentiment classifier \mathcal{P} and the language predictor \mathcal{Q} both take input from the feature extractor \mathcal{F} , and are optimized to excel in their own classification tasks. \mathcal{F} aims to learn features that help \mathcal{P} while **hindering** the adversarial \mathcal{Q} , in order to learn features helpful for sentiment classification and invariant across languages. Bilingual Word Embeddings will be discussed in Section 2.1.

data and *unlabeled* Chinese text as input, and explicitly transfers the knowledge learned on English sentiment analysis to Chinese. Our trained system directly operates on Chinese sentences to predict their sentiment.

We hypothesize that an ideal model for cross-lingual sentiment analysis should learn features that both perform well on the English sentiment classification task, and are invariant with respect to the shift in language. Therefore, ADAN has two discriminative components: i) a *sentiment classifier* \mathcal{P} for English; and ii) an *adversarial language predictor* \mathcal{Q} that tries to predict whether a sentence x is from English or Chinese. The structure of the model is shown in Figure 1. The two classifiers take input from the jointly learned feature extractor \mathcal{F} . While \mathcal{P} and \mathcal{Q} each tries to excel in its own classification task, \mathcal{F} is trained to maximize accuracy on English sentiment analysis and simultaneously to minimize the language predictor's chance of correctly predicting the language of the text. The intuition is that if a strong language predictor cannot tell the language of a given input sequence using the joint features, the features \mathcal{F} learned should be language-invariant. Upon successful training, the joint features (output of \mathcal{F}) are thus encouraged to be both discriminative for sentiment analysis and invariant across languages. This is also why the language predictor \mathcal{Q} is called “**adversarial**”.

The model is exposed to both English and Chinese sentences during training, but only the la-

beled English sentences pass through the sentiment classifier. The feature extractor and the sentiment classifier are then used for Chinese sentences at test time. In this manner, we can train the system with massive amounts of unlabeled text in Chinese.

The idea of incorporating an adversary in a neural network model has achieved great success in computer vision for image generation (Goodfellow et al., 2014) and domain adaptation (Ganin and Lempitsky, 2015; Ajakan et al., 2014). However, to our best knowledge, this work is the first to develop an adversarial network for a cross-lingual NLP task. While conceptually similar to domain adaptation, most research on domain adaptation assumes that the input from both domains share the same representation, such as image pixels for image recognition and bag of words for text classification. However, in our setting, the bag-of-word representation is infeasible because the two languages have completely different vocabularies.

In the following sections, we present our method in more detail and show experimental results in which ADAN significantly outperforms several baselines, some even with access to the powerful commercial MT system of Google Translate.

2 The ADAN Model

2.1 Network Architecture

As illustrated in Figure 1, the ADAN model is a feed-forward network with two branches. Hence

there are three main components in the network, a joint *feature extractor* \mathcal{F} that maps an input sequence x to the feature space, a *sentiment classifier* \mathcal{P} that predicts the sentiment label for x given the feature representation $\mathcal{F}(x)$, and a *language predictor* \mathcal{Q} that also takes the feature $\mathcal{F}(x)$ but predicts whether x is from English or Chinese.

An input document is modeled as a sequence of words $x = w_1, \dots, w_n$ where n is the number of tokens in x . The sentiment label of the input document is represented as y and the language label is denoted as $z \in \{\text{Eng}, \text{Chn}\}$. Each word $w \in x$ is represented by its word embedding v_w (Mikolov et al., 2013). As the same feature extractor \mathcal{F} is trained and tested on both English and Chinese sentences, it is favorable if the word representations for both languages align approximately in a shared space. To this end, bilingual word embeddings (Zou et al., 2013; Vulić and Moens, 2015; Gouws et al., 2015) attempt to induce distributed word representations that encode semantic relatedness between words across languages, so that similar words are closer in the embedded space regardless of language. Since many of these methods require a large amount of parallel corpus or extended training time, in this work we leverage the pre-trained bilingual word embeddings (BWE) in (Zou et al., 2013). Their work provides 50-dimensional embeddings for 100k English words and a different set of 100k Chinese words. Note that using the word embeddings in (Zou et al., 2013) makes our work implicitly dependent on a parallel corpus from the two languages, since it is required to train the bilingual embeddings. However, more recent approaches to train bilingual word embeddings require little or even no parallel corpus (Gouws et al., 2015; Vulić and Moens, 2015). These methods can alleviate or eliminate this dependence. For experiments and more discussions on word embeddings, see Section 3.4.

