MASKER: Masked Keyword Regularization for Reliable Text Classification

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Abstract

Pre-trained language models have achieved state-of-the-art accuracies on various text classification tasks, e.g., sentiment analysis, natural language inference, and semantic textual similarity. However, the reliability of the fine-tuned text classifiers is an often overlooked performance criterion. For instance, one may desire a model that can detect out-of-distribution (OOD) samples (drawn far from training distribution) or be robust against domain shifts. We claim that one central obstacle to the reliability is the over-reliance of the model on a limited number of keywords, instead of looking at the whole context. In particular, we find that (a) OOD samples often contain in-distribution keywords, while (b) cross-domain samples may not always contain keywords; over-relying on the keywords can be problematic for both cases. In light of this observation, we propose a simple yet effective fine-tuning method, coined masked keyword regularization (MASKER), that facilitates context-based prediction. MASKER regularizes the model to reconstruct the keywords from the rest of the words and make low-confidence predictions without enough context. When applied to various pre-trained language models (e.g., BERT, RoBERTa, and ALBERT), we demonstrate that MASKER improves OOD detection and cross-domain generalization without degrading classification accuracy. Code is available at https://github.com/alinlab/MASKER.

1 Introduction

Text classification (Aggarwal and Zhai 2012) is a classic yet challenging problem in natural language processing (NLP), having a broad range of applications, including sentiment analysis (Bakshi et al. 2016), natural language inference (Bowman et al. 2015), and semantic textual similarity (Agirre et al. 2012). Recently, Devlin et al. (2019) have shown that fine-tuning a pre-trained language model can achieve state-of-the-art performances on various text classification tasks without any task-specific architectural adaptations. Thereafter, numerous pre-training and fine-tuning strategies to improve the classification accuracy further have been proposed (Liu et al. 2019; Lan et al. 2020; Sanh et al. 2019; Clark et al. 2020; Sun et al. 2019; Mosbach, Andriushchenko, and Klakow 2020; Zhang et al. 2020). However, a vast majority of the works have focused on evaluating the accuracy of the models only and overlooked their reliability (Hendrycks et al. 2020), e.g., robustness to out-of-distribution (OOD) samples drawn far from the training data (or in-distribution samples).

While pre-trained language models are known to be robust in some sense (Hendrycks et al. 2020), we find that fine-tuned models suffer from the over-reliance problem, i.e., making predictions based on only a limited number of domain-specific keywords instead of looking at the whole context. For example, consider a classification task of ‘Apple’ visualized in Figure 1. If the most in-distribution samples contain the keyword ‘Apple,’ the fine-tuned model can predict the class solely based on the existence of the keyword. However, a reliable classifier should detect that the sentence “I ate an apple this morning” is an out-of-distribution sample (Hendrycks and Gimpel 2017, Shu, Xu, and Liu 2017, Tan et al. 2019). On the other hand, the sentence “Tim Cook said that . . . ” should be classified as the topic ‘Apple’ although it does not contain the keyword ‘Apple’ and the keyword ‘Tim Cook’ is not contained in the training samples. In other words, the reliable classifier should learn decision rules that
generalize across domains (Fei and Liu 2015; Bhatt, Semwal, and Roy 2015; Bhatt, Sinha, and Roy 2016).

This problematic phenomenon frequently happens in real-world datasets. To verify this, we extract the keywords from Amazon 50 class reviews (Chen and Liu 2014) dataset and sentiment analysis datasets (IMDB (Maas et al. 2011); SST-2 (Socher et al. 2013); Fine Food (McAuley and Leskovec 2013)), following the attention-based scheme illustrated in Section 2.1. Figure 2 shows the frequency of the keywords selected from the source class in the target class. Figure 2a shows that the keywords are often strongly tied with the class, which leads the model to learn a shortcut instead of the context. Figure 2b shows the results where the source and target classes are different classes of the Amazon reviews dataset. Here, OOD classes often contain the same keywords from the in-distribution classes, e.g., the class ‘Autos’ contains the same keywords as the class ‘Iron.’ On the other hand, Figure 2c shows the results where both source and target classes are sentiments (‘pos’ and ‘neg’) classes in IMDB, SST-2, and Fine Food datasets. While the same sentiment shares the same keywords, the alignment is not perfect; e.g., ‘IMDB (neg)’ and ‘Food (pos)’ contain the same keywords.

1.1 Contribution

We propose a simple yet effective fine-tuning method coined masked keyword regularization (MASKER), which handles the over-reliance (on keywords) problem and facilitates the context-based prediction. In particular, we introduce two regularization techniques: (a) masked keyword reconstruction and (b) masked entropy regularization. First, (a) forces the model to predict the masked keywords from understanding the context around them. This is inspired by masked language modeling from BERT (Devlin et al. 2019), which is known to be helpful for learning context. Second, (b) penalizes making high-confidence predictions from “cut-out-context” sentences, that non-keywords are randomly dropped, in a similar manner of Cutout (DeVries and Taylor 2017) used for regularizing image classification models. We also suggest two keyword selection schemes, each relying on dataset statistics and attention scores. We remark that all proposed techniques of MASKER can be done in an unsupervised manner.

