A Comprehensive Attempt to Research Statement Generation

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Abstract

For a researcher, writing a good research statement is crucial but costs a lot of time and effort. To help researchers, in this paper, we propose the research statement generation (RSG) task which aims to summarize one’s research achievements and help prepare a formal research statement. For this task, we conduct a comprehensive attempt including corpus construction, method design, and performance evaluation. First, we construct an RSG dataset with 62 research statements and the corresponding 1,203 publications. Due to the limitation of our resources, we propose a practical RSG method which identifies a researcher’s research directions by topic modeling and clustering techniques and extracts salient sentences by a neural text summarizer. Finally, experiments show that our method outperforms all the baselines with better content coverage and coherence.

1 Introduction

A research statement is a summary of research achievements and a proposal for future research. A research statement can assist in a job application and position promotion for an applicant. However, writing a research statement is tricky and requires much effort and time to collect evidence and summarize achievements from a lot of academic papers. Thus, we propose the task of automatic research statement generation (RSG), which aims to aid a researcher in preparing a formal research statement. In this paper, we mainly focus on automatically summarizing one’s achievements, which constitutes the main content of a research statement, according to his/her publications.

Here, the RSG task takes multiple academic papers as the input and a brief overview of one’s achievements as the output, which is similar to the multi-document summarization (MDS) task. Different from the general-purpose MDS, which is usually oriented with one event and conducted on the news datasets (Yasunaga et al., 2017; Gupta and Siddiqui, 2012), the RSG task focuses on multiple research directions and summarizes their content. Figure 1 shows a part of a real research statement and three papers. From this figure, we can see that Paper A and Paper B belong to the direction of topic segmentation and Paper C belongs to the direction of deep learning. The corresponding research statement describes the work in the two directions which have involved the three papers. At the same time, it is difficult for the RSG task to collect a sizeable corpus for model supervision as only a few senior researchers would like to release their research statements. Thus, in such a low-resource scenario of RSG, two key problems are faced with: (1) How to well represent papers and group them into different research directions; (2) How to get some salient sentences and organize them with better coherence for describing each research direction.

According to the analysis above, in this paper, we propose a practical RSG method which exploits unsupervised techniques to determine a researcher’s main research directions and then summarizes his/her achievements for each direction with the help of external resources. Specifically, to well represent the papers, we adopt the unsupervised neural topic model to explore the latent topic representations of text. Based on the topic representation, we cluster the papers into several directions using the affinity propagation (AP) clustering method, because this method does not require to predefine the number of clusters. To identify one’s achievements, we adopt the BERT-based method BERTSUM trained on an external scientific summarization corpus to pick out the sentences which are essential to expressing one’s achievements in all directions. Finally, we reorder the selected sentences
based on their topic representations to promote the coherence of the generated statement.

We also crawled and compiled a dataset of 62 statements with the corresponding 1,203 publications for the RSG task. With this corpus, we evaluate our proposed benchmark method. Our main contributions are summarized as follows:

- We first propose the research statement generation task which can help an applicant prepare his/her formal research statement.
- We design a benchmark method which can automatically determine one’s main research directions and summarize one’s achievements for each direction.
- We build a small dataset of RSG which is helpful to the research in the field.

2 RSG Task Definition and Dataset

2.1 Task Definition

In this work, we define the RSG task as generating a research statement according to a set of papers. Formally, for a researcher \( A \) with a paper set containing \( n_A \) papers \( P_A = \{p_1, p_2, p_3, \ldots, p_{n_A}\} \), the RSG task aims to output the statement \( R_A \). Then, RSG can be formalized as the function \( R_A = f(P_A) \). To the best of our knowledge, we are the first to formally propose the RSG task.

