Dependency Structure for News Document Summarization

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Abstract. In this work, we develop a neural network based model which leverages dependency parsing to capture cross-positional dependencies and grammatical structures. With the help of linguistic signals, sentence-level relations can be correctly captured, thus improving news documents summarization performance. Empirical studies demonstrate that this simple but effective method outperforms existing works on the benchmark dataset. Extensive analyses examine different settings and configurations of the proposed model which provide a good reference to the community.

Keywords: News summarization · Deep learning · Abstractive summarization.

1 Introduction

Multi-document summarization (MDS) is a critical task in natural language processing (NLP) aiming at generating a brief summary from a set of content-related documents. MDS enjoys a wide range of real-world applications, including the summarization of news, scientific publications, emails, product reviews, medical documents and software project activities [14]. There are two main types of summary generation: extractive summarization and abstractive summarization. Extractive summarization selects salient sentences from the original texts to form the summaries. In abstractive summarization, machine generates summaries from its understanding of the contents and it is more similar to human-written summaries. This characteristic makes abstractive summarization a challenging task. With the development of deep learning techniques, neural network-based models are widely applied in abstractive multi-document summarization [5,13,10]. These techniques enable better performances of the MDS models and significantly prosper the research of Multi-document summarization. The neural network-based models have strong fitting capabilities. One recent architecture Transformer [19] shows strong performances in various natural language processing tasks and is also adopted in multi-document summarization [5]. Transformer has natural advantages for parallelization and could retain long-range relations among tokens. However, similar to other neural network models, existing Transformer-based MDS models neglect linguistic knowledge in the sentences that may affect the summary qualities greatly.

In the family of linguistic information, dependency parsing is one of the most important knowledge. It retains the syntactic relations between words to form a dependency tree and offers discriminate syntactic paths on arbitrary sentences for information
propagation through the tree [17]. Inspired by the success of dependency parsing applied in variety NLP tasks, we introduce a generic framework to combine dependency parsing with the Transformer architecture to better capture the dependency relations and grammatical structures for abstractive summary generation. Our work is one of the first few to simultaneously leverage linguistic information and Transformer-based models for multi-document summarization. More specifically, the dependency information is processed to linguistic-guided attention. Later on, it is further merged with multi-head attention for better feature representation. With the assist of the linguistic signals, sentence-level relations can be correctly captured. The experimental results on the benchmark dataset indicate the proposed approach brings improvements over several strong baselines. The contributions of this work are summarized as follows:

- We propose a simple yet effective linguistic-guided attention mechanism to incorporate dependency relations into Transformer’s multi-head attention. The proposed linguistic-guided attention can be deployed seamlessly to multiple mainstream Transformer-based MDS models to improve their performances.
- We evaluate and compare the proposed model with several baseline models and multiple competitive MDS models. The results demonstrate that the models equipped with the linguistic-guided attention receive superior performances over the comparing models.
- We provide extensive analysis on various settings and configurations of the two versions of the proposed model ParsingSum. These results could help understand the intuitiveness of the proposed model and could serve as an informative reference to the multi-document summarization research community.

2 Related Work

Abstractive multi-document summarization task gains increasing attention in recent years. Compared to single document summarization, multi-document summarization requires the model to generate summaries from multiple documents in a more comprehensive manner. However, abstractive summarization have met fewer successes due to the lack of sufficient datasets, non-trivial effort to extend sequence-to-sequence structure from single document summarization to multi-document summarization [13,10] and lack of approach to address cross-document relations. Liu et al. [12] constructed a large-scale multi-document summarization dataset and adopted Transformer model to multi-document summarization. The selected top-K tokens are fed into a decoder-only sequence transduction to generate the Wikipedia articles. Based on this work, Yang et al. [13] proposed a hierarchical Transformer (HT) architecture that contains token-level and paragraph-level Transformer layers to capture cross-document relationships. Inspired by HT, Li et al. [10] incorporated graph representation into encoding and decoding layers to capture rich relations among documents and lead the summary generation process. Jin et al. [7] proposed a Transformer-based multi-granularity interaction network to unify the extractive and abstractive multi-document summarization. However, these Transformer-based models do not take consider dependency relations in the source documents into account.
3 Linguistic-guided Multi-document Summarization

