Learning to Share by Masking the Non-shared for Multi-domain Sentiment Classification

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Abstract

Multi-domain sentiment classification deals with the scenario where labeled data exists for multiple domains but insufficient for training effective sentiment classifiers that work across domains. Thus, fully exploiting sentiment knowledge shared across domains is crucial for real-world applications. While many existing works try to extract domain-invariant features in high-dimensional space, such models fail to explicitly distinguish between shared and private features at the text-level, which to some extent lacks interpretability. Based on the assumption that removing domain-related tokens from texts would help improve their domain-invariance, we instead first transform original sentences to be domain-agnostic. To this end, we propose the BertMasker network which explicitly masks domain-related words from texts, learns domain-invariant sentiment features from these domain-agnostic texts, and uses those masked words to form domain-aware sentence representations. Empirical experiments on a well-adopted multi-domain sentiment classification dataset demonstrate the effectiveness of our proposed model on both multi-domain sentiment classification and cross-domain settings, by increasing the accuracy by 0.94% and 1.8% respectively. Further analysis on masking proves that removing those domain-related and sentiment irrelevant tokens decreases text’s domain distinction, resulting in the performance degradation of a BERT-based domain classifier by over 12%

1 Introduction

Sentiment classification (Pang et al., 2002; Liu, 2012) is one of the key tasks in Natural Language Processing. Recent success of sentiment classification relies heavily on deep neural networks trained with a large number of carefully annotated data. However, as the diversity of domains leads to the discrepancy of sentiment features, models trained on existing domains may not perform ideally on the domain of interest. Meanwhile, as not all domains have adequate labeled data, it is necessary to leverage existing annotations from multiple domains. For instance, in both DVD and Video domains, picture and animation can be opinion targets and thrilling and romantic are frequent polarity words. Exploiting such sharedness would help improve both in-domain and out-of-domain sentiment classification results.

In this work, we focus on the task of multi-domain sentiment classification (MDSC) where we need to make full use of limited annotated data and large unlabeled data from each domain to train a classifier that achieves best average performance on all domains. There exist two major lines of work attempting to tackle this challenge. One line is to exploit the shared-private framework (Bousmalis et al., 2016; Wu and Huang, 2015), where domain-agnostic features are captured by the networks shared across all domains and domain-specific representations by feature extractor of each domain. (Liu et al., 2017; Chen and Cardie, 2018) applied domain adversaries to shared features for better learning of domain-invariant representations. The other major line of work (Liu et al., 2018; Zheng et al., 2018; Cai and Wan, 2019) implicitly utilized such share-private ideas where they first learned domain-specific query vectors (or domain embeddings) and then used these to compose
domain-aware representation by attending features from shared sentence encoder. So far, these two major methods have not been effectively combined.

While shared-private models learn domain-agnostic features in high-dimensional space, the discrimination between shared and private features cannot be directly interpreted to humans at text-level. Therefore, we propose to distinguish domain-related and domain-agnostic tokens before further feature extractions, based on the intuition that removing domain-related words from texts would help improve their domain-invariance. Given two sentences from Sports and Book domains respectively in Figure 1, after removing domain-related words like helmet from Sports domain and cookbook from Book domain, these sentences become more domain-agnostic. Meanwhile, the most salient sentiment-related semantics are mostly preserved in the remaining texts. In this way, it would be possible to tell what features are domain-related and what features are shared by all domains to some extent.

