Abstract

While pre-trained large-scale deep models have garnered attention as an important topic for many downstream natural language processing (NLP) tasks, such models often make unreliable predictions on out-of-distribution (OOD) inputs. As such, OOD detection is a key component of a reliable machine learning model for any industry-scale application. Common approaches often assume access to additional OOD samples during the training stage, however, outlier distribution is often unknown in advance. Instead, we propose a post hoc framework called POORE - POsthoc pseudo Ood REgularization, that generates pseudo-OOD samples using in-distribution (IND) data. The model is fine-tuned by introducing a new regularization loss that separates the embeddings of IND and OOD data, which leads to significant gains on the OOD prediction task during testing. We extensively evaluate our framework on three real-world dialogue systems, achieving new state-of-the-art in OOD detection.

1 Introduction

Detecting Out-of-Distribution (OOD) (Goodfellow et al., 2014; Hendrycks and Gimpel, 2016; Yang et al., 2021) samples is vital for developing reliable machine learning systems for various industry-scale applications of natural language understanding (NLP) (Shen et al., 2019; Sundararaman et al., 2020) including intent understanding in conversational dialogues (Zheng et al., 2020; Li et al., 2017), language translation (Denkowski and Lavie, 2011; Sundararaman et al., 2019), and text classification (Aggarwal and Zhai, 2012; Sundararaman et al., 2022). For instance, a language understanding model deployed to support a chat system for medical inquiries should reliably detect if the symptoms reported in a conversation constitute an OOD query so that the model may abstain from making incorrect diagnosis (Siedlikowski et al., 2021).

Although OOD detection has attracted a great deal of interest from the research community (Goodfellow et al., 2014; Hendrycks and Gimpel, 2017; Lee et al., 2018), these approaches are not specifically designed to leverage the structure of textual inputs. Consequently, commonly used OOD approaches often have limited success in real-world NLP applications. Most prior OOD methods for NLP systems (Larson et al., 2019; Chen and Yu, 2021; Kamath et al., 2020) typically assume additional OOD data for outlier exposure (Hendrycks et al., 2018). However, such methods risk over-fitting to the chosen OOD set, while making the assumption that a relevant OOD set is available during the training stage. Other methods (Gangal et al., 2020; Li et al., 2021; Kamath et al., 2020) assume training a calibration model, in addition to the classifier, for detecting OOD inputs. These methods are computationally expensive as they often require re-training the model on the downstream task.

Motivated by the above limitations, we propose a framework called POsthoc pseudo Ood REgularization (POORE) that generates pseudo-OOD data using the trained classifier and the In-Distribution (IND) samples. As opposed to methods that use outlier exposure, our framework doesn’t rely on any external OOD set. Moreover, POORE can be easily applied to already deployed large-scale models trained on a classification task, without requiring to re-train the classifier from scratch. In summary, we make the following contributions:

1. We propose a Mahalanobis-based context masking scheme for generating pseudo-OOD samples that can be used during the fine-tuning.
2. We introduce a new Pseudo Ood Regularization (POR) loss that maximizes the di-
tance between IND and generated pseudo-OOD samples to improve the OOD detection.

3. Though extensive experiments on the three benchmarks, we show that our approach performs significantly better than existing baselines.

2 Related Works

**OOD Detection.** It is a binary classification problem that seeks to identify unfamiliar inputs during inference from in-distribution (IND) data observed during training. Standard OOD methods can be divided into two categories. The first category (Lee et al., 2018; Podolskiy et al., 2021; Nalisnick et al., 2019; Ren et al., 2019) corresponds to approximating a density \( p_{IND}(x) \), where density is used as a confidence estimate for binary classification. The second category of approaches (Hendrycks and Gimpel, 2016, 2017; Li et al., 2017; Gal and Ghahramani, 2016) use the predictive probability to estimate the confidence scores. In our experiments, we compare against approaches from both the categories.

**OOD Detection in NLP.** There have been several methods developed for OOD detection in NLP. Li et al. (2021) proposed using \( k \) sub models, where each model is trained with different masked inputs. Kamath et al. (2020) uses an external OOD set to train an additional calibration model for OOD detection. Most related to our proposed framework is MASKER (Moon et al., 2021) that leverages IND data to generate pseudo-OOD samples, and uses self-supervision loss inspired from Devlin et al. (2018) and predictive entropy regularization for pseudo-OOD inputs. We also use BERT self-supervision inspired keyword masking, however, for pseudo-OOD inputs. We also use BERT self-supervision inspired keyword masking, however, for pseudo-OOD inputs. We also use BERT self-supervision inspired keyword masking, however, for pseudo-OOD inputs.

