A Deep Reinforced Sequence-to-Set Model for Multi-Label Text Classification

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Abstract

Multi-label text classification (MLTC) aims to assign multiple labels to each sample in the dataset. The labels usually have internal correlations. However, traditional methods tend to ignore the correlations between labels. In order to capture the correlations between labels, the sequence-to-sequence (Seq2Seq) model views the MLTC task as a sequence generation problem, which achieves excellent performance on this task. However, the Seq2Seq model is not suitable for the MLTC task in essence. The reason is that it requires humans to predefine the order of the output labels, while some of the output labels in the MLTC task are essentially an unordered set rather than an ordered sequence. This conflicts with the strict requirement of the Seq2Seq model for the label order. In this paper, we propose a novel sequence-to-set framework utilizing deep reinforcement learning, which not only captures the correlations between labels, but also reduces the dependence on the label order. Extensive experimental results show that our proposed method outperforms the competitive baselines by a large margin.

Introduction

Multi-label text classification (MLTC) is an important yet challenging task in natural language processing (NLP), which aims to assign multiple labels to each sample in the dataset. It can be applied in many real-world scenarios, such as text categorization (Schapire and Singer 2000), tag recommendation (Katakis, Tsoumakas, and Vlahavas 2008), information retrieval (Gopal and Yang 2010), and so on. Early work exploring the MLTC task focuses on traditional machine learning algorithms. For instance, binary relevance (BR) (Boullay et al. 2004) decomposes the MLTC task into independent binary classification problems. However, it ignores the correlations between labels. Much of the following work, including ML-DT (Clare and King 2001), Rank-SVM (Eliseeff and Weston 2002), LP (Tsoumakas and Katakis 2006), ML-KNN (Zhang and Zhou 2007), and CC (Read et al. 2011), strives to model the correlations between labels. However, they are computationally intractable when high-order label correlations are considered.

Recent studies turn to deep neural networks, which have achieved great success in the field of NLP. Although they demonstrate a certain degree of improvements, most neural network models (Zhang and Zhou 2006; Nam et al. 2013; Benites and Sapozhnikova 2015; Baker and Korhonen 2017) do not capture the high-order correlations between labels very well. Yang et al. (2018) propose to apply the Seq2Seq model with attention mechanism to address the MLTC task, which achieves excellent performance. The high-order correlations between labels are well captured through the powerful ability of recurrent neural network (RNN) to model sequence dependencies.

However, the Seq2Seq model is not suitable for the MLTC task in essence. The Seq2Seq model is trained with the maximum likelihood estimation (MLE) method and the cross-entropy loss function, which relies on strict label order. Previous work (Vinyals, Bengio, and Kudlur 2015) proves that the order has a great impact on the performance of the Seq2Seq model, which is also verified in our experiments. Thus, the order of the output labels needs to be predefined carefully. It is reasonable to apply the Seq2Seq model to the MLTC task only when there exists a perfect label order. The perfect label order means that there is a strict order in the output labels and this true label order is known in practice. However, the perfect label order is usually unavailable for the following reasons:

- Some labels are naturally unordered. Imposing order to these labels is unreasonable.
- Even though there exists a strict order of the output labels, this true label order is usually unknown in practice.

It is more appropriate to treat these labels that do not show a perfect label order as an unordered set rather than an ordered sequence. An important property of the unordered set is swapping-invariance, which means that swapping any two elements in the set will make no difference. This conflicts with the strict requirement of the Seq2Seq model for the label order. Therefore, it is inappropriate to directly apply the traditional Seq2Seq model trained with the MLE method to the MLTC task. Otherwise, one of the practical problems that may result is wrong penalty. Wrong penalty means that the model may be wrongly penalized by the MLE method due to inconsistent label order when generating labels that do not show a perfect label order. For instance, when the true labels are \{A, B, C\}, the Seq2Seq model still receives a great penalty for generating a label sequence \{C, A, B\}, even
Although the perfect label order is usually unavailable in practice, sometimes the human prior knowledge of the label order can provide valuable information for label prediction to improve the model performance. For instance, when labels are organized in a directed acyclic graph (DAG), Nam et al. (2017) take advantage of label hierarchies to place the labels that have same ancestors in the graph next to each other to improve the performance of the Seq2Seq model. However, even if we can grasp the prior knowledge of label order, the Seq2Seq model is still likely to suffer from potential wrong penalty because perfect label order may not exist. Therefore, an appropriate model for the MLTC task should make use of the human prior knowledge rationally and be free from the strict restriction of the label order.