We demonstrate that MASKER, applied to the pre-trained language models: BERT (Devlin et al. 2019), RoBERTa (Liu et al. 2019), and ALBERT (Lan et al. 2020), significantly improves the OOD detection and cross-domain generalization performance, without degrading the classification accuracy. We conduct OOD detection experiments on 20 Newsgroups (Lang 1995), Amazon 50 class reviews (Chen and Liu 2014), Reuters (Lewis et al. 2004), IMDB (Maas et al. 2011), SST-2 (Socher et al. 2013), and Fine Food (McAuley and Leskovec 2013) datasets, and cross-domain generalization experiments on sentiment analysis (Maas et al. 2011; Socher et al. 2013; McAuley and Leskovec 2013), natural language inference (Williams, Nangia, and Bowman 2017), and semantic textual similarity (Wang et al. 2019) tasks. In particular, our method improves the area under receiver operating characteristic (AUROC) of BERT from 87.0% to 98.6% for OOD detection under 20 Newsgroups to SST-2 task, and reduce the generalization gap from 19.2% to 10.9% for cross-domain generalization under Fine Food to IMDB task.

1.2 Related Work

Distribution shift in NLP. The reliable text classifier should detect distribution shift, i.e., test distribution is different from the training distribution. However, the most common scenarios: OOD detection and cross-domain generalization are relatively under-explored in NLP domains (Hendrycks et al. 2020; Marasović 2018; Hendrycks et al. 2020) found that pre-trained models are robust to the distribution shift compared to traditional NLP models. We find that the pre-trained models are not robust enough, and we empirically show that pre-trained models are still relying on undesirable dataset bias. Our method further improves the generalization performance, applied to the pre-trained models.
Shortcut bias. One may interpret the over-reliance problem as a type of shortcut bias (Geirhos et al. 2020), i.e., the model learns an easy-to-learn but not generalizable solution, as the keywords can be considered as a shortcut. The shortcut bias is investigated under various NLP tasks (Sun et al. 2019), e.g., natural language inference (McCoy, Pavlick, and Linzen 2019), reasoning comprehension (Niven and Kao 2019), and question answering (Min et al. 2019). To our best knowledge, we are the first to point out that the over-reliance on keywords can also be a shortcut, especially for text classification. We remark that the shortcut bias is not always harmful as it can be a useful feature for in-distribution accuracy. However, we claim that they can be problematic for unexpected (i.e., OOD) samples, as demonstrated in our experiments.

Debiasing methods. Numerous debiasing techniques have been proposed to regularize shortcuts, e.g., careful data collection (Choi et al. 2018), bias-tailored architecture (Agrawal et al. 2018), and adversarial regularization (Clark, Yatskar, and Zettlemoyer 2019; Minderer et al. 2020; Nam et al. 2020). However, most prior work requires supervision of biases, i.e., the shortcuts are explicitly given. In contrast, our method can be viewed as an unsupervised debiasing method, as our keyword selection schemes automatically select the keywords.

2 Masked Keyword Regularization

We first introduce our notation and architecture setup; then propose the keyword selection and regularization approaches in Section 2.1 and Section 2.2, respectively.

Notation. The text classifier \( f : x \mapsto y \) maps a document \( x \) to the corresponding class \( y \in \{1, \ldots, C\} \). The document \( x \) is a sequence of tokens \( t_i \in \mathcal{V} \), i.e., \( x = [t_1, \ldots, t_T] \) where \( \mathcal{V} \) is the vocabulary set and \( T \) is the length of the document. Here, the full corpus \( D = \{(x, y)\} \) is a collection of all documents, and the class-wise corpus \( D_c = \{(x, y) \in D \mid y = c\} \) is a subset of \( D \) of class \( c \). The keyword set \( K \subset \mathcal{V} \) is the set of vocabularies which mostly affects the prediction. The keyword \( k = [k_1, \ldots, k_L] \) of the document \( x \) is given by \( k = [t_i \in x \mid t_i \in K] \), where \( L \leq T \) is the number of keywords in the document \( x \).

Architecture. We assume the pre-trained language model follows the bi-directional Transformer (Vaswani et al. 2017) architecture, widely used in recent days (Devlin et al. 2019; Liu et al. 2019; Lan et al. 2020). They consist of three components: embedding network, document classifier, and token-wise classifier. Given document \( x \), the embedding network produces \( a \) (a document embedding (for an entire document), and \( b \) (token embeddings), which correspond to each input token. The document and token-wise classifier predict the class of document and tokens, respectively, from the corresponding embeddings. For the sake of simplicity, we omit the shared embedding network and denote the document and token-wise classifier as \( f_{doc} : x \mapsto y \) and \( f_{tok} : x = [t_1, \ldots, t_T] \mapsto s = [s_1, \ldots, s_T] \), respectively, where \( s_t \in \mathcal{V} \) is a target token corresponds to \( t_i \).