To combine the advantage of both paradigms in multi-domain sentiment analysis, a model should employ the shared-private framework, where the shared part learns domain-agnostic sentiment features and the private part captures a domain-aware sentiment representation based on the shared feature extractors (contrary to separate extractors for each domain in (Liu et al., 2017)). To learn good shared sentiment features with better interpretability at text level, a model should be capable of discriminating between domain-related and domain-agnostic tokens at first. To this end, we propose the BertMasker model. The BertMasker model learns to first select domain-related tokens from texts, then mask those tokens from original text and acquires domain-agnostic sentiment features for the shared part. As the masked tokens are domain-related, they are appropriate for learning domain-aware sentiment representations of texts from different domains. We incorporate this advantage into the private part of BertMakser. Since simple models are not adequate for learning good sentiment features from fractional texts, we turn to BERT (Devlin et al., 2019) for text encoding as it shares similar input format during its pre-training phase of Masked Language Model (MLM). Motivated by previous work (Sun et al., 2019) utilizing Next Sentence Prediction task in BERT, we also expect inputting texts with MASK at both training and inference time would boost the performance in multi-domain sentiment analysis tasks. Though we have no accurate prior knowledge of what domain-related tokens are, the BertMasker takes a detour of learning domain-related tokens as we have some knowledge of what domain-related tokens should not be for our sentiment classification task. In other words, tokens from general sentiment lexicons and commonly used stopwords are domain-agnostic. We enhance this prior knowledge as constraints to our model and train a domain classification model to guide more accurate learning of domain-related tokens. Those tokens serves as the key to learn both shared and private sentiment features.

Our contributions can be summarized as follows:

- We propose a novel model named BertMasker to better learn shared representation across domains by masking domain-related tokens from text.
- Our model combines both shared-private framework and domain-aware feature learning, where token masking networks in the shared part of learns domain-invariant text transformation and in the private part to aggregates domain-aware sentiment features.
- Evaluation results on benchmark multi-domain sentiment classification datasets demonstrate the superiority of our proposed model. Further analysis on masked tokens and remaining texts proves the plausibility and effectiveness of token masking mechanism.

2 Related Work

Our work uses a BERT-based model for multi-domain sentiment classification. We describe related work from these two perspectives.

2.1 Multi-domain Sentiment Classification

The task of multi-domain sentiment classification (Li and Zong, 2008) aims at training models that leverage data from multiple domains to improve the overall classification performance on all domains. Currently, there exists mainly two lines of related methods. One line of methods (Liu et al., 2017, 2018; Chen and Cardie, 2018; Bousmalis et al., 2016) is to exploit shared-private framework, where domain-agnostic features are usually captured with adversarial training or gradient reversal layer (Ganin et al., 2016) at the shared part.
Meanwhile, domain-specific representations are learnt by feature extractors of each domain. Further, (Guo et al., 2018; Chen et al., 2019) apply mixture-of-expert (Jacobs et al., 1991) approach to explicitly capture knowledge shared among similar domains. The other line of methods (Zheng et al., 2018; Cai and Wan, 2019) is to learn domain representations through domain classification and use these as queries to acquire domain-sensitive representations of input texts.

Our proposed BertMasker combines the power of both paradigms. It employs a shared-private framework. It first learns to select domain-related words. Then, our model obtains shared sentiment features by exploiting texts without those words and using these selected words to obtain domain-aware sentiment representations.

2.2 BERT-based Models in Sentiment Analysis

BERT is one of the key innovations in the recent advances of contextualized representation learning (McCann et al., 2017; Peters et al., 2018; Howard and Ruder, 2018; Devlin et al., 2019). Its success relies on two pre-training tasks, namely Masked Language Model (MLM) and Next Sentence Prediction (NSP). Currently, there are mainly two ways to utilize BERT for downstream tasks. One is fine-tuning for each end task. For instance, to make the input format consistent with that of NSP, (Sun et al., 2019) constructs auxiliary sentences for aspect-based sentiment classification in four ways. And the other is injecting task-specific knowledge (Ke et al., 2019; Tian et al., 2020) using new pre-training tasks. Such injections are usually done along with MLM where other objectives like POS tag, sentiment polarity (Ke et al., 2019), and sentiment targets (Tian et al., 2020) are introduced.

Our work is partially motivated by (Sun et al., 2019), as we both transform inputs to have same format as one of the pre-training task of BERT (they use NSP while we use MLM instead). To our best knowledge, we are the first to make usage of MLM at both training and test time in sentiment analysis tasks. As MLM aims at predicting masked words based on context from both left and right, the BERT model can recover the semantic of current word being masked. In other words, the BERT model could retain much of overall features of the sentences while a small portion of its constituent tokens being masked. We make use of such advantage and design a model that could automatically learn to mask some (domain-related) words. In this way, a sentence could be transformed to be domain-invariant while still retaining its most salient sentiment features.