Based on this motivation, we propose a novel sequence-to-set model, which can not only integrate human prior knowledge rationally, but also reduce the dependence on the label order. The core component of the proposed model is the bi-decoder structure, which consists of a sequence decoder and a set decoder. The sequence decoder trained by the MLE method is used to fuse human prior knowledge of the label order and the set decoder aims to reduce the dependence of the model on the label order. For the set decoder, we apply the policy gradient method to directly optimize a specific metric that is independent of the label order. Since this specific metric satisfies swapping-invariance of the set, the dependence of the model on the label order can be reduced. To the best of our knowledge, this work is the first endeavor to apply reinforcement learning algorithm to the MLTC task.

The contributions of this paper are listed as follows:

- We systematically analyze the drawbacks of the current models for the multi-label text classification task.
- We propose a novel sequence-to-set model based on deep reinforcement learning, which not only captures the correlations between labels, but also reduces the dependence on the label order.
- Extensive experimental results show that our proposed method outperforms the baselines by a large margin. Further analysis demonstrates the effectiveness of the proposed method in addressing the wrong penalty.

**Proposed Approach**

**Overview**

Here we define some notations and describe the MLTC task. Given a text sequence \( x \) containing \( m \) words, the task is to assign a subset \( y \) containing \( n \) labels in the label space \( \mathcal{L} \) to \( x \). From the perspective of sequence generation, once the order of the output labels is predefined, the MLTC task can be regarded as the prediction of target label sequence \( y \) given a source text sequence \( x \).

An overview of the proposed model is shown in Figure 1. The proposed model consists of an encoder \( \mathcal{E} \) and two decoders \( \mathcal{D}_1, \mathcal{D}_2 \). First, if we have a prior knowledge of the label order, we can utilize it to sort the label sequence to assist the model in achieving better performance. Here we sort labels by frequency in a descending order (from frequent to rare labels). Besides, the bos and eos symbols are added to the head and tail of the label sequence, respectively. Given the input text sequence \( x \), the encoder \( \mathcal{E} \) and the sequence decoder \( \mathcal{D}_1 \) jointly work like the standard Seq2Seq model to generate corresponding hidden representations \( \hat{s} = (\hat{s}_0, \hat{s}_1, \ldots, \hat{s}_n) \), which aims to learn a preliminary label order that conforms to possible human prior knowledge. The set decoder \( \mathcal{D}_2 \) takes both the hidden state vectors of \( \mathcal{E} \) and \( \mathcal{D}_1 \) as input to generate final predicted labels sequentially. The policy gradient method with self-critical training (Rennie et al. 2016) is used to reduce the dependence of the model on the label order and alleviate the potential wrong penalty problem.

**Neural Sequence-to-Set Model**

The overview of the proposed neural sequence-to-set model is shown in Figure 1(a), which consists of encoder \( \mathcal{E} \), se-
sequence decoder $D_1$ and set decoder $D_2$.

**Encoder $E$:** Here we employ a bidirectional LSTM as the encoder $E$. The encoder $E$ reads the input text sequence $x$ from both directions and compute the hidden states for each word,

$$\overrightarrow{h}_i = \text{LSTM}(\overrightarrow{h}_{i-1}, x_i) \quad (1)$$

$$\overleftarrow{h}_i = \text{LSTM}(\overleftarrow{h}_{i+1}, x_i) \quad (2)$$

The final hidden representation of the $i$-th word is $h_i = [\overrightarrow{h}_i; \overleftarrow{h}_i]$, which semicolon represents the vector concatenation.

