Density-Based Dynamic Curriculum Learning for Intent Detection

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\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|}
\hline
 & Simple & Medium & Complex \\
\hline
#Misclassified & 673 & 720 & 823 \\
#Total Samples & 2860 & 1213 & 927 \\
Error Rate & 23.53\% & 59.36\% & 88.78\% \\
\hline
\end{tabular}
\caption{Eigenvector distribution of samples with various difficulty levels from TNEWS dataset, using t-SNE algorithm for visualization. Simple samples have a much lower error rate compared to complex samples. Besides, the eigenvectors of simple samples are in a higher density, while the eigenvectors of complex samples are in a lower density.}
\end{table}

ABSTRACT
Pre-trained language models have achieved noticeable performance on the intent detection task. However, due to assigning an identical weight to each sample, they suffer from the overfitting of simple samples and the failure to learn complex samples well. To handle this problem, we propose a density-based dynamic curriculum learning model. Our model defines the sample’s difficulty level according to their eigenvectors’ density. In this way, we exploit the overall distribution of all samples’ eigenvectors simultaneously. Then we apply a dynamic curriculum learning strategy, which pays distinct attention to samples of various difficulty levels and alters the proportion of samples during the training process. Through the above operation, simple samples are well-trained, and complex samples are enhanced. Experiments on three open datasets verify that the proposed density-based algorithm can distinguish simple and complex samples significantly. Besides, our model obtains obvious improvement over the strong baselines.

KEYWORDS
intent detection, eigenvector density, dynamic curriculum learning

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1 INTRODUCTION
Intent detection is a crucial portion in understanding user queries, which usually predicts intent tags by semantic classification. It is widely used in search, task-based dialogue, and other fields [2].

Recently, with the development of pre-trained language models, BERT-based models have achieved remarkable enhancement on multiple intent detection corpora. Nevertheless, there exist some major drawbacks yet. For instance, all samples are treated equally, leading to the overfitting of simple samples and barely satisfactory process on complex samples. As demonstrated in Figure 1, we use BERT as the classifier on a real dataset. Complex samples have a much higher error rate than simple samples.

One of the effective solutions to address the aforementioned problems is curriculum learning [1], as imitated from the bionic method of human learning. Curriculum learning can better guide the model to make the utmost of samples with various difficulty levels, by the paradigm that learns from simple to complex. Hence, the model is capable of achieving a more preferable outcome than conventional approaches.

In fact, there already have several works on how to introduce curriculum learning into NLP tasks [7, 8], which achieve satisfying performance. The key of curriculum learning is to define the sample’s difficulty level. For instance, [11] uses multiple pre-trained sub-models to evaluate the difficulty of samples. However, these curriculum learning models suffer from the following issues: (1) They focus on the independent information of a single sample to define samples’ difficulty, such as classification result of correct or wrong, without considering the overall distribution of all samples. (2) The capability of sub-models to define simple or complex samples is fixed from the initial phase and cannot be dynamically updated. However, the model’s capability is actually different during various training stages.
Fortunately, we find that the eigenvectors extracted from samples are of different density distribution. Moreover, there is a corresponding relation between the complexity and eigenvectors’ density. Consequently, the overall distribution of all samples could be exploited rather than just a single sample’s information like [11]. We separate samples from TNEWS dataset into three difficulty levels, project their eigenvectors into two-dimensional space. As shown in Figure 1, simple samples have a higher density of eigenvectors, while more complex samples have a lower density.

Based on the above observations, we propose a density-based dynamic curriculum learning model, which contains two parts as below. (1) We use the distribution density of sample’s eigenvector to define the difficulty level. In this way, samples’ difficulty can be considered from the interaction of all samples in the entire spatial distribution, rather than the difficulty of each sample alone, like [11]. (2) After defining the difficulty of samples, the dynamic curriculum learning strategy changes the proportion of samples with various difficulty levels. New eigenvectors are extracted according to the model’s current capability, which is updated in the training process other than remains constant like [8].

To verify the effectiveness of our model, we conduct abundant experiments on three open datasets. Empirical results show that exploiting the eigenvector distribution density can distinguish the simple and complex samples significantly. Combined with a dynamic curriculum learning strategy, the proposed model obtains evident improvement compared with the strong baselines.

2 RELATED WORK

Intent detection. Intent is the purpose of an utterance such as a query generated by users. Actually, the essence of intent detection is text classification. Given a labeled training set, the model tries to predict the intent of a query in the existing intent sets. Massive researches have been done during the past few decades [2, 10] for intent detection.

