Unsupervised Text Summarization of Long Documents using Dependency-based Noun Phrases and Contextual Order Arrangement

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Abstract

Unsupervised extractive summarization has recently gained importance since it does not require labeled data. Among unsupervised methods, graph-based approaches have achieved outstanding results. These methods represent each document by a graph, with sentences as nodes and word-level similarity among sentences as edges. Common words can easily lead to a strong connection between sentence nodes. Thus, sentences with many common words can be misinterpreted as salient sentences for a summary. This work addresses the common word issue with a phrase-level graph that (1) focuses on the noun phrases of a document based on grammar dependencies and (2) initializes edge weights by term-frequency within the target document and inverse document frequency over the entire corpus. The importance scores of noun phrases extracted from the graph are then used to select the most salient sentences. To preserve summary coherence, the order of the selected sentences is re-arranged by a flow-aware orderBERT. The results reveal that our unsupervised framework outperformed other extractive methods on ROUGE as well as two human evaluations for semantic similarity and summary coherence.

Keywords: Extractive Summarization, Graph, Dependency, Summary Coherence

1 Introduction

Text summarization helps in preserving and compressing representative information from long documents. This work aims at the extractive summarization, which condenses a document by extracting a few salient sentences.

It produces fluent sentences with less training data than abstractive methods.

Most extractive summarization research focuses on supervised learning methods (Narayan et al., 2018; Dong et al., 2018; Yao et al., 2018; Wu and Hu, 2018; Liu and Lapata, 2019) to derive models for automatically observing salient sentences based on specified golden labels. Nonetheless, it is impractical to expect the availability of such high-quality training datasets on the rich unpaired data. In this method, researchers model textual content into sentence-level (Erkan and Radev, 2004; Mihalcea and Tarau, 2004; Mallick et al., 2019; Zheng and Lapata, 2019) or hybrid (Tarau and Blanco, 2019) graphs and adopt PageRank-based algorithms (Page et al., 1999) to retrieve the salient sentences in a document. Due to the characteristics of the graph, the extracted salient sentences are easily affected by common or function words that have high connectivities and are overestimated as key nodes. In addition, coherence is considered as an important attribute in summarization as it keeps the flow of concepts smooth and logical. However, few studies take coherence into consideration.

To address the above issues, this work assumes the major concepts in a document are expressed by key noun phrases and constructs a phrase-level graph specific for noun phrases that leverage grammar dependencies. With salient sentences extracted by key noun phrases, a sentence re-ordering step is applied to ensure the flow of concepts is contextually correct for the reader’s understanding. There are two major steps in the proposed framework: key noun phrase extraction and salient sentence extraction, as shown in Figure 1. Our
contributions are summarized as:

- An unsupervised extractive framework is proposed by constructing a novel phrase-level graph to obtain key noun phrases for salient sentence extraction. The proposed framework not only outperformed all extractive baselines on ROUGE, but also achieved results closer to the SOTA supervised transformer-based methods.

- The proposed orderBERT reorders the summary sentences with respect to sentence-level context, which improves 9% over using sentence’s original position in a human-reader evaluation.

- The proposed noun phrase hyper relation extraction method can obtain more relations and less duplicates. These rich relations then provide more nodes and edges information to the phrase-level graph.

2 Key Noun Phrase Extraction

Keyphrases represent important information in sentences and documents but not all of them contribute the same amount of information. With noun phrases indicated as the most commonly occurring structures among different types of corpora (Le et al., 2016), the proposed method assumes that they potentially provide coverage of the major conceptual points of the document. By focusing on extracting key noun phrases from documents, this work proposes a graph-based keyphrase extraction for noun phrases in an unsupervised manner.

The key noun phrase extraction is separated into two steps: noun phrase hyper relation extraction and graph-based keyphrase scoring. The former is designed to extract the noun phrases along with the relations between them in a complete as possible manner according to the grammar dependency. To extract important noun phrases and avoid an undue influence of common words, further relations are adopted as a guide in constructing the dependency graph for specific noun phrases.