**Sequence decoder $D_1$:** Given the hidden state vectors $(h_1, \cdots, h_m)$ of the encoder $E$, the sequence decoder $D_1$ performs decoding as the standard Seq2Seq model, which aims to learn a rough label order that conforms to possible human prior knowledge. When $D_1$ predicts different labels, not all text words make the same contribution. Therefore, the attention mechanism is used to aggregate the hidden representations of informative words. In particular, the hidden state $\hat{s}_{t+1}$ of $D_1$ at time-step $t+1$ is computed as follows:

$$e_{t,i} = \mathbf{v}^T_a \tanh(W_a s_t + U_a h_i) \quad (3)$$

$$\alpha_{t,i} = \frac{\exp(e_{t,i})}{\sum_{j=1}^{m} \exp(e_{t,j})} \quad (4)$$

$$c_t = \sum_{i=1}^{m} \alpha_{t,i} h_i \quad (5)$$

$$\hat{s}_{t+1} = \text{LSTM}(\hat{s}_t, [e(y_t); c_t]) \quad (6)$$

where $[e(y_t); c_t]$ means the concatenation of the vectors $e(y_t)$ and $c_t$. $s_t$, $W_a$, and $U_a$ are weight parameters. $e(y_t)$ is the embedding of the label which has the highest probability at the last time-step. The probability distribution over the label space is computed as follows:

$$o_t = W_o f(W_d s_t + V_d c_t) \quad (7)$$

$$y_t \sim \text{softmax}(o_t + I_t) \quad (8)$$

where $W_o$, $W_d$, and $V_d$ are weight parameters, $I_t \in \mathbb{R}^L$ is the mask vector which is used to prevent the sequence decoder $D_1$ from generating repeated labels, $f$ is a nonlinear activation function.

$$\langle I_t \rangle_i = \begin{cases} -\infty & \text{if the } i\text{-th label has been predicted.} \\ 0 & \text{otherwise.} \end{cases} \quad (9)$$

**Set decoder $D_2$:** The set decoder $D_2$ is our main model, which aims to capture the correlations between labels and get rid of a strong dependence on the label order. After the sequence decoder $D_1$ generates the corresponding hidden state sequence, the set decoder $D_2$ refers to the hidden states of $D_1$ to generate more accurate labels sequentially. Due to the strong ability of the LSTM structure to model sequence dependencies, the set decoder $D_2$ is able to capture the correlations between labels. In detail, given $(h_1, \cdots, h_m)$ (the hidden state vectors of the encoder $E$) and $(\hat{s}_0, \cdots, \hat{s}_n)$ (the hidden state vectors of the sequence decoder $D_1$), two attention mechanisms similar to Eq. [3] - Eq. [5] aggregate the hidden representations of the encoder and sequence decoder respectively to form the encoder-side context $c^n$ and the sequence-decoder-side context $c^d$. The hidden state $s_{t+1}$ of the set decoder $D_2$ at time-step $t+1$ is computed as follows:

$$s_{t+1} = \text{LSTM}(s_t, [e(y_t); c^n_t; c^d_t]) \quad (10)$$

The mask vector and softmax layer similar to Eq. [8] - Eq. [9] are used to get the final predicted labels.