The feature extractor \mathcal{F} is a Deep Averaging Network (DAN) (Iyyer et al., 2015). \mathcal{F} first calculates the arithmetic mean of the word vectors in the input sequence, then passes the average through a feed-forward network with ReLU nonlinearities. The activations of the last layer in \mathcal{F} is considered the extracted features for the input and is then passed on to \mathcal{P} and \mathcal{Q} . The sentiment classifier \mathcal{P} and the language predictor \mathcal{Q} are standard feed-forward networks, with a softmax layer on top for classification. We chose DAN as the feature extrac-

tor due to its simplicity to better illustrate the effectiveness of our cross-lingual framework. However, in principle other architectures could also be adopted.

2.2 Training

The ADAN model can be trained end-to-end with standard back-propagation, which we detail in this section. For the two classifiers \mathcal{P} and \mathcal{Q} parameterized by θ_p and θ_q respectively, we use the traditional cross-entropy loss, denoted as $L_p(\hat{y}, y)$ and $L_q(\hat{y}, y)$, where \hat{y} and y are the predicted and true labels respectively. L_p is the negative log-likelihood of the model \mathcal{P} predicting the correct sentiment label, and L_q is that of \mathcal{Q} predicting the correct language. We therefore seek the minimum of the following loss functions for \mathcal{P} and \mathcal{Q} :

$$\min_{\theta_p} J_p(\theta_p, \theta_f) \equiv \mathbb{E}_{(x_i, y_i)} [L_p(\mathcal{P}(\mathcal{F}(x_i; \theta_f); \theta_p), y_i)]$$

$$\min_{\theta_q} J_q(\theta_q, \theta_f) \equiv \mathbb{E}_{(x_i, z_i)} [L_q(\mathcal{Q}(\mathcal{F}(x_i; \theta_f); \theta_q), z_i)]$$

To accomplish the aforementioned joint learning of features, the feature extractor \mathcal{F} , parameterized by θ_f , solves the following optimization problem:

$$\min_{\theta_f} J_p(\theta_p, \theta_f) - \lambda J_q(\theta_q, \theta_f) \quad (1)$$

where λ is a hyper-parameter that balances between the two branches \mathcal{P} and \mathcal{Q} . The loss of the adversarial \mathcal{Q} is negated since \mathcal{F} aims to hinder the performance of \mathcal{Q} . The intuition is that while \mathcal{P} and \mathcal{Q} are individually trying to master their own classification tasks, \mathcal{F} drives its parameters to extract hidden representations that help the sentiment prediction of \mathcal{P} and hamper the language prediction of \mathcal{Q} . Therefore, upon successful training, \mathcal{F} extracts language-invariant features suitable for sentiment analysis.

There are two approaches to train ADAN. The first one, inspired by Goodfellow et al. (2014), performs alternate training: first the sentiment classifier and the feature extractor are trained together, then the adversarial language predictor is trained while the other two are “frozen”. This method has more control towards convergence when the learning progress of \mathcal{P} and \mathcal{Q} are not fully in sync. For instance, in (Goodfellow et al., 2014), a hyper-parameter k is introduced to train one component for k iterations then the other for one, which is helpful since their generator learns faster than the discriminator.

The other method is to use a Gradient Reversal Layer (GRL) proposed by Ganin and Lempitsky (2015). The GRL does nothing during forward propagation, but negates the gradients it receives during backward propagation. Specifically, a GRL R_λ with hyper-parameter λ behaves as follows:

$$\begin{cases} R_\lambda(x) &= x \\ \nabla_x R_\lambda(x) &= -\lambda I \end{cases} \quad (2)$$

where I is the identity matrix. After a GRL is inserted between \mathcal{F} and \mathcal{Q} , running standard Stochastic Gradient Descent (SGD) on the entire network optimizes for (1).

In our experiments, we found that GRL is easier to work with since the entire network can be optimized *en masse*. On the other hand, we also observed that the training progress of \mathcal{P} and \mathcal{Q} is not usually in sync and it takes more than one batch of training for the language predictor to adapt to the changes in the joint features. Therefore, the first method’s flexibility in coordinating the training of \mathcal{P} and \mathcal{Q} is indeed important. Thus, we combine both approaches by adapting the GRL method to perform alternate training. This is achieved by setting λ to a non-zero value only once out of k batches. When $\lambda = 0$, the gradients from \mathcal{Q} will not be back-propagated to \mathcal{F} . This allows \mathcal{Q} more iterations to adapt to \mathcal{F} before \mathcal{F} makes another adversarial update. We set $\lambda = 0.02$ and $k = 3$ in all experiments, which is selected based on the performance on a held-out validation set.

