Towards Abstractive Multi-Document Summarization Using Submodular Function-Based Framework, Sentence Compression and Merging

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Abstract

We propose a submodular function-based summarization system which integrates three important measures namely importance, coverage, and non-redundancy to detect the important sentences for the summary. We design monotone and submodular functions which allow us to apply an efficient and scalable greedy algorithm to obtain informative and well-covered summaries. In addition, we integrate two abstraction-based methods namely sentence compression and merging for generating an abstractive sentence set. We design our summarization models for both generic and query-focused summarization. Experimental results on DUC-2004 and DUC-2007 datasets show that our generic and query-focused summarizers have outperformed the state-of-the-art summarization systems in terms of ROUGE-1 and ROUGE-2 recall and F-measure.

1 Introduction

Existing multi-document summarization techniques mainly fall into two categories: extractive and abstractive. Extractive approach selects important source sentences to cover the overall concepts of the document set (Erkan and Radev, 2004; Lin and Bilmes, 2010; Boudin et al., 2015; Parveen and Strube, 2015; Parveen et al., 2015; Cheng and Lapata, 2016; Nallapati et al., 2017). This method is very popular because of its simplicity and speed. But it mostly generates less condensed summaries with redundant information. On the other hand, abstractive summarization is a way of natural language generation and using this approach, it is possible to produce human-like summaries (Rush et al., 2015; Chopra et al., 2016; Wang and Ling, 2016). It requires deep language understanding. Though this technique is complex and less popular than the extractive approach, it is possible to produce more informative and fluent summary. For generating abstractive summaries, researchers often try to modify the candidate sentences by either shortening and compressing it (Knight and Marcu, 2000; Berg-Kirkpatrick et al., 2011; Filippova et al., 2015) or by merging several sentences which is called sentence fusion (Barzilay and McKeown, 2005; Cheung and Penn, 2014; Bing et al., 2015).

In this paper, we divide the whole task of summarization in two main phases: document shrinking and summarization. In the first phase, we apply sentence compression and merging to produce concise and new candidate sentences for the summary. In the second phase, we represent summarization as a submodular function maximization problem under budgeted constraints. While generating summaries, our system considers three important measures namely importance, coverage, and non-redundancy to ensure summary quality. We design three submodular functions for each these measures. The importance property of the summary considers how much relevant information present in a summary. The coverage measure ranks the sentences based on the fact of how representative they are of the document cluster. The third objective function is designed for measuring non-redundancy of the summaries. This metric assigns a score to a sentence based on how many distinct concepts it contains and how dissimilar it is with the other summary sentences. We design the summarization model for both generic and query-focused summarization. Finally, a modified greedy algorithm is applied which obtains near optimal summaries guaranteed to be within \((1 - 1/\sqrt{e})\) of the optimal solution.
2 Related Work

Most of the research on document summarization are extractive which principally based on two important objectives, namely maximizing the relevance and minimizing the redundancy (Carbonell and Goldstein, 1998; Erkan and Radev, 2004). Besides, formulation of summarization as a maximum coverage problem with knapsack constraint (MCKP) (Takamura and Okumura, 2009; Morita et al., 2011) have been used. Recently, summarization has also been considered as a submodular function maximization (Lin and Bilmes, 2010, 2011; Dasgupta et al., 2013) where greedy algorithms were adopted to achieve near optimal summaries. However, the main drawback of all the extractive approaches is that they can not avoid the inclusion of insignificant information which degrades the summary quality.

On the other hand, the abstractive approach in a multi-document setting aims at generating summaries by deeply understanding the contents of the document set and rewriting the most relevant information in natural language. Two recent abstractive techniques are most commonly used to accomplish the task: sentence compression (Knight and Marcu, 2000) and sentence fusion (Barzilay and McKeown, 2005). In the recent years, sentence compression is jointly used with the extractive system to improve summary quality (Berg-Kirkpatrick et al., 2011; Martins and Smith, 2009). In addition, sentence fusion-based models have also been proposed where sentence fragments from multiple sentences are combined to cover more information in a concise manner (Barzilay and McKeown, 2005; Filippova et al., 2015; Ganesan et al., 2010; Thadani and McKeown, 2013; Cheung and Penn, 2014; Bing et al., 2015).

3 Document Shrinking

In this phase, we used sentence compression and sentence merging to prepare a better and more concise document set before approaching the actual summarization task.

3.1 Sentence Compression

Sentence compression is a technique of shortening sentences which can be used with the extractive system to improve summary quality. Consider the following example sentence as a candidate sentence of the summary:

“According to a newspaper report, a total of 4,299 political opponents died or disappeared during Pinochet’s term.”

In this sentence, we can see the part shown in the italic font is not carrying much significance and can be removed. We removed these sort of insignificant sub-parts of sentences following Berg-Kirkpatrick et al., (2011)’s compression technique.