2.1 Noun Phrase Hyper Relation Extraction

In traditional relation extraction methods, noun phrases are extracted based on co-occurrence within a predefined window size, which might encounter a window size limitation; in other words, noun phrases whose relations are outside of the window size will be ignored. To overcome this limitation, this paper adapted the concept of open information extraction (OpenIE) to enable the extraction of both short and long relations between noun phrases based on grammar relations, which is denoted by relation triples as in Definition 1.

**Definition 1.** (Relation Triple). Let \( s, o, r, N, \) and \( NP \) denote a subject, object, their relation, the set of nouns, and the set of noun phrases, respectively. The relation triple set \( RT \) is presented as follows:

\[
RT = \{(s, r, o) | s, o \in N \cup NP\} \tag{1}
\]

The goal of phrase relation extraction is to retrieve a set of triples \( RT \) from each sentence. However, existing OpenIE tools mainly focus on the direct relations between subjects, verbs, and objects. Consequently, complex relations cannot be captured, e.g., the intra-clause relation of two nouns and nested clauses. Except for adopting existing OpenIE tools, our approach proposes rules to capture complex relations based on the grammar dependencies as defined in Definition 2.

**Definition 2.** (Grammar Dependency). Let \( \zeta \) be the grammar dependency type between a source word \( \gamma \) and a target word \( \tau \) in a given sentence \( st \). A set of grammar dependencies \( GD_{\zeta} \) with type \( \zeta \) in a given sentence \( st \) is presented as \( GD_{\zeta} = \{\gamma, \tau\} \).

With the dependency parsing tool from Stanford CoreNLP (Manning et al., 2014), a set of dependencies \( GD^{st} \) and the corresponding word pairs are first extracted. In Figure 2, the extracted dependencies can be presented as \( GD^{st} = \{GD^{nsubj}, GD^{case} \ldots, GD^{amod}\} \). \( GD^{case} = \{\text{success, for, (models, of)}\} \). These dependencies \( GD^{st} \) are then used to construct the triples \( RT \) for each sentence by algorithms proposed in the following sections.

2.1.1 Inter-clause Relation

To extract relations in the same clause, the proposed procedures are shown below.

**Definition 3.** (RT from Nominal Subjects). Let \( Nsubj, OBJ, OBL, XCOMP, COP, \) and \( AUX \)
Some reasons for the success of additive models are their increased flexibility.

However, some relations are still missing after these extraction processes, such as relations between nouns and the corresponding appositions, which are ignored. Two algorithms in Definitions 6 and 7 are then proposed.

**Definition 6. (RT from Conjunction).** Let CONJ denote the conjunction dependency type and RT denote the set of all extracted triples. The triple set \( RT^{\text{CONJ}} \) is extracted based on Algorithm 1 for each \((s, r, o) \in RT\).

**Algorithm 1 RT Construction from CONJ**

For \((\gamma, \tau) \in GD_{\text{CONJ}}\),

\[
\text{if } \gamma == \tau \text{ then if } \tau.\text{isVerb()} \land \tau.\text{hasNoSubject()} \text{ then object } \leftarrow \text{getObj}(GD_{\text{obj}}, \tau) \text{ return } (s, r, \text{object}) \text{ else if } \gamma == o \text{ then return } (s, r, \tau)\]

**Definition 7. (RT from Appositional Modifier).** Let APPPOS denote the appositional-modifier dependency type. Let \((\gamma, \tau) \in GD_{\text{APPPOS}}(s, r, o) \in RT\), and \(\phi\) denote an empty relation word. The triples are built as \( RT^{\text{APPPOS}} = \{(\gamma, \phi, \tau) | \gamma = s \lor \gamma = o\} \).

2.1.2 Intra-clause Relation

For dependencies in the independence and subordinate clauses, the dependencies of which the object or subject in a subordinate clause provides complements for an independent clause are leveraged. Two subordinate clauses are considered and defined below.