For unsupervised cross-lingual sentiment analysis, we have access to labeled English data and *unlabeled* Chinese data during training. To train the ADAN model, we assemble mini-batches of samples drawn from both English and Chinese training data with equal probability, and use them to train the ADAN network. However, only the labeled English instances go through the *sentiment classifier* \mathcal{P} during training, while both English and Chinese instances go through the *language predictor* \mathcal{Q} . At test time, to predict the sentiment of a Chinese sentence, we pass it through the trained \mathcal{F} and then \mathcal{P} .

3 Experiments and Discussions

To demonstrate the effectiveness of our model, we experiment on sentence-level sentiment classification with 5 labels (--, -, 0, +, ++).

3.1 Data

Labeled English Data. We use a balanced dataset of 700k Yelp reviews from Zhang et al. (2015) with their ratings as labels (scale 1-5). We also adopt their train-validation split: 650k reviews form the training set and the remaining 50k form a validation set used in English-only benchmarks.

Labeled Chinese Data. Since ADAN does not require labeled Chinese data for training, this annotated data is solely used to validate the performance of our model. 10k balanced Chinese hotel reviews from Lin et al. (2015) are used as validation set for model selection and parameter tuning. The results are reported on a separate test set of another 10k hotel reviews.

Unlabeled Chinese Data. We use another 150k unlabeled Chinese hotel reviews for training.

3.2 Cross-Lingual Sentiment Classification

Our main results are shown in Table 1. Note in our settings, traditional features like bag-of-words etc. cannot be used since English and Chinese have completely different vocabularies. Therefore, bilingual word embeddings (BWE) are used to connect between Chinese and English in ADAN and the baseline systems. The DAN and LR baseline models use bilingual word embeddings to map both English and Chinese words to the same space and are trained using only English Yelp reviews. We can see from Table 1 that the bilingual embedding by itself does not suffice to transfer knowledge of English sentiment classification to Chinese, and the performance of DAN+BWE is poor (29.11%). Even LR+BWE yields slightly higher performance, despite the fact that DAN outperforms LR by a large margin on English validation set (not shown in table). This might suggest that fitting tightly on the English data does not necessarily entail good performance on Chinese due to the distributional discrepancy.

We then compares ADAN with domain adaptation baselines, which did not yield satisfactory results for our task. TCA (Pan et al., 2011) did not work since it requires quadratic space in terms of the number of samples (650k in our case). SDA (Glorot et al., 2011) and the subsequent mSDA (Chen et al., 2012) are proven very effective for cross-domain sentiment classification on Amazon reviews. However, as shown in Table 1, mSDA did not perform competitively. We postulate that this is because many domain adapta-

Model	Accuracy
Logistic Regression + Bilingual WE	30.58%
English DAN + Bilingual WE	29.11%
mSDA (Chen et al., 2012)	31.44%
Logistic Regression + Google Translate	34.01%
English DAN + Google Translate	39.66%
ADAN + Random WE (300d)	30.22%
ADAN + Bilingual WE (50d) + Random Padding (250d)	38.58%
ADAN + Bilingual WE	41.04%[†]

[†] $p = 0.05$ under a McNemar test.

Table 1: ADAN performance for fine-grained Chinese hotel review sentiment classification without using Chinese labeled data.

tion models including mSDA were designed for the use of bag-of-words features, which are ill-suited in these tasks where the two languages have completely different vocabularies. We instead use the same input representation as DAN for mSDA, the averaged word vector for each instance, which may violate the underlying assumption of mSDA and thus leading to poor results. In summary, this suggests that even strong domain adaptation algorithms cannot be used out of the box for our task to get satisfactory results.

One strong baseline we compare against is *English DAN with MT*. We use the commercial Google Translate engine¹, which is highly engineered, trained on enormous resources, and arguably one of the best MT systems in the world. It translates the Chinese reviews into English and makes predictions using the best-performing DAN model trained on Yelp reviews. Previous studies (Banea et al., 2008; Salameh et al., 2015) on sentiment analysis for Arabic and European languages claim this MT approach to be very competitive and can sometimes match the state-of-the-art system trained on that language. On the other hand, as shown in Table 1, our ADAN model significantly outperforms the MT baseline, indicating that our adversarial model can successfully perform cross-lingual sentiment analysis without annotated data on the target language.

