Generating Coherent Summaries of Scientific Articles
Using Coherence Patterns

Daraksha Parveen Mohsen Mesgar
NLP Group and Research Training Group AIPHES
Heidelberg Institute for Theoretical Studies gGmbH
Heidelberg, Germany
{daraksha.parveen|mohsen.mesgar|michael.strube}@h-its.org

Abstract

Previous work on automatic summarization does not thoroughly consider coherence while generating the summary. We introduce a graph-based approach to summarize scientific articles. We employ coherence patterns to ensure that the generated summaries are coherent. The novelty of our model is twofold: we mine coherence patterns in a corpus of abstracts, and we propose a method to combine coherence, importance and non-redundancy to generate the summary. We optimize these factors simultaneously using Mixed Integer Programming. Our approach significantly outperforms baseline and state-of-the-art systems in terms of coherence (summary coherence assessment) and relevance (ROUGE scores).

1 Introduction

The growth in the scientific output of many different fields makes the task of automatic summarization imperative. Automatic summarizers assist researchers to have an informative and coherent gist of long scientific articles. An automatic summarizer produces summaries considering three properties:

Importance: The summary should contain the important information of the input document.
Non-redundancy: The summary should contain non-redundant information. The information should be diverse in the summary.
Coherence: Though the summary should comprise diverse and important information of the input document, its sentences should be connected to one another such that it becomes coherent and easy to read.

If we do not ensure that a summary is coherent, its sentences may not be properly connected. This results in an obscure summary. In previous work coherence has not been thoroughly considered. Parveen and Strube (2015) use single sentence connectivity in the input document as a coherence measure. They measure coherence by calculating the outdegree of a sentence in a graph representation of an input document. This has two disadvantages: first, since it is computed only based on one sentence, it is not sufficient to generate coherent summaries; second, it is obtained based on sentence connectivity in the input document rather than in the summary.

In this work, we focus on the coherence aspect of summarization. We use discourse entities as the unit of information that relate sentences. Here, discourse entities are referred to as head nouns of noun phrases (see Section 2). The main goal is to extract sentences which refer to those entities which are important and unique, and also to entities which connect the extracted sentences in a coherent manner. Entities in connected sentences can be used to create linguistically motivated coherence patterns (Daněš, 1974). Recently, Mesgar and Strube (2015) modeled these coherence patterns by subgraphs of the graph representation (nodes represent sentences and edges represent entity connections among sentences) of documents. They show that the frequency of coherence patterns can be used as features for coherence.

The key idea of this paper is to apply coherence patterns to long scientific articles to extract (possibly) non-adjacent sentences which, however, are already coherent. Based on the assumption that ab-
Cardiometabolic diseases are a growing concern across sub-Saharan Africa (SSA).

According to current estimates, the prevalence of diabetes among adults aged 20–79 y in Africa is 3.8% and will increase to 4.6% by 2030.

Urban environments and associated lifestyles, including diets high in salt, sugar, and fat, and physical inactivity, have been widely implicated as leading causes of the rise in cardiometabolic diseases.

If and how these changes affect the health of rural residents, however, remains poorly understood.

Existing research on lifestyle risk factors for cardiometabolic diseases has almost exclusively focused on exposures to urban environments.

Our experimental results show that using coherence patterns for summarization produces more informative (but not redundant) and coherent summaries as compared to several baseline methods and state-of-the-art methods based on ROUGE scores and human judgements.

2 Method

We solve the task of creating coherent summaries by employing coherence patterns. We tightly integrate determining importance, non-redundancy and coherence by applying global optimization, i.e., MIP.

2.1 Document Representation

We use the entity graph (Guinaudeau and Strube, 2013) to represent scientific articles. The entity graph is a bipartite graph which consists of entities and sentences as two disjoint sets of nodes (Figure 2, ii). Entity nodes are connected only with sentence nodes and not among each other. An entity node is connected with a sentence node if and only if the entity is present in the sentence. Entities are the head nouns of noun phrases.