In this work, we propose a linguistic-guided approach that leverage dependency parsing for abstractive multi-document summarization. We first overview the proposed model in Section 3.1. Then we focus on the detailed steps to form dependency information matrices in Section 3.2 and how to incorporate this linguistic information into the attention mechanism in Section 3.3.

3.1 Model Overview

**Problem Definition.** Given a set of documents \( D = (d_1, d_2, ..., d_p) \), where \( p \) is the number of documents, multi-document summarization is to generate the correct summary \( Sum \) distilling knowledge from the document set. In our linguistic-guided model, we further define that for any sentence \( s_{ij} \) of a document \( d_j \), an external dependency parser generate a tree \( T_{ij} \). Our task can be defined as \( D + T \rightarrow Sum \) that is to find a way to combine the knowledge delivered by the tree for better summary generation.

Figure 1 presents the framework of our proposed model, named ParsingSum. The model follows an encoder-decoder architecture. Our proposed model is generic and...
flexible to be hanged in different Transformer structures. Inside the model, the encoder is a representation learner to learn distinctive feature representations from the source documents and decoder is able to decipher representations into language domain for summary generation. More concretely, the document sets are first fed into the an Transformer-based encoder for feature representation. At the same time, the documents are passed into an external dependency parser to fetch the dependency relations. In the encoder, these relations will be processed into a linguistic-guided attention mechanism to further fuse with multi-head attention later on. With the assist of the linguistic information, the model is able to grasp the linguistic relations of the input documents to guide the summary generation. In this paper, we focus on how to integrate parsing information into the model for better representation learning in the encoder. Followed by ashish et al. [19], we build a similar decoder.

3.2 Dependency Information Matrix

Dependency parsing is a family of grammar formalisms playing an important role in contemporary speech and language processing. It is appropriate to adopt it to deal with languages that are morphological-rich with unrestrained ordering of words. Given a sentence, dependency parsing extracts a dependency tree that represents its grammatical structure and defines the relations between head words and dependent words. This information could be utilized to guide the summarization.

We generate the dependency tree using an existing dependency parser [3] for each input sentence and obtain a set of dependency trees. These trees contain dependency relations between any pair of dependent words in the given sentences. We record the trees into a matrix by $T_{ij}$. Let $P$ denotes the dependency information matrix for the given input sentences $s_{ij}$, where $P_{ij}$ indicates the dependency weights between word $i$ and word $j$. We simplify the weights definition as shown in Eq.(1).

$$P_{ij} = \begin{cases} 
1 & \text{dependency relation exists} \\
0 & \text{no dependency relation}
\end{cases}$$

In the process of constructing dependency information matrix, our proposed method ignores the direction of head word and dependent word. For other pairs, as long as there is a dependency relation between two words, the dependency information matrix is assigned a value of 1, otherwise it will be set to 0. We hope to keep all dependency relations between the pair words in a simple yet effective manner.

3.3 Linguistic-Guided Encoding Layer

In order to process source documents effectively and preserve salient source relations in the summaries, we propose a novel linguistic-guided attention (LGA) mechanism that can extend the Transformer architecture [19] in the encoding process. Figure 2 depicts this mechanism on a exemplary sentence from Multi-News [5] dataset. LGA can joint the dependency parsing information and the source documents to generate semantic rich features in a complementary way. The linguistic-guided attention mechanism can be viewed as learning a graph representation for the sentences from the input documents.
The issues are vexing and complex.