**Training and Testing**

**Multi-Label Text Classification as a RL Problem** In order to free the model out of the label order as much as possible, here we model the MLTC task from the perspective of reinforcement learning. Thanks to its ability to directly optimize a specific metric, the policy gradient method has achieved great success in the field of NLP (Ranzato et al. 2015; Li et al. 2016; Rennie et al. 2016; Yu et al. 2017). From the perspective of reinforcement learning, our set decoder $D_2$ can be viewed as an agent, whose state at time-step $t$ is the current generated labels $(y_0, \cdots, y_{t-1})$. A stochastic policy defined by the parameters $\theta$ of the set decoder $D_2$ decides the action, which is the prediction of the next label. Once a complete label sequence $y$ ending with $eos$ is generated, the agent $D_2$ will observe a reward $r$. The goal of training is to minimize the negative expected reward:

$$L(\theta) = -\mathbb{E}_{y \sim p_\theta}(r(y)) \quad (11)$$

In our approach, we use the self-critical policy gradient training algorithm (Rennie et al. 2016; Paulus, Xiong, and Socher 2017). The overview of the self-critical training method is shown in Figure 3(b). For each training example in the minibatch, the expected gradient of Eq. [11] can be approximated as:

$$\nabla_{\theta} L(\theta) \approx -[r(y^*) - r(y)] \nabla \log (p_\theta(y^*)) \quad (12)$$

where $y^*$ is the sampled label sequence from the probability distribution $p_\theta$ and $y$ is the generated label sequence using the greedy search algorithm. $r(y^*)$ in Eq. [12] is the baseline, which is used to reduce the variance of gradient estimate and enhance the consistency of the model training and testing to alleviate exposure bias (Ranzato et al. 2015).

**Reward Design** In order to free the model from the strict restriction of label order and alleviate the potential **wrong penalty**, we give an effective solution based on a simple but intuitive idea: if the reward $r(y)$ can well evaluate the quality of generated label sequence $y$ and satisfy swapping-invariance of output labels at the same time, then the dependence of model on the label order can be reduced. Based on this motivation, we design the reward $r$ as the F1 score calculated by comparing the output labels with true labels:

$$r(y) = F_1(y, y^*) \quad (13)$$

where $y$ and $y^*$ are the generated label sequence and the ground-truth label sequence, respectively.

\(^2\)When calculating $F_1$ score, we convert $y$ and $y^*$ into $L$-dimensional sparse vectors.
| Dataset      | Words/Sample | Labels/Sample |
|--------------|--------------|---------------|
| RCV1-V2      | 123.94       | 3.24          |
| AAPD         | 163.42       | 2.41          |

Table 1: Statistics of datasets. Words/Sample and Labels/Sample are the average number of words and labels per sample, respectively.

**Training Objective** We encourage the sequence decoder $D_1$ to generate preliminary label sequence whose order conforms to possible human prior knowledge. Therefore, the $D_1$ is trained by maximizing the conditional likelihood of the ground-truth label sequence $y^* = (y_0^*, \cdots, y_n^*)$. Specially,

$$L(\phi) = - \sum_{t=0}^{n} \log(p(y_t^* | y_{<t}^*, x)) \quad (14)$$

where $\phi$ represents the parameters of $D_1$ and $y_{<t}^*$ denotes the sequence $(y_0^*, \cdots, y_{t-1}^*)$. The final objective function is as follows:

$$L_{total} = (1 - \lambda) L(\phi) + \lambda L(\theta) \quad (15)$$

In Eq. (15), $L(\phi)$ aims to fuse the human prior knowledge of the label order into the model and $L(\theta)$ is responsible for reducing the dependence on the label order. $\lambda$ is a hyper-parameter, which is used to control the trade-off between $L(\phi)$ and $L(\theta)$.

**A Simplified Variant**

Here we provide a simplified variant of the above model. Both the complete model and the simplified model can substantially outperform the previous work and they apply to different scenarios, respectively. There is no clear conclusion as to which of the two proposed models is better. Which model to use depends on the specific task. The complete model is more suitable for the situation where we can grasp a certain amount of prior knowledge of the label order. Otherwise, the simplified model tends to perform better. Detailed analysis is provided in Section Comparison between Two Proposed Methods.

