Topic Driven Adaptive Network for Cross-Domain Sentiment Classification

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Abstract
Cross-domain sentiment classification has been a hot spot these years, which aims to learn a reliable classifier using labeled data from the source domain and evaluate it on the target domain. In this vein, most approaches utilized domain adaptation that maps data from different domains into a common feature space. To further improve the model performance, several methods targeted to mine domain-specific information were proposed. However, most of them only utilized a limited part of domain-specific information. In this study, we first develop a method of extracting domain-specific words based on the topic information. Then, we propose a Topic Driven Adaptive Network (TDAN) for cross-domain sentiment classification. The network consists of two sub-networks: semantics attention network and domain-specific word attention network, the structures of which are based on transformers. These sub-networks take different forms of input and their outputs are fused as the feature vector. Experiments validate the effectiveness of our TDAN on sentiment classification across domains.

Introduction
Sentiment classification aims to automatically predict sentimental labels of given documents. With the development of deep learning, sentiment classification has achieved outstanding performance (Zhang, Wang, and Liu 2018). However, traditional sentiment classification methods based on supervised learning rely on a large amount of manually annotated data, and constructing such datasets is a laborious and expensive process. To address this problem, cross-domain sentiment classification has been proposed (Pan et al. 2010). It eases the need for a large amount of labeled data in the target domain (where labeled data are few) by training the classifier with labeled data from the source domain (where labeled data are rich).

Recent works on cross-domain sentiment classification mainly focused on domain-invariant features extraction, also known as domain adaptation (Peng et al. 2018; Li et al. 2018; Zhang et al. 2019). Data from both domains are mapped into a common feature space where all data points are assumed to be independent and identically distributed.

Most works trained a classifier based on the domain-invariant features extracted from the source domain. Specifically, Peng et al. (2018) explicitly restricted the discrepancy between features from both domains and some other works (Li et al. 2018; Zhang et al. 2019) adopted adversarial methods to extract the domain-invariant features by confusing a domain discriminator.

To further improve the performance, methods of exploiting additional information have been proposed (Li et al. 2018; Peng et al. 2018; He et al. 2018; Hu et al. 2019; Bahdanau, Cho, and Bengio 2015). Among these works, Peng et al. (2018) and He et al. (2018) introduced semi-supervised learning methods to utilize the target domain information. Hu et al. (2019) and Zhang et al. (2019) leveraged the aspects of documents to assists sentiment classification. Li et al. (2018) designed a hierarchical attention network that automatically finds pivots, i.e., domain-shared sentiment words, and non-pivots, i.e., domain-specific sentiment words. Both pivots and non-pivots help in cross-domain sentiment classification.

From the previous works, we can conclude that there are two types of words in the cross-domain sentiment classification task: domain-shared words and domain-specific words. Domain-shared words occur in both domains. Most words that directly reflect sentiment polarity are shared between domains, such as good and bad. Domain-shared words that reflect sentiment polarity are also known as pivots (Li et al. 2018). Domain-specific words occur in a single domain and most of them don’t carry sentiment information with them. Most domain-specific words describe the background information of documents, such as book and internet. However, domain-specific words can also include sentiment words, i.e., non-pivots (Li et al. 2018). Therefore, there are two kinds of domain-specific words: non-pivots and background words. Non-pivots are sentiment words and background words that provide us with background information about a document.

The utilization of domain-shared words has been widely explored in previous works (Blitzer, McDonald, and Pereira 2006; Blitzer, Dredze, and Pereira 2007; Li et al. 2018, 2020). However, domain-specific words are not thoroughly utilized. Previous works typically only pay attention to one type of domain-specific word. HATN (Li et al. 2018) only pays attention to domain-specific words that reflect senti-
To utilize both types of domain-specific words, we introduce topics to extract domain-specific words before training the classification network. The benefit of using topics to identify domain-specific words in two domains is that such words can be better captured compared with methods based on word co-occurrences or mutual information. Firstly, topics can help extract both types of domain-specific words while methods based on word co-occurrences or mutual information might fail to capture both types. Secondly, the proposed method helps capture polysemous words such as “right”. When “right” means “correct”, it is a domain-shared word. On the other hand, the above word is domain-specific when it means “interest”. The topic model performs soft clustering on words which means that the same word occurring in different topics may hold different semantics and this helps to separate the different semantics of the polysemous words, deciding whether it is domain-shared or domain-specific. Particularly, we calculate topic occurrence possibilities in two domains to decide whether a topic is specific to a domain and check every word’s most related topic to decide whether it is domain-specific. Domain-specific words are encoded using the domain-specific word attention network to generate feature vectors. The reason why we do not extract domain-shared words is that previous works (Li et al. 2017, 2018) showed that attention-based networks combined with domain adaptation methods would automatically capture pivots. Therefore, the semantics sub-network in our work that takes original documents as input can utilize domain-shared words, and an extra sub-network that takes domain-shared words as input is unnecessary.