We consider a deep learning model \( g \circ f(x) \) composed of an encoder \( f : \mathcal{X} \rightarrow \mathcal{F} \) and a classifier \( g \) that maps \( f(x) \) to the output space, where \( x \in \mathcal{X} \) corresponds to natural sentences composed of a sequence of tokens \( v_1 \in \mathcal{V}, \) i.e. \( x = [v_1, \ldots, v_T], T \) is the length of the sequence, and \( \mathcal{V} \) is the token vocabulary. For a downstream classification task, the class prediction is defined as \( p(y|x) = \text{softmax}(g(f((x)))) \).

**Architecture.** In this work, we construct \( f \) using the bi-directional Transformer architecture (Vaswani et al., 2017). Specifically, we use the encoder architecture proposed in Devlin et al. (2018) such that \( f(x) \) is the final hidden representation of the CLS token. We use a two-layer multi-layer perceptron (MLP) as the classifier \( g \).

**Mahalanobis OOD Scoring.** OOD methods typically learn a confidence estimator that outputs a score \( s(x) \in \mathbb{R} \) such that \( s(x_{\text{ind}}) > s(x_{\text{ood}}) \), where \( x_{\text{ind}} \) and \( x_{\text{ood}} \) are sampled from IND distribution \( D_{\text{IND}} \) and OOD distribution \( D_{\text{OOD}} \) respectively. Lee et al. (2018) proposed using Mahalanobis distance estimator for OOD detection that uses pre-trained features of the softmax neural classifier. Namely, given feature of a test sample \( \phi(x) \), the mahalanobis score \( s_M(x) \) is computed as follows

\[
d(x, c) = (\phi(x) - \hat{\mu}_c)^T \hat{\Sigma}^{-1} (\phi(x) - \hat{\mu}_c) \quad (1)
\]

\[
s_M(x) = - \min_c d(x, c) \quad (2)
\]

where \( \phi \) is an intermediate layer of the neural classifier and \( c \) denotes the class. The parameters of the estimator \( \{\hat{\mu}_c, \hat{\Sigma}\} \) denote the class-conditional mean and the tied covariance of the IND features.

4 Post hoc Pseudo-OOD Regularization

In this section, we describe our framework called POsthoc pseudo Ood REgularization (POORE), which uses pseudo-OOD samples for fine-tuning a pre-trained classifier. We first describe our masking-based approach to generate pseudo-OOD samples from the IND samples available during training. These generated pseudo-OOD samples are used to regularize the encoder during post-hoc training of a pre-trained classifier, which leads to improved robustness of the model towards OOD samples.

4.1 Masking for Pseudo-OOD Generation

We perform context masking of IND samples for generating pseudo OOD samples. To generate context-masked pseudo OOD samples, we first identify a set of tokens \( v \in \mathcal{K} \subset \mathcal{V} \) that have high attention scores and consequently, a higher influence in model predictions. Given the set of keywords, we perform random masking of non-keywords in a given IND sample \( x \) to generate
a pseudo OOD sample $\tilde{x}$.

**Keyword Selection.** We follow the attention-based keyword identification method proposed in Moon et al. (2021). The token importance is measured using average model attention values computed in the final layer of the pre-trained transformer encoder. While this approach generates context-deprived inputs, the identified tokens are uniformly selected from all the IND samples in the training data. Instead, we propose a novel weighting criterion for keyword selection, such that a higher weight is given to the tokens belonging to the training inputs that have a higher distance from the overall IND distribution determined by $\{\mu_c, \Sigma\}$. This encourages the selection of keywords that belong to IND inputs which are far from the estimated IND distribution. Specifically, we propose the importance score criterion as follows:

$$I_M(v) = \frac{1}{n_v} \sum_{x \in D_{IND}} \left( \sum_{i=1}^{T} v_{i=v} \cdot a_i \right) \cdot \hat{s}_M(x), \quad (3)$$

where $\hat{s}_M(x) = \frac{s_{\text{max}} - s_M(x)}{s_{\text{max}} - s_{\text{min}}}$, $s_{\text{min}} = \min_{x \in D_{IND}} s_M(x')$, $s_{\text{max}} = \max_{x \in D_{IND}} s_M(x')$. The total loss used during post hoc fine-tuning is defined as