Amazon 50 Class Reviews

| Frequency Based | Attention Based |
|-----------------|-----------------|
| 305 forerunner watches monitor hand Heart wrist radar router | watches wi wireless ethernet watch chips streaming router monitor |

Figure 3: Top 10 keywords chosen from the frequency-based and attention-based selection schemes under the Amazon 50 class reviews dataset. The frequency-based scheme chooses uninformative words (e.g., ’305’), while the attention-based scheme chooses more informative ones (e.g., ’watch’).

2.1 Keyword Selection Schemes

We consider two keyword selection schemes, based on the dataset statistics (model-free) and trained models. While the former is computationally cheaper, the latter performs better; hence, one can choose its purpose.

Frequency-based. We first choose the keywords using the relative frequency of the words in the dataset. Specifically, we use the term frequency-inverse document frequency (TF-IDF; Robertson 2004) metric, which measures the importance of the token by comparing the frequency in the target documents (term frequency) and the entire corpus (inverse document frequency). Here, the keywords are defined as the tokens with the highest TF-IDF scores. Formally, let \( x \) be a large document that concatenates all tokens in a class-wise corpus \( D_c \), and \( D = \{X_1, \ldots, X_C\} \) is a corpus of such large documents. Then, the frequency-based score of token \( t \) is given by

\[
s_{freq}(t) = \max_{c \in \{1, \ldots, C\}} tf(t, X_c) \cdot idf(t, D) \tag{1}
\]

where \( tf(t, X) = 0.5 + 0.5 \cdot n_{t, x}/\max\{n_{t, x} : t' \in X\} \), \( idf(t, D) = \log(|D|/|\{X \in D : t \in X\}|) \), and \( n_{t, x} \) is number of token \( t \) in document \( x \). Note that the frequency-based selection is model-agnostic and easily computed, but does not reflect the contribution of the words to the prediction.

Attention-based. We also choose the keywords using the model attention as it is a more direct and effective way to measure the importance of words on model prediction. To this end, we first train a model with a standard approach using the cross-entropy loss \( \mathcal{L}_{CE} \), which leads the model to suffer from the over-reliance (on keywords) issue. Our idea is to use the attention values of the model for choosing the keywords. Here, the keywords are defined as the tokens with the highest attention values. Formally, let \( a = [a_1, \ldots, a_T] \in \mathbb{R}^T \) be attention values of the document embedding, where \( a_t \) corresponds to the input token \( t_i \). Then, the attention-based score of token \( t \) is given by

\[
s_{attn}(t) = \sum_{(x, y) \in D} \frac{1}{n_{t, x}} \sum_{i \in \{1, \ldots, T\}} \|I(t_i = t) \cdot a_i \| \tag{2}
\]

where \( I \) is an indicator function and \( \|\cdot\| \) is \( l_2 \)-norm.
We choose the keywords by picking the top \( K \) tokens according to the scores in Eq. (1) and Eq. (2) for each selection scheme, respectively. We also test the class-balanced version, i.e., pick the top \( K/C \) tokens for each class, but the class-agnostic one performed better.

Comparison of the selection schemes. We observe that the frequency-based scheme often selects uninformative keywords that uniquely appears in some class. In contrast, the attention-based scheme selects more general keywords that actually influence the prediction. Figure 3 shows the keywords chosen by both selection schemes: the frequency-based scheme chooses uninformative words such as ‘305’ and ‘forerunner,’ while the attention-based scheme chooses more informative ones such as ‘watch’ or ‘chips.’

2.2 Regularization via Keyword Masking

Using the chosen keywords, we propose two regularization techniques to reduce the over-reliance issue and facilitate the model to look at the contextual information.

Masked keyword reconstruction. To enforce the model to look at the surrounding context, we guide the model to reconstruct the keywords from keyword-masked documents. Note that it resembles the masked language model (Devlin et al. 2019), but we mask the keywords instead of random words. Masked keyword reconstruction only regularizes sentences with keywords, and we omit the loss for ones without any keywords. Formally, let \( \hat{k} \) be a random subset of the full keyword \( k \) (selected as in Section 2.1), that each element is chosen with probability \( p \) independently. We mask \( k \) from the original document \( x \) and get the masked document \( \tilde{x} = x - k \). Then, the masked keyword reconstruction (MKR) loss is

\[
\mathcal{L}_{MKR}(\tilde{x}, v) := \sum_{i \in \text{index}(\hat{k})} \mathcal{L}_{CE}(f_{tok}(\tilde{x}), v_i) \quad (3)
\]

where \( \text{index}(\hat{k}) \) is the index of the keywords \( \hat{k} \) with respect to the original document \( x \), \( v_i \) is the index of the keywords with respect to the vocabulary set. We remark that the reconstruction part is essential; we also test simply augmenting the masked documents, i.e., \( \mathcal{L}_{CE}(f_{doc}(\tilde{x}), y) \), but it performed worse. Choosing proper keywords is also crucial; attention-based keywords performs better than frequency-based or random keywords, as shown in Table 1 and Table 3.

