Highlights

Experiments in Extractive Summarization: Integer Linear Programming, Term/Sentence Scoring, and Title-driven Models

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- We do in depth investigation of parameterizing different scoring schemes.
- We leverage integer linear programming to extractive summarization.
- We create new formulations of integer linear programming for summarization.
- We show our tool, NewsSumm, can be used to efficiently improve supervised methods.
Experiments in Extractive Summarization: Integer Linear Programming, Term/Sentence Scoring, and Title-driven Models

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ABSTRACT

In this paper, we revisit the challenging problem of unsupervised single-document summarization and study the following aspects: (i) Integer linear programming (ILP) based algorithms, (ii) Parameterized normalization of term and sentence scores, and (iii) Title-driven approaches for summarization. We describe a new framework, NewsSumm, that includes many existing and new approaches for summarization including ILP and title-driven approaches. NewsSumm’s flexibility allows to combine different algorithms and sentence scoring schemes seamlessly. Our results combining sentence scoring with ILP and normalization are in contrast to previous work on this topic, showing the importance of a broader search for optimal parameters. We also show that the new title-driven reduction idea leads to improvement in performance for both unsupervised and supervised approaches considered.

1. Introduction

Manual summarization of text documents is both expensive and time consuming (Lin, 2004). Thus development of automated systems for text summarization is a topic of considerable interest among the research community. Research on automated summarizers began in the late 50s (Luhn, 1958), with a system that uses term frequencies for assigning weights to sentences to build a summary.

Summarization research has come a long way since then with automated summarizers aiming to generate the best possible summary. Summaries can be classified into two groups - (a) Abstractive: These are generally created by using lexically similar words and phrases to report the important information in the original article. Such a summary avoids using sentences verbatim from the source. It could also use other vehicles such as word graphs for displaying the important content. (b) Extractive: Such a summary is a collection of sentences from the source document purportedly containing the most relevant information.

Summaries can be single or multi-document based on the number of documents used as the source material. With the DUC summarization conference, extractive multi-document summarization gained more popularity over single document summarization right after 2001-2002. A reason for this sudden drop was the absence of a system that could beat the lead-based baseline summaries (Svore et al., 2007) for news articles. Thus, finding innovative techniques for single document summarization has a set of challenges different from that of multi-document summarization (Barrera and Verma, 2012).

Our research returns to unsupervised single document summarization. We focus on unsupervised summarization, since: (i) it does not need annotated datasets, and (ii) it can be orders-of-magnitude faster as neither training nor hyper-parameter optimization phases are necessary. We investigate several new aspects of this topic and make multiple contributions:

1. We parameterize the most promising word scoring methods to improve ranking of words and also sentence score normalization (Section 3.1). By parameterizing the scoring methods, we show that the optimal scores are achieved when parameter values are rarely equal to 1, which is how they are often used in previous literature (Section 5).

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2. We utilize integer linear programming (ILP) to solve a maximum coverage model of summarization (Section 3.2) and extend ILP formulation with budget constraint and with alternative scoring metrics (Section 3.3). The combination of ILP with \textit{tfidf} proves to be the best of the unsupervised methods researched (Section 5.3).

3. We leverage titles to drive the modeling of extractive summarization (Section 3.4). In particular, we show that, using our title-driven reduction idea, can also improve even a state-of-the-art \textit{supervised} summarization algorithm as well (Section 5.4).

In addition to these contributions, we incorporate the algorithms and approaches into a tool, NewsSumm, that can be used as an extractive summarizer. Since the output comes directly from the original document, the summary can be used as a part of a larger pipeline (e.g. NewsSumm used to extract salient information of target document).

The rest of this paper is organized as follows. We discuss the most closely related previous work in the next section. In Section 3, we introduce NewsSumm, our ILP formulations, parametrizations, and title-driven reduction ideas. In Section 4, we present the experiments and the baselines for comparisons. The quantitative and qualitative results and discussion are in Section 5 and Section 6 concludes.

2. Related Work

Summarization of articles like news, research papers, blog posts etc., has always been a difficult task for both humans as well as machines. Automated summarizers have come a long way since the 1950s with current systems using supervised learning methods like the use of submodular optimization models (Sipos et al., 2012a) for determining maximum information coverage with minimum redundancy, theme-based summarization using rank-based clustering (Yang et al., 2014). Unsupervised approaches for text document summarization used in previous research include greedy selection algorithms like Maximal Marginal Relevance (Carbonell and Goldstein, 1998) as well as dynamic programming algorithms (McDonald, 2007), which view document summarization as a ‘knapsack problem.’ Summarization is a vast topic so we review only the most closely related previous work here, and refer the reader to Gambhir and Gupta (2017); Dong (2018) for more comprehensive overviews. Naturally, we focus on single document summarization.