In addition, we removed the sub-clauses related to the reporting verbs from sentences following (Chali and Uddin, 2016), like in the following example sentence:

Cambodian parties agreed to a Coalition government led by Hun Sen, the official said.

We considered mostly used reporting verbs such as said, told, reported, and announced to find out subclause. It is known that the sentence which contains a reporting verb is always the ‘root’ of the dependency tree. Following this rule, we traversed the tree to find out the subclause related to the reporting verb and removed it from the sentence.

3.2 Sentence Merging

Sentence merging is a technique to create a more informative sentence by merging the information from different source sentences. According to Bing et al., (2015), human summary writers usually merge the important facts in different verb phrases (VPs) about the same entity into a single sentence. Based on this assumption, we design a sentence merging technique. While Bing et al., (2015), took phrases as the basic linguistic unit and merge phrases to produce a summary, we take sentences as the basic linguistic units and merge them to generate new sentences for the summary. For example, the following sentences: (1) Cambodian prime minister Hun Sen has ruled through violence, (2) Hun Sen threatened to eliminate opponents can be merged as (3) Hun Sen has ruled through violence and threatened to eliminate opponents. For merging two sentences, we identify the sentences which start with a coreferent subject in order to preserve the grammaticality of the newly generated sentence, which is a key challenge in abstractive summarization.

Our system first applies Stanford Coreference Resolution engine (Lee et al., 2013) on each sentence of a document. From this step, we obtain a set of clusters containing the noun phrases that refer to the same entity in a document. A new sen-
sentence is generated from two sentences if they share a coreferent NP as the subject but have different VPs. We picked the sentences closest to each other for merging and produced the new sentences. The natural order of the sentences has thus been preserved.

After this phase, we obtain a cluster of documents containing concise sentences. Now, this document set is the input of our document summarization phase.

4 Document Summarization

We consider text summarization as a budgeted submodular function maximization problem similar to the recent works of (Lin and Bilmes, 2011), but our proposed monotone submodular objective function is significantly different from their work, which is discussed in this section.

4.1 Problem Definition

Suppose $U$ be the finite set of all textual-units (sentence) in the documents. Our task of summarization is to select a subset $S \subseteq U$ that maximizes the submodular function. Since there is a length constraint in standard summarization tasks (e.g., DUC evaluations), we consider the problem as a submodular function maximization with budgeted constraints:

$$\max_{S \subseteq U} \left\{ f(S) : \sum_{i \in S} \text{cost}_i \leq B_{\text{max}} \right\} \quad (1)$$

where, $\text{cost}_i$ is the non-negative cost of selecting the textual-unit $i$ and $B_{\text{max}}$ is the budget. The value of $B_{\text{max}}$ could be the number of words or bytes in the summary. $f(S)$ is the submodular objective function that scores the summary quality.

4.1.1 Generic Summarization

We design a monotone submodular objective function composed of three important objectives for document summarization. These objectives are responsible for measuring summary’s importance, coverage and non-redundancy property. The proposed objective function is:

$$f(S) = \alpha r(S) + \beta c(S) + \Lambda h(S) \quad (2)$$

where, $r(S)$ measures summary’s importance quality, $c(S)$ measures summary’s coverage quality, $h(S)$ measures summary’s non-redundancy quality and $\alpha$, $\beta$, and $\Lambda$ are non-negative trade-off coefficients which can be tuned empirically.

As we know, the linear combination of the submodular functions is submodular (Lin and Bilmes, 2011) and all the proposed subparts of our objective function are submodular, the function $f(S)$ is also submodular.

One of the basic requirements of a good summary is that it should contain the most important information across multiple documents. To model this property, we introduce a new monotone nondecreasing submodular function based on the atomic concept. In our definition, atomic concepts are the atomic terms that bear significance in a sentence. Our system, therefore, considers only verbs, named-entities, and adjectives as atomic concepts (excluding the stop words). Our proposed submodular function is:

$$r(S) = \sum_{i=1}^{N} \frac{1}{\text{pos}(S_i)} \Omega_i \lambda S_i \quad (3)$$

where, $\lambda S_i \in \{0, 1\}$, $\lambda S_i = 1$ if sentence $S_i$ is in the summary, otherwise $\lambda S_i = 0$. $\Omega_i$ is the importance score of sentence $S_i$ and pos($S_i$) denotes the position of sentence $S_i$ in the document.

We consider the relevance of the summary as the summation of the importance scores of the sentences in it. First, we utilize the Markov random walk model used by (Hong and Nenkova, 2014; Mihalcea and Tarau, 2004) to score each concept from the document set. Then we score every sentence based on the weight of the constituent words in the sentence. We only decrease the weight of the constituent concepts when it appears in multiple sentences in the summary. While sentence similarity-based approaches (Lin and Bilmes, 2011) do not consider the individual word’s importance to model the importance property, our proposed submodular function is based on the atomic concept and this model encourages coverage of most of the important concepts across the documents.