Semi-supervised Learning In practice, it is usually not very difficult to obtain at least a little bit of annotated data. ADAN can be readily adapted to exploit such extra labeled data in the target language, by letting those labeled instances pass through the sentiment classifier \mathcal{P} as the En-

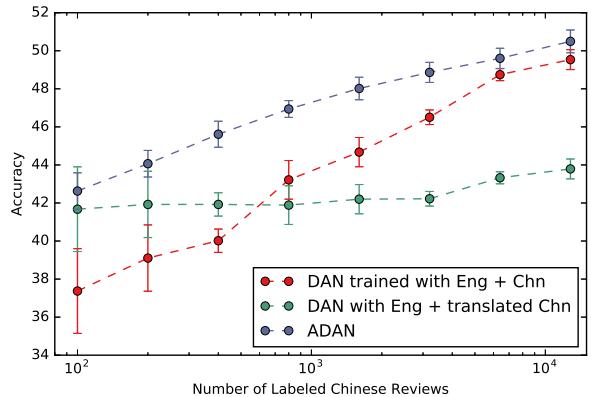


Figure 2: ADAN performance in the semi-supervised setting when using various amount of labeled Chinese data.

glish samples do during training. We simulate this semi-supervised scenario by adding labeled Chinese reviews for training. We start from adding 100 labeled reviews and keep doubling the number until 12800. As shown in Figure 2, when adding the same number of labeled reviews, ADAN can better utilize the extra supervision and outperform the DAN baseline trained with combined data. The margin is naturally decreasing as more supervision is incorporated, but ADAN is still superior when adding 12800 labeled reviews. On the other hand, the DAN with translation baseline seems not able to effectively utilize the added supervision in Chinese, and the performance only starts to show a slightly increasing trend when adding 6400 or more labeled reviews. One possible reason is that when adding into the training data a small number of English reviews translated from the labeled Chinese data, the training signals they produce might be lost in the vast number of English training sam-

¹<https://translate.google.com>

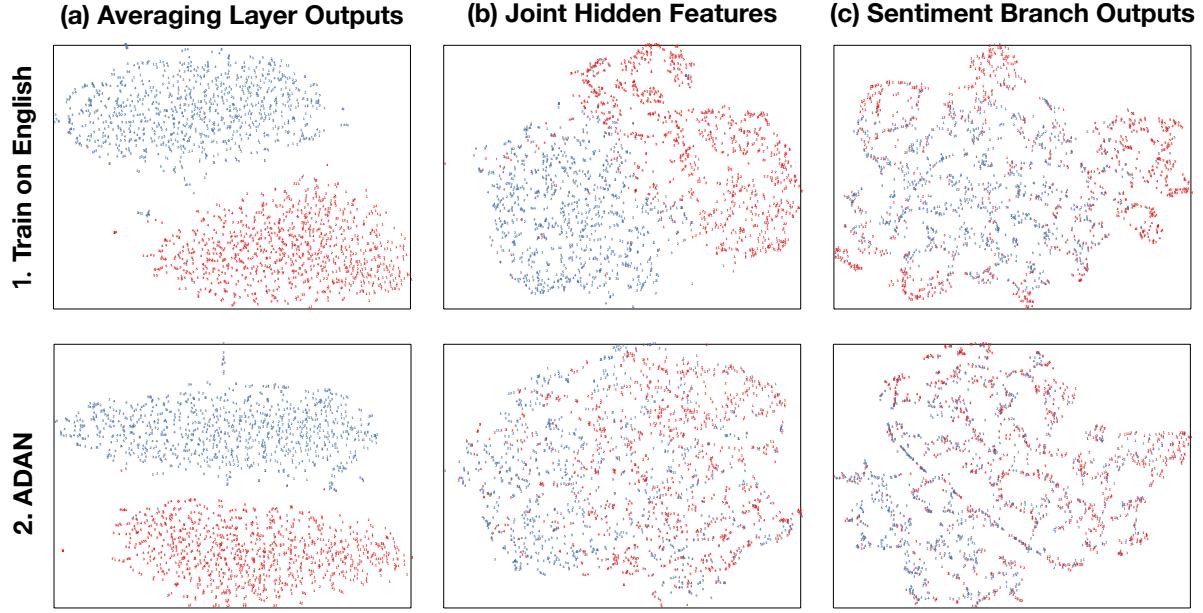


Figure 3: t-SNE Visualizations of activations at various layers for the train-on-English baseline model (top) and ADAN (bottom). The three columns are activations taken from the (a) averaging layer, (b) the end of the joint feature extractor \mathcal{F} , and (c) the last hidden layer in the sentiment classifier \mathcal{P} before softmax. Red dots are English samples and blue dots are Chinese (Better viewed in color). Numbers indicate the class labels for each instance (zoom in for details). The distributions of the two languages are brought much closer in ADAN as they are represented deeper in the network (left to right).