In the simplified variant, the sequence decoder $D_1$ can be removed so that the simplified model only consists of the encoder $E$ and the set decoder $D_2$. The simplified model only uses the policy gradient method with self-critical training algorithm for training, and the formula is exactly the same as Eq. (12).

**Experiments**

In this section, we introduce the datasets, evaluation metrics, the baseline models as well as our experiment settings.

**Datasets**

**Reuters Corpus Volume I (RCV1-V2):** The RCV1-V2 dataset is provided by [Lewis et al. (2004)](Lewis et al. 2004), which consists of over 500,000 manually categorized newswire stories. There are 103 topics in total and multiple topics can be assigned to each newswire story.

**Arxiv Academic Paper Dataset (AAPD):** This dataset is provided by [Yang et al. (2018)](Yang et al. 2018). The dataset consists of the abstract and corresponding subjects of 55,840 academic papers. The total number of subjects is 54 and each paper can have multiple subjects. The target is to predict subjects of an academic paper according to the content of the abstract.

For both datasets, we filter out samples with more than 500 words, which removes about 0.5% of the samples in each dataset. We divide each dataset into training, validation and test sets. The statistic information of the two datasets is shown in Table 1.

| Dataset      | Vocab Size | Embed Size | LSTM Layer | Hidden Size | $\lambda$ |
|--------------|------------|------------|------------|-------------|-----------|
| RCV1-V2      | 50,000     | 256        | (2, 3)     | (256, 512)  | 0.80      |
| AAPD         | 30,000     | 256        | (2, 2)     | (256, 512)  | 0.95      |

Table 2: Main experimental hyper-parameters. For the LSTM layer and hidden size, we use $(\cdot, \cdot)$ to represent the hyper-parameter of the encoder and decoder, respectively.

**Evaluation Metrics**

Following the previous work [Zhang and Zhou 2007; Yang et al. 2018], we adopt hamming loss and micro-F$_1$ score to evaluate the performance of our models. For reference, the micro-precision as well as micro-recall are also reported.

- **Hamming-loss (Schapire and Singer 1999)** is the fraction of labels that are incorrectly predicted.
- **Micro-F$_1$ (Manning et al. 2008)** is the weighted average of F$_1$ score of each class.

**Baselines**

We compare our methods with the following baselines:

- **Binary Relevance (BR) (Boutell et al. 2004)** amounts to independently training one binary classifier for each label.
- **Classifier Chains (CC) (Read et al. 2011)** transforms the MLTC task into a chain of binary classification problems to model the correlations between labels.
- **Label Powerset (LP) (Tsoumakas and Katakis 2006)** creates one binary classifier for every label combination attested in the training set.
- **CNN (Kim 2014)** uses multiple convolution kernels to extract text feature, which is then inputted to the linear transformation layer followed by a sigmoid function to output the probability distribution over the label space.
- **CNN-RNN (Chen et al. 2017)** presents an ensemble approach of CNN and RNN to capture both the global and the local textual semantics.
- **Seq2Seq (Yang et al. 2018)** applies the sequence-to-sequence model (Bahdanau, Cho, and Bengio 2014) to perform multi-label text classification.

We tune hyper-parameters of all baselines on the validation set based on the micro-F$_1$ score.
Experiment Settings

We implement our experiments in PyTorch on an NVIDIA 1080Ti GPU. The hyper-parameters of the model on two datasets are shown in the Table 2. For both datasets, the batch size is set to 64 and out-of-vocabulary (OOV) words are replaced with unk. The word embedding is randomly initialized and learned from scratch. We use the Adam (Kingma and Ba 2014) optimizer to minimize the objective function. The learning rate is initialized to a value between 0.0001 and 0.0003 and it is halved after every training epoch. Besides, we use the dropout method (Srivastava et al. 2014) to avoid overfitting and clip the gradients (Pascanu, Mikolov, and Bengio 2013) to the maximum norm of 10.