$$\mathcal{L} = \mathcal{L}_{CE} + \lambda_{\text{SKL}} \cdot \mathcal{L}_{\text{SKL}} + \lambda_{\text{POR}} \cdot \mathcal{L}_{\text{POR}} \quad (10)$$

where $\mathcal{L}_{CE}$ is the standard cross-entropy (CE) loss, and $\mathcal{L}_{\text{SKL}}$ is the self-supervised keyword loss (SKL) proposed in Devlin et al. (2018). The SKL loss has been found to improve the generalization of the model by avoiding overfitting of the model to certain tokens in the training data (Moon et al., 2021). The post hoc training process finetunes the model using (10). Note that the post hoc fine-tuning is carried on a model previously trained on the downstream task using the standard $\mathcal{L}_{CE}$ loss.

**5 Experiments**

We demonstrate the effectiveness of our proposed approach in this section. For reproducibility of the experiments, we include the codebase in the supplementary.

**5.1 Datasets**

We use three task-oriented dialogue datasets for OOD detection. Namely, Schema-guided Dialog Dataset for Transfer Learning (STAR) (Mosig et al., 2020), SM Calendar flow (FLOW) (Andreas et al., 2020), and Real Out-of-Domain Sentence From Task-oriented Dialog (ROSTD) (Gangal et al., 2020). We follow the data splits and pre-processing steps as described in Chen and Yu (2021). A detailed description of these tasks is provided in Appendix A.

**5.2 Experimental Setup**

Our approach is demonstrated on the BERT pre-trained model (Devlin et al., 2018) with around 110M parameters trained on a single Titan-X GPU.
Table 1: AUROC and FPR@90 of Baseline and POORE on the three target benchmarks. MASKER uses Maxprob for inference, MASKER-Maha and POORE use use Mahalanobis for OOD detection during inference.

| Methods                        | STAR (AUROC↑, FPR@90↓) | FLOW (AUROC↑, FPR@90↓) | ROSTD (AUROC↑, FPR@90↓) |
|--------------------------------|-------------------------|-------------------------|--------------------------|
| Maxprob (Hendrycks and Gimpel, 2017) | 68.27, 77.18             | 61.10, 84.23            | 91.49, 54.30             |
| Dropout (Gal and Ghahramani, 2016)      | 52.77, 100.0            | 51.86, 100.0           | 55.25, 100.0            |
| Entropy (Lewis and Gale, 1994)          | 70.29, 77.84            | 62.02, 79.45           | 91.86, 53.83           |
| Gradient Embed                        | 67.61, 80.80            | 71.21, 70.25           | 98.53, 2.58            |
| BERT Embed (Podolskiy et al., 2021)    | 71.96, 73.56            | 61.16, 87.26           | 98.88, 2.27           |
| Mahalanobis (Lee et al., 2018)         | 76.89, 65.25            | 73.13, 63.84           | 99.45, 1.00            |
| MASKER (Moon et al., 2021)             | 71.54, 72.82            | 68.16, 67.52           | 86.95, 54.26           |
| MAXKES-Maha (Enhanced)                 | 79.38, 59.97            | 72.99, 65.23           | 99.41, 1.15            |
| POORE (Ours)                          | 81.11, 48.30            | 74.08, 69.26           | 99.51, 0.97            |

Figure 1: AUROC (↑) and FPR@90 (↓) using Maxprob, ODIN, Entropy, and BERT. The average improvements across estimators on AUROC are 5% on STAR (1a) and 4% on FLOW (1b). The FPR@90 improvements on an average are 8% on STAR (1c) and 2% on FLOW (1d).

5.3 Results

Table 1 shows the performance gains from our approach relative to all the baseline methods on three target tasks namely STAR, FLOW, and ROSTD. POORE outperforms existing evaluation baselines by significant margins. Specifically on the STAR dataset, relative to Bert Embed and Mahalanobis baselines, we observe 9% and 4% respective absolute improvement in AUROC, while observing 26% and 17% respective absolute reduction in FPR@90. Similarly on FLOW, the AUROC gains were 13%, and 1% relative to BERT Embed and Mahalanobis, while doing worse only on the FPR@90 metric compared to the Mahalanobis baseline. We noted similar consistent gains on the ROSTD.