ples, thus not effectively improving the performance. Another interesting find is that it seems a very small amount of supervision (e.g. 100 labels) could significantly help DAN. However, with the same number of labeled reviews, ADAN still outperforms the DAN baseline.

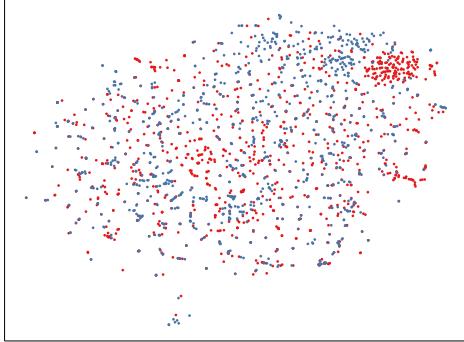
3.3 Qualitative Analysis and Visualizations

To qualitatively demonstrate how ADAN bridges the distributional discrepancies between English and Chinese instances, t-SNE (Van der Maaten and Hinton, 2008) visualizations of the activations at various layers are shown in Figure 3. We randomly select 1000 reviews from the Chinese and English validation sets respectively, and plot the t-SNE of the hidden node activations at three locations in our model: the averaging layer, the end of the joint feature extractor, and the last hidden layer in the sentiment classifier before softmax. The train-on-English model is the DAN+BWE baseline in Table 1. Note that there is actually only one “branch” in this baseline model, but in order to compare to ADAN, we conceptually treat the first three layers as the feature extractor. In addition, t-SNE plot of the bilingual word embeddings of the most frequent 1000 words in both languages are

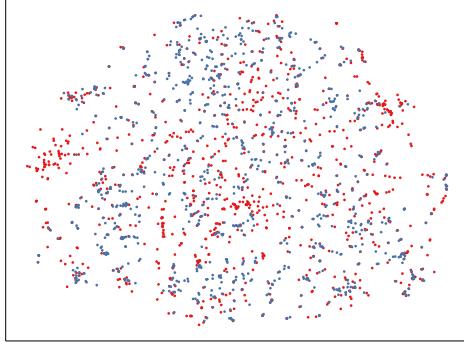
shown in Figure 4.

It can be seen from Figure 4 that BWE indeed provide a somewhat mixed distribution for words across languages. There are still some dense clusters of monolingual words in the pre-trained BWE, which is slightly alleviated after ADAN training which updates the word embeddings.

A somehow surprising finding in Figure 3a is the clear dichotomy between the averaged word vectors in the two languages despite the distributions of the word embeddings themselves being mixed (Figure 4). This might suggest that the diversion between languages are not only determined by word semantics, but also largely depends on the way how words are used. Therefore, one needs to look beyond word representations when tackling cross-lingual NLP problems. Furthermore, we can see in Figure 3b that the distributional discrepancies between Chinese and English are significantly reduced after passing through the joint feature extractor (\mathcal{F}), and the learned feature in ADAN brings the distributions in the two languages dramatically closer compared to the monolingually trained baseline. Finally, when looking at the last hidden layer activations in the sentiment classifier of the baseline model (Figure 3c), there



(a) Original Bilingual Word Embeddings



(b) Trained Word Embeddings in ADAN

Figure 4: t-SNE Visualizations of the Word Embeddings of the most frequent 1000 words from both languages. Red dots are English words and blue ones are Chinese (better viewed in color). (a) is the pre-trained embeddings from (Zou et al., 2013), and (b) is the updated embeddings in the trained ADAN model.

are several notable clusters of the red dots (English data) that roughly correspond to the class labels. However, most Chinese samples are not close to one of those clusters due to the distributional diversion and may thus cause degraded performance in Chinese sentiment classification. On the other hand, the Chinese samples are more in line with English ones in ADAN model, which results in the accuracy boost over the baseline model.