We perform a one-mode projection on sentence nodes to create a directed one-mode projection graph (Figure 2, iii). Two sentence nodes in the one-mode projection graph are connected if they share at least one entity in the entity graph. Edge directions encode the sentence order in the input document.

2.2 Mining Coherence Patterns

We use one-mode projection graphs of abstracts in the PubMed corpus (see Section 3.1) to mine coherence patterns. The weight of a coherence pattern, \( \text{weight}(\text{pat}_u) \), is its frequency in the PubMed corpus normalized by the maximum number of its occurrence in abstracts in the PubMed corpus (Equation 1).

\[
\text{weight}(\text{pat}_u) = \frac{\sum_{k=1}^{q} \text{freq}(\text{pat}_u, g_k)}{\max_{k=1}^{q} \text{freq}(\text{pat}_u, g_k)},
\]

where \( q \) is the number of graphs associated with abstracts in the corpus, and \( g_k \) represents the graph of the \( k^{th} \) abstract in the PubMed corpus.
The overall rates of cesarean delivery are increasing significantly in the world.

In the United States and Australia rates of more than 35% have been reported and in China and South America, including Brazil and Paraguay, cesarean rates of between 40% and 50% are common.

Concerns have been expressed regarding the impact of subsequent pregnancy particularly the rate of subsequent stillbirth, miscarriage, and ectopic pregnancy.

Hypothesized biological mechanisms include placental abnormalities, prior infection, and adhesion formation due to cesarean section.

The overall rates of cesarean delivery are increasing significantly in the world.

In Equation 4, sim(sent_i, title) is the cosine similarity between the scientific article’s title and sentence sent_i. In Equation 5, ent_j refers to the jth entity in the entity graph. After applying the HITS algorithm on the entity graph using the above initialization, the final rank of a sentence is its importance.

Non-redundancy (fR(E)): In the objective function, fR(E) represents the non-redundancy of information in the summary. Intuitively, if the summary has unique information in every sentence then the summary is non-redundant. We measure non-redundancy as follows:

\[ f_R(E) = \sum_{j=1}^{m} e_j, \]

where m is the number of entities and e_j is a binary variable for each entity. The summary becomes non-redundant if we include only unique entities.

On the basis of \( f_1(S) \) and \( f_R(E) \) we define the following optimization constraints:

\[ \sum_{i=1}^{n} |Sent_i| \cdot s_i \leq l_{max}, \]

\[ \sum_{j \in E_i} e_j \geq |E_i| \cdot s_i \quad \text{for } i = 1, \ldots, n, \]
The constraint in Equation 7 limits the length of the summary. $l_{\text{max}}$ is the maximal length of the summary and $|\text{Sent}_i|$ is the length of sentence $\text{sent}_i$.

In Equation 8, the constraint ensures that if sentence $\text{sent}_i$ is selected ($s_i = 1$), then all entities $E_i$ present in sentence $\text{sent}_i$ must also be selected. In Equation 9, $S_j$ represents the set of binary variables of sentences which contain entity $\text{ent}_j$. This constraint prescribes that if entity $\text{ent}_j$ is selected ($e_j = 1$), then at least one of the sentences in $S_j$ must be selected, too.

**Coherence ($f_C(P)$):** We use the mined patterns to extract sentences from the input document of *PLOS Medicine* to create a coherent summary. We extract sentences, if the connectivity among nodes in their projection graph matches the connectivity among nodes in a coherence pattern. In Figure 3 we overlay the projection graph from Figure 2, (ii) with the coherence pattern from Figure 1, (i). This results in three instances of this coherence pattern. However, we select only one since we simultaneously optimize for importance and non-redundancy.

\[
\sum_{s_i \in S_j} s_i \geq e_j \quad \text{for } j = 1, \ldots, m. \tag{9}
\]

In the objective function, $f_C(P)$ measures the coherence of the summary based on the weights of the coherence patterns occurring in it (Section 2.2):

\[
f_C(P) = \sum_{u=1}^{U} \text{weight}(\text{pat}_u) \cdot p_u, \tag{10}
\]

where $p_u$ is a boolean variable associated with coherence pattern $\text{pat}_u$.