2.2 Dataset Construction

As the first attempt at RSG, we collect and compile a dataset mainly for evaluation. It is difficult to construct such a corpus because only a small number of researchers post their research statements online, and their published papers scatter in different conferences and journals some of which may be inaccessible. We have collected 110 research statements written by different researchers using search engines. In these statements, some of them are not suitable for our task; for example, the master students’ statements for Ph.D. applications only contain a small number of publications and mainly focus on future plans. After we remove all the informal or unqualified statements manually, only 62 research statements are kept and belong to different research fields of computer science, including Natural Language Processing (NLP), Information Security, etc. We use a Java library Cermine (Tkaczyk et al., 2015) to convert the PDF files into the XML format for getting high-quality texts. Next, based on the content of each statement, we use a crawler to automatically search for the corresponding papers which appear in the reference list of each statement and download them.

Our final RSG dataset contains 62 research statements written by 62 distinct researchers with their corresponding 1,203 publications. On average, each statement is composed of 89.4 sentences or 1,967 words. To add an explanatory note, the scale of our corpus is not large, but is comparable to that of some multi-document summarization (MDS) datasets such as DUC or TAC MDS corpus each of which is not up to 50 topics with the average of 25 documents per topic (Hoa, 2006; Dang...
Table 1: Information coverage of different sections over research statements

and Owczarzak, 2008, 2009), whose small scale is mainly caused by costly manual summarization of multiple documents. In addition, compared to previous MDS task with much shorter reference summary (a maximum of 250 words), RSG requires to output a longer overview and is more challenging.

3 Analysis of Research Statements

We analyze the content coverage of each research statement over its corresponding paper set. Through this analysis, we explore the upper bound of extractive methods and provide more inspiration for further research.

As we know, the content of a research statement is not necessarily covered by the corresponding research papers. In many statements, researchers may summarize their contributions using new words which are different from those in the papers. Noticing the possible lack of information that exists in the research papers, we are curious about the effectiveness of using the extractive method.

Here we concatenate certain parts of papers as a forged research statement similar to (Verma and Lee, 2017) and use ROUGE Recall to evaluate information coverage over the ground-truth statement. We also define the metric of Sentence Ratio which calculates the ratio between the sentence numbers of the forged statement and the ground truth. High ROUGE scores with a low Sentence Ratio is the ideal result. Usually, we seek a balance between the ROUGE and Sentence Ratio. From the results in Table 5, we can see that the combination of full papers (fullpaper) nearly covers all the unigrams and bi-grams of the statements but the Sentence Ratio is very high. Meanwhile, All the abstract plus introduction sections (Abs+Intro) contain about 80% of the unigrams on average, and the Sentence Ratio is about 1:9.38. Compared to Abs+Intro, it is more difficult to use full paper (with Sentence Ratio of 1:75) as the source text for sentence selection. Combining all the abstracts (Abs) only covers less than a half of the unigrams in the statement and cannot provide enough information for further summarization. Thus, Abs+Intro can be seen as a balance to serve as the source text for RSG. It is also noted that Abs+Intro performs poorly with respect to ROUGE-2, meaning that many ground-truth sentences do not directly come from these two parts. This conforms to our statistics: 15.2% of ground-truth sentences come from the abstracts, 25.3% from the Introduction sections and 59.5% from other sections. This means only using the content of Abstract and Introduction as source text also limits the upper bound of our extractive method. How to make full use of other sections will a future focus.

4 Our RSG Method

The overall architecture of our RSG method is shown in Figure 2. First, we adopt the neural topic model (NTM) to represent text based on which we cluster papers into different research directions, and select and order the sentences which can summarize the achievements.

4.1 Topic Representation of Text

A research statement is concisely organized by research directions each of which is composed of papers involving similar fine-grained topics. For example, papers in the direction of text generation may involve the topics like seq2seq methods or abstractive summarization. With such idea, we explore topic modeling methods and adopt the variational autoencoder based neural topic model (NTM) (Miao et al., 2017) to discover latent topics which are derived from word co-occurrence. Compared to previous Bayesian topic models such as LDA (Blei et al., 2003), NTM does not rely on much expertise involvement such as predefining many prior hyper-parameters, but provides parameter-estimable distributions which permit training by backpropagation.