3 Model

3.1 Overview

Basically, our model adopts the popular adversarial shared-private framework, where the shared part is utilized for extracting domain-invariant features and private part for domain-specific features. An overview of our model is shown in Figure 2. For a given sentence, BertMasker first models each word in its context. Then it determines whether a token/word is domain-related with token masking networks from shared and private part. In the shared part, it replaces those domain-related tokens
with [MASK] symbol in original text and feed the transformed, more domain-invariant text to BERT for invariant sentiment feature learning. In the private part, it instead choose those masked tokens to learning domain-aware sentiment representations with attention mechanism. Finally, the concatenation of shared and private features are used for sentiment prediction. In the following, we introduce key components of our model in details.

3.2 Sentence Modeling with BERT

Given an input sequence \(X = \{x_1, x_2, \ldots, x_N\}\), we first get the contextualized representation \(h_i\) of tokens \(x_i\) using BERT encoder:

\[
\{h_1, h_2, \ldots, h_N\} = BERT(x_1, x_2, \ldots, x_N) \tag{1}
\]

The MLM task of BERT enables it processing sequences whose tokens are partially replaced with [MASK] symbol. We exploit such intrinsic advantage of BERT to facilitate our idea of modeling text after removal of domain-related tokens. Suppose \(K\) tokens in the given sequence are selected and we have the masked text \(X^M = \{x_1, x_2, \ldots, [Masks], \ldots, [Masks], \ldots, x_N\}\). Then we could model the new text with Equation 1 and obtain \(H^{masked} = \{h_1, h_2, \ldots, h_{\text{mask}_1}, \ldots, h_{\text{mask}_K}, \ldots, h_N\}\).

Following previous sentiment classification tasks using BERT, we can choose the hidden feature \(h_{\text{cls}}\) from token [CLS] as sequence representation.

3.3 Token Masking Networks

In this part, we describe how to select domain-related words and generate masked results for shared and private part.

Shared Part It is straightforward to assume that if we remove tokens that are domain-related from a text sequence, the remaining part should be more domain-agnostic than the original sequence. Based on this assumption, the token masking network first decides whether a token \(x_i\) should be selected according to its contextualized representation \(h_i\). Follow the idea in (Liu et al., 2018), we also introduce domain descriptors \(D = \{d_1, d_2, \ldots, d_J, \ldots, d_M\}\) for each domain to encode most representative characteristics of that domain from the training data, where \(M\) is the number of domains involved in training and test. As we have the domain label for every instance at both training and test time, we can use its domain descriptors to help decide whether a token is highly correlated with the current domain. For each token \(x_i\), we combine its hidden representation \(h_i\) and its domain descriptor \(d_j\) as \(z_i\). We use simple feed-forward neural works with tanh non-linearity (referred to as MLP) for measuring relatedness \(l_i\) between a token and the domain of its text. To generate discrete decision of mask, we apply GumbelSoftmax (Jang et al., 2016) to \(l_i\). The choice \(P_{\text{shared}}\) of removing token \(x_i\) or not can be calculated as follows:

\[

g_{\text{shared}}(z_i) = h_i \oplus d_j \tag{2}
\]

\[
\hat{l}_i = MLP(z_i) \tag{3}
\]

\[
\hat{p}_i = \text{GumbelSoftmax}(\hat{l}_i) \tag{4}
\]

Private Part The main difference between token masking networks in shared and private part is that instead of only using domain descriptor \(d_j\) of current text, we adopt a mixture of domain descriptors for each sequence in private part. The motivation behind this is to better collect domain-related words for each individual sentence if it shares similarities with other domains. We treat \(h_{\text{CLS}}\) as the current sentence representation and measure its relatedness to all domain descriptors. We apply simple inner-product attention through following equations:

\[
\hat{z}_j = h_{\text{CLS}} \oplus d_j \tag{5}
\]

\[
\hat{s}_i = \langle d_i, \hat{z}_j \rangle \tag{6}
\]

\[
a_i = \text{Softmax}(s_i) \tag{7}
\]

\[
\hat{d}_j = \sum_{i=1}^{M} a_i * d_i \tag{9}
\]

where \(d_j\) is the corresponding domain descriptor of current text and \(M\) is the number of domains. Then we follow similar steps of Equation 2-4 except that \(d_j\) in Equation 2 is replaced with \(\hat{d}_j\). We denote the masking result of private part as \(P_{\text{private}}\).