Based on the extracted domain-specific words, we propose a Topic Driven Domain Adaptation Network (TDAN) for cross-domain sentiment classification. TDAN incorporates domain-specific information to enhance the model performance. It consists of two sub-networks: semantics attention network and domain-specific word attention network. The sub-networks use different forms of inputs and the output vectors of each network are fused as the final feature vector. Then, the network adopts the adversarial method (Goodfellow et al. 2014) to map the feature vector into a domain-invariant space.

The main contributions are summarized as follows:

- Our work is the first one to utilize the topic model to extract domain-specific words.
- Our work is the first one to utilize both types of domain-specific words for cross-domain sentiment classification.
- We develop a novel network that combines different forms of input to classify sentiments across domains.

Related Work

**Domain adaption:** The fundamental problem of cross-domain learning is that the source and target domains hold different data distributions. Directly employing a classifier trained with source domain data shows low performance because of the varied data distributions in the target domain. Therefore, domain adaptation is proposed to reduce the discrepancy between two distributions. In a preliminary study, Blitzer, McDonald, and Pereira (2006) proposed Structural Correspondence Learning (SCL) to classify documents utilizing human-selected pivot feature. The pivot features are shared words between both domains that indicate opinions. Some works (Pan et al. 2010, Gu, Li, and Han 2011, Li, Zhao, and Lu 2016) further extended the feature selection method. Ganin et al. (2015) introduced adversarial learning into domain adaptation. It mapped data from both domains into a domain-invariant domain by fooling a domain discriminator. Some works (He et al. 2018, Peng et al. 2018) introduced semi-supervised learning methods to further utilize the target domain-specific information. Other works (Li et al. 2017, 2018, Hu et al. 2019, Zhang et al. 2019) utilized the attention mechanism. Among them, Li et al. (2018) proposed an effective hierarchical attention transfer network (HATN) that automatically locates pivots and non-pivots in both domains. Zhang et al. (2019) put forward an interactive attention transfer network (IATN) to utilize the aspects of documents in cross-domain sentiment classification.

**Topic model:** Topic model (Blei, Ng, and Jordan 2003) is a generative probabilistic model for mining the topic distribution of documents. Recently, variational auto-encoder (Kingma and Welling 2014) based methods have been introduced to topic models which increased the topic construction performance and speed (Miao, Yu, and Blunsom 2016, Miao, Grefenstette, and Blunsom 2017, Srivastava and Sutton 2017). Topic model has been applied in many natural language processing (NLP) tasks like text classification (Qiuxing, Lixiu, and Jie 2016, Pavlinek and Podgereces 2017, Wang et al. 2019, Wang and Wang 2020) while it has not yet been applied in cross-domain sentiment classification. In this paper, we mainly adopt LDA (Blei, Ng, and Jordan 2003) as our topic encoding network to assist cross-domain sentiment classification. We have also tried other topic models such as prodLDA (Srivastava and Sutton 2017) and it turns out that different topic models have little influence on the classification accuracy. Therefore, the experiment results reported in this work are all based on LDA.

**Attention mechanism in NLP:** The attention mechanism in NLP is firstly used for the machine translation task (Bahdanau, Cho, and Bengio 2015). It got intuition from the fact that human allocates varied importance to different tokens in a sentence when trying to parse it. Based on the attention mechanism, the transformer (Vaswani et al. 2017) puts forward a new kind of attention: self-attention, which allows each token to calculate its relative importance with other tokens. The self-attention mechanism has been proven
Domain label

Sentiment label

Transformer
Encoder

Sentiment label

GRL

Domain label

Interactive connection

MLP-attention

Transformer
Encoder

Word Embedding

Positional Embedding

Domain-Specific Word Extraction

SAN

x_t

DAPWAN

Figure 1: The framework of TDAN

as effective in many tasks, such as language understanding, text classification and semantic role labeling (Vaswani et al. 2017) [Devlin et al. 2019] [Tan et al. 2018]. In this paper, the networks are based on transformers (Vaswani et al. 2017) and we also utilize the MLP attention mechanism (Bahdanau, Cho, and Bengio 2015) to get fixed-length feature vectors.

