SGM: Sequence Generation Model for Multi-Label Classification

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Outline

1. Introduction to Multi-Label Classification
2. Proposal: Sequence Generation Model
3. Experiments and Analysis
4. Conclusion

Introduction to Multi-Label Classification

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Using Deep Neural Networks to Translate Multi-lingual Threat Intelligence

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3. **Applications:**
   - Text categorization, information retrieval, and so on.

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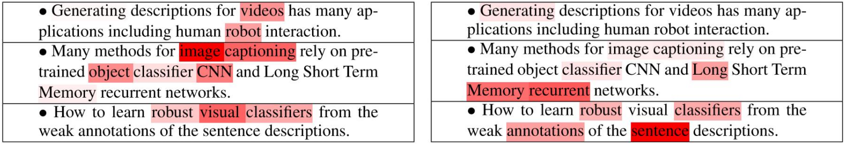
   - **Label correlations:** Some labels are closely correlated.
2. Ignore differences in the contributions of textual content when predicting different labels.



(a) Visual analysis when the SGM model predicts "*CV*".

(b) Visual analysis when the SGM model predicts "*CL*".

Figure 1: Visualization of attention.

Proposal: Sequence Generation Model

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Transform classification task into generation task.

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   - View the text as the source language and the label as target language.
   - Base on sequence-to-sequence model.

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1. **Key ideas:**
   - View the text as the source language and the label as target language.
   - Base on sequence-to-sequence model.
2. **Advantages:**
   - **Capture label correlations:** Generate labels sequentially, and predict the next label based on its previously generated labels.
   - **Consider differences in contributions of textual content:** Apply the attention mechanism.

Proposal: Sequence Generation Model

Difficulties and solutions:

1. **Repeated labels:**
    - Use the masked softmax layer to smooth the probability distribution.

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   - Use the adaptive gate to introduce the global information of previous time-steps.

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1. **Repeated labels:**
   - Use the masked softmax layer to smooth the probability distribution.
2. **Exposure bias:**
   - Use the adaptive gate to introduce the global information of previous time-steps.
3. **Sequence order:**
   - Sort the label sequence of each sample according to the frequency of labels and high-frequency labels are placed in the front.

Proposal: Sequence Generation Model

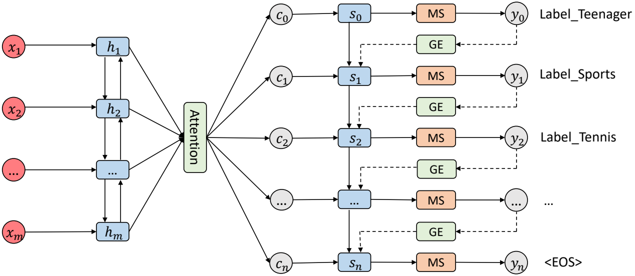

Figure 2: The overview of SGM with global embedding. MS denotes the masked softmax layer. GE denotes the global embedding.

- The proposed model is based on the Seq2Seq model, which consists of an encoder and a decoder with global embedding.

Proposal: Masked Softmax Layer

Masked softmax layer: Prevent the decoder from predicting repeated labels.

1. y_t is the probability distribution over the label space $\mathcal{L}$ at time-step t.

$$y_t = softmax(o_t + I_t) \tag{1}$$

2. $I_t \in \mathbb{R}^L$ is the mask vector.

$$(I_t)_i = \begin{cases} -\infty & \text{if the label } l_i \text{ has been predicted.} \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

Proposal: Global Embedding

Global embedding: Introduce the global information of previous time-steps to alleviate the *exposure bias*.

$$\bar{e} = \sum_{i=1}^{L} y_{t-1}^{(i)} e_i \tag{3}$$

$$g(y_t) = (1 - H) \odot e + H \odot \bar{e} \tag{4}$$

$$H = \boldsymbol{W}_1 e + \boldsymbol{W}_2 \bar{e} \tag{5}$$

1. e is the embedding vector of the label which has the highest probability under distribution y_{t-1}.
2. e_i is the embedding vector of the i-th label.
3. $\boldsymbol{W}_1, \boldsymbol{W}_2 \in \mathbb{R}^{L \times L}$ are weight matrices.

Experiments and Analysis

Datasets and Evaluation Metrics

1. **Datasets:**
   - **RCV1-V2:** Reuters Corpus Volume I.
   - **AAPD:** Arxiv Academic Paper Dataset.
2. **Evaluation metrics:**
   - Hamming loss and micro-F_1 score are our main evaluation metrics.
   - Micro-precision and micro-recall are also reported to assist the analysis.

Results

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
SGM	0.0081	0.887	0.850	0.869
+ GE	**0.0075**	0.897	**0.860**	**0.878**

(a) Performance on RCV1-V2 test set.

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
SGM	0.0251	0.746	0.659	0.699
+ GE	**0.0245**	0.748	**0.675**	**0.710**

(b) Performance on AAPD test set.

Table 1: Comparison between our methods and all baselines on two datasets. GE denotes the global embedding. HL, P, R, and F1 denote hamming loss, micro-precision, micro-recall, and micro-F_1, respectively.