The optimization considers pattern $\text{pat}_u$ for summarizing the input article, if $\text{pat}_u$ is a subgraph of the projection graph of the article. To find the coherence pattern in a projection graph we apply a graph matching algorithm (Lerouge et al., 2015).

![Figure 3](image1.png)

**Figure 3:** (i) A projection graph; (ii) several instances of a coherence pattern in Figure 1, (ii).

To model the graph matching problem between projection graph $g = (V_g, E_g)$ and patterns $\text{pat}_u = (V_{\text{pat}_u}, E_{\text{pat}_u})$, two kinds of mapping binary variables are used: $x_{i,k}$ for the node map, and $y_{ij,kl}$ for the edge map. $x_{i,k} = 1$, if vertices $i \in V_{\text{pat}_u}$ and $k \in V_g$ match. $y_{ij,kl} = 1$, if for each pair of edges $ij \in E_{\text{pat}_u}$ and $kl \in E_g$ match (Figure 4). Constraints for graph matching are as follows:

- Every node of the pattern matches at most one unique node of the graph:

\[
\sum_{k \in V_g} x_{i,k} \leq 1 \quad \forall i \in V_{\text{pat}_u}. \tag{11}
\]

- Every edge of the pattern matches at most one unique edge of the graph:

\[
\sum_{kl \in E_g} y_{ij,kl} \leq 1 \quad \forall ij \in E_{\text{pat}_u}. \tag{12}
\]
• Every node of the graph matches at most one node of the pattern:
\[ \sum_{i \in \text{V}_{\text{pat}_u}} x_{i,k} \leq 1 \quad \forall k \in \text{V}_g. \] (13)

• A node of pattern \( \text{pat}_u \) matches a node of graph \( g \) if an edge originating from the node of \( \text{pat}_u \) matches an edge originating from the node of \( g \):
\[ \sum_{k,l \in \text{E}_g} y_{ij,kl} = x_{i,j} \quad \forall l \in \text{V}_g, \forall ij \in \text{E}_{\text{pat}_u}. \] (14)

• A node of pattern \( \text{pat}_u \) matches a node of graph \( g \) if an edge targeting the node of \( \text{pat}_u \) matches an edge targeting the node of \( g \):
\[ \sum_{k,l \in \text{E}_g} y_{ij,kl} = x_{j,l} \quad \forall l \in \text{V}_g, \forall ij \in \text{E}_{\text{pat}_u}. \] (15)

• We need a constraint to extract induced patterns:\footnote{Pattern \( \text{pat}_u \) is an induced subgraph of graph \( g \) if \( \text{pat}_u \) contains all possible edges which appear in \( g \).}
\[ \sum_{i \in \text{V}_{\text{pat}_u}} x_{i,k} + \sum_{j \in \text{V}_{\text{pat}_u}} x_{j,l} - \sum_{ij \in \text{E}_{\text{pat}_u}} y_{ij,kl} \leq 1 \quad \forall kl \in \text{E}_g. \] (16)

The constraints in Equations 11 – 16 are defined to find pattern \( \text{pat}_u \) in projection graph \( g \) of the input article. However these constraints do not ensure that the pattern is in the summary. For this, we define constraints in Equations 17 – 19 to assure that an existing pattern in an article is selected if there are some sentences in the summary which constitute the pattern.