Topic Driven Adaptive Network

Problem Definition

There are two domains in our problem: the source domain $D_s$ and the target domain $D_t$. $X_s$ represents the set of data from $D_s$ and the dataset size is noted as $N_s$. $X_s$ consists of two subsets, i.e., the labeled subset $X_s^l$ and the unlabeled subset $X_s^u$. Each data point in $X_s$ is noted as $x_s^i$ with label $y_s^i$ if having one. Besides, unlabeled dataset $X_t$ from $D_t$ is available and the dataset size is noted as $N_t$. Each data point in $X_t$ is noted as $x_t^i$. A data point in $X_s$ or $X_t$ is noted as $x_i$. In this work, domain-specific words $X^{sp}$ are extracted for each document. For document $x_i$, its corresponding domain-specific words are noted as $x_i^{sp}$.

Network Structure

Before training the network, we generate topics using documents from both domains. For each cross-domain task, domain-specific words are generated. The domain-specific words are treated as unordered sets.

As shown in Figure 1, the proposed TDAN consists of two sub-networks: semantics attention network (SAN) and domain-specific word attention network (DSPWAN). Both SAN and DSPWAN utilize the attention mechanism (Bahdanau, Cho, and Bengio 2015). Moreover, DSPWAN is interactively connected with SAN to provide more background information as in Zhang et al. (2019).

Domain-specific Word Extraction

In our work, domain-specific words are generated using a topic model. The topic model we adopt here is LDA (Blei, Ng, and Jordan 2003). After the training process, for each document $x_i$, we can obtain its topic distribution vector $p_i \in \mathbb{R}^k$, where $k$ is the number of topics. $p_i^l$ represents topic distribution vectors of source document $x_i^l$ and $p_i^u$ represents topic distribution vectors of target document $x_i^u$. The topic model also provides us with the topic-word distribution matrix $\beta \in \mathbb{R}^{V \times k}$, where $V$ is the vocabulary size.

Then, for each cross-domain task, domain-specific words are extracted with the topic model. Algorithm 1 shows the detailed extraction process, where $tol$ is a hyperparameter. For each topic $t$ in the topic model, it is classified as the domain-specific topic if the average possibility difference between two domains is larger than $tol$. For each word $w_j$ in document $x_i$, it is classified as a domain-specific word if its most related topic is a domain-specific one. The most related topic $t_j$ of a word $w_j$ in document $x_i$ is calculated by:

$$p_d = \beta \odot p_i, \quad t_j = \arg \max_l \{p_d[l][w_j]\},$$  \hspace{1cm} (1)

where $p_i$ is the topic distribution vector of $x_i$, $\beta$ is the topic-word distribution matrix and $p_d \in \mathbb{R}^{V \times k}$ is the unnormalized word-topic distribution matrix, each row of which denotes the topic distribution of a word in the document. An element-wise multiplication operation is performed between $\beta$ and $p_i$ to generate matrix $p_d$. The most related topic $t_j$ for word $w_j$ is the max element in the corresponding row.

Algorithm 1: Domain-specific word extraction process

**Input:**
- The average topic occurrence possibility in source domain, $p_s$;
- The average topic occurrence possibility in target domain, $p_t$;
- The tolerance bound, $tol$;
- Documents from source and target domains, $X_s$ and $X_t$;

**Output:**
- Domain-specific words, $X^{sp}$;

1: Initialize two empty topic sets: source domain-specific topic set $s_{sp}$ and target domain-specific topic set $t_{sp}$;
2: for each topic $t$ do
3: \hspace{1em} if $p_s[t] - p_t[t] > tol$ then
4: \hspace{2em} Insert $t$ into $s_{sp}$;
5: \hspace{1em} else if $p_t[t] - p_s[t] > tol$ then
6: \hspace{2em} Insert $t$ into $t_{sp}$;
7: \hspace{1em} end if
8: end for
9: for each document $x_i^t$ in $X_t$ do
10: \hspace{1em} for each word $w_j$ in $x_i^t$ do
11: \hspace{2em} Calculate the most related topic $t_j$ of $w_j$;
12: \hspace{1em} if $t_j$ is in $s_{sp}$ then
13: \hspace{2em} insert $w_j$ to $x_i^{sp}$;
14: \hspace{1em} end if
15: \hspace{1em} end if
16: end for
17: Perform similar operations on $X_t$ to add words to $X^{sp}$;
The average topic occurrence possibilities in two domains, i.e., $p_s$ and $p_t$ are calculated as follows:

$$P_s = \frac{1}{N_s} \sum_{i=1}^{N_s} p_{s,i},$$

$$P_t = \frac{1}{N_t} \sum_{i=1}^{N_t} p_{t,i}. \quad (2)$$

After conducting the extraction process in Algorithm 1, the domain-specific words of a document are obtained. These words are assembled as a sequence and feed into DSPWAN. The domain-specific word sequence corresponding to a document is noted as $x_{i}^{sp} \in \mathbb{R}^{d_{sp}}$, where $d_{sp}$ is the sequence length. Since the extracted domain-specific words are sparse in a document and their relative order contains little useful information, we remove positional embedding vectors in DSPWAN.

Also, $x_{i}^{sp}$ can be empty while empty input for the attention network is not legal. Therefore, a special token (specific_token) is added to $x_{i}^{sp}$ to smooth the input.

**Semantics Attention Network**

SAN aims at mining the semantics information from given documents. SAN is based on the attention mechanism. It consists of two components: transformer component (Vaswani et al., 2017) and MLP attention layer. The transformer is used to extract the context vector $C$ from the input document $x_i$ and the MLP attention layer is used to generate the feature vector used for sentiment classification. For simplicity, we would illustrate the transformer component structure in this section and the MLP-attention layer structure will be introduced in subsequent sections.

In this work, the transformer encoder (Vaswani et al., 2017) is used as an encoder for documents to generate context vectors. For each word $w_j$ in the input document $x_i$, it is mapped into the embedding space combining the pre-trained word vector $h_j^{sp}$ and the position embedding vector $h_j^{pos}$. The embedding vector $h_j^{sp} \in \mathbb{R}^{d_h}$ of each word is calculated as $h_j^{sp} = h_j^{sp} + p_j^{pos}$, where $h_j^{sp} \in \mathbb{R}^{d_h}$ and $p_j^{pos} \in \mathbb{R}^{d_h}$. In our experiment, the position embedding is generated as follows:

$$PE(pos, 2l) = \sin(pos/10000^{2l/d_{h}}),$$

$$PE(pos, 2l + 1) = \cos(pos/10000^{2l/d_{h}}). \quad (3)$$

where pos is the position and $l$ is the dimension. Each embedding vector $h_j^{sp}$ of a $d_l$ length document is stacked together to form the matrix $H \in \mathbb{R}^{d_l \times d_h}$. $H$ is encoded using a multi-layer transformer encoder consisting of six multi-head self-attention layers, each followed by a feed-forward layer as in Vaswani et al. (2017). Context vector $C \in \mathbb{R}^{d_l \times d_h}$ is noted as the output of the transformer encoder where each column $c_j$ in $C$ represents the context-aware vector of word $w_j$.

**Domain-specific Word Attention Network**

DSPWAN aims at encoding domain-specific words to generate the feature vector. Similar to SAN, DSPWAN firstly utilizes the transformer to encode the input into context vectors. Then, an MLP-attention operation is performed on the context vectors to extract the feature vector. Different from SAN, DSPWAN doesn’t include positional embedding in the transformer component because the input domain-specific words are unordered. For each word $w_j^{sp}$ in $x_i^{sp}$, its embedding vector is noted as $h_j^{sp} \in \mathbb{R}^{d_h}$. Then, the input document $x_i^{sp}$ is mapped into the embedding space as $H^{sp} \in \mathbb{R}^{d_{sp} \times d_h}$, where $H^{sp}$ is stacked using each $h_j^{sp}$.

Then, the context vector $C^{sp}$ is generated from $H^{sp}$ as $C^{sp} = Transformer(H^{sp})$, where $Transformer$ notes the transformer encoder component.

**Interactive Connection**

SAN and DSPWAN are interactively connected to allow them to incorporate information from each other as in Zhang et al. (2019). Domain-specific words include background information in them and connecting DSPWAN to SAN provides more information for it to utilize. Also, information from SAN enables DSPWAN to better extract useful information from domain-specific words. The specific method is slightly different with Zhang et al. (2019) in that the average pooling operation is replaced with an MLP-attention layer. We would introduce the MLP-attention mechanism first before illustrating the interactive connection process.