A good summary has the capability to cover most of the important aspects of a document set. To formulate this, we consider a submodular objective function which utilizes the following ‘sentence similarity-based approach’ based on “facil-

1http://www-nlpir.nist.gov/projects/duc/index.html

[^1]: The values for the coefficients are 1.0, 1.0 and 5.0 for $\alpha$, $\beta$, and $\Lambda$ respectively, as found empirically using DUC-2003 development set during the experiments.
ity location objective” (Cornuejols et al., 1977).\[ d(S) = \sum_{i \in V} \max_{j \in S} \text{sim}(i, j) \quad (4) \]

where, sim(i, j) denotes the deep semantic sentence similarity between sentence i and j. For measuring the similarity between sentences, we used the Word2Vec sentence similarity measure (Mikolov et al., 2013). We first remove all the stop words\(^3\) which do not add much meaning to the sentence and then run Word2Vec\(^4\) on the words in both sentences. We calculate the average vector for all words in both sentences and use cosine similarity between vectors to find the semantic similarity between sentences. Finally, following equation (4), a sentence’s eligibility to be included in the summary depends on how similar it is with all the other sentences in the document cluster.

Minimizing redundant information in the summary is handled by the following submodular function:

\[ h(S) = \sum_{C_k \in \eta(S)} \sigma(C_k) - \sum_{i,j \in S, i \neq j} \text{sim}(i, j) \quad (5) \]

where, sim(i, j) is the deep semantic sentence similarity between summary sentence i and j, \( \sigma(C_k) \) is the weight of k-th concept term, and \( \eta(S) \) is the set of all distinct terms in the summary.

The first part of the function \( h(S) \) is based on atomic concept which scores the summary by measuring the weighted sum of the unique concept terms in the summary. In the second part, we penalize the summary redundancy by measuring semantic similarity among the summary sentences. Finally, our task is to maximize the proposed submodular function \( f(S) \) to produce a relevant, well-covered, and non-redundant summary using the modified greedy algorithm for submodular function (Lin and Bilmes, 2010).

The reason behind choosing this algorithm is that a solution is guaranteed to be within a constant factor \((1 - 1/\sqrt{\epsilon})\) of the optimal solution when the objective function is monotone submodular. Since the scoring function \( f(s) \) of our proposed summarizer is non-decreasing monotone submodular, we thus use the following greedy algorithm to obtain the near optimal solution.

\(^3\)http://fmnrl.org/papers/volume5/lewis04a/a11-smart-stop-list/english.stop
\(^4\)https://code.google.com/archive/p/word2vec/

**Algorithm 1** A Greedy algorithm for maximizing the objective function

**Require:** A minimization LP in standard form.

**Ensure:** Integral solution, IR1 to the LP.

1. \( S \leftarrow \emptyset, M \leftarrow \{1, \ldots, N\} \)
2. while \( M \neq 0 \) do
3. \( q \leftarrow \arg \max_{p \in M} \frac{f(S \cup \{p\}) - f(S)}{c_p} \)
4. if \( \sum_{j \in S} C_j + C_q \leq B_{\text{max}} \) and \( f(S \cup \{q\}) - f(S) \geq 0 \) then
5. \( S \leftarrow S \cup \{q\} \)
6. end if
7. \( M \leftarrow M \setminus \{q\} \)
8. end while
9. \( t^* \leftarrow \arg \max_{t \in \{1, \ldots, N\}, c_t \leq B_{\text{max}}} f\{t\} \)
10. if \( f(t^*) > f(S) \) then
11. return \( t^* \)
12. else return \( S \)
13. end if

**4.2 Query-focused Summarization**

For the query-focused summarization phase, we propose the following objective function:

\[ f(S) = \alpha r(S) + \Upsilon q(S) + \Lambda h(S) \quad (6) \]

where, \( r(S) \) measures summary’s importance quality, \( q(S) \) measures summary’s query relevance quality, \( h(S) \) measures summary’s non-redundancy quality and \( \alpha, \Upsilon, \text{ and } \Lambda \) are non-negative trade-off coefficients which can be tuned empirically\(^5\). We keep the importance and non-redundancy reward function similar to the generic summarizer described in the previous section. In addition, we design a query relevance objective function which considers the two important aspects: (1) how related summary sentences are with the query?, and (2) how much query dependent information is covered in the summary?