Curriculum learning. CL has acquired striking results in lots of fields [4, 5, 9]. Defining the samples’ difficulty is the essential step in curriculum learning. In the machine translation task of NLP, [8] exploits the norm of words’ vectors to define the samples’ difficulty, where frequent words and context-insensitive words have smaller norms. Concerning QA generation, [7] proposed a model to make full use of the complexity and quality of QA pairs to generate a natural answer.

3 METHOD

3.1 Model Overview

Exhibited in Figure 2, we use the initial model such as original BERT to extract the encoded vector from the training set. Through the above preprocess, we acquire the eigenvector of each sample. Next, the distribution density of eigenvectors is leveraged to cluster and define the difficulty level of sample. After that, we employ a dynamic curriculum learning scheduler. It changes the proportion of simple and complex samples, concurrently, pays distinct attention to various samples. Then, we get the intent detection model, which replaces the initial model and renovates the capability of defining difficulty level at various training stages. Last, repeating the operation until the end of training.

\[ D_i = \sum_{j=1}^{n} Z_{ij}, \quad Z_{ij} = \begin{cases} 1, & \text{if } d_{ij} < d_{flag} \\ 0, & \text{otherwise} \end{cases} \]

Figure 2: The illustration of density-based dynamic curriculum learning framework. We employ the initial model to obtain sample's eigenvector, and exploit the density-based cluster algorithm to define the difficulty level of all samples simultaneously. Then, we use dynamic curriculum learning to train the intent detection model, which replaces the initial model and renovates the capability for definition.

3.2 Density-Based Sample Difficulty Level

In this submodule, we define the sample’s difficulty level by the density of eigenvectors. Suppose a query \( Q_i \) of sample \( S_i \). The corresponding category is \( C_i \). We exploit the initial model like BERT to extract the encoded vector \( V_i \) of query \( Q_i \), such as [CLS], which is defined as the eigenvector of sample. Take category \( C_t \) as an example, we calculate Manhattan distance \( d_{ij} \) between samples within the same category \( C_t \) by the following:

\[ d_{ij} = |V_i - V_j| \quad (1) \]

where \( V_i \) is the eigenvector of sample \( S_i \), \( V_j \) is the eigenvector of another sample \( S_j \) in the identical category \( C_t \).

After that, we obtain an array of distance \( \{d_{12}, ..., d_{jj}, ..., d_{n(n-1)}\} \) between eigenvectors within category \( C_t \). \( n \) is the total number of samples in category \( C_t \). After sorting the above array in ascending order, we select the distance value ranked at \( \theta \% \) to be the demarcation flag \( d_{flag} \). Threshold \( \theta \) is a hyperparameter set as 60. For each sample in category \( C_t \), if the distance \( d_{ij} \) between it and another sample in the same category \( C_t \) is less than the demarcation flag \( d_{flag} \), the density value is accumulated by one. The samples in this category eventually get their own accumulated density value through the equation as below:

\[ D_i = \sum_{j=1}^{n} Z_{ij}, \quad Z_{ij} = \begin{cases} 1, & \text{if } d_{ij} < d_{flag} \\ 0, & \text{otherwise} \end{cases} \quad (2) \]
3.3 Dynamic Curriculum Learning Scheduler

After acquiring the difficulty level of each sample, we design a dynamic curriculum learning strategy. To better utilize both simple and complex samples as well as pay different attention to them, we change the proportion and calculate the attention weight $\omega_k$ during each epoch as:

$$\omega_k = f_k(\lambda^{(\text{-epoch})}), \ k \in \{1, 2, ..., K\}$$  \hspace{1cm} (3)

where $\text{epoch}$ is the number of current epoch, $f_k$ is the scheduler function, $k$ is the exact difficulty level of sample, $k = K$ represents the difficulty level of most complex samples. We exploit $\lambda^{(\text{-epoch})}$, which makes a narrower fluctuation margin of the sample number in the later stage of training. $\lambda$ is a hyperparameter. Then the new number ($Num'_k$) of samples in difficulty level $k$ for training is calculated by:

$$Num'_k = \omega_k \times Num_k$$  \hspace{1cm} (4)

where $Num_k$ is the original number of samples. As training progressing, simple samples are gradually reduced, while complex samples are selected. Moreover, suppose the number of complex samples is not reduced compared to the previous round. In this case, the number of different samples remains the same as the previous round, which encourages the model to find a better partition of training set containing fewer complex samples. So that models’ capability of defining difficulty level is updated at each round.