**Definition 8. (RT from Adjective Clausal Modifier of Noun).** Let ACL be the adjective-clausal-modifier dependency type. Let \((\gamma, \tau) \in GR_{\text{ACL}}, (\hat{\gamma}, \hat{\tau}) \in GR_{\text{OBJ}}\). Triples are extracted as \( RT^{\text{ACL}} = \{(\tau, \gamma, \hat{\tau}) | \gamma = \hat{\gamma}\} \).
As the adjective clauses provide extra information for the noun, there exists relations between the corresponding object of the verb in an adjective clause and the noun. Such relations could be extracted by Definition 8. For an adverbial clause, there are two major cases to be captured. First, all the extracted triples are considered, as an adverbial clause describes the conditions or reasons (such as if or since) for the action of a subject with regard to the corresponding object in the independent clause. Second, for a subject in the passive voice, it may not have a corresponding object and thus cannot be extracted by the previous methods. The details and an example are shown in Definition 9 and Figure 3, respectively. For brevity, all the extracted triples to this end are denoted as RT.

Lastly, due to the design of CoreNLP, the extracted (noun) words in RT are still uni-grams. To present the noun phrase, a uni-gram is combined with the previous word if there exists a grammar type for a compound or adjectival modifier. Let a target word be the subject s or object o from an extracted triple (s, r, o) ∈ RT of the sentence st. If the relation r between the target word and of any its previous word is compound, this work considers that this previous word is able to modify the meaning of the target word and, thus, combine these words.

### 2.2 Graph-based Keyphrase Extraction

Let S, R, and O denote the sets of subjects, relations, and objects in the extracted relation triples RT from all the sentences in a document, respectively. A bi-directional graph G is built as G = (V, E), where V represents noun phrase nodes and E denotes the edges, such that V = S ∪ O and E = R.

With all the triples RT transformed into a graph G, a keyphrase extraction method is proposed to retrieve important noun phrases through this graph. The PageRank algorithm (Page et al., 1999) was adapted to score all the nodes in the graph. However, due to the nature of PageRank, the score of common phrases could be too high as they have more edges than other nodes. Thus, to avoid this common word issue, the term-frequency inverse document frequency (TFIDF) ratio was adapted for the edge weight in advance from all the training documents. It is computed by:

$$\text{TFIDF}(w) = \log_2(\text{freq}(w)) \times \log_2 \frac{|D|}{df(w)}$$

where freq(w) denotes the frequency of word w in the source document, |D| represents the number of total source documents in the collection, and df(w) is the number of documents that contain the word w. It is worth noting that the although common words have lower IDF values, they still achieve high scores due to their overly high frequencies. The log function is thus adopted for freq(w). The TFIDF scores are added into
graph \( G = (V, E, \Theta) \) as edge weights \( \Theta = \{\theta\} \) by the following equation:

\[
\theta_{i,j} = |Relation_{i,j}| \cdot \frac{TFIDF_j}{TFIDF_i + TFIDF_j} \tag{8}
\]

where \( \theta_{i,j} \) is the edge weight, and \( |Relation_{i,j}| \) is the number of relations among nodes \( v_i, v_j \). PageRank is adopted in the end to obtain the importance scores for noun phrase nodes.

3 Salient Sentence Extraction

Consistent with our assumption that noun phrases potentially provide coverage of the major conceptual aspects of a document, the salient sentences are also selected based on these noun phrases with the corresponding importance scores derived by the weighted graph. In the following section, a context-aware BERT is derived to perform sentence reordering for the top salient scores in order to maintain summary coherence.

3.1 Salient Sentence Score Calculation

With important scores of noun phrases, they are utilized to calculate the salient score for each sentence in the document. Let \( d = \{s_t\}, \) \( s_t = \{p_k\}, G^{(d)}, \) and \( V^{(d)} \) be a document, sentence, graph, and set of nodes, respectively, where \( s_t \) represents the \( i \)th sentence in document \( d \), \( p_k \) denotes the \( k \)th noun phrase in \( s_t \), \( G^{(d)} \) denotes the graph constructed by \( d \), and \( V^{(d)} \in G^{(d)} \). Sum aggregation was applied to score the salience value for a given sentence:

\[
Score_{sent_a} = \sum_{p_k \in (sent_a \cap V)} Score_{p_k} \tag{9}
\]

where \( Score_{p_k} \) is the importance score of noun phrase \( p_k \) calculated by \( G^{(d)} \). Note that different sentence scoring methods were also proposed, such as the average aggregation, yet the sum aggregation performs the best.