We predefine $K$ fine-grained latent topics and represent each document as a distribution over the
two different documents by their topical distributions. Formally, for two documents \(d_1\) and \(d_2\), with their corresponding topic representations \(\theta_1\) and \(\theta_2\), we define their topical similarity as:

\[
T_{\text{sim}}(d_1, d_2) = \theta_1^T \theta_2
\]

In this way, papers with similar topic distribution tend to belong to the same research direction.

### 4.3 Sentence Extraction and Statement Generation

Here, we adopt the state-of-the-art summarization method to extract important sentences and reorder them according to their research directions to compose of the final research statement. Specifically, we use the state-of-the-art extractive summarization method BERTSUM (Liu, 2019) which applies BERT (Devlin et al., 2018) to encode each sentence and calculate its salience score. Since such neural network-based summarization models are data-hungry and need thousands of documents and their summaries for training, direct training with our RSG dataset suffers from severe data sparsity problem. Thus, it is important to obtain a large summarization dataset, which is composed of scientific publications, for training. Fortunately, Collins et al. (2017) have recently released a dataset CSPubSum for scientific summarization, which is created by exploiting the existing resource ScienceDirect\(^2\). Then, we use CSPubSum to train BERTSUM with the cross-entropy loss.

To extract important sentences which can reflect a researcher’s main contributions, we regard the set of published papers as one whole document and segment it into sentences. Then, we apply the trained BERTSUM model to rank the salience of each sentence. With the salience scores, we apply the Maximum Marginal Relevance (MMR) method (Carbonell and Goldstein, 1998) to reduce redundancy while maintaining to include the most salient sentences into the statement.

After sentence selection, we organize the selected sentences into different research directions as illustrated in Algorithm 1. Here, we restore the sentence to its original paper and utilize the research direction of the paper as the research direction of the sentence. To reorder the sentences in each research direction, first, we gather sentences from the same paper and sort them by their appearing orders in the paper. Second, we randomly

\(^2\)www.sciencedirect.com
We do not adopt the alternative method because our preliminary experiments showed that the clustering error may be propagated to the final statement. At last, we compose all the ordered sentence sequences of all research directions into the final statement.

It is noted that we adopt the summarization technique in sentence extraction and then order the extracted sentences according to their research directions which are determined by document clustering method. An alternative method is to first extract important sentences and then cluster them. We do not adopt the alternative method because research directions should be determined by the content of papers, but not by sentences. Another alternative method is to extract important sentences for each direction respectively. This method is not adopted because our preliminary experiments show that the clustering error may be propagated to the extraction step and degrade the whole performance. Overall, our method is a practical solution to the RSG task at the limitation of our resources.

5 Experiments

5.1 Experiment Setup

For the neural topic model, we select a vocabulary list of 2,000 most frequent words after removing the stop words. We set the latent topic number to 100 and use Adam optimizer for training. For sentence extraction, we fine-tune BERTSUM on ‘bert-base-uncased’. Using the crawler script for getting the CSPubSum corpus (Collins et al., 2017), we get 8,953 scientific publications for train-

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Algorithm 1: Sentence reordering for a cluster

Data: Input Cluster-Paper set C = (P_1, P_2, ...);
Paper-sentence set P_i = (s_{i,1}, s_{i,2} ...)