Token Transfer

Self-Attention

Fig. 2. The Linguistic-Guided Attention Mechanism. The given exemplary sentence The issues are vexing and complex. is from Multi-News dataset [5]. Different properties of vocabularies and relations between words are included in the parsing information. At the same time of generating self-attention, the sentence is feed into an external parser to fetch the dependency tree. Later on, the dependency tree are processed into a dependency information matrix P. Then, it is merged into the original multi-head attention.

We model the dependencies across source documents with linguistic-guided attention. For the input token $x_i \in s(i = 1, 2, \ldots, l)$ and attention head $\text{head}_j \in \text{Head}(j = 1, 2, \ldots, z)$. We have:

$$q_{i, \text{head}_j} = W^{q, \text{head}_j} \cdot x_i$$

$$k_{i, \text{head}_j} = W^{k, \text{head}_j} \cdot x_i$$

$$v_{i, \text{head}_j} = W^{v, \text{head}_j} \cdot x_i$$

(2)

where $W^{q, \text{head}_j}, W^{k, \text{head}_j}, W^{v, \text{head}_j} \in \mathbb{R}^{n \times m}$ are weight matrices, $q_{i, \text{head}_j}, k_{i, \text{head}_j}, v_{i, \text{head}_j} \in \mathbb{R}^{n \times i}$ are sub-query, sub-key and sub-values in different head. We than concatenate these sub-query, sub-key and sub-values respectively.

$$q_i = \text{concat}(q_{i, \text{head}_1}, q_{i, \text{head}_2}, \ldots, q_{i, \text{head}_z})$$

$$k_i = \text{concat}(k_{i, \text{head}_1}, k_{i, \text{head}_2}, \ldots, k_{i, \text{head}_z})$$

$$v_i = \text{concat}(v_{i, \text{head}_1}, v_{i, \text{head}_2}, \ldots, v_{i, \text{head}_z})$$

(3)

where $q_i, k_i, v_i \in \mathbb{R}^{z \times i}$ are corresponding key, query and value for later attention calculation. The linguistic-guided attention merge the semantic dependency information $P$ with multi-head attention.

$$LG\text{Att}_{ij} = (\alpha P_{ij} + \mathbb{I}) \odot \text{att}_{ij}$$

(4)

$$\text{att}_{ij} = \text{softmax} \left( \frac{q_i \cdot k_j}{\sqrt{\text{head}}} \right)$$

(5)

$$\text{Context}_i = \sum_j LG\text{Att}_{ij} \cdot v_j$$

(6)
where \( \alpha \) is a trade-off hyper-parameter to balance the linguistic-guide information and multi-head attention map, \( \mathbb{I} \in \mathbb{R}^{z \times z} \) is an identity matrix, \( d_{\text{head}} \) is the dimension of heads, \( \odot \) is element-wise Hadamard product, \( \text{Context}_i \in \mathbb{R}^{z \times n} \) representation the context vectors generated by linguistic-guide attention. Later on, two layer-normalization operations are applied to \( \text{Context}_i \):

\[
\hat{x}_i = \text{LayerNorm} \left( k_i + \text{FFN} \left( k_i \right) \right) \quad (7)
\]

\[
k_i = \text{LayerNorm} \left( x_i + \text{Context}_i \right) \quad (8)
\]

\( \hat{x}_i \) denotes the output of next encoding layers, where FFN is a two-layer feed-forward network with ReLU as activation functions. Then, the learner feature representations are passed to the decoder layers for summary generation. As the components of the decoder are similar to Flat Transformer structure [19], we focus on the construction of linguistic-guided attention in encoding layers.

4 Experiments

In this section, we report the effectiveness of the proposed Linguistic-guided attention. We first introduce the experimental settings and then overall model performances are presented. We further provide extensive analysis on how to select a suitable fusion weights in linguistic-guided attention, as well as the influence of batch size. Later on, discussion on different fusion methods and its visualization are conducted.