3.2 Coherence Order Arrangement

With the salient score of each sentence in a document, sentences are ranked according to their scores. An intuitive solution to maintain the summary coherence in the extractive summarization is to reorder these top-\( n \) sentences according to their original position order in the source document (Zhong et al., 2020). However, the flow of selected sentences might be disrupted and, hence, damage the readability of the generated summary. With regard to the challenge, a flow-aware orderBERT is proposed for sentence order arrangement.

3.2.1 orderBERT

The orderBERT is a fine-tuned BERT by a modified objective of the next sentence prediction (NSP) (Devlin et al., 2019). Given a sentence pair \((s_{t_a}, s_{t_b})\), the goal of NSP is to predict whether the second sentence \( s_{t_b} \) is the sentence after the first sentence \( s_{t_a} \).

In the original NSP, its negative samples are sentence pairs sampled from different documents. However, these training data may result in two objectives while pretraining: (1) BERT can successfully classify the “order” and “context” in which the given sentences are in the incorrect order or from different documents are classified as negative; instead, (2) it only predicts whether two input sentences originate from the same document or from different ones. It is difficult to ensure that BERT is aware of the order of the given sentences. Thus, this study finetunes BERT by the sentence order based on a context-aware NSP fine-tuning strategy. Specifically, as additional negative samples, a set of sentence pairs are constructed by inverse order of two consequent sentences within a single source article. The number of inverse-order false samples are set to be the same as the number of original consequent sentence pairs, as done in the original work (Devlin et al., 2019).

To this end, the training dataset contains (1) correct order consequent sentence pairs within a document (positive sample), (2) sentence pairs from different documents (negative sample), and (3) inverse-order consequent sentence pairs within a document (negative sample). With this training set, orderBERT was trained to predict whether the second sentence is next in order after the first sentence (Huang et al., 2021), thereby going beyond merely recognizing whether or not the sentences are from the same document. Note that this process remains unsupervised since its labels are obtained naturally from documents.

3.2.2 Summary Sentence Reordering

With the trained orderBERT, given a pivot sentence and a set of candidate sentences, we
let orderBERT go through all the pairs of pivot sentence and candidates to obtain the most suitable candidate connected after the pivot sentence. Finally, given a set of salient sentences, orderBERT then maintains the coherence of summary by re-ordering the extracted salient sentences, as defined in Algorithm 3.

Overall, after the sentences reordering, a machine-generated extractive summary is obtained in an unsupervised manner, in which the summary comprises of \( n \) number of salient sentences from the original document. It is important to note that the salient sentences are selected based on the key noun-phrases and, thus, several important terminologies are present in each sentence of the summary. For the summary coherence, the improvement is not only contributed by sentence rearrangement step, the important terms (noun phrases) also play important role in connecting the concept through different sentences while the readers go through the summary.

**Algorithm 3** Sentence Reordering

```python
ST = Salient sentence list ordered by each one’s original positions
s_pivot = ST.deque()
ordered_ST = [s_pivot]
while len(ST) ≠ 0 do
    s_pivot = getNextByOrderBERT(s_pivot, ST)
    ST.remove(s_pivot)
    ordered_ST.append(s_pivot)
return ordered_ST
```

4 Experimental Setup

4.1 Dataset and Preprocessing

This work focuses on long document summarization as the key concepts in long documents are more dispersed than in short ones. Two different long-document datasets, PubMed and arXiv from Cohan et al. (2018), were considered with the introductions as the source documents and their abstracts as the summaries. For pre-processing, documents with its introduction less than 10 sentences were removed, as there were an insufficient number of sentences from which to select. The statistics of the datasets are summarized in Table 1.