• The constraint in Equation 17 ensures that if sentences \( s_k \) and \( s_l \) are selected for the summary then the edge between them is selected (\( z_{kl} = 1 \)), too:
\[ s_k \cdot s_l = z_{kl} \quad \forall k,l \in \text{V}_g. \] (17)

• Pattern \( \text{pat}_u \) is present in the summary (\( p_u = 1 \)) if and only if one of its instances in the projection graph is included in the summary, i.e., some of the selected sentence nodes must be present in an instance of pattern \( \text{pat}_u \). \(|\text{V}_{\text{pat}_u}|\) is the number of nodes in pattern \( \text{pat}_u \), and \(|\text{E}_{\text{pat}_u}|\) is the number of edges in pattern \( \text{pat}_u \). This constraint is shown below:
\[ \sum_{i \in \text{V}_{\text{pat}_u}, k \in \text{V}_g} s_k \cdot x_{i,k} + \sum_{ij \in \text{E}_{\text{pat}_u}, kl \in \text{E}_g} z_{kl} \cdot y_{ij,kl} = p_u(|\text{V}_{\text{pat}_u}| + |\text{E}_{\text{pat}_u}|). \] (18)

• If a sentence is selected then it has to match a node of at least one of the patterns:
\[ \sum_{\text{pat}_u \in \text{P}} \sum_{i \in \text{V}_{\text{pat}_u}} x_{i,k} \geq s_k \quad \forall k \in \text{V}_g. \] (19)

3 Experiments

In this section we discuss the datasets and the experimental setup. We evaluate our model using ROUGE scores and human judgements.

3.1 Datasets

PLOS Medicine: This dataset contains 50 scientific articles. In this dataset every scientific article is accompanied by a summary written by an editor of the month. This editor’s summary has a broader perspective than the authors’ abstract. We use the editor’s summary as a gold summary for calculating the ROUGE scores. We use 700 different PLOS Medicine articles from the PubMed\footnote{http://www.ncbi.nlm.nih.gov/pmc/tools/ftp/} corpus to mine coherence patterns from their abstracts and to calculate patterns’ weights.

DUC: The DUC 2002 dataset has been annotated for the Document Understanding Conference 2002. It contains 567 news articles for summarization. Every article is accompanied by at least two gold summaries. DUC 2002 articles are shorter than PLOS Medicine articles (25 vs. 154 sentences average length). We use all (300) DUC 2005 human summaries to mine coherence patterns and to calculate their weights.

3.2 Experimental Setup

First, we extract the text of an article. We remove figures, tables, references and non-alphabetical characters. Then we use the Stanford parser (Klein and...
Manning, 2003) to determine sentence boundaries. We apply the Brown coherence toolkit (Elsner and Charniak, 2011) to convert the articles into entity grids (Barzilay and Lapata, 2008) which then are transformed into entity graphs. We use gSpan (Yan and Han, 2002) to extract all subgraphs from the projection graphs of the abstracts of the PubMed corpus.

It is possible that patterns with a large number of nodes are not at all present in the projection graph. Hence, we use coherence patterns with 3 and 4 nodes, referred to as $CP_3$ and $CP_4$, respectively. We use Gurobi (Gurobi Optimization, Inc., 2014) to solve the MIP problem. We use a pronoun resolution system (Martschat, 2013) to replace all pronouns in the summary with their antecedents.

We determine the best values for $\lambda_I$, $\lambda_R$, and $\lambda_c$ on the development sets. $\lambda_I = 0.4$, $\lambda_R = 0.3$, and $\lambda_c = 0.3$ are the best weights for the $PLOS$ Medicine development set. Weights for the DUC 2002 development set are $\lambda_I = 0.5$, $\lambda_R = 0.2$ and $\lambda_c = 0.3$.

3.3 Results

We evaluate our model in two ways. First, we use ROUGE scores to compare our model with other models. Second, we explicitly evaluate the coherence of the summaries by human judgements.

3.3.1 ROUGE Assessment

The ROUGE score (Lin, 2004) is a standard evaluation score in automatic text summarization. It calculates the overlap between gold summary and system summary. In automatic text summarization ROUGE 1, ROUGE 2 and ROUGE SU4 are usually reported (see Graham (2015) for an assessment of evaluation metrics for summarization).