Masked entropy regularization. Furthermore, we regularize the prediction of the context-masked documents, that context (non-keyword) words are randomly dropped. The model should not classify the context-masked documents correctly as they lost the original context. Formally, let \( \hat{c} \) be a randomly chosen subset of the full context words \( c = x - k \), where each element is chosen with probability \( q \) independently. We mask \( \hat{c} \) from the original document \( x \) and get the context-masked document \( \tilde{x} = x - \hat{c} \). Then, the masked entropy regularization (MER) loss is

\[
\mathcal{L}_{MER}(\tilde{x}) := D_{KL}(U(y)||f_{doc}(\tilde{x})) \quad (4)
\]

where \( D_{KL} \) is the KL-divergence and \( U(y) \) is a uniform distribution. We remark that MER does not degrade the classification accuracy since it regularizes non-realistic context-masked sentences, rather than full documents. Table 1 shows that MER does not drop the classification accuracy in original domain, while Table 2 and Table 3 show that MER improves the cross-domain accuracy. On the other hand, MER differs from the prior sentence-level objectives, e.g., next sentence prediction (Devlin et al. 2019), as our goal is to regularize shortcuts, not learning better in-domain representation.

To sum up, the final objective is given by

\[
\mathcal{L}_{total} = \mathcal{L}_{CE} + \lambda_{MKR}\mathcal{L}_{MKR} + \lambda_{MER}\mathcal{L}_{MER} \quad (5)
\]

where \( \lambda_{MKR} \) and \( \lambda_{MER} \) are hyperparameters for the MKR and MER losses, respectively. Figure 4 visualizes the proposed losses, and the overall procedure is in Appendix B.
We demonstrate the effectiveness of MASKER, applied to the pre-trained models: BERT (Devlin et al. 2019), RoBERTa (Liu et al. 2019), and ALBERT (Lan et al. 2020). We choose $10 \times C$ keywords in a class agnostic way, where $C$ is the number of classes. We drop the keywords and contexts with probability $p = 0.5$ and $q = 0.9$ for all our experiments. We use $\lambda_{\text{MKR}} = 0.001$ and $\lambda_{\text{MER}} = 0.001$ for OOD detection, and the same $\lambda_{\text{MKR}} = 0.001$ but $\lambda_{\text{MER}} = 0.0001$ for cross-domain generalization, as the entropy regularization gives more gain for reliability than accuracy (Pereyra et al. 2017). We modify the hyperparameter settings of the pre-trained models (Devlin et al. 2019; Liu et al. 2019), specified in Appendix A.

### 3.1 Experimental setup

We demonstrate the effectiveness of MASKER, applied to the pre-trained models: BERT (Devlin et al. 2019), RoBERTa (Liu et al. 2019), and ALBERT (Lan et al. 2020). We choose $10 \times C$ keywords in a class agnostic way, where $C$ is the number of classes. We drop the keywords and contexts with probability $p = 0.5$ and $q = 0.9$ for all our experiments. We use $\lambda_{\text{MKR}} = 0.001$ and $\lambda_{\text{MER}} = 0.001$ for OOD detection, and the same $\lambda_{\text{MKR}} = 0.001$ but $\lambda_{\text{MER}} = 0.0001$ for cross-domain generalization, as the entropy regularization gives more gain for reliability than accuracy (Pereyra et al. 2017). We modify the hyperparameter settings of the pre-trained models (Devlin et al. 2019; Liu et al. 2019), specified in Appendix A.

#### 1-vs-rest classifier.
Complementary to MASKER, we use 1-vs-rest classifier (Shu, Xu, and Liu 2017) as it further improves the reliability (see Table 1 and Table 2). Intuitively, 1-vs-rest classifier can reject all classes (all prediction scores are low); hence detect OOD samples well.

### 3 Experiments

We demonstrate the effectiveness of our proposed method, MASKER. In Section 3.1, we describe the experimental setup. In Section 3.2 and 3.3, we present the results on OOD detection and cross-domain generalization, respectively.

### 3.2 OOD Detection

We use the highest softmax (or sigmoid) output of the model as confidence score for OOD detection task. We use 20 News-groups (Lang 1995) and Amazon 50 class reviews (Chen and Liu 2014) datasets for in-distribution, and the rest as OOD. The reported results are averaged over five trials, subscripts denote standard deviations, and the best results are highlighted in bold. All components of our method contribute to the OOD detection performance (%).

#### Table 1: Ablation study on OOD detection under the Amazon 50 class reviews. We use 25% of classes as in-distribution, and the rest as OOD. The reported results are averaged over five trials, subscripts denote standard deviations, and the best results are highlighted in bold. All components of our method contribute to the OOD detection performance (%).

| Method         | Classifier | Keyword | MKR | MER | AUROC ↑ | EER ↓ | Detection Accuracy ↑ | Classification Accuracy ↑ |
|----------------|------------|---------|-----|-----|----------|------|----------------------|--------------------------|
| OC-SVM         | -          | -       | -   | -   | 57.01±1.08 | 91.42±0.90 | 72.99±1.69 | -                        |
| OpenMax        | -          | -       | -   | -   | 53.02±3.34 | 95.52±0.93 | 74.01±1.58 | 79.01±0.51                |
| DOC            | -          | -       | -   | -   | 75.12±3.06 | 95.55±1.54 | 80.21±1.76 | 83.14±0.82                |