3.4 Impact of Bilingual Word Embeddings

In this section we discuss the effect of the bilingual word embeddings, which we deem as a key factor for future improvement. In our experiments, we observe that the small dimensionality of the BWE poses a limitation to DAN’s performance of monolingual sentiment classification in English. Even using 300 dimensional random embeddings outperforms the 50d BWE (58.55% vs. 58.15%), and is only marginally worse than padding the BWE to 300 dimensions (58.62%). Furthermore, with a better word embedding *word2vec* (Mikolov et al., 2013), the performance is 2% higher (60.15%) and close to the state of the art (Zhang et al., 2015).

Nevertheless, when performing cross-lingual training for ADAN, random WE no longer works, as seen in Table 1. This intuitively makes sense because the word representations from both languages are drawn from one identical random distribution, so the adversarial language predictor receives little useful information to distinguish between the underlying language distributions, hence producing rather useless gradients. We can see that adding randomness to the BWE also

yields worse performance and the best performing model only uses the 50 dimensional BWE. However, from the results in the monolingual setting, the accuracy of ADAN could probably be further improved if we can increase the quality or at least the dimensionality of the BWE.

3.5 Implementation Details

For all our experiments, the feature extractor \mathcal{F} has three fully-connected hidden layers with ReLU non-linearities, while both \mathcal{P} and \mathcal{Q} have two. All hidden layers contains 900 hidden units. This choice is more or less ad-hoc, and the performance could potentially be improved with more careful model selection. Batch Normalization (Ioffe and Szegedy, 2015) is used in each hidden layer. We corroborate the observations by Ioffe and Szegedy (2015) (2015) that Batch Normalization can sometimes eliminate the need for Dropout (Srivastava et al., 2014) or Word Dropout (Iyyer et al., 2015), which make little difference in our experiments. We use Adam (Kingma and Ba, 2015) with a learning rate of 0.05 for optimization. ADAN is implemented in Torch7 (Collobert et al., 2011).

Training is very efficient for ADAN due to its simplicity. It takes less than 6 minutes to finish one epoch ($1.3M$ instances) on one Titan X GPU. We train ADAN for 30 epochs and use early stopping to select the best model on the validation set.

4 Related Work

Sentiment Classification is a popular NLP task on which neural network models have demon-

strated tremendous power when coupled with copious data (Socher et al., 2013; Irsay and Cardie, 2014a; Le and Mikolov, 2014; Tai et al., 2015; Iyyer et al., 2015). Among these, the Deep Averaging Network (DAN) is a very simple neural network model that yields surprisingly good performance, comparable to complicated syntactic models like recursive neural networks (Iyyer et al., 2015). For each document, DAN takes the arithmetic mean of the document word vectors (Mikolov et al., 2013; Pennington et al., 2014) as input, and passes it through several fully-connected layers until a softmax for classification.

Cross-lingual Sentiment Analysis is motivated by the lack of high-quality labeled data in many non-English languages (Mihalcea et al., 2007; Banea et al., 2008; Banea et al., 2010). For Chinese in particular, there are several representative works (Wan, 2008; Wan, 2009; He et al., 2010; Lu et al., 2011). Our work is comparable to these papers in objective but very different in method. The work by Wan uses machine translation to directly convert English training data to Chinese; this is one of our baselines. Lu et al. (2011) instead uses labeled data from both languages to improve the performance on both.

Domain Adaptation tries to learn effective classifiers for which the training and test samples are from different underlying distributions (Blitzer et al., 2007; Pan et al., 2011; Glorot et al., 2011; Chen et al., 2012; Liu et al., 2015). This can be thought of as a generalization of cross-lingual text classification. However, one main difference is that, when applied to text classification tasks such as sentiment analysis, most works in domain adaptation evaluate on adapting product reviews from one domain to another (e.g. books to electronics), where the divergence in distribution is less significant than that between two languages. See Section 3.2 for experiments on this. In addition, for cross-lingual sentiment analysis, it might be difficult to find data from exactly the same domain in two languages, in which case our model still demonstrates impressive performance.

Adversarial Networks have enjoyed much success in computer vision (Goodfellow et al., 2014; Ganin and Lempitsky, 2015), but to the best of our knowledge, have not yet been applied in NLP with comparable success. We are the first to apply adversarial training to the cross-lingual setting in NLP. A series of work in image gener-

ation has used architectures similar to ours, by pitching a neural image generator against a discriminator that learns to classify real versus generated images (Goodfellow et al., 2014; Denton et al., 2015). More relevant to this work, adversarial architectures have produced the state-of-the-art in unsupervised domain adaptation for image object recognition: Ganin and Lempitsky (2015) train with many labeled source images and unlabeled target images, similar to our setup.