Masking Constraints Though final sentiment classification result is good for BertMasker without preset rules, preliminary results show that masking rate is over 30% on average for all domains and many irrelevant tokens are selected, making the remaining texts less interpretable for humans. This may owe to the existence of non-robust features (Ilyas et al., 2019) in these multi-domain datasets. Thus, to alleviate this, we add some human priors of what we think should not be domain-related.
words, namely stop words and sentiment words in lexicons. We explicitly ignore relevant masking decisions. We use stop words from this site \footnote{https://github.com/amueller/word_cloud} and sentiment words from (Hu and Liu, 2004). We also add common negation and intensifier words into the constraints.

### 3.4 Domain-invariant Sentiment Feature Extraction

After acquiring the masking result $P_{\text{shared}}$ from token masking network in the shared part, we replace the chosen words with [MASK] symbol and feed the new sequence into the shared BERT again. We use hidden output $h_{\text{cls}}^s$ of token [CLS] as domain-invariant sentiment representation.

**Adversarial Feature Learning** To ensure sequence representations learned from previous masking process are domain-agnostic, we pass the feature outputs $h_{\text{cls}}^s$ from BERT through a Gradient Reversal Layer (Ganin et al., 2016) and perform domain classification as follows:

\[
\begin{align*}
    h_{\text{grl}} &= GRL(h_{\text{cls}}^s) \\
    l_d &= MLP(h_{\text{grl}}) \\
    p_d &= \text{Softmax}(l_d) \\
    L_{ds} &= \text{CrossEntropy}(p_d, y_d)
\end{align*}
\]

Here, we adopt cross-entropy loss and we refer to $h_{\text{cls}}^s$ as $h_{\text{shared}}$.

### 3.5 Domain-specific Sentiment Feature Extraction

**Domain Informative Feature** Similarly, we can obtain domain-related tokens $X_j = \{x_{j1}, x_{j2}, \ldots, x_{jk}\}$ from private token mask layer, where $K$ is the number of selected domain-related tokens in input sequence $P_{\text{private}}$. Then, hidden representation of those tokens is aggregated as domain-related clue $h_j$:

\[
h_j = \frac{1}{K} \sum_{j_1}^{j_K} h_{j_1}
\]

Besides, we enforce these clues to be domain-related following Equation 11-13 and the loss is $L_{dp}$.

**Domain-aware Sequence Encoding** Since we have the domain-related clue $h_j$, we can use it as the query vector and apply attention mechanism to find the most relevant feature of current input and its corresponding domain. Here, we use simple inner-product attention for its simplicity. The formulas are listed as follows:

\[
\begin{align*}
    \beta_t &= \langle h_j, h_t \rangle \\
    \alpha_t &= \text{Softmax}(\beta_t) \\
    h_{\text{private}} &= \sum_1^N \alpha_t * h_t
\end{align*}
\]

### 3.6 Sentiment Classification

The final feature for sentiment classification is the concatenation of $h_{\text{shared}}$ and $h_{\text{private}}$. We use a shared sentiment classifier for all domains and the probability of each sentiment is calculated as follows:

\[
\begin{align*}
    h_{\text{concat}} &= h_{\text{shared}} \oplus h_{\text{private}} \\
    l_s &= MLP(h_{\text{concat}}) \\
    p_s &= \text{Softmax}(l_s)
\end{align*}
\]

We use the cross entropy loss between the predictions and true labels as $L_s$ for training a sentiment classifier:

\[
L_s = \text{CrossEntropy}(p_s, y_s)
\]

To make feature representations from shared and private part more sentiment-oriented and further boost the performance for final sentiment classification, we add layers similar to Equation 19-21 to $h_{\text{shared}}$ and $h_{\text{private}}$ and get their corresponding loss as $L_{ss}$ and $L_{sp}$.