4 EXPERIMENTS

4.1 Experimental Setup

Datasets. We mainly experiment on three open datasets, TNEWS, BANKING77, and CLINC150. TNEWS, proposed by [12], has identical essence with intent detection. It includes 53360 samples in 15 categories. The provided test set are without gold labels. So we regard the validation set as the test set and randomly divide 5000 samples from the train set for validation. BANKING77, proposed by [3], has 13083 samples. It is the inquire dataset of online banking, consists of 77 intents in a single domain. CLINC150 proposed by [6], contains 150 intents of 10 domains and 22500 total samples.

Implementation Details. For baseline methods, we use BERT-based models as strong competitors. Then, we reproduce the base-lines, and the results are almost equal to the published metrics. We set the difficulty level $K = 3$ unless otherwise specified. Besides, we employ Adam as the optimizer and search learning rate in $[2e-5, 3e-5]$, with epochs in $[15, 19]$. To make full use of GPU memory, we set batch size equal to 256. The type of GPU is Tesla V100.

4.2 Overall Comparison

Comparison Settings. In order to verify the effectiveness of our model, extensive experiments have been conducted on the above three datasets. We choose BERT and RoBERTa as the baselines for analysis, and regard the accuracy as the main evaluation metrics, Precision (P), Recall (R), and F1 for comparison as well.

Comparison Results. As illustrated in Table 1, we clearly see the following observations: (1) No matter which dataset we choose, different baselines combined with our strategy can obtain a better consequence in all metrics. (2) Take CLINC150 dataset as an example, the error rate of our model drops 8.44% on BERT relatively, while a 7.77% reduction on RoBERTa. (3) Results demonstrate the availability of our strategy that pays different attention to simple and complex samples throughout training.

4.3 Other Curriculum Learning Comparison

Comparison Settings. We horizontally compared with other CL methods on TNEWS dataset. One, refer to [8], sample’s difficulty is defined as the norm of the eigenvector. The other, [11] uses multiple sub-models for cross-review. According to [11], we divide the training set into 3 disjoint meta-datasets, train the sub-models separately as teachers, then each sample is deduced by other teachers except the one it belongs to. We sum the scores as difficulty level.

Table 2: Different curriculum learning strategy results.

| Curriculum Learning Strategy | Accuracy |
|-----------------------------|----------|
| BERT                        | 55.63    |
| Norm-based CL (ACL2020[8])  | 56.02    |
| Multiple sub-models CL (ACL2020[11]) | 56.07 |
| Density-based CL (Ours)     | 56.55    |

Comparison Results. The experimental results, displayed in Table 2, show that other curriculum learning methods attain a certain enhancement of accuracy compared with BERT, as 0.4+%, while they are slightly weaker than our model, as 0.92%, due to the reason that they fail to exploit the overall distribution information of all samples to define sample’s difficulty level simultaneously. Besides, their models’ capability of defining difficulty level is fixed from the start of training, without dynamic renovation.

4.4 Validity of Density-Based Difficulty Level

4.4.1 Analysis of Error Rate. Comparison Settings. Error rate is the proportion of samples that are misclassified in the total samples.
under the same difficulty level. We analyze the sample’s error rate under various K difficulty level settings \(2, 3, 4, 7, 10\) on the validation set of TNEWS, which has 2216 misclassified samples with 5000 samples in total. Due to the space constraints, we only show the exact number of samples with difficulty level settings in \(2, 10\).

Comparison Results. As Figure 3 depicts: (1) More complex samples are incorrectly classified at a much higher rate. The error rate of the most complex samples is about 3-6 times above the simplest samples under various level settings. (2) For instance, if we divide samples into 10 levels, the error rate of simplest samples is 15.12%, while the error rate of most complex samples is as high as 95.44%. (3) This dulcet observation confirms that our density-based method can distinguish simple and complex samples remarkably.

4.4.2 Impact of Various Difficulty Level. Comparison Settings. The total difficulty level number of samples is the number of clusters \(K\) that training samples are separated into. The specific cluster operation process is described in Sec. 3.2. We experiment on TNEWS dataset and set \(K\) in \(2, 3, 4, 7, 10\).