5 Conclusion and Future Work

In this work, we presented ADAN, an adversarial deep averaging network for cross-lingual sentiment classification. ADAN leverages the affluent resources on English to help sentiment categorization on other languages where little or no annotated data exist. We validate our hypothesis by empirical experiments on Chinese sentiment categorization, where we have labeled English training data and only *unlabeled* Chinese data. Experiments show that ADAN outperforms several baselines including domain adaptation models and a highly competitive MT baseline using Google Translate. Furthermore, we show that in the presence of labeled data in the target language, ADAN can naturally incorporate this additional supervision and yields even more competitive results.

For future work, one direction is to explore better bilingual word embeddings, which we identify as one key factor limiting the performance of ADAN. In another direction, our adversarial framework for cross-lingual text categorization can be applied not only to DAN, but also many other neural models such as LSTM, etc. Further, our framework is not limited to text classification tasks, and can be extended to, for instance, phrase level opinion mining (Irsay and Cardie, 2014b) by extracting phrase-level opinion expressions from sentences using deep recurrent neural networks. Our framework can be applied to these phrase-level models for languages where labeled data might not exist.

References

- [Ajakan et al.2014] Hana Ajakan, Pascal Germain, Hugo Larochelle, François Laviolette, and Mario Marchand. 2014. Domain-adversarial neural networks. In *Second Workshop on transfer and Multi-Task Learning (NIPS 2014)*.
- [Banea et al.2008] Carmen Banea, Rada Mihalcea,

- Janyce Wiebe, and Samer Hassan. 2008. Multilingual subjectivity analysis using machine translation. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing*.
- [Banea et al.2010] Carmen Banea, Rada Mihalcea, and Janyce Wiebe. 2010. Multilingual subjectivity: Are more languages better? In *Proceedings of the 23rd international conference on computational linguistics*.
- [Blitzer et al.2007] John Blitzer, Mark Dredze, and Fernando Pereira. 2007. Biographies, bollywood, boom-boxes and blenders: Domain adaptation for sentiment classification. In *Proceedings of the 45th Annual Meeting of the Association of Computational Linguistics*.
- [Chen et al.2012] Minmin Chen, Zhixiang Xu, Kilian Weinberger, and Fei Sha. 2012. Marginalized denoising autoencoders for domain adaptation. In *Proceedings of the 29th International Conference on Machine Learning*.
- [Collobert et al.2011] Ronan Collobert, Koray Kavukcuoglu, and Clément Farabet. 2011. Torch7: A matlab-like environment for machine learning. In *BigLearn, NIPS Workshop*.
- [Denton et al.2015] Emily L Denton, Soumith Chintala, Rob Fergus, et al. 2015. Deep generative image models using a laplacian pyramid of adversarial networks. In *Advances in Neural Information Processing Systems*.
- [Ganin and Lempitsky2015] Yaroslav Ganin and Victor Lempitsky. 2015. Unsupervised domain adaptation by backpropagation. In *Proceedings of the 32nd International Conference on Machine Learning*. JMLR Workshop and Conference Proceedings.
- [Glorot et al.2011] Xavier Glorot, Antoine Bordes, and Yoshua Bengio. 2011. Domain adaptation for large-scale sentiment classification: A deep learning approach. In *Proceedings of the 28th International Conference on Machine Learning*.
- [Goodfellow et al.2014] Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron C. Courville, and Yoshua Bengio. 2014. Generative adversarial nets. In *Advances in Neural Information Processing Systems 27: Annual Conference on Neural Information Processing Systems 2014*.
- [Gouws et al.2015] Stephan Gouws, Yoshua Bengio, and Greg Corrado. 2015. Bilbowa: Fast bilingual distributed representations without word alignments. In *Proceedings of the 32nd International Conference on Machine Learning*.
- [He et al.2010] Yulan He, Harith Alani, and Deyu Zhou. 2010. Exploring english lexicon knowledge for chinese sentiment analysis.
- [Ioffe and Szegedy2015] Sergey Ioffe and Christian Szegedy. 2015. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In *Proceedings of The 32nd International Conference on Machine Learning*.
- [Irsoy and Cardie2014a] Ozan Irsoy and Claire Cardie. 2014a. Deep recursive neural networks for compositionality in language. In *Advances in Neural Information Processing Systems 27*.
- [Irsoy and Cardie2014b] Ozan Irsoy and Claire Cardie. 2014b. Opinion mining with deep recurrent neural networks. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing*.
- [Iyyer et al.2015] Mohit Iyyer, Varun Manjunatha, Jordan Boyd-Graber, and Hal Daumé III. 2015. Deep unordered composition rivals syntactic methods for text classification. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing*.
- [Kingma and Ba2015] Diederik Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. In *International Conference on Learning Representations*.
- [Le and Mikolov2014] Quoc Le and Tomas Mikolov. 2014. Distributed representations of sentences and documents. In *Proceedings of the 31st International Conference on Machine Learning*.
- [Lee and Renganathan2011] Huey Yee Lee and Hemnaath Renganathan. 2011. Chinese sentiment analysis using maximum entropy. In *Proceedings of the Workshop on Sentiment Analysis where AI meets Psychology (SAAIP), IJCNLP 2011*.
- [Lin et al.2015] Yiou Lin, Hang Lei, Jia Wu, and Xiaoyu Li. 2015. An empirical study on sentiment classification of chinese review using word embedding. In *Proceedings of the 29th Pacific Asia Conference on Language, Information and Computation: Posters*.
- [Liu et al.2015] Biao Liu, Minlie Huang, Jiashen Sun, and Xuan Zhu. 2015. Incorporating domain and sentiment supervision in representation learning for domain adaptation. In *Proceedings of the 24th International Conference on Artificial Intelligence*.
- [Lu et al.2011] Bin Lu, Chenhao Tan, Claire Cardie, and Benjamin K Tsou. 2011. Joint bilingual sentiment classification with unlabeled parallel corpora. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*.
- [Mihalcea et al.2007] Rada Mihalcea, Carmen Banea, and Janyce Wiebe. 2007. Learning multilingual subjective language via cross-lingual projections.