### 3.7 Final Loss

The total loss of our model can be computed as follows:

\[
L_{\text{total}} = \lambda_{ds} * L_{ds} + \lambda_{dp} * L_{dp} + \gamma_s * L_s + \gamma_{ss} * L_{ss} + \gamma_{sp} * L_{sp} + \lambda \|\theta\|^2
\]

where $\lambda_{ds}$ and $\lambda_{dp}$ are coefficients for domain classification, $\gamma_s$, $\gamma_{ss}$, and $\gamma_{sp}$ are coefficients for sentiment classification.

### 4 Experiments

#### 4.1 Dataset

We use the dataset from (Liu et al., 2017) \footnote{http://pfliu.com/paper/adv-mlt.html} for multi-domain sentiment classification task, which consists product and movie reviews from 16 domains. Following previous work, we partition
Table 1: Statistics of datasets from 16 domains.

| Dataset | Train | Dev. | Test | Avg. Length |
|---------|-------|------|------|-------------|
| Books   | 1400  | 200  | 400  | 159         |
| Electronics | 1398 | 200  | 400  | 101         |
| DVD     | 1400  | 200  | 400  | 173         |
| Kitchen | 1400  | 200  | 400  | 89          |
| Apparel | 1400  | 200  | 400  | 57          |
| Camera  | 1397  | 200  | 400  | 130         |
| Health  | 1400  | 200  | 400  | 81          |
| Music   | 1400  | 200  | 400  | 136         |
| Toys    | 1400  | 200  | 400  | 90          |
| Video   | 1400  | 200  | 400  | 156         |
| Baby    | 1300  | 200  | 400  | 104         |
| Magazines | 1370 | 200  | 400  | 117         |
| Software | 1315 | 200  | 400  | 129         |
| Sports  | 1400  | 200  | 400  | 94          |
| IMDB    | 1400  | 200  | 400  | 269         |
| MR      | 1400  | 200  | 400  | 21          |

dataset in each domain into training, development and testing sets according to the proportion of 70%, 10%, and 20%. The detailed statistics of all the datasets are listed in Table 1.

4.2 Implementation Details

We adopt BERT\textsubscript{base}, to be specific, its implementation 3 in PyTorch for all the experiments. The maximum sequence length for BERT model is set to 128. The mini-batch size is set to 8 and we train the model for 15 epochs. The model with highest averaged accuracy on development sets is chosen for final comparison. SGD is applied to optimize all our models with an initial learning rate of 0.0003. The coefficients $\lambda_{ds}$ and $\lambda_{dp}$ for domain classification loss are set to 0.002 and $\gamma$, $\gamma_{as}$, and $\gamma_{sp}$ for sentiment classification loss are chosen as 0.4, 0.3, 0.3 respectively. The dimension is set to 200 for domain descriptors. For multi-domain sentiment classification, we train over domain classification task for the first 2000 steps and sentiment classification in each domain for the next 3000 steps. After that, we train the model with both sentiment classification loss and domain classification loss. For cross-domain experiments, the only difference is that no target sentiment data is used during the latter two training phase.

4.3 Multi-domain Classification

We experiment with multi-domain sentiment classification on 16 test sets respectively. We compare with several baselines and previous state-of-the-art models.

**Single Task.** We use a bi-directional LSTM and a simple CNN model as single task baselines which are trained on each domain independently.

**BERT.** BERT (Devlin et al., 2019) is a pre-trained contextualized representation learning model which has achieved state-of-the-art results on many tasks. We use pre-trained BERT-base model and fine-tune it for each domain.

**ASP-MTL.** The model used in (Liu et al., 2017) with adversarial training on the shared part and separate LSTMs for each domain in the private part.

**DA-MTL.** DA-MTL (Zheng et al., 2018) dynamically generates query vector for each instance and then uses this query vector to attend over the hidden representations of input sentence.

**DSR-at.** DSR-at (Liu et al., 2018) is also based on share-private scheme. Different from ASP-MTL, it applies memory network as private feature extractor.

**DAEA.** DAEA (Cai and Wan, 2019) is an attention based method which first generates domain-specific query vector and domain-aware word embeddings. It then use the query vector to attend over the hidden representations from BLSTM with domain-aware word embeddings as input.

**DAEA+BERT.** DAEA+BERT (Cai and Wan, 2019) improves DAEA by using BERT as word initialization. It is the previous state-of-the-art model in multi-domain sentiment classification.