Exploration of Global Embedding

1. **Goal:** Explore how the performance of our model is affected by the proportion between two kinds of embeddings.
2. **Settings:**
   - Adaptive gate:

$$g(y_t) = (1 - H) \odot e + H \odot \bar{e} \tag{6}$$
$$H = \boldsymbol{W}_1 e + \boldsymbol{W}_2 \bar{e} \tag{7}$$

   - Coefficient averaging:

$$g(y_t) = (1 - \lambda) * e + \lambda * \bar{e} \tag{8}$$

Exploration of Global Embedding

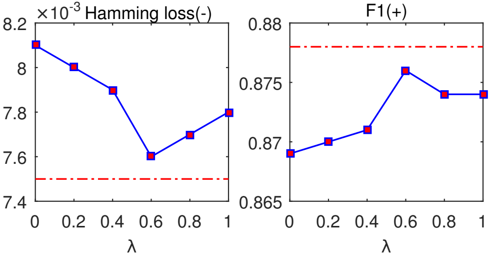

Figure 3: The performance of the SGM when using different λ. The red dotted line represents the results of using the adaptive gate.

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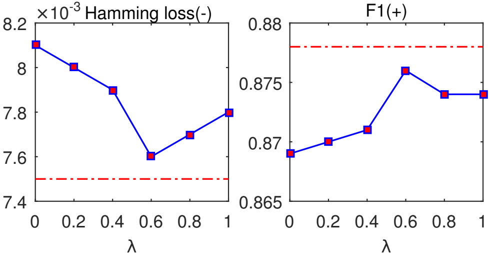

Figure 3: The performance of the SGM when using different λ. The red dotted line represents the results of using the adaptive gate.

1. The weighted average embedding contains richer information, leading to the improvement in the performance of the model.
2. The adaptive gate can automatically determine the most appropriate λ value according to the actual condition.

Ablation Study

Models	HL(-)	F1(+)
SGM	0.0081	0.869
w/o mask	0.0083(↓ 2.47%)	0.866(↓ 0.35%)
w/o sorting	0.0084(↓ 3.70%)	0.858(↓ 1.27%)

(a) Ablation study for SGM.

Models	HL(-)	F1(+)
SGM + GE	0.0075	0.878
w/o mask	0.0078(↓ 4.00%)	0.873(↓ 0.57%)
w/o sorting	0.0083(↓ 10.67%)	0.859(↓ 2.16%)

(b) Ablation study for SGM with GE.

Table 2: Ablation study on the RCV1-V2 test set. GE denotes global embedding. ↓ indicates that the performance of the model is degraded.

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Table 2: Ablation study on the RCV1-V2 test set. GE denotes global embedding. ↓ indicates that the performance of the model is degraded.

1. Sorting is important because humans need to predefine the order of output labels.
2. The mask module has little impact because label cardinality is small.

Error Analysis

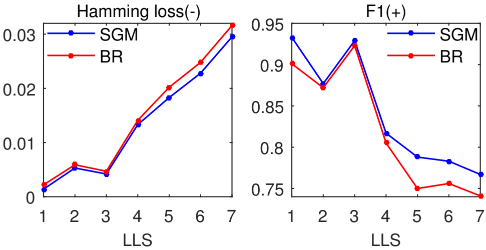

Figure 4: The performance of SGM on different subsets of the RCV1-V2 test set. LLS represents the length of label sequence of each sample in the subset.

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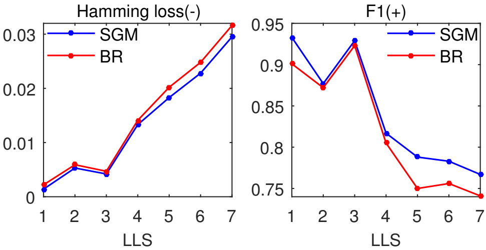

Figure 4: The performance of SGM on different subsets of the RCV1-V2 test set. LLS represents the length of label sequence of each sample in the subset.

1. The performance of all methods deteriorates when LLS increases.
2. The advantages of SGM are more significant when LLS is large.

Visualization of Attention

• Generating descriptions for videos has many applications including human robot interaction.
• Many methods for image captioning rely on pre-trained object classifier CNN and Long Short Term Memory recurrent networks.
• How to learn robust visual classifiers from the weak annotations of the sentence descriptions.

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Figure 5: An example abstract in the AAPD dataset, from which we extract three informative sentences. This abstract is assigned two labels: "*CV*" and "*CL*". They denote computer vision and computational language, respectively.

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- The attention mechanism can select the most informative words automatically when predicting different labels.

Case Study

Reference	BR	SGM	SGM + GE
CCAT, **C15, C152**, C41, C411	CCAT, C15, C13	CCAT, **C15, C152**	CCAT, **C15, C152**, C41, C411
CCAT, GCAT, ECAT, C31, GDIP, C13, C21, **E51, E512**	CCAT, GCAT, GDIP, E51	CCAT, ECAT, GDIP, **E51, E512**	CCAT, GCAT, ECAT, C31, GDIP, **E51, E512**, C312
GCAT, ECAT, **G15, G154, G151, G155**	GCAT, ECAT, GENV, G15	GCAT, ECAT, E21, **G15, G154, G156**	GCAT, ECAT, E21, **G15, G154, G155**

Figure 6: Several examples of generated label sequences on the RCV1-V2 dataset. The red bold labels in each example indicate that they are highly correlated.

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Figure 6: Several examples of generated label sequences on the RCV1-V2 dataset. The red bold labels in each example indicate that they are highly correlated.

1. The proposed SGM can capture the correlations between labels.
2. The SGM with global embedding predicts labels more accurately.

Conclusion

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1. The sequence generation model is able to capture the correlations between labels well.
2. The attention mechanism can select the most informative words automatically when predicting different labels.
3. The global embedding can alleviate *exposure bias* by introducing the global information of previous time-steps.

- If there is any question, please contact Pengcheng Yang (yang_pc@pku.edu.cn)
- The code and datasets are available at https://github.com/lancopku/SGM

Thank you!