Generating Pertinent and Diversified Comments with Topic-aware Pointer-Generator Networks

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Abstract

Comment generation, a new and challenging task in Natural Language Generation (NLG), attracts a lot of attention in recent years. However, comments generated by previous work tend to lack pertinence and diversity. In this paper, we propose a novel generation model based on Topic-aware Pointer-Generator Networks (TPGN), which can utilize the topic information hidden in the articles to guide the generation of pertinent and diversified comments. Firstly, we design a keyword-level and topic-level encoder attention mechanism to capture topic information in the articles. Next, we integrate the topic information into pointer-generator networks to guide comment generation. Experiments on a large scale of comment generation dataset show that our model produces the valuable comments and outperforms competitive baseline models significantly.

1 Introduction

Comments of online articles provide a form of discussion and improve user’s engagement. Automatic generation of article comments has a huge value in online forums and intelligent chatbots, etc (Qin et al., 2018). However, automatic generation of article comments is a new, challenging and not well-studied task in Natural Language Generation (NLG) (Zheng et al., 2018), it needs to understand the meaning of articles and generate multiple valuable comments.

Machine translation models (Xing et al., 2017) such as Sequence-to-sequence (Seq2seq) with attention (Bahdanau et al., 2015; Cho et al., 2015) tend to generate trival samples like “I am speechless” or “I don’t know”. In addition, for comment generation task, the models are hard to converge when we train models on articles with all comments about various topics. To generate pertinent comments, Lin et al. (2019) select the most related comment in an article, then generate one article-comment pair for training model. However, the model discards most of the article-comment pairs and are hard to generate diversified comments.

In this paper, we focus on the generation of pertinent and diversified comments for news articles. Given a news article, we understand topics covered in the article and generate comments toward these topics. The idea is motivated by our observation on comment written by human, people often associate a news article with topics in their mind. For example, when reading a news article about “Chinese Basketball Association”, people may think the core leader “Yao Ming”. Based on this knowledge, they may give a pertinent comment like “we expect the institution reformation by Yao Ming”. We consider simulating the way people write comments with topics and propose a topic-aware network to introduce the topic information as prior knowledge in comment generation. The topic words trained by LDA (Blei et al., 2003) topic model and the keywords extracted by Textrank (Mihalcea and Tarau, 2004) are encoded to the topic information by our proposed encoder attention mechanism. Finally, we leverage the topic information to guide comment generation.

2 Related Work

Comment generation models: the previous work (Qin et al., 2018; Lin et al., 2019) shows that seq2seq model (Sutskever et al., 2014), seq2seq with attention model and pointer-generator model lead to a poor performance, when these models are trained with an article and its corresponding all comments. To improve the performance, Lin et al. (2019) propose a series of methods to select the most related comment in the article and construct one article-comment pair to train a pointer-
generator model. However, the model can only generate a relevant comment for each article.

**Prior NLG models:** there is some work in other fields related to ours. The work (Xing et al., 2017; Wang et al., 2018) utilize topic words embeddings learned by topic models as prior knowledge to form informative responses or summaries respectively. Li et al. (2018) encodes the keywords information based on pointer-generator model to guide summarization generation. In general, our model guided by prior knowledge to produce pertinent and diversified comments.

### 3 Approach

In this section, we firstly introduce a standard pointer-generator network. Then, we summary the topic information by our keyword-level and topic-level encoder attention mechanism. Furthermore, we integrate the topic information into pointer-generator network to guide comment generation. Figure 1 gives the structure of a Topic-aware Pointer-Generator Networks (TPGN) model.

#### 3.1 Pointer-generator network

Pointer-generator network is a Seq2seq-attention model with pointer network (Vinyals et al., 2015). It can both copy words from input by pointer network and generate words from a fixed vocabulary. The tokens of the input article $x_i$ are fed into the encoder one-by-one, and producing a sequence of encoder hidden states $h_i$. At each decoding timestep $t$, the context vector $c_t$ is calculated by the attention mechanism (Bahdanau et al., 2015):

$$e_{ti} = v^T \tanh(W_h h_i + W_s s_t)$$

$$a_t = \text{softmax}(e_t)$$

$$c_t = \sum_{n=1}^{N} a_{ti} h_t$$

where $s_t$ is the decoder hidden state. The generation probability $p_{gen}$ at timestep $t$ is calculated by:

$$p_{gen} = \sigma(W_c c_t + W_s s_t + W_y y_{t-1} + b_{gen})$$

where $\sigma$ is the sigmoid function. The final distribution $P(w)$ to predict the next word is calculated as following:

$$P(w) = p_{gen} P_{v}(w) + (1 - p_{gen}) \sum_{i:w_i = w} a_{ti}$$

#### 3.2 Keyword-level and Topic-level encoder attention

**Keyword-level encoder attention:** we extract keywords from each article text by TextRank. The keywords for each article are fed into the BiLSTM one-by-one, then we get final hidden status $h_{n}$ as the keyword presentation $k_{kw}$. We use the keyword presentation $k_{kw}$ to align the article by the attention mechanism (Equation 1, 2, 3), then generate the relevant context information $C_{k_{kw}}$.

**Topic-level encoder attention:** inspired by (Xing et al., 2017), we obtain topic embeddings
by LDA topic model and use the collapsed Gibbs sampling algorithm (Heinrich, 2005) to estimate the parameters of the model on a dataset. After that, we select the top \( n \) noun words with the highest probabilities of each topic as topic words. We calculate the embedding of each topic word by:

\[
p(z|w) \propto \frac{C_{wz}}{\sum_{w'} C_{w'z}}
\]

where \( C_{wz} \) is the number of times that \( w \) is assigned to topic \( z \). After getting the embeddings of topic words, we use a multi-layer perceptron (MLP) to obtain the core topic presentation \( k_t \) for each article. From that, we convert the topic words for each article to the core topic presentation in current semantic space. Similarly, we use \( k_t \) to align the article, then generate the relevant context information \( C_{k_t} \). Finally, we concat \( k_{kw}, C_{k_{kw}}, k_t \) and \( C_{k_t} \) as the joint topic information \( k_j \).

\[
k_j = [k_{kw}, C_{k_{kw}}, k_t, C_{k_t}]
\]

### 3.3 Guiding comment generation

**Decoder attention**: we use the joint topic information \( k_j \) as extra input to decoder attention, changing equation (1) to:

\[
e_{ti} = v^T \tanh(W_w h_t + W_s s_t + W_k k_j)
\]

then we use the new \( e_{ti} \) to obtain new attention distribution \( a_t \) and new context vector \( c_t \).

**Pointer mechanism**: due to the limitation of the vocabulary size, some keywords may not appear in the vocabulary, which can significantly lack the information of them in the topic information. Therefore we should encode topic information to pointer network which can copy out-of-vocabulary keywords. Similar to (Li et al., 2018), we use the joint topic information \( k_j \), the context vector \( c_t \) and the decoder hidden state \( s_t \) as inputs to calculate \( p_{gen} \), changing equation (4) to:

\[
p_{gen} = \sigma(W_e^T c_t + W_s^T s_t + W_j^T k_j + b_{gen})
\]

### 4 Evaluation

#### 4.1 Dataset and evaluation metrics

We obtain a large-scale Chinese article commenting dataset (Qin et al., 2018) which has 174886 articles with four million users comments, and each article has a title, text body and metadata. The dataset is split into training/validation/test sets which contains 169023/1400/4463 samples respectively. For the evaluation of models, we use the same metrics (Lin et al., 2019), and get the script from Coco Caption (Chen et al., 2015).

#### 4.2 Evaluation models

We consider four different baselines and three variations of our propose approach. *Seq2Seq-Attn*: the Seq2Seq model with attention, we train the model with each article and its all comments; *pointer-generator + coverage*: the pointer-generator network (See et al., 2017), we construct training pairs like Seq2Seq-Attn; *pointer-generator + coverage + ES*: in this model (Lin et al., 2019), each article only corresponds to a comment selected by the ensemble score; *KIGN*: a guide network (Li et al., 2018) is the simplified version of our approach; *Keyword-level TPGN*: our approach which employs only the keyword-level encoder attention; *Topic-level TPGN*: our approach which employs only the topic-level encoder attention; *TPGN*: our approach which employs both the keyword-level and the topic-level encoder attentions.