#### Table 2: AUROC (%) on various OOD detection scenarios. The reported results are averaged over three trials, and the best results are highlighted in bold. Bracket denotes the relative gain of MASKER over the vanilla model.

| ID       | OOD       | OC-SVM | DOC | BERT       | Vanilla / Residual / MASKER | RoBERTa | ALBERT   |
|----------|-----------|--------|-----|------------|-----------------------------|---------|----------|
| Amazon   | 62.1      | 84.1   | 85.4/86.7/87.0 (+1.9%) | 85.3/85.9/87.2 (+2.3%) | 86.7/85.4/89.4 (+3.1%) |
| Reuters  | 53.9      | 60.0   | 91.8/93.0/97.7 (+6.4%) | 93.1/92.1/93.9 (+4.8%) | 93.3/92.0/94.7 (+1.6%) |
| Newsgroup| 59.8      | 88.6   | 94.6/95.7/98.5 (+4.1%) | 95.2/95.9/97.7 (+2.7%) | 94.5/92.6/96.6 (+2.2%) |
| IMDB     | 63.0      | 88.1   | 87.0/97.0/98.6 (+13.3%) | 94.7/94.9/98.2 (+3.6%) | 95.8/95.9/98.1 (+2.4%) |
| Fine Food| 62.8      | 81.3   | 85.3/87.3/93.4 (+9.5%) | 88.7/89.4/92.9 (+4.7%) | 77.6/86.9/91.6 (+18.1%) |
| Amazon   | 61.3      | 81.3   | 84.8/83.9/87.2 (+2.8%) | 87.9/86.6/91.0 (+3.5%) | 87.3/85.0/88.4 (+1.3%) |
| Reuters  | 55.5      | 79.8   | 89.7/89.7/93.5 (+4.2%) | 92.3/92.6/93.6 (+1.4%) | 93.1/93.5/94.3 (+1.5%) |
| IMDB     | 66.2      | 89.6   | 93.3/92.8/95.2 (+2.0%) | 90.1/87.0/93.3 (+3.5%) | 89.9/88.6/95.6 (+6.4%) |
| SST-2    | 60.9      | 91.5   | 93.0/88.9/95.6 (+2.8%) | 92.4/94.8/96.4 (+4.4%) | 93.4/91.9/96.9 (+3.7%) |
| Fine Food| 51.1      | 66.8   | 78.5/77.7/84.9 (+8.2%) | 74.9/80.0/80.7 (+7.8%) | 82.6/86.3/87.3 (+5.7%) |
while improving OOD detection. Also, the attention-based Amazon reviews dataset with a split ratio of 25%. All components of MASKER contribute to OOD detection. Note that MASKER does not degrade the classification accuracy while improving OOD detection. Also, the attention-based selection performs better than the frequency-based or random selection, which implies the importance of selecting suitable keywords. Recall that the attention-based scheme selects the keywords that contribute to the prediction, while the frequency-based scheme often chooses domain-specific keywords that are not generalizable across domains.

Table 3 presents the results on sentiment analysis, natural language inference (e.g., ‘astonishing’) while the vanilla BERT is biased to some degree of sentiment analysis task. The results are consistent with OOD detection, e.g., all components contribute to cross-domain generalization. Notably, while MER is not helpful for the original domain accuracy (see Table 1), it improves the cross-domain accuracy for most settings. In particular, MASKER improves the cross-domain accuracy from 75.6% to 80.0% for Fine Food to SST-2 task. We analyze the most influential keywords (see Appendix D) and find that MASKER extracts the sentiment-related (e.g., ‘astonishing’) while the vanilla BERT is biased to some domain-specific words (e.g., ‘moonlight’).

| Method       | Classifier | Keyword | MKR | MER | IMDB → SST-2 | IMDB → Food | SST-2 → IMDB | SST-2 → Food | Food → SST-2 | Food → IMDB |
|--------------|------------|---------|-----|-----|---------------|-------------|--------------|--------------|--------------|-------------|
| OpenMax      | -          | -       | -   | -   | 79.55 ± 0.78  | 75.41 ± 0.20 | 75.30 ± 0.44 | 62.19 ± 0.06 | 61.85 ± 0.63 | 67.50 ± 1.50 |
| DOC          | -          | -       | -   | -   | 77.90 ± 1.22  | 78.33 ± 1.52 | 76.88 ± 0.70 | 64.47 ± 2.52 | 62.00 ± 0.86 | 67.31 ± 1.28 |
| BERT         | Multi-class| -       | -   | -   | 85.92 ± 1.92  | 92.90 ± 2.47 | 85.74 ± 0.56 | 87.57 ± 1.13 | 67.55 ± 0.27 | 77.31 ± 2.09 |
| BERT         | 1-vs-rest  | -       | -   | -   | 84.28 ± 0.23  | 87.81 ± 3.91 | 85.34 ± 0.63 | 84.35 ± 1.48 | 64.57 ± 1.27 | 81.34 ± 0.78 |

Table 3: Ablation study on cross-domain generalization under sentiment analysis task. The reported results are averaged over five trials, subscripts denote standard deviations, bracketed numbers denote the generalization gap from the training domain accuracy, and the best accuracies are highlighted in bold. All components of our method contribute to the cross-domain accuracy (%).