4.1 Datasets

Multi-News [5] is a large-scale dataset containing various topics in news articles for multi-document summarization. It includes 56,216 article-summary pairs and it is further scattered with the ratio 8:1:1 for training, validation and test respectively. Each document set contains 2 to 10 articles with a total length of 2103.49 words. The golden summaries length is 263.66 on average.

4.2 Evaluation Metric

We evaluate the proposed model and compared its performances with multiple state-of-the-art models using ROUGE scores [11]. Unigram and bigram overlap (ROUGE-1 and ROUGE-2 scores) are adopted to indicate the literal quality of generated summaries. Besides, the longest common subsequence measuring of ROUGE (ROUGE-L) enables us to measure the similarity of the two text sequences in the sentence-level and the fluency of generated summaries. ROUGE F1 scores (denoted as ROUGE-F) are considered in our work.
4.3 Models for Comparison

We compared ParsingSum with the following models: LexRank computes the importance of a sentence based on the concept of eigenvector centrality in a sentence graph [4]. TextRank is a graph-based ranking model [13]. Maximal Marginal Relevance (MMR) algorithm [2] considers the importance and redundancy of a sentence in a complementary way to decide whether to add the sentence to the summary. BRNN is a bidirectional RNN based model for summarization task. Flat Transformer (FT) is a Transformer-based encoder-decoder model on a flat sequence. Hi-MAP [5] is an end-to-end model that incorporates MMR into a pointer-generator network. Hierarchical Transformer (HT) [13] is an abstractive summarizer that can capture cross-document relationships via hierarchical Transformer encoder and flat Transformer decoder.

4.4 Experimental Settings and Hyper-parameters

We equipped the proposed linguistic-guided attention model with both Hierarchical Transformer (HT) and Flat Transformer (FT) leading to two versions of the proposed model: ParsingSum-HT and ParsingSum-FT. For ParsingSum-HT, we followed the implementation of the Hierarchical Transformer model by using six local Transformer layers and two global Transformer layers with eight heads. For ParsingSum-FT, we followed Flat Transformer model settings and adopt four encoder layers and four decoder layers. Before training, we pre-processed the data by lowercase all English characters, and surround each target sentence with a delimiter. We also trunk 400 tokens of target documents and trunk 24 blocks of source documents in order to fit the models. For training, we set batch sizes as 13,000 and use Adam optimizer ($\beta_1=0.9$ and $\beta_2=0.998$). The dropout rates of both encoder and decoder are set to 0.1. The trade-off hyper-parameter $\alpha$ is 1. The initial learning rate is set to $1 \times 10^{-3}$. The first 8000 steps are trained for warming up and the models are trained with a multi-step learning rate reduction strategy.

4.5 Overall Performance

We evaluated the proposed model ParsingSum with two versions and compared its performances with different MDS models. For fair comparison, we reran all the comparing models on the same device with the same configuration settings. As shown in the table, we perceived the ParsingSum-HT model receives higher ROUGE scores (across all ROUGE-1, ROUGE-2 and ROUGE-L scores) steadily compared to the original HT model. The Linguistic-Guided Attention helps the model raise 0.45 on ROUGE-1 score and 0.24 on ROUGE-2 score, respectively. Similar phenomenon shows on the ParsingSum-FT model. More specifically, ParsingSum-FT surpasses FT model 1.34 on ROUGE-1 score, 0.87 on ROUGE-2 score and 0.66 on ROUGE-L score.

It is worth to note that the proposed ParsingSum-FT is able to outperform its baseline (i.e., FT model) by a large margin and also receives the highest ROUGE-L score.

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1 The default training steps for FT is 50,000 [3]. We only run 20,000 step and achieve promising results on FT and ParsingSum-FT. The performance would be better if continue training.