Table 3: Performance on various difficulty level.

| Method     | P     | R     | F1    | Accuracy  |
|------------|-------|-------|-------|-----------|
| BERT       | 55.85 | 55.62 | 55.58 | 55.63     |
| BERT+CL (K = 2) | 56.92 | 56.37 | 56.39 | 56.37     |
| BERT+CL (K = 3) | 56.84 | 56.55 | 56.50 | 56.55     |
| BERT+CL (K = 4) | 56.87 | 56.36 | 56.32 | 56.36     |
| BERT+CL (K = 7) | 56.65 | 56.14 | 56.12 | 56.14     |
| BERT+CL (K = 10) | 56.49 | 56.05 | 56.01 | 56.05     |

Comparison Results. Table 3 illustrates the corresponding accuracy and other metrics. The experimental results express that our model gains higher scores over the BERT model. When the difficulty level is set to 3, the model acquires the highest accuracy. Though the performance reduces as the difficulty level grows, our model still overmatches the baseline, which indicates that our model has certain robustness in the difficulty level settings.

5 DISCUSSION

Apart from the pre-trained models, we also experiment on models of the conventional structure. Accuracy is the main metric. As shown in Table 4, our strategy still outperforms the baselines.

Table 4: Performance on models of conventional structure.

| Model                  | TNEWS | BANKING77 | CLINC150 |
|------------------------|-------|-----------|----------|
| Word Average           | 51.69 | 48.36     | 46.32    |
| +CL (Ours)             | 53.06 | 50.37     | 48.09    |
| CNN                    | 52.53 | 81.72     | 92.57    |
| +CL (Ours)             | 53.47 | 82.44     | 92.97    |
| LSTM-Attn              | 51.09 | 83.24     | 89.25    |
| +CL (Ours)             | 51.97 | 83.84     | 89.58    |

6 CONCLUSION

In this work, we propose a density-based dynamic curriculum learning model for intent detection. Through the density of extracted eigenvectors, the overall distribution information of all samples is utilized to define the difficulty level simultaneously. With the help of dynamic curriculum learning, model’s capability to define difficulty level updates adaptively during training. Results indicate that our model separate simple and complex samples conspicuously, meanwhile, achieve better performance over strong baselines.

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REFERENCES

[1] Yoshua Bengio, Jérôme Louradour, Ronan Collobert, and Jason Weston. 2009. Curriculum learning. In IJCAI. 41–48.
[2] David J Brenes, Daniel Gayo-Avello, and Kilian Pérez-González. 2009. Survey and evaluation of query intent detection methods. In Proceedings of the 2009 Workshop on Web Search Click Data. 1–7.
[3] Inigo Casanueva, Tadas Temˇcinas, Daniela Gerz, Matthew Henderson, and Ivan Vuˇcli. 2020. Efficient intent detection with dual sentence encoders. arXiv preprint arXiv:2003.04807 (2020).
[4] N. Ferro, C. Lucchese, Maria Maistro, and R. Perego. 2018. Continuation Methods and Curriculum Learning for Learning to Rank. CIKM (2018).
[5] Sheng Guo, Weilin Huang, Haozhi Zhang, Chenfan Zhuang, Dengke Dong, Matthew R Scott, and Dinglong Huang. 2018. Curriculumnet: Weakly supervised learning from large-scale web images. In ECCV. 135–150.
[6] Stefan Larson, Anish Mahendran, Joseph J Peper, Christopher Clarke, Andrew Lee, Parker Hill, Jonathan K Kummerfeld, Kevin Leach, Michael A Laurenzano, Lingjia Tang, et al. 2019. An evaluation dataset for intent classification and out-of-scope prediction. arXiv preprint arXiv:1909.02027 (2019).
[7] Cao Liu, Shihui He, Kang Liu, Jun Zhao, et al. 2018. Curriculum Learning for Natural Answer Generation. In IJCAI. 4223–4229.
[8] Xuebo Liu, Houtin Lai, Derek F Wong, and Lidia S Chao. 2020. Norm-Based Curriculum Learning for Neural Machine Translation. In ACL. 427–436.
[9] Gustavo Penha and C. Hauss. 2010. Curriculum Learning for User Intent Prediction. In CIKM. 6095–6104.
[10] Feng Wang, J. Xu, Chun-Yi Liu, H. Feng, Z. Li, and Jie ping Ye. 2020. Masked-field Pre-training for User Intent Prediction. CIKM (2020).
[11] Benfeng Xu, Licheng Zhang, Zhendong Mao, Quan Wang, Hongtao Xie, and Yongdong Zhang. 2020. Curriculum learning for natural language understanding. In ACL. 6095–6104.
[12] Liang Xu, Xuanwei Zhang, Lu Li, Hai Hu, Chenjie Cao, Weitang Liu, Junyi Li, Yudong Li, Kai Sun, Yechen Xu, et al. 2020. Clue: A chinese language understanding evaluation benchmark. arXiv preprint arXiv:2004.05986 (2020).