#### 4.3 Experimental setting

For all experiments, we use two 256-dimensional LSTMs for the encoder and one 256-dimensional LSTM for the decoder. We use a word embedding with a size of 128 with a vocabulary size of 9k. We train models by using Adagrad (Duchi et al., 2011) with learning rate 0.1 and an initial accumulator value of 0.1. For KIGN model and our approach, we extract keywords from each article by TextRank. Comments in the article can be matched by the combinations of different keywords. Then, we obtain a series of triple (article, keywords, matched comment) for each article. If can’t find a matched comment for the article, we randomly choose a comment under this article. We use a LDA model to achieve the embeddings of topic words, and the number of topics \( T \) is set to 100. For each topic, we select the top 500 words as topic words. If can’t find corresponding topic words for the article, we obtain the uniform distribution on the dimension of the number of topics.

#### 4.4 Results and analysis

For each article, our models can produce multiple comments according to different keywords\(^1\). In predict stage, we select keywords by Textrank from every sentence in the article.
| Model                        | TOP-N | ROUGE-L | BLEU-1 | CIDEr | METEOR |
|-----------------------------|-------|---------|--------|-------|--------|
| Seq2Seq-Attn                | N=1   | 32.07   | 60.65  | 5.21  | 12.98  |
| pointer-generator + coverage| N=1   | 33.47   | 63.97  | 5.57  | 13.21  |
| pointer-generator + coverage + ES | N=1 | 35.77   | 66.01  | 4.69  | 15.21  |
| KIGN                        | N=1   | 40.74   | 72.21  | 11.88 | 17.98  |
|                            | N=3   | 37.78   | 66.96  | 9.93  | 16.52  |
|                            | N=5   | 36.67   | 64.91  | 9.18  | 15.98  |
| Keyword-level TPGN          | N=1   | 41.45   | 73.25  | 13.17 | 18.56  |
|                            | N=3   | 37.97   | 66.63  | 10.30 | 16.82  |
|                            | N=5   | 36.43   | 63.65  | 9.18  | 16.09  |
| Topic-level TPGN            | N=1   | 42.01   | 75.10  | 13.39 | 18.61  |
|                            | N=3   | 38.08   | 67.41  | 10.13 | 16.56  |
|                            | N=5   | 36.01   | 63.48  | 8.61  | 15.52  |
| TPGN                        | N=1   | 45.16   | 81.47  | 16.64 | 20.73  |
|                            | N=3   | 40.88   | 74.01  | 12.98 | 18.39  |
|                            | N=5   | 38.34   | 69.48  | 10.87 | 17.05  |

Table 1: Results on generation models. Higher scores are better.

| Model                        | Keywords and Topic words | Generated Comment |
|-----------------------------|--------------------------|------------------|
| pointer-generator + coverage| -                        | 我也是醉了..... （I am speechless.....） |
| pointer-generator + coverage + ES | -               | 刘亦菲最帅...... （Liu Yifei is the most handsome.....） |
| KIGN                        | Yang Yang, Liu Yifei     | 我觉得刘亦菲演的很好看。 （I think Liu Yifei is good at acting.） |
|                             | (Luo Jin, Costume)      | 罗晋最帅！！！！！！ （Luo Jin is the most handsome.....） |
| TPGN                        | Yang Yang, Liu Yifei     | 刘亦菲杨洋版本本来就不错。 （The movie version of Liu Yifei and Yang Yang are supposed to be really good.） |
|                             | (Luo Jin, Costume)      | 玄女好看，我喜欢罗晋的服装搭配。 （Xuan Nv is beautiful, I like the costume of Luo Jin.） |

Table 2: The generated comments from different generation models (bold denotes Topic words).

so we also calculate top N highest scores. Table 1 shows that KIGN model achieves the best scores in baselines, the models of our approach all outscore the best baseline model while N in (1, 3, 5). In average, KIGN, Keyword-level TPGN, Topic-level TPGN and TPGN model respectively generate 2.9, 5.1, 4.8 and 6.2 different comments for each article after removing duplicates. It means that almost comments generated by our models are used to calculate evaluation scores. In addition, TPGN model achieves the best performance while N equals 1, and exceeds KIGN model by (+4.4 ROUGE-L, +9.2 BLEU-1, +4.8 CIDEr, +2.8 METEOR). Table 2 compares our model with three baselines using an example. We find that pointer-generator + coverage model generates a trivial comment such as “I am speechless”. Pointer-generator + coverage + ES model captures the key information of the article, but produces a repetitive and uninteresting comment. KIGN model generates two useful comments according to the different combinations of keywords. Moreover, our TPGN model, which associates with the topic information, generates more pertinent and diversified comments.