- [Mikolov et al.2013] Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. 2013. Distributed representations of words and phrases and their compositionality. In *Advances in Neural Information Processing Systems*.
- [Pan et al.2011] Sinno Jialin Pan, Ivor W Tsang, James T Kwok, and Qiang Yang. 2011. Domain adaptation via transfer component analysis. *IEEE Transactions on Neural Networks*.
- [Pennington et al.2014] Jeffrey Pennington, Richard Socher, and Christopher D Manning. 2014. Glove: Global vectors for word representation. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing*.
- [Salameh et al.2015] Mohammad Salameh, Saif Mohammad, and Svetlana Kiritchenko. 2015. Sentiment after translation: A case-study on arabic social media posts. In *Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*.
- [Socher et al.2013] Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D. Manning, Andrew Ng, and Christopher Potts. 2013. Recursive deep models for semantic compositionality over a sentiment treebank. In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*.
- [Srivastava et al.2014] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. 2014. Dropout: A simple way to prevent neural networks from overfitting. *The Journal of Machine Learning Research*.
- [Tai et al.2015] Kai Sheng Tai, Richard Socher, and Christopher D. Manning. 2015. Improved semantic representations from tree-structured long short-term memory networks. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing*.
- [Tan and Zhang2008] Songbo Tan and Jin Zhang. 2008. An empirical study of sentiment analysis for chinese documents. *Expert Systems with Applications*.
- [Van der Maaten and Hinton2008] Laurens Van der Maaten and Geoffrey Hinton. 2008. Visualizing data using t-sne. *Journal of Machine Learning Research*.
- [Vulić and Moens2015] Ivan Vulić and Marie-Francine Moens. 2015. Bilingual word embeddings from non-parallel document-aligned data applied to bilingual lexicon induction. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 2: Short Papers)*.
- [Wan2008] Xiaojun Wan. 2008. Using bilingual knowledge and ensemble techniques for unsupervised chinese sentiment analysis. In *Proceedings of the conference on empirical methods in natural language processing*.
- [Wan2009] Xiaojun Wan. 2009. Co-training for cross-lingual sentiment classification. In *Proceedings of the Joint Conference of the 47th Annual Meeting of the ACL and the 4th International Joint Conference on Natural Language Processing of the AFNLP*.
- [Zhang et al.2015] Xiang Zhang, Junbo Zhao, and Yann LeCun. 2015. Character-level convolutional networks for text classification. In *Advances in Neural Information Processing Systems*.
- [Zou et al.2013] Will Y. Zou, Richard Socher, Daniel Cer, and Christopher D. Manning. 2013. Bilingual word embeddings for phrase-based machine translation. In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*.