MLP-attention layer (Bahdanau, Cho, and Bengio, 2015) generates a fixed-length feature vector $h \in \mathbb{R}^{d_h}$ using context vector $C$.

Firstly, for every context vector $c_j$ in $C$, the alignment score $f(c_j, q)$ with an abstract query $q \in \mathbb{R}^{d_h}$ is calculated as follows:

$$f(c_j, q) = w^T \tanh(W^{(1)}c_j + W^{(2)}q), \quad (4)$$

where $q \in \mathbb{R}^{d_h}, w \in \mathbb{R}^{d_h \times d_h}, W^{(1)} \in \mathbb{R}^{d_h \times d_h}, W^{(2)} \in \mathbb{R}^{d_h \times d_h}$ are randomly initialized and updated during the training process. $q$ can be viewed as an high level query on the context vectors about “which context vector is important”.

Secondly, the weight $\alpha_j$ of each context vector $c_j$ is computed as follows:

$$\alpha_j = \frac{\exp(f(c_j, q))}{\sum_{i=1}^{d_h} \exp(f(c_j, q))}, \quad (5)$$

Finally, the feature vector $h$ is calculated as a weighted sum of the context vectors as $h = \sum_{i=1}^{d_h} \alpha_j c_j$.

With the MLP-attention layer described above, the pooling vectors of SAN and DSPWAN are generated from context vectors as follows:

$$h_{sp}^{'} = MLP\_Attention(C),$$

$$h_s^{'} = MLP\_Attention(C^{sp}), \quad (6)$$

where $h_{sp}^{'}$ and $h_s^{'}$ are pooling vectors. The pooling vectors contain high-level information of raw documents and domain-specific words, which are added to context vectors as follows:

$$C_{sp}^{'} = \text{concat}(C, h_{sp}^{'}),$$

$$C_{sp}^{'} = \text{concat}(C^{sp}, h_s^{'}). \quad (7)$$
where \( \text{concat} \) is the function performing concatenation operation. \( C' \in \mathbb{R}^{(d_i + 1) \times d_h} \) and \( C'_{sp} \in \mathbb{R}^{(d_i + 1) \times d_h} \) are context vectors containing information from each other. The feature vectors of SAN and DSPWAN are generated from \( C' \) and \( C'_{sp} \) using MLP-attention layers as follows:

\[
\begin{align*}
    h_{sp} &= \text{MLP}_{\text{Attention}}(C'), \\
    h_s &= \text{MLP}_{\text{Attention}}(C'_{sp}),
\end{align*}
\]

where \( h_{sp} \) is the output feature vector of DSPWAN and \( h_s \) is the output feature vector of SAN.

**Sentiment Classification**

After generating two feature vectors, we fuse them together and obtain the final feature vector \( h_f \in \mathbb{R}^{d_h} \) as follows:

\[
    h_f = \text{relu}(W^{(f)} \text{concat}(h_s, h_{sp}) + b^{(f)}),
\]

where \( W^{(f)} \in \mathbb{R}^{d_h \times (2d_h)} \) and \( b^{(f)} \in \mathbb{R}^{d_h} \) are learnable parameters. Sentiment classification is performed on \( h_f \). The sentiment prediction vector \( y^i_c \in \mathbb{R}^2 \) for the \( i_{th} \) document is calculated as follows:

\[
    \hat{y}^i_c = \text{softmax}(W^{(c)}h_f + b^{(c)}),
\]

where \( W^{(c)} \in \mathbb{R}^{2 \times d_h} \) and \( b^{(c)} \in \mathbb{R}^2 \) are learnable parameters. The sentiment classification loss \( L_{cls} \) is defined by:

\[
    L_{cls} = -\frac{1}{N_s + N_t} \sum_{i=1}^{N_s+N_t} L_c(y^i_c, \hat{y}^i_c),
\]

where \( \hat{y}^i_c \in \mathbb{R}^2 \) is the ground truth label and \( L_c \) is the cross-entropy loss function. The sentiment classifier is trained by minimizing \( L_{cls} \).