We present results of multi-domain text classification in Table 2. Generally, using data from multiple domains improves average classification performance. We can see that BERT achieves superior performance on single domain setting, even outperforming ASP-MTL and DSR-at which simultaneously use sentiment classification data from multiple domains. Our model BertMasker achieves the best performance, outperforming other methods in 12 out of 16 domains.

Compared with the state-of-the-art DAEA+BERT model, our model still achieve 0.93% performance gain in terms of average accuracy of all domains. It is worth noting that our model brings nearly 6.75% increase in MR domain. The main reason for the improvement

3https://github.com/huggingface/transformers
Table 2: Results of multi-domain sentiment classification. Accuracy (%) is adopted for evaluation.

| Domain     | Single Domain          | Multiple Domains        |
|------------|------------------------|-------------------------|
|            | BLSTM | CNN   | BERT | ASP-MTL | DA-MTL | DSR-at | DAEA | DAEA+BERT | BertMasker |
| Books      | 81.00 | 85.30 | 87.00 | 84.00    | 88.50  | 89.10  | 89.00 | N/A       | 93.00      |
| Electronics| 81.80 | 87.80 | 88.30 | 86.80    | 89.00  | 87.90  | 91.80 | N/A       | 93.25      |
| DVD        | 83.30 | 76.30 | 85.60 | 85.50    | 88.00  | 88.10  | 88.30 | N/A       | 89.25      |
| Kitchen    | 80.80 | 84.50 | 91.00 | 86.20    | 89.00  | 85.90  | 90.30 | N/A       | 90.75      |
| Apparel    | 87.50 | 86.30 | 90.00 | 87.00    | 88.80  | 87.80  | 89.00 | N/A       | 92.25      |
| Camera     | 87.00 | 89.00 | 90.00 | 89.20    | 91.80  | 90.00  | 92.00 | N/A       | 92.75      |
| Health     | 87.00 | 87.50 | 88.30 | 88.20    | 90.30  | 92.90  | 89.80 | N/A       | 95.25      |
| Music      | 81.80 | 81.50 | 86.80 | 82.50    | 85.00  | 84.10  | 88.00 | N/A       | 89.50      |
| Toys       | 81.50 | 87.00 | 91.30 | 88.00    | 89.50  | 85.90  | 91.30 | N/A       | 93.75      |
| Video      | 83.00 | 82.30 | 88.00 | 84.50    | 89.50  | 90.30  | 92.30 | N/A       | 91.25      |
| Baby       | 86.30 | 82.50 | 91.50 | 88.20    | 90.50  | 91.70  | 92.30 | N/A       | 92.75      |
| Magazines  | 92.00 | 86.80 | 92.80 | 92.20    | 92.00  | 92.10  | 96.50 | N/A       | 94.50      |
| Software   | 84.50 | 87.50 | 89.30 | 87.20    | 90.80  | 87.00  | 92.80 | N/A       | 93.00      |
| Sports     | 86.00 | 85.30 | 90.80 | 85.70    | 89.80  | 85.80  | 90.80 | N/A       | 92.50      |
| IMDB       | 82.50 | 83.30 | 85.80 | 85.50    | 89.00  | 89.80  | 90.80 | N/A       | 86.00      |
| MR         | 74.80 | 79.00 | 74.00 | 76.70    | 75.50  | 73.30  | 77.00 | N/A       | 83.75      |
| Avg        | 83.80 | 84.49 | 88.16 | 86.09    | 88.61  | 87.86  | 90.16 | 90.5      | 91.47      |

Table 3: Results of cross-domain (15-to-1) sentiment classification. Accuracy (%) is adopted for evaluation.