We compare our system ($CP_3$ and $CP_4$) with four baselines: Lead, Random, Maximal Marginal Relevance (MMR) and TextRank. Lead selects adjacent sentences from the beginning of an input article. Random selects sentences randomly. MMR (Carbonell and Goldstein, 1998) uses a trade-off between relevance and redundancy. TextRank is a graph-based system using sentences as nodes and edges weighted by cosine similarity between sentences (Mihalcea and Tarau, 2004).

We compare our system with three state-of-the-art systems: $E_{Coh}$ (Parveen and Strube, 2015), $T_{Coh}$ (Parveen et al., 2015), and Mead (Radev et al., 2004). $E_{Coh}$ uses entity graphs which consists of entities and sentences, and $T_{Coh}$ uses topical graphs where entities are replaced by the topics. They both use the outdegree of sentence nodes in the unweighted and the weighted projection graph, respectively, as the coherence measure of each sentence. Mead employs a linear combination of three features: centroid score, position score and overlap score. The linear combination is used to add sentences to the summary up to the required length. The centroid score gives the highest score to the most central sentence in the cluster of sentences, the position score gives a higher score to the sentences which are in the beginning of the document, and the overlap score computes the similarity between the sentences of a document. All three features do not take care of the coherence of a summary as they do not have any notion of the order and the structure of a summary.

To compare with the state-of-the-art systems on PLOS Medicine, $E_{Coh}$ (Parveen and Strube, 2015) and $T_{Coh}$ (Parveen et al., 2015), we limit the length of summaries to 5 sentences. Table 1 reports ROUGE scores of different systems. Our system outperforms baselines and state-of-the-art systems.

Since the word length limit of a summary is more meaningful than the sentence length limit of a summary, we limit the length of a summary to the average length of editor’s summaries in the dataset (750 words). Table 2 shows the performance of different systems with 750 words limit for a summary. In Table 2, we use different versions of ROUGE-SU4 and ROUGE-2 where W/WO stands

| Systems    | R-SU4 | R-2 |
|------------|-------|-----|
| **Baselines** |       |     |
| Lead       | 0.067 | 0.055 |
| Random     | 0.048 | 0.031 |
| MMR        | 0.069 | 0.048 |
| TextRank   | 0.068 | 0.048 |
| **State-of-the-art** |       |     |
| $E_{Coh}$  | 0.131 | 0.098 |
| $T_{Coh}$  | 0.129 | 0.095 |
| Mead       | 0.084 | 0.068 |
| **Our Model** |       |     |
| $CP_3$     | 0.135 | 0.103 |

Table 1: PLOS Medicine, editor’s summaries with 5 sentences.
for With/Without. Here, $WO_{\text{Stop}}$ means without considering stopwords while calculating ROUGE scores, and $WO_{\text{Stem}}$ means without applying the Porter Stemmer on summaries while calculating ROUGE scores. Our models outperform baseline and state-of-the-art systems (Table 2). We compute statistical significance between $E_{\text{Coh}}$ and $CP_3$ on both scores, ROUGE SU4 is significantly different by 95%. ROUGE 2 is significantly different by 99%.

Upper Bound in Table 2 represents maximum ROUGE scores that can be achieved in extractive summarization on the PLOS Medicine dataset. It is calculated by considering the whole scientific article as a summary and the corresponding editor’s summary as the gold standard. The Upper Bound scores are not very high showing that a significant improvement in ROUGE scores on the PLOS Medicine dataset is difficult. Thus, the performance achieved by our systems, $CP_3$ and $CP_4$, is a considerable improvement on the PLOS Medicine dataset.