**Domain Classification**

The domain classifier in TDAN aims to distinguish feature vectors \( h_f \) from different domains. The domain prediction vector \( y^i_d \in \mathbb{R}^2 \) for the \( i_{th} \) document is calculated as follows:

\[
    \hat{y}^i_d = \text{softmax}(W^{(d)}h_f + b^{(d)}),
\]

where \( W^{(d)} \in \mathbb{R}^{2 \times d_h} \) and \( b^{(d)} \in \mathbb{R}^2 \) are learnable parameters of the domain classifier. Domain classification loss \( L_{dom} \) is defined by the cross-entropy loss:

\[
    L_{dom} = -\frac{1}{N_s + N_t} \sum_{i=1}^{N_s+N_t} L_c(y^i_d, \hat{y}^i_d),
\]

where \( \hat{y}^i_d \in \{0, 1\} \). \( y^i_d \) is the ground truth label and \( L_c \) is the cross entropy loss function. The domain classifier is trained by minimizing \( L_{dom} \).

Besides, a Gradient Reversal Layer (GRL) is added before the domain classifier \( \text{(Ganin et al. 2016)} \). Mathematically, GRL is defined as \( Q_{\lambda}(x) = x \) with a reversal gradient \( \frac{\partial Q_{\lambda}(x)}{\partial x} = -\lambda x \). Training with GRL is adversarial because the domain classifier would try to distinguish feature vectors from different domains while the reversed gradient helps the generator produce indistinguishable feature vectors. This is how domain adaptation is performed in our work. Ideally, the generator in TDAN would generate feature vectors in a common feature space.

**Training Strategy**

Our model is trained by minimizing the loss item \( L_{total} \), which is calculated as \( L_{total} = L_{cls} + \rho L_{dom} \). \( \rho \) is a hyperparameter to balance the relative importance of loss items. The sentiment classification is performed only in source labeled data, therefore \( L_{cls} \) is calculated with \( X_{s1} \). The domain classification utilizes all data points in \( X_s \) and \( X_t \), therefore \( L_{dom} \) is calculated with \( X_{s1} \) and \( X_t \). Each mini-batch in training steps contains balanced data points from the source and target domains.

**Datasets**

Our network is evaluated on the Amazon reviews dataset \( \text{(Blitzer, Dredze, and Pereira 2007)} \) and the Yelp reviews dataset.\[^1\] The Amazon reviews dataset contains reviews from four domains: Book(B), DVD (D), Electronics (E), and Kitchen appliances (K). Each domain contains 6000 reviews, where 3000 reviews are positive (higher than 3 stars) and 3000 reviews are negative (lower than 3 stars). Besides, each domain contains lots of unlabeled data. The Yelp reviews dataset contains 8635403 restaurant reviews and each review is attached with a score from 1 to 5. A review is treated as positive if its score is higher than 3 and negative if lower or equal to 3. The Yelp reviews dataset is treated as a unique domain (Y). In experiments, 3000 positive reviews and 3000 negative reviews are randomly selected from the Yelp dataset to keep the same domain data size as the Amazon reviews dataset. Based on the five domains in two datasets, we construct twenty cross-domain tasks, each noted by A \( \rightarrow \) B where A is the source domain and B is the target domain. The cross-domain tasks between two datasets can help avoid bias on a single dataset.

**Experiments**

In our experiment, word embedding dimension \( d_w \) is set to 300 and we adopt pretrained word embeddings provided by \[^2\]Google.\[^2\] The dimension of hidden vector \( d_h \) is set to 300. The tolerance bound \( tol \) is set to 0.08. The topic number \( k \) is set to 50. The hyperparameter \( \rho \) is set to 1. All model weights are Xavier initialized \( \text{(Glorot and Bengio 2010)} \). Model weights are optimized using the ADAM optimizer \( \text{(Kingma and Ba 2015)} \) with a learning rate of 0.0002 and weight decay rate of 5e-5. Dropout \( \text{(Srivastava et al. 2014)} \) is adopted and the dropout rate is set to 0.25. The adaptation rate \( \lambda \) is increased as \( \lambda = \min(\frac{2}{1 + \exp(-10 \frac{t}{T})} - 1, 0.1) \) where \( t \) is the current epoch, and \( T \) is the maximum epoch which is set to 50. The self-attention layer number is 6 for SAN and 3 for DSPWAN. The multi-head number of self-attention is 4 for each sub-network.