4.2 Baselines

To evaluate performance, we compared our framework with different baselines as follows:

(a) **LEAD-5** and (b) **ORACLE** generally represent the lower-bound and upper-bound of extractive summarization tasks; for unsupervised methods, we adopted (c) **TextRank** (Mihalcea and Tarau, 2004) with co-occurrence relations with window size set at 2 for graph-based keyphrases and Equation 9 for sentences scores; (d) **DeepRank** (Tarau and Blanco, 2019) contains a word-sentence heterogeneous graph with PageRank for sentence scores; (e) **LexRank** (Erkan and Radev, 2004) is a sentence-level undirected graph with edge weight threshold set to 0.1 according to its paper and calculates a cosine similarity between sentences; and (f) **PacSum** (Zheng and Lapata, 2019) builds a sentence-level directed graph with TFIDF or BERT for the edge weights. For supervised methods, the following were adopted: (g) **Pointer Generator** (See et al., 2017) with attention and beam search algorithm; (h) **BertSum** (Liu and Lapata, 2019), three SOTA BERT-based models for both extractive and abstractive summarization that included BertExt, BertAbs, and BertExtAbs. The summary of each extractive method can contain at most 5 sentences.

For evaluation, ROUGE 1, 2, and L (Lin and Och, 2004) were first applied to examine the information-preserving capabilities. Secondly, a human evaluation of the coherence of the summaries was conducted.

5 Results and Discussion

5.1 Model Performance on ROUGE

The performance comparison for different methods on two datasets is demonstrated in Table 2. Overall, the proposed unsupervised keyword-based method outperformed all the extractive summarization baselines, including the SOTA transformer method, namely BertExt. For the BertAbs and BertExtAbs models that were trained under supervision, it is worth mentioning that our method still outperformed both of them with the PubMed dataset. As the size of the data in arXiv was ten times more than the PubMed dataset, BertAbs and BertExtAbs largely benefited from the supervised learning process; our methods then performed slightly worse than them. However, this still indicates that by leveraging key noun-phrases using grammar de-
5.2 Noun for Information Preserving

As this work focuses on the representative noun phrases for concept preserving. Statistics were conveyed on the average frequencies of nouns from all graph-based baselines as shown in Table 3. This showed that the summary generated by our method contained mostly words that were nouns, which probably helped our method to preserve most of the concepts and obtain the best ROUGE performance.

5.3 Graph Construction Comparison

The other phrase-level method, TextRank, did not have as good a performance as ours. The only difference between our framework and TextRank is the way the phrase-level graph is constructed. Our framework utilizes rule-based relation extraction from grammar relations, while TextRank applies co-occurrence relations. To compare the differences, graphs were visualized with the same sentence as shown in Figure 4. In Figure 4a, there are only four adjective-noun combinations. The co-occurrence relations ignore many important relation between phrases due to the limited window size. In contrast, the graph by our method (Figure 4b) contains more relations between phrases that contributes to a dense graph and benefits for the keyword extraction.

As compared to a heterogeneous graph, DeepRank built a graph from both words and sentences. As there are many edges that connect from keyphrases to sentences, it results in the scores of important keyphrases being distributed uniformly to these sentences. The top-five salient sentences were examined as to whether they contained the top keyphrase. The average keyphrase counts in top-5 sentences from DeepRank were 0.748 and 0.864 while our method obtained 3.003 and 3.321 on arXiv and PubMed, respectively. This also indicates that it is better to separate phrases and sentences for summarization.

Table 1: Dataset statistics

| Dataset | # of Doc. | Avg. Abstract | Avg. Introduction | Avg. Doc. |
|---------|-----------|---------------|-------------------|-----------|
|         | train/valid/test | # word | # sentence | # word | # sentence | # word |
| PubMed  | 10k / 2k / 1.25k | 201.9 | 6.8 | 1013.1 | 37.3 | 3224.4 |
| arXiv   | 83k / 19.8k / 20k | 177.7 | 6.6 | 1077.0 | 42.8 | 6913.8 |