2 In this case, our results may be different with what the models’ papers reported.
Table 1. Models Comparison in ROUGE-F. For each part, ROUGE-1, ROUGE-2 and ROUGE-L scores are examined. The best result for each column are in bold.

| Models          | ROUGE-F          |
|-----------------|------------------|
|                 | 1    | 2    | L    |
| LexRank         | 37.92| 13.10| 16.86|
| TextRank        | 39.02| 14.54| 18.33|
| MMR             | 33.20| 9.89 | 16.41|
| BRNN            | 38.36| 13.55| 19.33|
| FT              | 42.98| 14.48| 20.06|
| Hi-MAP          | 42.98| 14.85| 20.36|
| HT              | 36.89| 12.76| 20.37|
| ParsingSum-HT (Ours) | 37.34| 13.00| 20.42|
| ParsingSum-FT (Ours) | **44.32** | **15.35** | **20.72** |

Table 2. The Analysis of Fusion Weights of Linguistic-guided attention on HT and FT based model. The results are shown in ROUGE-1, ROUGE-2 and ROUGE-L scores of ROUGE-F. The best result for each column within a section are bolded.

| Models          | ROUGE-F          |
|-----------------|------------------|
|                 | 1    | 2    | L    |
| HT              | 36.09| 12.64| 20.10|
| ParsingSum-HT (α=1) | 36.77| 12.93| 20.35|
| ParsingSum-HT (α=2) | 36.27| 12.27| 19.93|
| ParsingSum-HT (α=3) | **37.34** | **13.00** | **20.42** |
| FT              | 42.98| 14.48| 20.06|
| ParsingSum-FT (α=1) | 44.03| 15.00| 20.21|
| ParsingSum-FT (α=2) | **44.32** | **15.23** | **20.72** |
| ParsingSum-FT (α=3) | 44.02| 15.20| 20.31|

The Analysis of the Fusion Weights in Linguistic-guided Attention  In ParsingSum, the trade-off factor $\alpha$ controls the intensity of attention from linguistic perspective and the multi-head attention. To analyze its importance and influence, we conducted experiments by setting $\alpha$ to 0, 1, 2 and 3 ($\alpha$ = 0 denotes the naive Transformer model without linguistic-guided attention) on the two versions of ParsingSum. The results are shown in Table 2 where the ROUGE-1, ROUGE-2 and ROUGE-L scores are reported. Noted that the results show that the ParsingSum model performs differently with different $\alpha$. Generally, there is an increasing trend with the increment of $\alpha$. This rising trend further prove assigning a relative larger $\alpha$ in a suitable range is able to improve the performance of summarization models. ParsingSum-HT achieves the best result when $\alpha$ =3, and ParsingSum-HT achieves the best performance when when $\alpha$ =2.
The Analysis of Batch Size  The batch size is considered to affect the training and testing process of a deep learning model, thus further affects the model’s performance. To validate this empirically, we adjusted the batch size of HT model and ParsingSum-HT to a smaller batch size 4,500 (the large batch size is 13,000) and tested them with different trade-off factor $\alpha$. The results are shown in Figure 3. As shown, smaller batch size reduces the model performance on all the evaluation metrics. Interestingly, in the small batch size setting, the ROUGE scores are steadily increasing with $\alpha$ changes from 1 to 3; while trained with large batch size, the increasing trend are retained but the ROUGE scores are jittering when $\alpha$ equals to two. It indicates different batch sizes have different sensitivities towards the change of $\alpha$.

4.6 Analysis

Analysis of the Fusion Methods for Parsing information  How to integrate the parsing information into the Transformer-based model is an important task at the beginning of the work. In addition to the fusion method introduced in Section 3.3, we attempted several other fusion methods under small batch size setting of the ParsingSum-HT model.