The model is trained using mini-batch. Considering the varied size of data points needed for calculating each loss, a batch size of 40 is used, with 20 data points coming from \( X_s \) and 20 data points coming from \( X_t \). \( L_{cls} \) is calculated

\[^1\]https://www.yelp.com/dataset
\[^2\]https://code.google.com/archive/p/word2vec/
Table 1: Classification accuracy on the Amazon reviews dataset.

| Task | Baselines | Our Methods |
|------|-----------|-------------|
|      | SCL       | SFA         | DANN        | HATN<sub>h</sub> | IATN | ACAN | TPT  | TDAN<sub>-</sub> | TDAN<sub>f</sub> | TDAN |
| B→D | 0.803     | 0.826       | 0.827       | 0.863         | 0.868 | 0.865 | 0.828 | 0.871          | 0.868          | 0.869 |
| B→E | 0.742     | 0.771       | 0.804       | 0.851         | 0.854 | 0.8278 | 0.806 | 0.848          | 0.853          | 0.859 |
| B→K | 0.774     | 0.786       | 0.843       | 0.852         | 0.859 | 0.848 | 0.833 | 0.842          | 0.861          | 0.862 |
| D→B | 0.764     | 0.802       | 0.825       | 0.865         | 0.859 | 0.8622 | 0.826 | 0.868          | 0.864          | 0.864 |
| D→E | 0.740     | 0.765       | 0.809       | 0.856         | 0.842 | 0.8342 | 0.819 | 0.844          | 0.852          | 0.854 |
| D→K | 0.757     | 0.778       | 0.849       | 0.865         | 0.858 | 0.840 | 0.824 | 0.841          | 0.858          | 0.866 |
| E→B | 0.703     | 0.727       | 0.774       | 0.819         | 0.809 | 0.8184 | 0.772 | 0.821          | 0.829          | 0.840 |
| E→D | 0.724     | 0.756       | 0.781       | 0.838         | 0.815 | 0.825 | 0.812 | 0.816          | 0.839          | 0.842 |
| E→K | 0.823     | 0.845       | 0.881       | 0.886         | 0.891 | 0.899 | 0.867 | 0.895          | 0.890          | 0.897 |
| K→B | 0.704     | 0.733       | 0.718       | 0.835         | 0.836 | 0.8182 | 0.771 | 0.832          | 0.842          | 0.844 |
| K→D | 0.737     | 0.758       | 0.789       | 0.841         | 0.839 | 0.8274 | 0.799 | 0.823          | 0.836          | 0.844 |
| K→E | 0.824     | 0.844       | 0.846       | 0.878         | 0.882 | 0.8784 | 0.874 | 0.877          | 0.878          | 0.893 |
| AVG  | 0.758     | 0.782       | 0.812       | 0.854         | 0.850 | 0.845 | 0.819 | 0.849          | 0.856          | 0.861 |

Table 2: Classification accuracy between Amazon reviews dataset and Yelp reviews dataset.

| Task | Baselines | Our Methods |
|------|-----------|-------------|
|      | SCL       | SFA         | DANN        | HATN<sub>h</sub> | IATN | ACAN | TPT  | TDAN<sub>-</sub> | TDAN<sub>f</sub> | TDAN |
| B→Y | 0.776     | 0.768       | 0.835       | 0.868         | 0.869 | 0.852 | 0.850 | 0.862          | 0.870          | 0.871 |
| D→Y | 0.749     | 0.791       | 0.815       | 0.869         | 0.871 | 0.876 | 0.870 | 0.872          | 0.882          | 0.876 |
| E→Y | 0.747     | 0.743       | 0.803       | 0.873         | 0.852 | 0.872 | 0.864 | 0.874          | 0.889          | 0.885 |
| K→Y | 0.753     | 0.793       | 0.821       | 0.869         | 0.884 | 0.872 | 0.840 | 0.880          | 0.883          | 0.887 |
| Y→B | 0.712     | 0.735       | 0.750       | 0.821         | 0.819 | 0.809 | 0.762 | 0.809          | 0.818          | 0.823 |
| Y→D | 0.704     | 0.704       | 0.756       | 0.812         | 0.818 | 0.813 | 0.752 | 0.825          | 0.825          | 0.833 |
| Y→E | 0.738     | 0.761       | 0.775       | 0.841         | 0.859 | 0.823 | 0.751 | 0.833          | 0.840          | 0.844 |
| Y→K | 0.748     | 0.791       | 0.783       | 0.851         | 0.857 | 0.834 | 0.796 | 0.842          | 0.851          | 0.863 |
| AVG  | 0.741     | 0.761       | 0.792       | 0.851         | 0.854 | 0.843 | 0.810 | 0.850          | 0.857          | 0.860 |

on the 20 data points from $X_s$. $L_{dom}$ are calculated on the full mini-batch.

We randomly select 1000 data points from the target domain as the development set and the other 5000 data points as the testing set. The positive and negative instances in the development and testing sets are balanced. We perform early stop in training when evaluation results no longer increase for 10 epochs. Also, the hyperparameters mentioned above are selected using the development set.