3.3 Cross-domain Generalization

We conduct the experiments on sentiment analysis (IMDB (Maas et al. 2011); SST-2 (Socher et al. 2013); Fine Food (McAuley and Leskovec 2013)), natural language inference (MNL, Williams, Nganla, and Bowman (2017)), and semantic textual similarity (STS-B, Wang et al. (2019) dataset) tasks, following the settings of Hendrycks et al. (2020).

In Figure 5a and Figure 5b, we visualize the t-SNE (Maaten and Hinton 2008) plots on the document embeddings of BERT and MASKER, under the Amazon reviews dataset with a split ratio of 25%. Blue and red points indicate in- and out-of-distribution samples, respectively. Unlike the samples that are entangled in the vanilla BERT, MASKER clearly distinguishes the OOD samples.
Table 4: Accuracy (%) of original domain and cross-domain on (a) sentiment analysis, (b) natural language inference, and (c) semantic textual similarity tasks, respectively. The reported results are averaged over three trials for sentiment analysis and semantic textual similarity, and a single trial for natural language inference. Bold denotes the best results among the three methods, and bracket denotes the relative gain of MASKER over the vanilla model.

| Train | Test | OpenMax | DOC | BERT | Vanilla / Residual / MASKER | RoBERTa | ALBERT |
|-------|------|---------|-----|------|-------------------------------|---------|--------|
| IMDB  | IMDB | 87.7    | 88.0| 93.5/92.8/93.5 | 95.3/94.0/95.6 | 91.6/91.4/90.8 |
| SST-2  | 79.6 | 77.9 | 85.9/86.9/88.1 (+2.6%) | 89.7/90.2/91.8 (+2.3%) | 89.8/89.0/89.9 (+0.1%) |
| Fine Food | 75.4 | 78.3 | 92.9/92.5/93.6 (+0.8%) | 92.6/92.7/93.0 (+0.4%) | 87.1/87.8/92.1 (+5.7%) |
| SST-2  | IMDB | 82.9 | 83.1 | 92.5/90.3/92.3 | 94.5/92.0/94.3 | 91.9/90.9/91.5 |
| Fine Food | 75.3 | 76.9 | 85.7/86.2/88.4 (+3.2%) | 86.0/85.7/87.3 (+1.5%) | 83.0/83.0/83.8 (+1.0%) |
| Fine Food | IMDB | 62.2 | 64.5 | 87.6/88.2/89.2 (+1.8%) | 86.5/87.8/89.6 (+3.6%) | 79.0/80.6/84.9 (+7.5%) |
| SST-2  | IMDB | 93.6 | 93.3 | 96.5/94.8/96.5 | 96.9/95.7/97.1 | 95.5/95.4/96.6 |
| Fine Food | 67.5 | 67.3 | 77.3/81.1/85.6 (+10.7%) | 84.1/84.6/86.6 (+2.9%) | 74.7/80.4/84.8 (+13.5%) |
| Fine Food | SST-2 | 61.9 | 62.0 | 67.6/67.8/80.0 (+18.3%) | 78.5/80.1/83.8 (+6.8%) | 71.7/73.2/83.3 (+16.2%) |

(a) Sentiment analysis

(b) Natural language inference

(c) Semantic textual similarity

Figure 5: t-SNE plots on the document embeddings of BERT and MASKER, on (a,b) OOD detection (Amazon 50 class reviews with split ratio 25%), and (c,d) cross-domain generalization (Fine Food to SST-2). (a,b) Blue and red dots indicate the in- and out-of-distribution samples, respectively. (c,d) Blue and red dots indicate the samples from the same classes ('negative') from training and test domains, respectively. MASKER better distinguishes OOD samples and entangles cross-domain samples.

4 Conclusion

The reliability of text classifiers is an essential but under-explored problem. We found that the over-reliance on some keywords can be problematic for out-of-distribution detection and generalization. We propose a simple yet effective fine-tuning method, coined masked keyword regularization (MASKER), composed of two regularizers and keyword selection schemes to address this issue. We demonstrate the effectiveness of MASKER under various scenarios.

contrast, MASKER facilitates contextual information rather than removing the keyword information, which regularizes the over-reliance in a softer manner.