Direct fusion. In this method, denoted as ParsingSum-HT (P0.25), we weighted the dependency parsing matrix and added it directly to multi-head attention:

$$LGA_{ij} = 0.25P_{ij} + att_{ij}$$  \hspace{1cm} (9)$$

Gaussian-based fusion. We adopted the idea from [10] and applied Gaussian weights to the product of the dependency information matrix and the multi-head attention. In this experiment, the Gaussian weights are set to 0.25 and 8 and denoted as ParsingSum-HT (G0.25) and ParsingSum-HT (G8) respectively:

$$LGA_{ij} = \frac{(1 - att_{ij}P_{ij})^2}{0.25} + att_{ij}$$  \hspace{1cm} (10)$$

$$LGA_{ij} = \frac{(1 - att_{ij}P_{ij})^2}{8} + att_{ij}$$  \hspace{1cm} (11)$$

Table 3 presents the performances of the mentioned fusion methods. We see our method ParsingSum-HT with $\alpha=3$ receives the best results for ROUGE-1, ROUGE-2
and ROUGE-L scores. The potential reason is through direct weighted (including Gaussian weighted) sum of dependency parsing matrix and multi-head attention, the scale of the original multi-head attention has been lost, which leading to pose the dependency parsing matrix in a dominate position. In this case, the normal gradient back propagation process has been disturbed. This experiment indicates that a direct summation of the weighed dependency parsing matrix and multi-head attention may damage the original attention. Thus, a “soft” fusion (when $\alpha$ is adopted as mentioned in Section 3.3) of these two attentions can achieve the best results.

### Table 3. Performance of ParsingSum-HT via Different Fusion Methods.

| Models                  | ROUGE-F   |
|-------------------------|-----------|
|                         | 1  | 2  | L  |
| ParsingSum-HT (P0.25)   | 19.50 | 3.40 | 12.59 |
| ParsingSum-HT (G0.25)   | 16.84 | 1.92 | 11.36 |
| ParsingSum-HT (G8)      | 20.18 | 3.55 | 13.00 |
| ParsingSum-HT ($\alpha=3$) | 36.30 | 12.39 | 20.04 |

![Fig. 4. Attention Maps. (a) HT model; (b) Heatmap of dependency parsing matrix; (c) ParsingSum-HT ($\alpha=1$); (d) ParsingSum-HT ($\alpha=2$); (e) ParsingSum-HT (P0.25); (f) ParsingSum-HT (G0.25).](image)

We further visualized the attention maps for different fusion methods as shown in Figure 4. Figure 4(a) represents the heatmap of multi-head attention within HT model and Figure 4(b) shows the heatmap of our dependency parsing matrix. Figure 4(c) to 4(f) illustrate the attention maps of different fusion methods. More specifically, subfigure (c) and (d) are the “soft” augmentation of multi-head attention with the linguistic-guided
knowledge; subfigure (e) and (f) are the “hard” combination of multi-head attention with dependency matrices.

5 Conclusion

In this paper, we explored the importance of dependency parsing in news document summarization and propose a generic framework to leverage dependency relations among documents for abstractive summarization performance improvement. The experiments show that the proposed model outperforms several strong baselines. It confirms that utilizing dependency relations of the source documents is beneficial to guide the final summaries generation. We also conduct the sensitivity test for choosing the best parsing weights and batch size. Analysis of different ways to incorporate parsing information is further performed to indicate that a “soft” method can receive the best results compared to direct weighted sum of dependency parsing matrix and multi-head attention.