Result: Ordered sentence set R

1. def Coherence(P_m, P_n)
2. return T_cos( P_m[-1], P_n[1] );
3. Sort sentences in every P_i by their orders in original document;
4. Randomly select m*n_set P_m in C;
5. Add all sentences in P_m to R;
6. Del P_m, in C;
7. while C not empty do
8. Find P_k ∈ C maximize Coherence(P_m, P_k);
9. Add sentences in P_k to R;
10. P_m = P_k;
11. Del P_k from C;
```

select one paper and sort its sentences as the first ones in this direction, as we think that a statement can start from summarizing any one paper. Next, we order the papers in this direction by greedily choosing the paper which has the maximum topical similarity with the last ordered paper. If one paper is ordered at an earlier position, its selected sentences will also appear at the earlier positions in the statement. At last, we compose all the ordered sentence sequences of all research directions into the final statement.

5.2 Automatic Evaluation Metric

For a fair comparison, we set the length limit of the generated statement to 500 words as Sun et al. (2019) suggested that it is unfair to use ROUGE-F to evaluate summaries with different lengths. The metrics below are used to automatically compare our method with the baselines.

**ROUGE.** We follow the evaluation way of long text generation (Liu et al., 2018) and only apply ROUGE-L (Lin, 2004) to measure the informativeness of the generated statements.

**BERT-S.** We use BERTScore⁴ (Zhang et al., 2019) to evaluate semantic similarity of the generated statements with their references. XLNet (Yang et al., 2019) based BERTScore⁵ is applied here.

**Entity Recall (ER).** We design a new metric ER to measure the overlap percentage of scientific terms that appear both in the reference and generated statements. As a good generated statement should share more common scientific terms with the reference. To extract scientific terms, we use the NER model Scibert⁶ (Beltagy et al., 2019), which is pretrained on scientific corpus and tuned on the NER dataset SciERC (Luan et al., 2018).

We use the AP method to determine the research directions. To evaluate its performance, we adopt the Davies-Bouldin Index (DBI): a commonly used clustering evaluation metric. A lower DBI value means that the model can better separate the clusters. That is, the papers being clustered into the same research direction are more similar and different directions are well separated.

![Table 2: Statistics of RSG Data](image)

| Evaluation | Paper/#/statement avg | max | min | statement Len. avg | max | min |
|------------|------------------------|-----|-----|---------------------|-----|-----|
|            |                      |     |     |                     |     |     |
| Train      | 17.4                  | 66  | 6   | 1912                | 6141| 120 |
| Test       | 21.4                  | 127 | 5   | 2023                | 5731| 536 |

³BERTSUM achieves outstanding performance as 0.47, 0.24 and 0.43 in ROUGE-1,2,L respectively on the CSPubSum test set of 149 publications after trained for approximately 30 minutes on a single NVIDIA 1080Ti

⁴https://github.com/Tiiiger/bert_score

⁵The default BERT based BERTScore has the restriction of 512 words for the input length.

⁶https://github.com/allenai/scibert
Table 3: Automatic Evaluation of Methods

| Model       | ROUGE-L | BERT-S | ER  |
|-------------|---------|--------|-----|
| ORACLE      | 52.67   | 72.17  | 15.4|
| Random      | 24.12   | 57.98  | 2.26|
| Multi-Lead  | 25.20   | 60.01  | 3.92|
| TextRank    | 25.39   | 60.12  | 3.47|
| LexRank     | 25.72   | 59.31  | 3.34|
| SUMO        | 25.32   | 59.61  | 4.15|
| Ours\textsuperscript{−MMR} | 27.67   | 60.74  | 4.81|
| Ours        | 27.74   | 60.77  | 4.96|

Table 4: Comparison of clustering methods with the DBI metric

| AP         | DBI    |
|------------|--------|
| AP(tf-idf) | 1.0905 |
| AP(BERT)   | 1.1452 |
| K-Means(K=2) | 0.4325 |
| K-Means(K=3) | 0.4927 |
| K-Means(K=4) | 0.4867 |
| K-Means(K=5) | 0.5892 |

5.3 Human Evaluation Metric

Since it is difficult to automatically evaluate text organization and language quality, we also manually measure the generated statements. Here we choose two metrics of content coverage and text coherence. Content coverage (CC) measures whether the research statement describes all the research directions discussed in the reference statement by providing concise and informative sentences. Text coherence (TC) mainly evaluates whether the research statement is well-organized in different directions and whether the text describing each research direction is coherent. Three volunteers with academic background in computer science score the statements from 1 to 10 for each metric. The higher the score, the better the statement is.