Furthermore, we apply $CP_3$ on the dataset introduced by Liakata et al. (2013). The dataset consists of 28 scientific articles from the chemistry domain. The state-of-the-art system on this dataset is CoreSC, which is developed by Liakata et al. (2013). CoreSC considers discourse information while summarizing a scientific article. The ROUGE-1 score of $CP_3$ (0.96) is significantly better than CoreSC (0.75) and Microsoft Office Word 2007 AutoSummarize (0.73) (García-Hernández et al., 2009), in respect of abstracts. This shows that our system performs well in other domains.

We further calculate the average number of sentences per summary obtained by Mead and $CP_3$. On average Mead produces 17.5 sentences per summary whereas $CP_3$ produces 27.2 sentences per summary. The possibility of longer sentences containing more topic irrelevant entities is higher than shorter sentences (Jin et al., 2010).

We calculate the average percentage of sentences selected from the sections Introduction, Method, Results and Discussion by different systems. $CP_3$ extracts sentences mainly from Introduction (32.5%) and Method (38.5%), but also a considerable number of sentences from Results (17.67%) and Discussion (11.33%). The distribution is quite similar to TextRank and MMR. Lead, obviously, extracts only from Introduction (80.59%) and Method (19.41%). Mead extracts maximum sentences from the beginning of the document using its positional feature. The sentences in a summary extracted by $CP_3$ are evenly distributed indicating that they are not biased to any sections. This clearly represents that coherence patterns not only seeks for nearby sentences but also for any distant sentences of a scientific article.

Table 3 shows the results on DUC 2002 to compare the results with state-of-the-art systems. There is no significant difference between the ROUGE scores of using $CP_3$ and $CP_4$ on DUC 2002. Thus, we only report the results of using $CP_3$ on DUC 2002.

In Table 3, LREG is a baseline system us-
Systems | R-1 | R-2 | R-SU4
--- | --- | --- | ---
Baselines | | | |
Lead | 0.459 | 0.180 | 0.201
DUC 2002 Best | 0.480 | 0.228 |
TextRank | 0.470 | 0.195 | 0.217
LREG | 0.438 | 0.207 |
State-of-the-art | | | |
Mead | 0.445 | 0.200 | 0.210
ILP\_phrase | 0.454 | 0.213 |
URANK | 0.485 | 0.215 |
UniformLink (k = 10) | 0.471 | 0.201 |
\(E_{Coh} \) | 0.485 | 0.230 | 0.253
\(T_{Coh} \) | 0.481 | 0.243 | 0.242
NN-SE | 0.474 | 0.230 |
Our Model | | | |
CP\_3 | 0.490 | 0.247 | 0.258

Table 3: ROUGE scores on DUC 2002.

ing logistic regression and hand-made features (Cheng and Lapata, 2016). We compare our model to previously published state-of-the-art systems. These systems show reasonable performance on the DUC 2002 summarization task. \(ILP\_phrase\) is a phrase-based extraction model, which selects important phrases and combines them via integer linear programming (Woodsend and Lapata, 2010). \(URANK\) utilizes a unified ranking process for single-document and multi-document summarization tasks (Wan, 2010). \(UniformLink (k=10)\), considers similar documents for document expansion in the single-document summarization task (Wan and Xiao, 2010). The more recent system, \(NN-SE\), utilizes a neural network hierarchical document encoder and an attention-based extractor to extract sentences from a document for a summary (Cheng and Lapata, 2016). ROUGE scores of our approach on this dataset are better than baselines and state-of-the-art systems. This shows that our system performs well even in a different genre (robust) and with considerably shorter input documents (scalable).

3.3.2 Coherence Assessment

ROUGE scores do not evaluate summary coherence, since ROUGE only calculates overlapping recall scores and does not consider the structure of the summary. Haghighi and Vanderwende (2009), Celikyilmaz and Hakkani-Tür (2010) and Christensen et al. (2013) evaluate the overall summary quality by asking human subjects to rank system generated summaries. Parveen and Strube (2015) and Parveen et al. (2015) assess the coherence by asking human assessors to rank system generated summaries and compare their system with baseline systems.