In Figure 5 and Figure 5d, we provide the t-SNE plots on the document embeddings of BERT and MASKER, under the Fine Food to STS-2 task. Blue and red points indicate original and cross-domain samples, respectively. MASKER better entangles the same classes in training and test datasets (of the different domains) while BERT fails to do so.
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A Experimental Details

A.1 Training Details
Following Devlin et al. (2019); Liu et al. (2019), we select the best hyperparameters from the search space below. We choose learning rate from \{1e^{-5}, 2e^{-5}, 5e^{-5}\} and batch size from \{16, 32\}. We halve the learning rate for the embedding layers of MASKER since the regularizer for fits to the classifier, and directly updating the embedding layers can be unstable. We also use the batch size of 4 for random word reconstruction due to the large vocabulary size. We use the Adam (Kingma and Ba 2015) optimizer for all experiments. We train vanilla BERT and ALBERT for 3~4 epochs, and RoBERTa for 10 epochs following Devlin et al. (2019) and Liu et al. (2019), respectively. For MASKER, we train BERT+MASKER, ALBERT+MASKER for 6~8 epochs, and train RoBERTa+MASKER for 12 epochs. We remark that all the models are trained until convergence. Since MER cannot be directly applied to the regression tasks (e.g., STS-B), we only use MKR for such settings.

A.2 Dataset Details
We use the pre-defined train and test splits if they exists: for IMDB (Maas et al. 2011), SST-2 (Socher et al. 2013), MNLI (Williams, Nangia, and Bowman 2017), and STS-B (Wang et al. 2019) datasets. If pre-defined splits not exists, we randomly divide the dataset with 70:30 ratio, using them for train and test splits, respectively: for 20 Newsgroups (Lang 1995), Amazon 50 class reviews (Chen and Liu 2014), and Fine Food (McAuley and Leskovec 2013) datasets. We do not use any pre-processing methods, e.g., removing headers.

A.3 Evaluation Metrics
Let TP, TN, FP, and FN denotes true positive, true negative, false positive, and false negative, respectively. We use the following metrics for OOD detection:

- **Area under the receiver operating characteristic curve (AUROC).** The ROC curve is a graph plotting true positive rate (TPR) = TP / (TP+FN) against the false positive rate (FPR) = FP / (FP+TN) by varying a threshold. AUROC measures the area under the ROC curve.
- **Equal error rate (EER).** EER is the error rate when the confidence threshold is located where FPR is the same with the false negative rate (FNR) = FN / (TP+FN).
- **Detection accuracy.** Measures the maximum classification probability among all possible threshold sets.
- **TNR at TPR 80%.** Measures true negative rate (TNR) = TN / (FP+TN) when TPR = 80%.

AUROC measures the overall performance varying thresholds, and the other three metrics measure the performance for some fixed threshold.

B Overall Procedure of MASKER
Figure 7 visualizes the overall procedure of MASKER, including the keyword selection scheme (attention-based selection using a vanilla model), masked keyword reconstruction, and masked entropy regularization.

C Additional Experimental Results
Table 5 presents the additional OOD detection results, including the split settings of 20 Newsgroups and Amazon reviews datasets (Shu, Xu, and Liu 2017). Our method consistently outperforms the baseline methods. Table 6 presents the classification accuracy of the baselines and MASKER, which validates that MASKER does not degrade the accuracy. Table 7 presents the other cross-domain results under the STS-B dataset, shows the effectiveness of our method. We also try to regularize attention weights to be uniform directly, but it harms both classification accuracy and OOD detection performance for vanilla models.