5.4 Method Analysis

To evaluate our RSG method, we test each module by comparing with some representative baselines.

Summarizer Module

We first evaluate the summarizing module. Ours is our adopted summarizer which is trained on CSPubSum. textit{ORACLE} greedily selects the sentences that are most similar to the ground-truth statements, and can be seen as the upper bound of an extractive method for RSG. The Random method randomly selects some sentences from the papers as the statement. Multi-Lead picks out the lead sentences from each paper’s abstract and combines them into a research statement. TextRank (Mihailea and Tarau, 2004) and LexRank (Erkan and Radev, 2004) are two unsupervised extractive summarization methods which are based on sentence similarity and graph-based ranking algorithms.

SUMO is a recent supervised extractive summarization model, which induces a sentence-level tree structure for one document and predicts the root node as the summary based on the Transformer architecture (Liu et al., 2019). We also train SUMO on CSPubSum.

Table 3 shows the results of all methods with respect to ROUGE-L, BERT-S and ER. As we expect, Random performs the worst among all the methods. Especially, its low ER value implies its negligence of extracting important scientific terms. Unlike Lead-3 which extracts the first 3 sentences and achieves a good performance on news summarization, the performance of Multi-Lead on RSG is mediocre, though much better than Random. This implies that abstracts contain more useful information than the other parts of papers, but the first sentences from abstracts usually talk about some general background and may cause redundancy when summarizing papers with similar topics.

We also observe that the supervised model SUMO performs almost on a par with the two unsupervised methods TextRank and LexRank with regard to ROUGE-L and BERT-S, but better on the ER metric. We infer that SUMO may benefit from supervision of CSPubSum which can help to capture more scientific terms, while TextRank and LexRank score sentences based on sentence similarity which do not distinguish between scientific and non-scientific terms. Our method unsurprisingly performs better than SUMO, showing the power of BERT in text representation. From the bottom block of Table 3, we can also find that MMR can improve the overall performance by penalizing redundancy.

Through model comparison, we can see that our method is an acceptable and practical solution to the RSG task, though its overall performance is still far from ORACLE and can be further improved.

Clustering Module

We also perform extra evaluations on our clustering module. As the AP clustering method automati-
cally determine the number of research directions for each researcher, we show the statistics of research directions as in Figure 3. We can see that the researcher with more papers tends to be involved in more research directions and most researchers have less than 6 directions. We use the DBI metric to compare the performance of some typical clustering methods to verify the effectiveness of choosing AP clustering with topical similarity (AP). AP(tf-idf) and AP(BERT) uses tf-idf and BERT (without fine-tuning) representations for similarity computation respectively. K-Means methods with different K values are also used for comparison. From Table 4, we can find that K-Means tends to keep the cluster number between 2 and 4, which is consistent with the clustering results by AP. AP with topical similarity achieves the best performance, indicating that it is effective to automatically determine the cluster number and topical representation is suitable to similarity measurement in our task.

Further, we conduct human evaluation to measure the effects of the clustering and reordering modules. The results are shown in Table 5. A strong baseline is named Abs-Comb which combines all the corresponding abstracts into a research statement. For the fairness of comparison, we use our model to extract sentences until we have the same number of sentences as Abs-Comb. w/o reordering only removes the sentence reordering process which orders sentences from different papers and +w/o clustering further removes the clustering module. Concerning the metric of content coverage (CC), all the models perform nearly the same. Abs-Comb can cover a little more content than our method while sacrificing text coherence(TC). For example, similar sentences may appear several times in the results of Abs-Comb. We can also see that text coherence has dropped considerably from 5.92 to 4.92 without reordering. Without clustering, the performance continues to decline from 6.08 to 5.92 in CC and from 4.92 to 4.50 in TC, meaning that clustering is helpful to organizing the sentences. It is interesting that +w/o clustering does not reduce the selected sentences but makes a worse impression in content coverage compared to the results with clustering.