During training, we train the model for a fixed number of epochs and monitor its performance on the validation set after 100 updates. Once the training is finished, we select the model with the best micro-F1 score and learning rate on the validation set and Bengio 2013) to the maximum norm of 10.

Results and Discussion

In this section, we report the results of our experiments on two datasets. For simplicity, we denote our proposed deep reinforced sequence-to-set model as Seq2Set.

Results

The experimental results of our methods and the baselines on the RCV1-V2 dataset are shown in Table 3. Results show that both of our proposed methods outperform all baselines by a large margin and the proposed Seq2Set model achieves the best performance in the main evaluation metrics. For instance, our Seq2Set model achieves a reduction of 18.60% hamming-loss and an improvement of 3.38% micro-F1 score over the most commonly used baseline BR. In addition, it also has a large margin over the traditional Seq2Seq model, which shows that the use of reinforcement learning is of great help to improve the accuracy of classification.

Table 3: Performance on the RCV1-V2 test set. HL, P, R, and F1 denote hamming loss, micro-precision, micro-recall and micro-F1, respectively. The symbol “+” indicates that the higher the value is, the better the model performs. The symbol “-” is the opposite. Seq2Set (simp.) denotes the simplified Seq2Set model.

| Models      | HL(-) | P(+ ) | R(+ ) | F1(+ ) |
|------------|-------|-------|-------|-------|
| BR         | 0.0086| 0.904 | 0.816 | 0.858 |
| CC         | 0.0087| 0.887 | 0.828 | 0.857 |
| LP         | 0.0087| 0.896 | 0.824 | 0.858 |
| CNN        | 0.0089| 0.922 | 0.798 | 0.855 |
| CNN-RNN    | 0.0085| 0.889 | 0.825 | 0.856 |
| Seq2Seq    | 0.0081| 0.889 | 0.848 | 0.868 |
| Seq2Set (simp.) | 0.0073| 0.900 | 0.858 | 0.879 |
| Seq2Set    | 0.0070| 0.890 | 0.884 | 0.887 |

Table 4: Performance on the AAPD test set. Detailed explanations of symbols can be found in Table 2.

| Models      | HL(-) | P(+ ) | R(+ ) | F1(+ ) |
|------------|-------|-------|-------|-------|
| BR         | 0.0316| 0.644 | 0.648 | 0.646 |
| CC         | 0.0306| 0.657 | 0.651 | 0.654 |
| LP         | 0.0312| 0.662 | 0.608 | 0.634 |
| CNN        | 0.0256| 0.849 | 0.545 | 0.664 |
| CNN-RNN    | 0.0278| 0.718 | 0.618 | 0.664 |
| Seq2Seq    | 0.0255| 0.743 | 0.646 | 0.691 |
| Seq2Set (simp.) | 0.0247| 0.739 | 0.674 | 0.705 |
| Seq2Set    | 0.0249| 0.744 | 0.659 | 0.698 |

but also reduce the dependence of the model on the label order and alleviate the wrong penalty, leading the performance much better than the traditional Seq2Seq model.

Exploring the Impact of the Label Order

In order to verify that our models can reduce the dependence on the label order and alleviate the wrong penalty, we explore the impact of label order on model performance in two different cases.

Uncorrelated Labels

In practice, some labels are naturally unordered, for instance, when these labels are uncorrelated. It is not appropriate to use the Seq2Seq model for the MLTC task in this case. To verify that our methods also apply to this case, we rebuilt a new uncorrelated dataset based on the original RCV1-V2 dataset.

First, we build a collection of uncorrelated labels. The maximum correlation coefficient between these labels is 0.28, indicating that these labels are uncorrelated. Then, we pick out the samples whose labels are all from the uncorrelated label set. We use these samples to rebuild a label-uncorrelated dataset. Table 5 shows the performance of various models on the rebuilt dataset.

