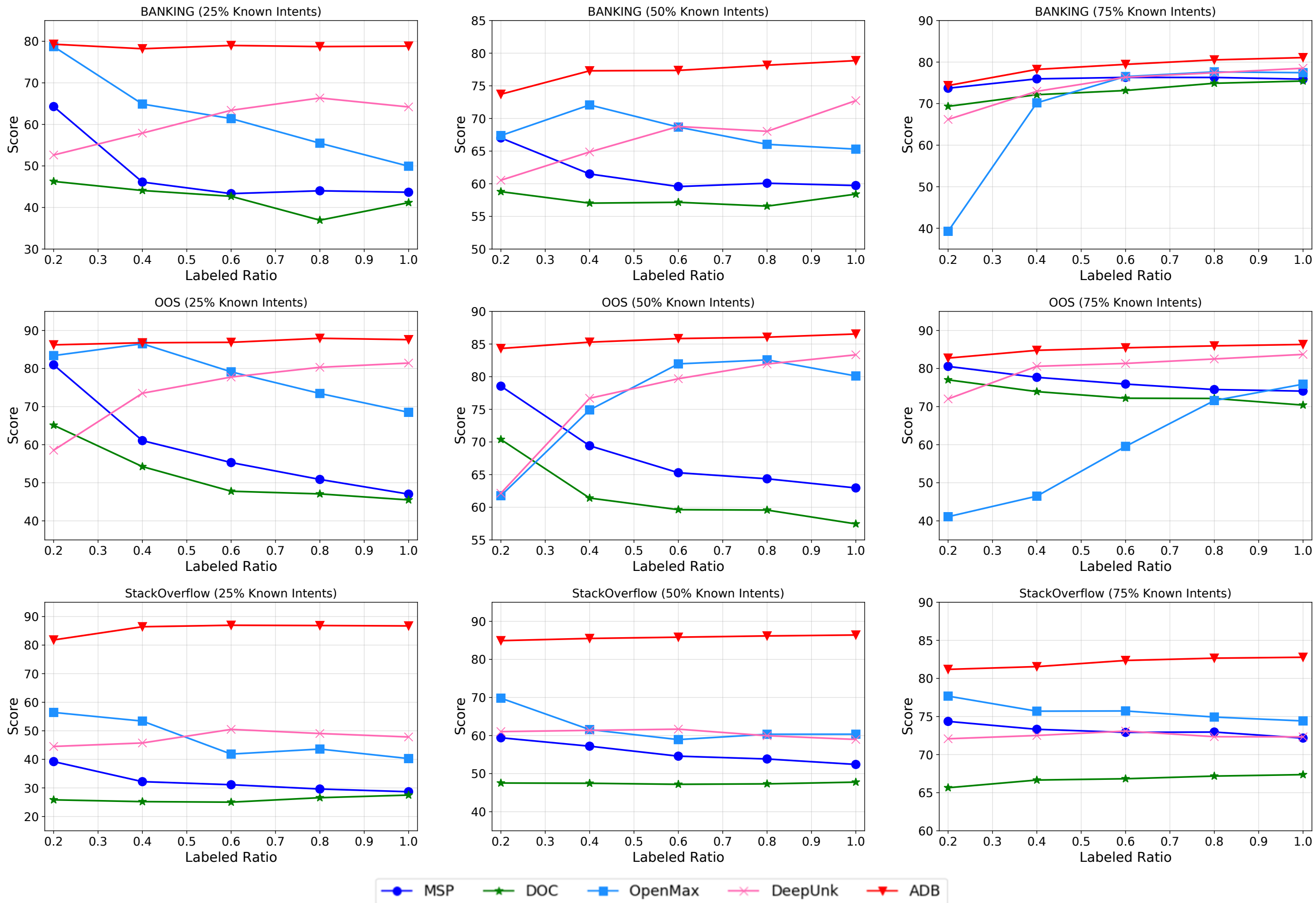

Figure 5: Influence of the labeled ratio on three datasets with different known class proportions (25%, 50%, 75%).

Discussion

Boundary Learning Process

Figure 3 shows the decision boundary learning process. At first, most parameters are assigned small values near zero after initialization, which leads to small radius with the $\mathrm{Softplus}$ activation function. As the initial radius is too small, the empirical risk plays a dominant role. Therefore, the radius of each decision boundary expands to contain more known intent samples belonging to its class. As the training process goes on, the radius of the decision boundary learns to be large enough to contain most of the known intents. However, the large radius will also introduce redundant open intent samples. In this case, the open space risk plays a dominant role, which prevents the radius from enlarging. Finally, the decision boundaries converge with a balance between empirical risk and open space risk.

Effect of Decision Boundary

To verify the effectiveness of the learned decision boundary, we use different ratios of Δ as boundaries during testing. As shown in Figure 4, ADB achieves the best performance with Δ among all assigned decision boundaries, which verifies the tightness of the learned decision boundary. Moreover, we notice that the performance of open classification is sensitive to the size of the decision boundaries. Overcompact decision boundaries will increase the open space risk by misclassifying more known intent samples to the open intent. Correspondingly, overrelaxed decision boundaries will increase the empirical risk by misclassifying more open intent samples as known intents. As shown in Figure 4, both of these two cases perform worse compared with Δ.