5 Conclusion

In this work, we propose a topic-aware generation model for comment generation. Firstly, we design an encoder attention mechanism to capture the topic information in the articles. Then, we leverage the topic information to guide comment
generation. Experiments show that our model produces the pertinent and diversified comments and achieves the state-of-the-art performance.

References

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2015. Neural machine translation by jointly learning to align and translate. In 3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings.

David M. Blei, Andrew Y. Ng, and Michael I. Jordan. 2003. Latent dirichlet allocation. Journal of Machine Learning Research, 3:993–1022.

Xinlei Chen, Hao Fang, Tsung-Yi Lin, Ramakrishna Vedantam, Saurabh Gupta, Piotr Dollár, and C. Lawrence Zitnick. 2015. Microsoft COCO captions: Data collection and evaluation server. CoRR, abs/1504.00325.

Kyunghyun Cho, Aaron C. Courville, and Yoshua Bengio. 2015. Describing multimedia content using attention-based encoder-decoder networks. IEEE Trans. Multimedia, 17(11):1875–1886.

Gregor Heinrich. 2005. Parameter estimation for text analysis. Technical report, Technical report.

Chenliang Li, Weiran Xu, Si Li, and Sheng Gao. 2018. Guiding generation for abstractive text summarization based on key information guide network. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT, New Orleans, Louisiana, USA, June 1-6, 2018, Volume 2 (Short Papers), pages 55–60.

Zhaojiang Lin, Genta Indra Winata, and Pascale Fung. 2019. Learning comment generation by leveraging user-generated data. In ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 7225–7229. IEEE.

Rada Mihalcea and Paul Tarau. 2004. Textrank: Bringing order into text. In Proceedings of the 2004 Conference on Empirical Methods in Natural Language Processing, EMNLP 2004, A meeting of SIGDAT, a Special Interest Group of the ACL, held in conjunction with ACL 2004, 25-26 July 2004, Barcelona, Spain, pages 404–411.

Lianhui Qin, Lemao Liu, Wei Bi, Yan Wang, Xiaojiang Liu, Zhiting Hu, Hai Zhao, and Shuming Shi. 2018. Automatic article commenting: the task and dataset. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics, ACL 2018, Melbourne, Australia, July 15-20, 2018, Volume 2: Short Papers, pages 151–156.

Abigail See, Peter J. Liu, and Christopher D. Manning. 2017. Get to the point: Summarization with pointer-generator networks. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, ACL 2017, Vancouver, Canada, July 30 - August 4, Volume 1: Long Papers, pages 1073–1083.

Ilya Sutskever, Oriol Vinyals, and Quoc V. Le. 2014. Sequence to sequence learning with neural networks. In Advances in Neural Information Processing Systems 27: Annual Conference on Neural Information Processing Systems 2014, December 8-13 2014, Montreal, Quebec, Canada, pages 3104–3112.

Oriol Vinyals, Meire Fortunato, and Navdeep Jaitly. 2015. Pointer networks. In Advances in Neural Information Processing Systems 28: Annual Conference on Neural Information Processing Systems 2015, December 7-12, 2015, Montreal, Quebec, Canada, pages 2692–2700.

Li Wang, Junlin Yao, Yunzhe Tao, Li Zhong, Wei Liu, and Qiang Du. 2018. A reinforced topic-aware convolutional sequence-to-sequence model for abstractive text summarization. In Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence, IJCAI 2018, July 13-19, 2018, Stockholm, Sweden., pages 4453–4460.

Chen Xing, Wei Wu, Yu Wu, Jie Liu, Yalou Huang, Ming Zhou, and Wei-Ying Ma. 2017. Topic aware neural response generation. In Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence, February 4-9, 2017, San Francisco, California, USA., pages 3351–3357.

Haitao Zheng, Wei Wang, Wang Chen, and Arun Kumar Sangaiah. 2018. Automatic generation of news comments based on gated attention neural networks. IEEE Access, 6:702–710.