We also evaluate our framework POORE by pairing it with other confidence estimators like Maxprob, ODIN (Liang et al., 2017), Entropy, and BERT Embed. Figure 1 compares a model trained using POORE with a standard model, while using various confidence estimators during inference. As shown in figure 1, we observe significant gains with our framework over the baseline model for all the confidence estimators. Specifically, the AUROC on FLOW using Bert Embed with POORE achieved an improvement of 9%. We also pair the above estimators with the MASKER baseline and evaluate these combinations in the ablation shown in Appendix C. In Appendix D, we show an ablation comparing our novel keyword selection criterion with the keyword selection criterion used in the MASKER baseline.

6 Conclusions

In this paper, we propose a novel framework, which we call POORE, for improving the robustness of model towards OOD data. Using a combination of
Mahalanobis distance and POR regularization that maximizes the distance between IND and OOD representations, we demonstrated significant performance gains in a number of target benchmark tasks. Further work could tap into the potential of using external OOD data to achieve even more gains over other baselines that use outlier exposure.
Limitations

While our work POORE has shown significant gains on the three benchmarks with minimal fine-tuning of a trained classifier, there are a few limitations of our proposed framework. The requirement of pair-wise correspondence for the Euclidean-distance-based regularization in our approach: For OOD data, the other approaches mentioned in related works use KL divergence-based loss, which is not dependent on pair-wise correspondence, but Euclidean-distance-based approaches assume that both vectors used in the distance calculation are in the same space. The approach we employ uses pseudo-OOD data from IND distribution, and hence this is not a limiting factor but may not hold for external OOD data.

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A Tasks

**STAR.** This is a dialog dataset with 6651 dialogues spanning multiple domains and intents (Mosig et al., 2020). Responses to dialogs that were marked either “ambiguous” or “out-of-scope” are used as OOD examples. The dataset has 29,104 examples with 104 intent labels.

**FLOW.** The FLOW dataset is a semantic parsing dataset with annotations for each turn of a dialog (Andreas et al., 2020). In FLOW, the OOD samples are from discussions where the user stays far away from the central topic. The dataset has 71,551 examples spanning 44 intents.

**ROSTD.** Gangal et al. (2020) designed ROSTD, a dataset proposed for OOD detection. They use external source for OOD samples, while the internal data represents IND. ROSTD contains 47,913 examples with 13 classes.

B OOD Evaluation Metrics

OOD detection is evaluated using the Area Under the Receiver-Operating Curve (AUROC) metric for the binary classification task based on the estimated confidence score. An OOD method that perfectly separates \(s(x^{\text{ind}})\) from \(s(x^{\text{ood}})\) achieves an AUROC score of 100%. Another common metric used to evaluate OOD detection is false positive rate (FPR) at a fixed recall.

C Adaptation of MASKER Baseline

In the table 2, improvised Masker baseline results can be seen, which include the results on a number of evaluation metrics. While the performance using improvised baseline is better than the GOLD baseline, our approach beats this model considerably.

### Table 2: Masker baseline and Adapted approaches.

| Methods       | STAR | FLOW | ROSTD |
|---------------|------|------|-------|
|               | AUROC | FPR@90 | AUROC | FPR@90 | AUROC | FPR@90 |
| Maxprob       | 71.54 | 7.28 | 68.16 | 65.32 | 85.95 | 54.26 |
| ODIN          | 72.45 | 71.86 | 68.57 | 66.84 | 86.86 | 54.25 |
| BERT          | 75.03 | 82.93 | 69.79 | 70.97 | 90.16 | 1.73  |
| Mahalanobis   | 75.58 | 99.93 | 72.99 | 65.23 | 99.41 | 1.15  |
| POORE (Ours)  | 81.11 | 48.30 | 74.08 | 69.26 | 99.51 | 0.97  |

D Ablation for choosing keywords

Table 3 compares the OOD detection performance of our proposed keyword selection approach described in Section 4.1 with the keyword selection criterion in the baseline MASKER in our proposed POORE framework.

### Table 3: Ablation for keywords

| Methods                          | STAR | FLOW | ROSTD |
|----------------------------------|------|------|-------|
|                                 | AUROC | FPR@90 | AUROC | FPR@90 | AUROC | FPR@90 |
| POORE with baseline keywords    | 80.69 | 58.71 | 73.41 | 68.08 | 99.52 | 1.06  |
| POORE (Ours)                     | 81.11 | 48.30 | 74.08 | 69.26 | 99.51 | 0.97  |