| Domain     | ASP-MTL | DSR-at | DAEA | BertMasker |
|------------|---------|--------|------|------------|
| Books      | 81.50   | 85.80  | 87.30 | 87.75      |
| Electronics| 83.80   | 89.50  | 85.80 | 93.00      |
| DVD        | 84.50   | 86.30  | 88.80 | 87.75      |
| Kitchen    | 87.50   | 88.30  | 88.00 | 87.76      |
| Apparel    | 85.30   | 85.80  | 88.80 | 91.25      |
| Camera     | 85.30   | 88.80  | 90.00 | 91.50      |
| Health     | 86.00   | 90.50  | 91.00 | 94.75      |
| Music      | 81.30   | 84.80  | 86.50 | 89.50      |
| Toys       | 88.00   | 90.30  | 90.30 | 91.50      |
| Video      | 86.80   | 85.30  | 91.30 | 89.00      |
| Baby       | 86.50   | 84.80  | 90.30 | 91.50      |
| Magazines  | 87.00   | 84.00  | 88.50 | 91.25      |
| Software   | 87.00   | 90.80  | 89.80 | 90.50      |
| Sports     | 87.00   | 87.00  | 90.50 | 91.25      |
| IMDB       | 84.00   | 83.30  | 85.80 | 86.75      |
| MR         | 72.00   | 76.30  | 75.50 | 82.50      |
| Avg        | 84.59   | 86.35  | 87.96 | 89.84      |

Thus, our model is outperformed by DAEA+BERT model which is skilled at learning domain-aware sentiment representations.

4.4 Cross-domain Experiments

Unlike multi-domain sentiment classification, the task of cross-domain sentiment classification doesn’t provide any training data for a target domain. Thus, it calls for better utilization of the shared knowledge across all domains. To further understand whether BertMasker achieves such capability, we also test our model on 15-to-1 cross-domain sentiment classification setting (Liu et al., 2017; Cai and Wan, 2019), where models are trained using the training data of sentiment and domain classification from 15 domains and training data of domain classification from the target domain.

As shown in Table 3, our model achieves 1.88% performance gain in averaged accuracy of all domains compared to previous best performing model DAEA. Besides, it outperforms all the other models in 12 out of 16 domains on cross-domain sentiment classification task. These results confirm the superiority of masking networks in BertMasker, which manifests in learning better shared representations for sentiment classification than other models.

4.5 Ablation Test

To further explore how well each component contributes to the prediction of sentiment, we carry out an ablation study of BertMasker on test set in multi-domain setting. As shown in Table 4, the performance decreases when removing either the shared or private network and the removal of pri-
Table 4: Ablation test results of BertMasker on multi-domain sentiment classification. Average accuracy is presented. w/o stands for without.

|                  | Avg. Accuracy (%) |
|------------------|-------------------|
| w/o shared part  | 91.0              |
| w/o private part | 88.56             |
| w/o shared mask  | 90.69             |
| w/o private mask | 91.21             |
| w/o sentiment word mask | 91.29 |
| w/o stop word mask | 91.17         |
| Full model       | 91.47             |

Table 5: The number and percentage of masked words in shared and private part of BertMasker on test set in multi-domain sentiment classification setting.

| Category   | Shared (No./Portion) | Private (No./Portion) | Avg. Length |
|------------|----------------------|-----------------------|-------------|
| Books      | 25.60/0.13           | 23.59/0.12            | 190         |
| Electronics| 21.76/0.17           | 20.14/0.16            | 128         |
| DVD        | 23.78/0.10           | 22.68/0.10            | 226         |
| Kitchen    | 21.21/0.19           | 22.00/0.20            | 111         |
| Apparel    | 15.09/0.20           | 15.25/0.21            | 74          |
| Camera     | 23.18/0.16           | 24.48/0.16            | 148         |
| Health     | 19.86/0.20           | 18.87/0.19            | 101         |
| Music      | 22.38/0.14           | 21.69/0.13            | 162         |
| Toys       | 22.04/0.20           | 21.18/0.19            | 112         |
| Videos     | 23.05/0.12           | 20.33/0.11            | 191         |
| Baby       | 23.91/0.19           | 21.64/0.17            | 128         |
| Magazines  | 22.88/0.16           | 20.45/0.14            | 144         |
| Software   | 21.14/0.14           | 21.74/0.14            | 151         |
| Sports     | 21.28/0.17           | 21.10/0.17            | 125         |
| IMDB       | 29.17/0.11           | 27.53/0.10            | 264         |
| MR         | 6.34/0.23            | 5.85/0.21             | 27          |
| Avg.       | 21.42/0.15           | 20.54/0.14            | 143         |

5.1 Number of Words Masked

As observed in Table 5, the number and percentage of masked tokens of each domain correlates with its average sentence length, where in general domains with longer average sequence length have more tokens masked and lower masking rate. Another interesting finding is that the final masking rates of both shared and private part are similar to the percentage (15%) of [MASK] token in the Mask Language Model pre-training task of BERT. We leave it as a future work to explore whether this rate correlates with implementation of mask in BERT or the number of domain-related tokens in original data distribution.