D Analysis on Attention Scores
In Figure 6 we visualize the most influential keywords measured by the attention scores. Our method makes predictions based on the generalizable keywords, e.g., sentiment-related keywords for sentiment analysis tasks.
Figure 7: The overall procedure of MASKER using the attention-based keywords. Vanilla training and our proposed method are presented as the red and blue boxes, respectively. Parameter sharing without back-propagation is presented as a dashed arrow.
| ID   | OOD     | Split Ratio | AUROC ↑ | EER ↓ | Detection Accuracy ↑ | TNR at TPR 80% ↑ | Classification Accuracy ↑ |
|------|---------|-------------|---------|-------|-----------------------|------------------|--------------------------|
|      |         |             | DOC / BERT / BERT+MAKSER (ours) |        |                      |                  |                          |
|      |         |             |         |       |                       |                  |                          |
| 10%  | Newsgroup|             | 83.7/85.4/87.0 | 23.1/22.9/21.0 | 81.0/90.9/91.5 | 61.0/67.4/75.2 | 98.7/99.0/98.9 |
| 25%  | Newsgroup|             | 86.1/89.0/91.0 | 18.7/19.1/17.0 | 82.7/83.0/86.9 | 78.5/80.5/84.8 | 93.9/95.3/94.9 |
| 50%  | Newsgroup|             | 80.4/82.4/83.0 | 28.2/25.4/25.0 | 72.3/75.0/76.8 | 65.0/68.0/71.8 | 89.9/94.4/94.0 |
|      | Amazon   | 10%         | 84.1/86.0/96.8 | 23.3/19.5/8.3 | 90.1/87.2/94.7 | 75.4/86.7/95.5 |                      |
|      | Amazon   | 25%         | 60.0/81.0/97.7 | 41.1/14.7/6.7 | 75.2/85.7/93.6 | 21.3/84.5/96.4 |                      |
|      | Amazon   | 50%         | 88.6/94.6/98.5 | 19.1/11.5/5.1 | 88.4/93.4/96.3 | 81.7/87.3/98.2 |                      |
|      | IMDB     | 100%        | 88.1/87.0/98.6 | 18.7/18.9/5.1 | 86.6/88.5/96.0 | 81.8/92.4/98.4 |                      |
|      | SST-2    | 10%         | 81.3/85.3/93.4 | 25.7/19.8/10.9 | 74.8/82.7/90.5 | 67.6/85.9/95.2 |                      |
|      | SST-2    | 25%         | 80.7/82.8/86.0 | 22.9/22.1/21.0 | 79.2/92.3/93.0 | 74.0/75.7/80.1 | 92.7/93.5/93.3 |
|      | SST-2    | 50%         | 75.1/78.5/85.5 | 25.6/28.3/22.3 | 80.2/81.2/85.0 | 66.0/66.3/74.1 | 83.1/84.8/85.2 |
|      | Fine Food | 10%         | 81.3/85.3/93.4 | 25.7/19.8/10.9 | 74.8/82.7/90.5 | 67.6/85.9/95.2 |                      |
|      | Fine Food | 25%         | 74.6/75.4/77.7 | 29.0/28.9/27.9 | 69.4/70.2/71.1 | 60.0/60.7/61.5 | 78.8/81.7/80.6 |
|      | Fine Food | 50%         | 81.3/84.8/87.2 | 23.0/21.6/20.0 | 80.0/81.5/83.5 | 72.7/77.0/80.4 |                      |
|      | Newsgroup| 10%         | 80.7/82.8/86.0 | 22.9/22.1/21.0 | 79.2/92.3/93.0 | 74.0/75.7/80.1 | 92.7/93.5/93.3 |
|      | Amazon   | 25%         | 75.1/78.5/85.5 | 25.6/28.3/22.3 | 80.2/81.2/85.0 | 66.0/66.3/74.1 | 83.1/84.8/85.2 |
|      | Amazon   | 50%         | 74.6/75.4/77.7 | 29.0/28.9/27.9 | 69.4/70.2/71.1 | 60.0/60.7/61.5 | 78.8/81.7/80.6 |

Table 5: AUROC (%) on various additional OOD detection scenarios. The reported results are averaged over three trials, and the best results are highlighted in bold. MASKER outperforms the baselines in all cases.

| Dataset | Openmax | DOC | Vanilla/Residual/MAKSER |
|---------|---------|-----|-------------------------|
|         |         |     | BERT | RoBERTa | ALBERT |
| Newsgroups | 85.8 | 86.9 | 90.4/89.5/90.1 | 90.9/88.1/90.7 | 89.3/89.7/89.7 |
| Amazon   | 63.0   | 66.6 | 70.8/70.3/70.0 | 71.0/69.1/71.2 | 68.7/64.2/68.6 |

Table 6: Classification accuracy (%) of the datasets used for OOD detection. MASKER shows a comparable accuracy with the vanilla models, while residual ensemble shows a marginal drop.

| Model   | MSRvid Images | MSRvid Images | MSRpar Headlines | Images | Images | MSRvid Images | MSRpar Headlines |
|---------|---------------|---------------|------------------|--------|--------|---------------|------------------|
| BERT    | 91.5          | 82.0          | 38.2             | 61.7   | 88.0   | 89.7          | 50.8             | 73.9             |
| +MASKER | 91.2          | 84.3          | 40.9             | 66.7   | 88.1   | 91.6          | 52.5             | 75.3             |
| RoBERTa | 94.2          | 88.0          | 66.0             | 80.3   | 91.8   | 92.9          | 68.4             | 84.1             |
| +MASKER | 93.7          | 88.0          | 67.1             | 84.0   | 91.3   | 94.1          | 70.1             | 85.3             |
| ALBERT  | 92.6          | 81.2          | 39.4             | 60.6   | 90.4   | 90.9          | 44.9             | 69.8             |
| +MASKER | 93.3          | 82.6          | 39.8             | 68.8   | 90.5   | 92.0          | 45.2             | 78.4             |

| Model   | Headlines MSRvid Images | MSRpar Images | Headlines |
|---------|-------------------------|---------------|-----------|
| BERT    | 86.1                    | 83.2          | 81.1      | 69.9      | 74.2      | 74.1      | 71.9      | 67.1      |
| +MASKER | 86.8                    | 88.0          | 83.6      | 75.8      | 77.6      | 79.1      | 75.9      | 67.7      |
| RoBERTa | 90.7                    | 93.3          | 90.1      | 75.5      | 86.4      | 88.2      | 85.8      | 85.4      |
| +MASKER | 88.2                    | 90.3          | 90.7      | 70.9      | 84.8      | 90.2      | 85.9      | 86.4      |
| ALBERT  | 86.8                    | 90.4          | 87.1      | 63.5      | 78.5      | 82.4      | 80.8      | 69.2      |
| +MASKER | 87.0                    | 90.0          | 87.1      | 67.5      | 76.7      | 82.7      | 81.7      | 75.8      |

Table 7: Total Pearson correlation (%) of four genres in the STS-B dataset. The reported results are averaged over 3 trials.