According to Table 5, there is no significant difference in the performance of the Seq2Seq model and the BR algorithm on the rebuilt dataset, which shows that the advantage of the Seq2Seq model is not significant in this case. The reason is that the Seq2Seq model makes a strict requirement on the label order, while there is not a strict order between labels in this case, leading that any label permutation will be unreasonable. The Seq2Seq model will suffer from serious wrong penalty. However, both of our proposed methods outperform the Seq2Seq model and the BR algorithm by a large margin, which shows that our methods are capable of achieving good performance even in the case where there is not a strict order between labels. Our models are trained using reinforcement learning, and the calculation of reward r satisfies swapping-invariance, leading that they reduce the dependence on the label order. This is the main reason for the robustness and universality of our models.

Shuffled Labels

In many real-world scenarios, even if there is a strict order between the labels, this true label order is unknown. We simulate this situation by shuffling the order of the label sequence, which represents that the true label order is unknown. The performance of various models on the label-shuffled RCV1-V2 dataset is shown in Table 6.

Table 5: Performance on the AAPD test set. Detailed explanations of symbols can be found in Table 2.

| Models      | HL(-) | P(+ ) | R(+ ) | F1(+ ) |
|------------|-------|-------|-------|-------|
| BR         | 0.0316| 0.644 | 0.648 | 0.646 |
| CC         | 0.0306| 0.657 | 0.651 | 0.654 |
| LP         | 0.0312| 0.662 | 0.608 | 0.634 |
| CNN        | 0.0256| 0.849 | 0.545 | 0.664 |
| CNN-RNN    | 0.0278| 0.718 | 0.618 | 0.664 |
| Seq2Seq    | 0.0255| 0.743 | 0.646 | 0.691 |
| Seq2Set (simp.) | 0.0247| 0.739 | 0.674 | 0.705 |
| Seq2Set    | 0.0249| 0.744 | 0.659 | 0.698 |
Comparison between Two Proposed Methods

We can note that there is no clear conclusion as to which of the two proposed models is better. For instance, Table 5 shows that the proposed Seq2Set model performs better. However, the simplified Seq2Set model achieves the better performance in Table 5 and Table 6. The reason is that in the cases of Table 5 and Table 6, the labels of training data appear out of order. We do not use valuable prior knowledge to pre-sort the label sequence. Unordered label sequence can cause the sequence decoder $D_1$ to suffer from the wrong penalty to some extent, resulting in the advantage of the Seq2Set model is not significant. Therefore, it is more suitable to use the simplified Seq2Set model in the case where we do not have enough prior knowledge of the label order.

However, if we can grasp a certain amount of prior knowledge of the label order, the Seq2Set model will perform better, which is the corresponding case in Table 5. In the case of Table 5, we pre-sort the label sequence based on the tree structure of the label set, which is valuable for label prediction. The sequence decoder $D_1$ encourages the generation of label sequences that conform to the human prior knowledge, which assists the model to achieve better performance. Therefore, the Seq2Set model performs better in this case.

Error Analysis

We find that all methods perform poorly when predicting low-frequency (LF) labels. This is reasonable because the samples assigned LF labels are sparse, making it hard for the model to learn an effective pattern to predict these LF labels. In fact, as the label set of the RCV1-V2 dataset shows a long-tail distribution, the empirical method of sorting labels from high-frequency to low-frequency is reasonable. However, the distribution of LF labels is relatively uniform, leading to a sharp decline in the performance of the Seq2Seq model. In contrast, since our proposed Seq2Set model reduces the dependence on the label order, we believe that it is more universal and robust to different label distributions. In order
### Models

| Reference | Case1 | Case2 | Case3 |
|-----------|-------|-------|-------|
|            | CCAT, C15, C151, C18, C181 | MCAT, ECAT, M11, E11 | CCAT, ECAT, E21, GCRIM, E212, C21, C12 |
| BR         | CCAT, C15, C151, C152 | MCAT, ECAT, M11 | CCAT, ECAT, E21, E212 |
| Seq2Seq    | CCAT, C15, C151 | MCAT, E11 | CCAT, ECAT, E21, GCRIM, C21, C12 |
| Seq2Set (simp.) | CCAT, C15, C151, C18, C181 | MCAT, ECAT, M11, E11 | CCAT, ECAT, E21, GCRIM, E212, C21, C12 |
| Seq2Set     | CCAT, C15, C151, C18, C181 | MCAT, ECAT, M11, E11 | CCAT, ECAT, E21, GCRIM, E212, C21, C12 |

Figure 4: Examples of the generated labels. The labels of the same color in each case are the highly correlated labels.