5.2 Top Words Masked

Apart from the number and percentage of masking, we also would like to investigate whether the token masking networks of BertMasker mask meaningful words. In Figure 3a and 3b, we use word cloud to illustrate tokens after masking from shared part and masked tokens from private part of all domains. Besides, we exhibit masked tokens from private part of Apparel and Music domains. From Figure 3b we can see that, the top tokens from the masked sequence in shared part are mostly domain-invariant sentiment-related words, which includes polarity words like good, great, well, negation words like but, not, no and intensifiers like really, very. This demonstrates that after token masking network removing domain-related tokens, the shared part focus more on domain-invariant sentiment features.

5.3 Domain Classification After Masking

To further verify whether masking “domain-related” tokens from a text improves its domain-invariance, we conduct domain classifications on both original and masked texts. Here, we utilize BERT-base
as a powerful feature extractor and apply an MLP similar to 11 for domain classification. We evaluate the results using accuracy.

As shown in Table 6, it’s relatively easy to distinguish domains based on original texts. Our mask network successfully degrades the domain classification performance by over 11% on masked texts. This reveals that our strategy of masking is working towards our expectations of domain-invariant text. However, as we don’t have direct knowledge of what domain-related tokens are, tokens extracted using the masking network constrained by external sentiment and stopword lexicons are sub-optimal for domain classification task. Thus, the result demonstrates that the remaining text still contains abundant clues for domain classification.

To further explore how the masking works on each domain, we visualize the confusion matrices of domain classification on original and remaining text separately in Figure 5. For example, by comparing the Sports row in Figure 5a and Figure 5b, we can see that shallow blocks in 5a become darker in 5b and opposite case happens to darker blocks. This reflects that domain classifier can’t find necessary features on the remaining texts, thus misclassifies more cases into domains sharing some similarities with Sports domain, eg. Electronics, Toys, Camera and even on Software domain.

From the above experiments, we can see that token-level masking strategy works to help transform the sentence to be more domain-invariant in the shared part and selecting domain-related words for better domain-aware sentiment feature learning.

5.4 Case Study and Error Analysis

We visualize the words selected by token masking networks in BertMasker from both shared and private part in Figure 4. As illustrated in Example 1, the model successfully masks domain-related

| Accuracy (%) |       |
|--------------|-------|
| On masked sequences | 65.21 |
| On original sequences | 77.95 |
| On masked words | 65.67 |

Table 6: Results of domain classification on original sequences, sequences after removing masked words and masked words.
words like fabric, cushion, baby in the sentence and make correct sentiment predictions based on those both domain-invariant and domain-aware representations. However, we also notice in many cases, due to the existence of unknown words and errors incurred by word-piece tokenizer used by BERT, the masked tokens may not be semantically adequate or meaningful. From Example2, we can see that as renown is not recognized by BERT, it further influences the masking result in the shared part. Besides, as we employ different masking strategies in shared and private part, the masking results diverge in both examples.

6 Conclusion

In this paper, we propose the BertMasker model which combines the power of two popular paradigms in multi-domain sentiment classification: shared-private structure and shared encoder with domain-aware aggregation. Instead of directly learning domain-variant features in a high-dimensional space, we propose to first transform sentences to be more domain-invariant through masking domain-related words, which alongside utilizes the power of BERT in learning good semantic representations from masked texts. Our model outperforms existing works in both multi-domain and cross-domain settings on the benchmark dataset. Detailed analysis of the masked words further proves effectiveness of our proposed masking strategy.

In the future, we would like to work on two directions: (1) replace the mask network with simpler network, e.g. distilled BEERT models, to accelerate training and inference of our model. (2) incorporate more external knowledge to guide fine-grained and accurate selection of domain-related words and phrases.

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