Effect of Labeled Data

To investigate the influence of labeled data, we vary the labeled ratio in the training set in the range of 0.2, 0.4, 0.6, 0.8 and 1.0. We use Accuracy as the score to evaluate the performance. As shown in Figure 5, ADB outperforms all the other baselines on three datasets on almost all settings. Besides, it keeps a more robust performance under different labeled ratios compared with other methods.

Notably, the statistic-based methods (e.g., MSP and DOC) show better performances with less labeled data. We suppose the reason is that the predicted scores are in low-confidence with less prior knowledge for training, which is helpful to reject the open intent with the threshold. However, as the number of labeled data increases, these methods tend to be biased towards the known intents, with the aid of strong feature extraction capability of DNNs (**?**). Therefore, the performances drop dramatically.

In addition, we notice that OpenMax and DeepUnk are two competitive baselines. We suppose the reason is that they both leverage the characteristics of intent feature distribution to detect the open class. However, OpenMax computes centroids of each known class with only corrective positive training samples. The qualities of centroids are easily influenced by the number of training samples. DeepUnk adopts a density-based novelty detection algorithm to perform open classification, which is also limited to the prior knowledge of labeled data. Thus, their performances all drop dramatically with less labeled data, as shown in Figure 5.

Effect of Known Classes

We vary the known class ratio between 25%, 50% and 75%, and show the results in Table 2 and Table 3. Firstly, we observe the overall performance in Table 2. Compared with other methods, our method achieves huge improvements on all settings of three datasets. All baselines drop dramatically as the known class ratio decreases. By contrast, our method still achieves robust results on accuracy score with fewer training samples.

Then, we observe the fine-grained performance in Table 3. We notice that all baselines achieve high scores on known classes, but they are limited to identify the open intent and suffer poor performance. However, our method still yields the best results on both known classes and the open class. It further demonstrates that the suitable learned decision boundaries are helpful to both balance the empirical risk and the open space risk.

Related Work

Intent Detection

There are many works for intent detection in dialogue systems in recent years (**?????**). Nevertheless, they all make assumptions of closed world classification without the open intent. **?** perform intent detection with the zero-shot learning (ZSL) method. However, ZSL is different from our task because it only contains novel classes during testing.

Unknown intent detection is a specific task for detecting the unknown intent. **?** propose an unsupervised approach to modeling intents, but fail to utilize the prior knowledge of known intents. **?** jointly train the in-domain (ID) classifier and out-of-domain (OOD) detector but need to sample OOD utterances. **?** adopt adversarial learning to generate positive and negative samples for training the classifier. **?** use a generative adversarial network (GAN) to train on the ID samples and detect the OOD samples with the discriminator. However, it has been shown that deep generative models fail to capture high-level semantics on real-world data (**??**). Recent methods try to learn friendly features for detecting the unknown intent (**???**), but they need to modify the model architecture, and fail to construct specific decision boundaries.

Open World Classification

At first, researchers use SVM to solve open set problems. One-class classifiers (**??**) find the decision boundary based on the positive training data. For multi-class open classification, One-vs-all SVM (**?**) trains the binary classifier for each class and treats the negative classified samples as the open class. **?** extend the method to computer vision and introduce the concept of open space risk. **?** estimate the unnormalized posterior probability of inclusion for open set problems. They fit the probability distributions to statistical Extreme Value Theory (EVT) by using a Weibull-calibrated multi-class SVM. **?** propose a Compact Abating Probability (CAP) model, which further improves the performance of Weibull-calibrated SVM by truncating the abating probability. However, all these methods need negative samples for selecting the decision boundary or probability threshold. Moreover, SVM cannot capture advanced semantic features of intents (**?**).

Recently, researchers use deep neural networks for open classification. OpenMax (**?**) fits Weibull distribution to the outputs of the penultimate layer, but still needs negative samples for selecting the best hyperparameters. MSP (**?**) calculates the softmax probability of known samples and rejects the low confidence unknown samples with the threshold. ODIN (**?**) uses temperature scaling and input preprocessing to enlarge the differences between known and unknown samples. However, both of them (**??**) need unknown samples to select the confidence threshold artificially. DOC (**?**) uses the sigmoid function and calculates the confidence threshold based on Gaussian statistics, but it performs worse when the output probabilities are not discriminative.

Conclusion

In this paper, we propose a novel post-processing method for open intent classification. After pre-training the model with labeled samples, our model can automatically learn specific and tight decision boundaries adaptive to the known intent feature space. Our method has no require for open intent or model architecture modification. Extensive experiments on three benchmark datasets show that our method yields significant improvements over the compared baselines, and is more robust with less labeled data and fewer known intents.

Acknowledgments

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