Table 2: Overall performance on ROUGE

| Method       | Type     | PubMed  | arXiv   |
|--------------|----------|---------|---------|
|              |          | ROUGE-1 | ROUGE-2 | ROUGE-L | ROUGE-1 | ROUGE-2 | ROUGE-L |
| LEAD-5       | *        | 0.2999  | 0.0865  | 0.2695  | 0.0137  | 0.0003  | 0.0137  |
| ORACLE       | *        | 0.4490  | 0.1817  | 0.3004  | 0.4610  | 0.1994  | 0.2784  |
| TextRank     |          | 0.3514  | 0.0944  | 0.3115  | 0.0324  | 0.0072  | 0.3035  |
| LexRank      |          | 0.3936  | 0.1169  | 0.3469  | 0.3592  | 0.1000  | 0.3151  |
| DeepRank     | Unsup.   | 0.3600  | 0.0904  | 0.2537  | 0.3835  | 0.1131  | 0.3341  |
| PacSum (TFIDF)| PacSum (BERT)| 0.3093  | 0.0677  | 0.2777  | 0.3595  | 0.1005  | 0.3146  |
| Pointer Generator |        | 0.2999  | 0.0865  | 0.2695  | 0.3554  | 0.1255  | 0.3192  |
| BertExt      | Sup.     | 0.3249  | 0.1012  | 0.2863  | 0.3829  | 0.1324  | 0.3311  |
| BertAbs      |          | 0.3199  | 0.0730  | 0.2909  | 0.3554  | 0.1255  | 0.3311  |
| BertExtAbs   |          | 0.3485  | 0.0802  | 0.3136  | 0.4269  | 0.1598  | 0.3802  |
| Ours         | Unsup.   | 0.3999  | 0.1174  | 0.3504  | 0.4075  | 0.1347  | 0.3569  |

Table 3: Noun usages of summaries

| Method      | Avg. # of Noun |
|-------------|----------------|
|             | PubMed | arXiv  |
| DeepRank    | 29.3   | 35.6   |
| LexRank     | 45.3   | 53.3   |
| PacSum (TFIDF)| 57.3 | 65.2   |
| PacSum (BERT)| 40.8  | 42.4   |
| TextRank    | 38.8   | 49.0   |
| Ours        | 64.5   | 71.0   |

Dependencies, there is a chance for unsupervised method to perform similarly to a supervised and pretrained method. In addition, one possible reason for the good performance with the more limited dataset (PubMed) was the usage of the grammar dependencies in constructing the graph for the keyphrases. Specifically, the rich grammar relations lay in the language usage implicitly, which allows our models to capture the key concepts of a document. The remaining evaluations focus on the comparisons among unsupervised baselines.
5.4 Human Questionnaire Evaluation

Human evaluation was conducted on Amazon Mechanical Turk (AMT) to compare the semantic similarity to gold summary and coherence performance among baselines that had the best ROUGE score or was the most coherent. An abstract (golden summary) and multiple summaries from the baselines were provided for each question. There were a total of 10 documents that were randomly sampled from arXiv and PubMed in the same proportion and assigned to 100 AMT workers for evaluations. Note that 21 workers were discarded as they submit inattentive answers to the questionnaire including the behaviors of quick answering, the same answer for all questions, and wrong answer for the trap question. The results from both datasets are together in Table 4.

| Method            | Similarity | Coherence |
|-------------------|------------|-----------|
| LexRank (TFIDF)   | 25.96%     | 27.22%    |
| PacSum (TFIDF)    | 19.61%     | 19.33%    |
| Ours + Orig. Pos. | 27.22%     | 21.17%    |
| Ours + orderBERT  | 27.21%     | 30.71%    |

Table 4: Percentage of human-preferred methods

From the semantic similarity question, our proposed methods outperform other unsupervised baselines. Noting that the sentences of two summaries generated by our methods are identical, only the orders are different. Therefore, their percentages are, therefore, almost the same—27.22% and 27.21%. It indicates that labelers struggled to select one of ours as the best semantic-similar summary from all options; with two of our methods together, most labelers selected our summaries as the most similar. For LexRank and PacSum (TFIDF), although they are comparable in ROUGE evaluation, the summaries by LexRank were more preferred by human readers.