### Multi-Label Text Classification

Multi-label text classification (MLTC) aims to assign multiple labels to each sample in the dataset. Early work on exploring the MLTC task focuses on machine learning algorithms, mainly including problem transformation methods and algorithm adaptation methods. Problem transformation methods, such as BR (Boutell et al. 2004), LP (Tsoumakas and Katakis 2006) and CC (Read et al. 2011), map the MLTC task into multiple single-label learning tasks. Algorithm adaptation methods extend specific learning algorithms to handle multi-label data directly. The corresponding representative work is ML-DT (Clare and King 2001), Rank-SVM (Elisseeff and Weston 2002), ML-KNN (Zhang and Zhou 2007), and so on. In addition, some other methods, such as ensemble methods (Tsoumakas, Katakis, and Vlahavas 2011), joint training methods (Li et al. 2015), etc., are also used for the MLTC task. However, they can only be used to capture the first or second order label correlations, or are computationally intractable when high-order label correlations are considered.

Recent years, some neural network models have also been successfully used for the MLTC task. For instance, the BP-MLL proposed by Zhang and Zhou (2006) applies a fully-connected network and the pairwise ranking loss to perform classification. Nam et al. (2013) further replace the pairwise ranking loss with cross-entropy loss function. Kurata, Xiang, and Zhou (2016) present an initialization method to model label correlations by leveraging neurons. Chen et al. (2017) present an ensemble approach of CNN and RNN so as to capture both global and local semantic information. The two milestones are Nam et al. (2017) and Yang et al. (2018), both of which utilize the Seq2Seq model to capture the label correlations. The former explores the impact of different label permutations on the performance of the model and the latter adds the global embedding to alleviate exposure bias. In parallel to our work, Lin et al. (2018) propose a semantic-unit-based dilated convolution model for the MLTC task and Li et al. (2018) apply a label distributed Seq2Seq model to learn semantic knowledge, which is a specific application of the MLTC task.
Reinforcement Learning

Reinforcement learning (RL) explores how an agent should take actions to interact with the environment so as to maximize cumulative reward. It is a long-standing problem, here we focus on its application in natural language processing. Ranzato et al. [2015] propose to train the Seq2Seq model using policy gradient method for machine translation and Bahdanau et al. [2017] present an approach to training neural networks to generate sequence using the actor-critic method. Rennie et al. [2016] design the self-critical training method on image captioning task to further alleviate the exposure bias. Li et al. [2016] apply deep reinforcement learning to model future reward in chatbot dialogue. SeqGAN (Yu et al. 2017) adapts the generative adversarial networks (Goodfellow et al. 2014) to the task of text generation by treating the procedure of generation as a stochastic policy. Recently, Liu et al. [2018] integrate local and global decision-making using reinforcement learning models to solve Chinese zero pronoun resolution. However, as far as we know, there is no work to directly apply the reinforcement learning algorithm to the MLTC task.

Conclusion

In this paper, we systematically analyze the drawbacks of the current models for the multi-label text classification task. A novel sequence-to-set model based on deep reinforcement learning is proposed to fuse the human prior knowledge rationally and reduce the dependence on the label order. Extensive experimental results show that the proposed method outperforms the competitive baselines by a large margin. Further analysis of experimental results demonstrates that our approach not only captures the correlations between labels, but also is free from the strict restriction of the label order, leading to better robustness and universality.

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