\[ q(S) = \psi \cdot \sum_{j \in S} \text{Sim}(q, s_j) + \theta n_{j,q} \quad (7) \]

where, \( \text{Sim}(i, j) \) is the similarity between summary sentence j and query q. Here similarity means the cosine similarity of the average word vectors obtained from Word2Vec (Mikolov et al., 2013) for the query and the summary sentence. \( n_{j,q} \) is the number of query terms present in the

\(^5\)The values for the coefficients are 1.0, 10.0, and 5.0 for \( \alpha, \Upsilon, \text{ and } \Lambda \) respectively, as found empirically using the development set DUC-2006 during the experiments.
summary sentence $j$. $\psi$, and $\theta$ are non-negative trade-off coefficients which have been tuned empirically during the experiments.\(^6\)

5 Experiments

To evaluate our generic and query-focused summaries, we use DUC-2004 and DUC-2007 datasets, respectively. We perform some basic preprocessing on all the documents such as tokenization, part-of-speech tagging and document coreference resolution using Stanford CoreNLP (Manning et al., 2014). We also use Porter’s stemmer (Porter, 1999) for stemming all the words and remove all the stop words from the smart stop words list.\(^7\) For query-focused summarization, we use word vectors from Word2Vec (Mikolov et al., 2013) which allows us to obtain better similarity scores between the sentences and the queries. We evaluate our system generated summaries using the automatic evaluation toolkit ROUGE version 1.5.5 (Lin, 2004).

We compare the results of our systems (i.e., document shrinking + summarization or document summarization + shrinking) with other state-of-the-art generic summarization methods. The comparison is shown in Table 1 where we report the values of ROUGE-1 recall and F-1 measure\(^8\) of different approaches. From the table, we can see that our generic multi-document summarizer (document shrinking + summarization) significantly outperforms those systems in all measures. This result suggests the effectiveness of sentence compression and merging phase in our system. It also shows the effectiveness of using semantic similarity measures to select important sentences in the summary. Moreover, our system also uses a separate redundancy function which also helps to generate summaries with less redundancy compared to the systems which only concentrate on summary’s coverage and relevance. These results also confirm that the proposed strategy can improve summary quality.

We compare our query-focused summarizer with other state-of-the-art query summarization methods. Table 2 shows the comparison in terms of ROUGE scores\(^9\) between our system and the best performing systems. From the table, we can say that our query-focused multi-document summarizer (document shrinking + summarization) outperforms the best-known systems in DUC-2007. It is notable that the best system in DUC-2007 takes the topic title as a query and uses Yahoo search engine to get a ranked set of retrieved documents which were used later to calculate the query relevance score (Pingali et al., 2007). However, our system is totally unsupervised and does not use any external source for the summary generation.

6 Conclusion

In this paper, we proposed a new summarization framework using different submodular functions with deep semantic features and abstraction-based methods. Abstraction-based methods help the system to obtain concise and more informative candidate summary sentences. We selected the best sentences for the summary by maximizing the submodular objective function. The empirical results show that our generic and query-focused summarization model outperform the state-of-the-art systems.

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\(^6\)The values for the query relevance coefficients are 4.0 and 2.0 for $\psi$ and $\theta$ respectively, as found empirically using the development set DUC-2006 during the experiments.

\(^7\)http://jmlr.org/papers/volume5/lewis04a/a11-smart-stop-list/english.stop

\(^8\)ROUGE runtime arguments for DUC-2004: ROUGE -a -c 95 -b 665 -m -n 4 -w 1.2

\(^9\)ROUGE runtime arguments for DUC-2007: ROUGE -n 2 -x -m -2 -4 -u -c 95 -r 1000 -f A-p 0.5-t 0-d

Table 1: Results on DUC-2004 Datasets

| Systems                              | R-1          | F-1          |
|--------------------------------------|--------------|--------------|
| Best system in DUC-04 (peer 65)      | 0.3828       | 0.3794       |
| (Takamura and Okumura, 2009)         | 0.385        | -            |
| (Lin and Bilmes, 2011)               | 0.3935       | 0.389        |
| (McDonald, 2007)                     | 0.362        | 0.338        |
| (Wang et al., 2009)                  | 0.3907       | -            |
| Document Shrinking + Summarization   | 0.4127       | 0.4133       |
| Document Summarization + Shrinking   | 0.3874       | 0.3882       |

Table 2: Results on DUC-2007 Datasets

| Systems                              | R-2          | F-2          |
|--------------------------------------|--------------|--------------|
| Best system in DUC-07 (peer 15)      | 0.1245       | 0.1229       |
| (Lin and Bilmes, 2011)               | 0.1238       | 0.1233       |
| (Toutanova et al., 2007)             | 0.1189       | 0.1189       |
| (Haghighi and Vanderwende, 2009)     | 0.118        | -            |
| Document Shrinking + Summarization   | 0.1258       | 0.1264       |
| Document Summarization + Shrinking   | 0.1133       | 0.1149       |
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