References

1. Bahdanau, D., Cho, K., Bengio, Y.: Neural Machine Translation by Jointly Learning to Align and Translate. In: Proceedings of the 3rd International Conference on Learning Representations (ICLR 2015). San Diego, USA (2015)
2. Carbonell, J.G., Goldstein, J.: The Use of MMR, Diversity-Based Reranking for Reordering Documents and Producing Summaries. In: Proceedings of the 21st Annual International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR 1998). pp. 335–336. Melbourne, Australia (1998)
3. Dozat, T., Manning, C.D.: Deep Biaffine Attention for Neural Dependency Parsing. In: Proceedings of the 5th International Conference on Learning Representations, (ICLR 2017). Toulon, France (2017)
4. Erkan, G., Radev, D.R.: LexRank: Graph-based Lexical Centrality as Salience in Text Summarization. Journal of Artificial Intelligence Research 22, 457–479 (2004)
5. Fabbri, A.R., Li, I., She, T., Li, S., Radev, D.R.: Multi-News: A Large-Scale Multi-Document Summarization Dataset and Abstractive Hierarchical Model. In: Proceedings of the 57th Conference of the Association for Computational Linguistics (ACL 2019). pp. 1074–1084. Florence, Italy (2019)
6. Fernandes, P., Allamanis, M., Brockschmidt, M.: Structured Neural Summarization. In: Proceedings of the 7th International Conference on Learning Representations (ICLR 2019). New Orleans, USA (2019)
7. Jin, H., Wang, T., Wan, X.: Multi-Granularity Interaction Network for Extractive and Abstractive Multi-Document Summarization. In: Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics (ACL 2020). pp. 6244–6254. Online (2020)
8. Jin, H., Wang, T., Wan, X.: Semsum: Semantic dependency guided neural abstractive summarization. In: Proceedings of the Thirty-Fourth AAAI Conference on Artificial Intelligence (AAAI 2020). pp. 8026–8033. New York, USA (2020)
9. Leite, D.S., Rino, L.H., Pardo, T.A., Nunes, M.d.G.V.: Extractive Automatic Summarization: Does more linguistic knowledge make a difference? In: Proceedings of the Second Workshop on TextGraphs: Graph-based Algorithms for Natural Language Processing. pp. 17–24 (2007)
10. Li, W., Xiao, X., Liu, J., Wu, H., Wang, H., Du, J.: Leveraging Graph to Improve Abstractive Multi-Document Summarization. In: Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics (ACL 2020). pp. 6232–6243. Online (2020)
11. Lin, C.Y.: Rouge: A Package for Automatic Evaluation of Summaries. In: Text Summarization Branches Out. pp. 74–81 (2004)
12. Liu, P.J., Saleh, M., Pot, E., Goodrich, B., Sepassi, R., Kaiser, L., Shazeer, N.: Generating wikipedia by summarizing long sequences. In: 6th International Conference on Learning Representations, ICLR 2018, Vancouver, BC, Canada, April 30 - May 3, 2018, Conference Track Proceedings (2018)
13. Liu, Y., Lapata, M.: Hierarchical Transformers for Multi-Document Summarization. In: Proceedings of the 57th Conference of the Association for Computational Linguistics, (ACL 2019). pp. 5070–5081. Florence, Italy (2019)
14. Ma, C., Zhang, W.E., Guo, M., Wang, H., Sheng, Q.Z.: Multi-document Summarization via Deep Learning Techniques: A Survey. arXiv preprint arXiv:2011.04843 (2020)
15. Mihalcea, R., Tarau, P.: TextRank: Bringing Order into Text. In: Proceedings of the 2004 Conference on Empirical Methods in Natural Language Processing (EMNLP 2004). pp. 404–411. Barcelona, Spain (2004)
16. Song, K., Lebanoff, L., Guo, Q., Qiu, X., Xue, X., Li, C., Yu, D., Liu, F.: Joint Parsing and Generation for Abstractive Summarization. In: Proceedings of the Thirty-Fourth AAAI Conference on Artificial Intelligence (AAAI 2020), pp. 8894–8901. New York, USA (2020)
17. Sun, K., Zhang, R., Mensah, S., Mao, Y., Liu, X.: Aspect-Level Sentiment Analysis Via Convolution over Dependency Tree. In: Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP 2019), pp. 5678–5687. Hong Kong, China (2019)
18. Takase, S., Suzuki, J., Okazaki, N., Hirao, T., Nagata, M.: Neural Headline Generation on Abstract Meaning Representation. In: Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing (EMNLP 2016). pp. 1054–1059. Austin, USA (2016)
19. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, L., Polosukhin, I.: Attention is All you Need. In: Proceedings of the Annual Conference on Neural Information Processing Systems 2017 (NIPS 2017). pp. 5998–6008. Long Beach, USA (2017)