**Baselines**
- **SCL** (Blitzer, Dredze, and Pereira 2007) induces correspondences among features from different domains for sentiment classification.
- **SFA** (Pan et al. 2010) is a linear method which aligns no-pivots from different domains into unified clusters via pivots.
- **DANN** (Ganin et al. 2016) is an adversarial domain-adaptation method. It performs domain adaptation on reviews encoded in 5000 dimensional feature vectors of unigrams and bigrams.
- **HATN<sup>h</sup** (Li et al. 2018) is a hierarchy attention network for cross-domain sentiment classification. Considering that HATN<sup>h</sup> performs better than HATN in Li et al. (2018), it is used in our experiments.
- **IATN** (Zhang et al. 2019) is an attention-based network which combines aspect information to help with the sentiment classification task.
- **ACAN** (Qu et al. 2019) is a method which enhances category consistency between the source domain and the target domain using two separate classifiers.
- **TPT** (Li et al. 2020) is a method of learning pivots and representations simultaneously using a pivot selector and a transferable transformer. Sentiment classification is performed on these domain-invariant representations.

**Result Analysis**
Following the typical experiment settings in previous works (Li et al. 2017, 2018; Zhang et al. 2019), we adopt classification accuracy as the evaluation metric. Table 1 shows cross-domain task results on the Amazon review dataset and Table 2 shows the cross-domain task results between two datasets. TDAN<sub>f</sub> is a variant of TDAN by simply fusing $h_s$ with $h_{sp}$ without applying the interactive interaction. TDAN<sub>-</sub> is a variant of TDAN by only using SAN. According to Table 1 and Table 2, TDAN outperforms previous methods. The traditional method SCL and SFA show limited performance. The methods based on adversarial domain adaptation and
Table 3: Attention visualization of two samples in B→K task. The left column is a document from the books domain and the right column is a document from the kitchen domain. Their domain-specific words are also included.

| books domain: | kitchen domain: |
|--------------|----------------|
| **document:** | **document:** |
| should be recommended reading. For everyone interested in this subject, Patrick Heron has done an excellent job explaining the nephilim. This book has answered all my questions. | **best** thing ever. One cup of coffee at a **time** doesn’t get better than this. **perfect** for a household of coffee drinkers that wake up at different times |
| **domain-specific words:** | **domain-specific words:** |
| reading interested patrick heron nephilim | cup coffee drinkers |

Table 4: Influence of different domain-specific word extraction methods on classification accuracy. The average accuracy on two datasets are reported.

| | HATN | IATN | TDAN |
|----------------|-----|-----|-----|
| Amazon         | 0.859 | 0.855 | 0.861 |
| Amazon and Yelp| 0.857 | 0.856 | 0.859 |

Attention Visualization

To show that TDAN can develop different attention strategies for different forms of input, we visualize the attention score of the MLP-attention layer in Table 3. We can see that the semantics attention network pays attention to pivots, such as excellent and perfect. It also notices words that affect the sentence semantics, such as doesn’t. The domain-specific word attention network pays attention to both background words and non-pivots. For example, the right document in Table 3 does not contain non-pivots in its domain-specific words and the domain-specific word attention network pays attention to background words such as coffee and drinkers. However, the left document in Table 3 contains non-pivots interested therefore the domain-specific word attention network pays most attention to it while allocating lower attention scores to other background words. This ability to pay attention to both background words and non-pivots is crucial for sentiment classification.

Influence of Domain-specific Word Extraction

To show the effect of our topic-based domain-specific word extraction method, we compare it with the other two methods from HATN and IATN. In HATN, non-pivots in NP-net are treated as domain-specific words. In IATN, aspects are treated as domain-specific words. To be fair, we use the same model, TDAN, to encode the input generated using different methods. The average accuracy results are reported in Table 4. It has been shown that our methods witness improvements in classification accuracy. The reason is that our method includes both non-pivots and background words in the extracted domain-specific words for sentiment classification.

Conclusions

In this work, we proposed a novel network TDAN for cross-domain sentiment classification. A new domain-specific word extraction method based on the topic information was proposed, aiming to assist sentiment classification. Specifically, both types of domain-specific words are included. Additionally, we utilize both self-attention and MLP-attention mechanisms to build TDAN. The experiment results show that our domain-specific word extraction method outperforms previous ones.
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