### 5.5 Case Study

We illustrate two intuitive examples to show the performance of our RSG method. Figure 4 displays a part of the system generated statement as well as the corresponding human statement. The human statement contains three sentences summarized from three papers with two contributions which are highlighted by different colors. We can observe that our model has selected three sentences which can cover the contributions included in the human statement. That is, our extractive method can well pick out the researchers’ contributions from the papers. Meanwhile, our method is limited to losing some content generalized by the researchers (e.g., the first sentence in the human statement).

Figure 5 shows an example of two sentence sequences before and after text reordering which in-
volves the research direction of PCA. The first sentence $s_{-1}$, which is the last sentence of the paper $P_1$, describes the disadvantages of convex techniques. Without reordering, this sentence is randomly succeeded by the first sentence of paper $P_2$ which discusses application in convex techniques given the topical similarity of the two sentences is 0.17. After reordering, $[P_1, s_{-1}]$ is right before the first sentence of paper $P_3$ which talks about a method that the author proposed to solve the disadvantages of convex techniques. This example shows that text reordering based on topical similarity can well improve the text coherence.

6 Related Work

Research statement generation is closely related to MDS techniques and should also care for the characteristics of scientific publications.

6.1 Multi-Document Summarization

MDS is pioneered by the work of (McKeown and Radev, 1999) and other early notable work includes (McKeown et al., 1999; Radev et al., 2004). For a long time, the mainstream MDS methods have been extraction based ones (Wan et al., 2007; Cao et al., 2015; Peyrard and Eckle-Kohler, 2017) which produce a summary by directly selecting a number of important sentences from multiple input documents. Usually, these models are composed of the two steps of sentence scoring and sentence ordering which are based on various kinds of machine learning techniques. Redundancy is one of the major problems in MDS and a well-known method for this problem is Maximal Marginal Relevance (Carbonell and Goldstein, 1998) and also recent DPP based methods (Kulesza and Taskar, 2011; Cho et al., 2019). With the development of sequence-to-sequence neural networks, some studies have attempted abstractive methods on MDS (Zhang et al., 2018; Lebanoff et al., 2018) and a large news dataset Multi-News (Fabbri et al., 2019) has been proposed. New MDS tasks like generating Wikipedia pages (Liu et al., 2018; Liu and Lapata, 2019; Li et al., 2020) and unsupervised abstractive MDS (Chu and Liu, 2018; Bražinskas et al., 2019) also attract much attention.

6.2 Scientific Summarization

There are two types of summarization tasks for scientific publications: article abstract generation and citation-based summarization (Cohan and Goharian, 2017). Article abstract generation aims to generate a summary for the article which may be better than the original abstract (Elkiss et al., 2008). Recently, some large dataset like CSPubSum (Collins et al., 2017), PubMed and arxiv (Cohan et al., 2018) for scientific publication summarization have build scientific publication summarization. The citation-based summarization method aims to summarize the content of a set of citations to a referenced article (Qazvinian and Radev, 2008; Qazvinian et al., 2013). How to make use of citation to supplement the statement will be our future consideration.

7 Conclusion and Future Work

In this paper, we propose the research statement generation (RSG) task which aims to summarize one’s research achievements and help prepare a formal research statement. For the RSG task, we propose a feasible method which uses topic modeling and AP clustering method to determine research directions and BERT-based summarization method to extract salient sentences. Our method is a first attempt on the RSG task and expects to inspire more efficient methods for reducing the efforts of writing a research statement.

In future work, we will conduct further research in two aspects. First, we will explore abstractive methods to further improve RSG performance. Second, we will introduce more evidence about a researcher’s contributions such as personal information and citations.
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A Example Appendix
This is an appendix.