With regard to summary coherence, with sentence re-ordering and key noun phrases, our method with orderBERT had better performance than others in terms of coherence evaluation. The results of two our methods also indicate a 9.5% improvement in coherence on the chosen ratio with the BERT reordering mechanism as compared to the summary that only reordered based on its original position (Ours + Orig. Pos.). Although adopting the original position for reordering works well in short document summarization, it may not be suitable to directly adopt for a long document. Interestingly, LexRank also obtained good results in the coherence questions. It is found that LexRank tends to select a few sentences with connecting/turning words that are helpful for coherence between sentences.

Example summaries are shown in Table 5. It is observed that the summary reordered by the original positions has multiple topic shifts and repetitions. The topic shifts from model-checking problem to timed automata, then to model-checking problem, and then to timed automata again. As for the summary by orderBERT, the topic first focuses on the model-checking problem and then provides the link between timed automata and model-checking problem instead of switching the topics between them. This shows that the original position method may produce topic gaps between salient sentences as there is more content in a long document. By reordering sentences at the sentence level, the mechanism with orderBERT could alleviate such an issue. Overall, the combined use of noun phrases and sentence reordering with orderBERT could provide better readability with respect to summary coherence than the other baselines.

5.5 Relation Extraction Comparison

To evaluate the proposed phrase extraction method, the latest OpenIE tool given by Stanford CoreNLP was compared as in Table 6.

For the Stanford CoreNLP tool, there was no triple extracted in Case 1 and all the results in Case 2 were almost the same. Al-
For this class of parametric timed automata, they focus on the emptiness problem: are there concrete values for the parameters so that the automaton has an accepting run? They show that when only one clock is compared to parameters, the emptiness problem is decidable. The model-checking problem for tctl extended with parameters over discrete- and dense-timed automata (without parameters) is decidable. Unfortunately, in all those previous works, the parameters are only in the model (expressed as a timed automaton) or only in the property (expressed as a temporal logic formula). Nevertheless, when expressing a temporal property of a parametric system, it is natural to refer in the temporal formula to the parameters used in the system.

In this paper, we further investigate the model-checking problem of real-time formalisms with parameters. For this class of parametric timed automata, they focus on the emptiness problem: Are there concrete values for the parameters so that the automaton has an accepting run? They show that when only one clock is compared to parameters, the emptiness problem is decidable. The model-checking problem for tctl extended with parameters over discrete- and dense-timed automata (without parameters) is decidable. In this paper, we study the model-checking problem of the logic tctl extended with parameters over the runs of a discrete-timed automaton with one parametric clock. On the negative side, we show that the model-checking problem of tctl extended with parameters is undecidable over timed automata with only one parametric clock.

| Table 5: Example Summaries from Unsupervised Methods (Key noun-phrases are highlighted in bold). |
|---|---|
| CoreNLP | Ours |
| Case 1 | of such estimators belong to the large class of regularized kernel based methods over a reproducing kernel hilbert space. | |
| CoreNLP | Ours |
| Case 2 | It is also a minimizer of the following optimization problem involving the original loss function. | (It, is minimizer of, optimization problem), (It, is minimizer of, following optimization problem), (It, is also minimizer of, optimization problem), …
| CoreNLP | Ours |
| (It, is minimizer of, optimization problem), (It, is minimizer of, following optimization problem), (It, is also minimizer of, optimization problem), …
| (It, is minimizer of, optimization problem), (It, is minimizer of, optimization problem), (It, is also minimizer of, optimization problem), … |

Table 6: Phrase Relation Extraction Comparison

though such duplication could be solved by post-processing, missing relations (such as the relation between a noun in a main clause and a noun in an adjective clause) were still not found. In addition, our framework could extract more useful triples from these cases.

6 Conclusion

In this research, a fully unsupervised framework is proposed for extractive summarization. The proposed method addresses the common word domination issue from a graph-based approach by using a phrase-level graph that focuses on key noun phrases based on grammar dependencies. The extracted key noun-phrases effectively capture the major concepts of a document and can be used to construct an extractive summary. Experiments showed that the proposed method outperformed all the extractive baselines, even for supervised methods. A human evaluation also showed that the use of keyphrases and sentence reordering successfully benefited the coherence of the summaries. In the future, we aim to adapt the proposed key noun-phrases for unsupervised abstractive summarization.
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