We perform summary coherence assessment by asking one Postdoc, two PhD students and one Masters student from the field of natural language processing. We provide them with the output summaries of four different systems for ten articles. We ask them to rank the summaries, i.e., the best summary gets rank 1, the second best gets rank 2, the third best gets rank 3, and the worst gets rank 4.

The four systems assessed are \(CP_3\), \(E_{Coh}\), \(TextRank\), and \(Lead\). We apply the Kendall concordance coefficient (W) (Siegel and Castellan, 1988) to measure whether the human assessors agree in ranking the four systems. With \(W = 0.6725\) the correlation between the human assessors is high. Applying the \(\chi^2\) test shows that W is significant at least at the 99% level indicating that the ranks provided by the human assessors are reliable and informative. Table 4 shows the overall average rank of a system given by the four human assessors. The lower the value of average human scores the more coherent the summary. Unsurprisingly \(Lead\) gets the best overall average rank. \(Lead\) extracts adjacent sentences from the beginning of the document. Hence, these summaries are as coherent as the author intends them to be, but they are not informative. However, \(CP_3\) is very close in coherence to \(Lead\) indicating that our strategy is successful. It also performs substantially better than \(TextRank\) and \(E_{Coh}\). This confirms that using coherence patterns for sentence extraction yields more coherent summaries.

4 Related Work

Summarizing scientific articles is as difficult as multi-document summarization because scientific articles are tend to be long and the important infor-
There are various approaches for summarizing scientific articles. Citations have been used by many researchers for summarization in this domain (Elkiss et al., 2008; Mohammad et al., 2009; Qazvinian and Radev, 2008; Abu-Jbara and Radev, 2011). Nanba and Okumura (2000) develop rules for categorizing citations by analyzing citation sentences. Newman (2001) analyzes the structure using a citation network. Similarly, Siddharthan and Teufel (2007) discover scientific attributions using citations. Discourse structure (but not necessarily coherence) has been used by Teufel and Moens (2002), Liakata et al. (2013) and others for summarizing scientific articles.

Several state-of-the-art extractive summarization systems implement summarization as maximizing an objective function using constraints. McDonald (2007) interprets text summarization as a global inference problem, where he is maximizing the importance score of a summary by considering the length constraint. Similarly, various approaches for summarization are based on optimization using ILP (Gillick et al., 2009; Nishikawa et al., 2010; Galanis et al., 2012; Parveen and Strube, 2015).

Until now, only few works have considered coherence while summarizing scientific articles. Abu-Jbara and Radev (2011) work on citation based summarization. They preprocess the citation sentences to filter out irrelevant sentences or sentence fragments, then extract sentences for the summary. Eventually, they refine the summary sentences to improve readability. Jha et al. (2015) consider Minimum Independent Discourse Contexts (MIDC) to solve the problem of non-coherence in extractive summarization. However, none of them deals with the problem of coherence within the task of sentence selection. Sentence selection and ensuring the coherence of summaries are not tightly integrated in their techniques. They model coherence in summarization by only considering adjacent sentences.

There are few methods (Hirao et al., 2013; Parveen and Strube, 2015; Gorinski and Lapata, 2015) which integrate coherence in optimization. These methods do not take into account the overall structure of the summary. Unlike earlier methods, we incorporate coherence patterns in optimization.

5 Conclusion

We introduce a novel graph-based approach to generate coherent summaries of scientific articles. Our approach takes care of coherence distinctively by coherence patterns. We have experimented with PLOS Medicine and DUC 2002. The results show that the approach is robust, works on both scientific and news documents and with input documents of different length. It considerably outperforms state-of-the-art systems on both datasets. We collected human assessments to evaluate the coherence of summaries. Our system substantially outperforms state-of-the-art systems, i.e., incorporating coherence patterns produces more coherent summaries. The results show that our approach performs well in human summary coherence assessment and relevance evaluation (ROUGE scores).

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