2.1. Extractive Summarization

\textbf{Scoring Methods.} A proposed syntax and semantic based approach in Barrera and Verma (2012) uses a scoring metric for ranking sentences from the original document, based on the semantics, word popularity as well as sentence position features. This approach outperforms the baseline when tested on a set of scientific magazine articles. This was followed by the use of vertex cover for summarization in Kumar et al. (2013). Garcia-Hernandez and Ledeneva (2009) investigate different weighting schemes based on the terms of a document. A number of word, sentence and graph scoring methods were investigated in Ferreira et al. (2013), with \textit{tfidf} emerging as the winner for word scoring methods. However, the researchers did not parameterize any of the scoring methods as we do in this paper.

Integer Linear Programming (ILP) has been used to improve efficient summarization. Martins and Smith (2009) used ILP to balance both sentence compression and extraction. ILP was studied for concept weighting by Oliveira et al. (2016), where sentence position and bigrams were found to be important, and for coherent summarization by Garcia et al. (2018), where an entity driven ILP approach was adopted. Extractive summaries can be generated from single documents with the use of genetic operators and guided local search algorithms (Mendoza et al., 2014).

\textbf{Clustering.} A common approach for unsupervised methods is to use clustering. Then sentences can be selected from different clusters to best represent the document. The K-means clustering algorithm (Zhang and Li, 2009) and Expectation-Maximization algorithm (Ledeneva et al., 2011) are two approaches that use this approach. Clustering has also been used in multi-document summarization (Gupta and Siddiqui, 2012).

\textbf{Evaluation of Summaries.} ROUGE, which is based on n-gram overlap of a summary with a gold-standard summary, is a popular method for summary evaluation. Another approach is Pyramid, which involves more human labor.

\textbf{Limit on ROUGE Recall and F-1 scores.} In Verma and Lee (2017), limits on ROUGE recall and F-1 scores are proved, using the idea that no extractive summarizer can do better than just returning the entire document as a summary, for DUC datasets for both single-document and multi-document extractive summarization.

\textbf{Tools.} A number of tools for automatic summarization have been described in the literature. DocSumm is a Python based extraction based summarizer (Verma and Lee, 2017). CaseSummarizer is also Python-based but it is built
specifically for the domain of legal texts (Polsley et al., 2016). PKUSUMSUM is a general purpose summarizer like DocSumm; however, it is for the Java programming language (Zhang et al., 2016).

Recently, SummIT (Feigenblat et al., 2017) is work done by researchers to apply summarization as a direct tool for human users. Humans must input a query to search for documents that they are seeking. However, SummIT’s goal is more in application of summarization than improving summarization itself.

There are also plenty of online tools that provide automatic summarization. Doing a simple Google search shows the prevalence of such tools. These tools fail to provide an avenue for further research, e.g., there is no method for bulk/batch summarization. The tools also do not provide a way to use them through scripts or program calls, which further hinders efficient evaluation. NewsSumm lends itself naturally to bulk and unattended testing.

Graph-based Models. A stochastic graph-based approach LexRank is proposed in Erkan and Radev (2004) for multi-document summarization, which builds the graph based on similarity of sentences, which are the nodes. The summary is generated by using the concept of sentence similarity. In Mihalcea and Tarau (2004a), TextRank uses the concepts of popular graph based scoring algorithms like PageRank (Page et al., 1999) and HITS (Kleinberg et al., 1999) for sentence similarity scoring. GRAPHSUM in Baralis et al. (2013) uses association rules for representing correlations among multiple terms for building a graph based model.

In Verma and Lee (2017), researchers frame the summarization problem as a bipartite graph. One set of nodes are the sentences themselves and the other disjoint set being “thought units.” The research frames the goal of summarization as a minimal subset of the sentence nodes that covers all the “thought units.” The DocSumm tool focuses on a special case of this model that treats the words of the sentence as the “thought unit”. We call this the set-cover model of summarization.

2.2. Abstractive Summarization

Several methods up to 2017 have been collected by Rachabathuni (2017). Recently the research on abstractive summarizers has been predominantly based on neural networks. Some of the flavors of the neural network architectures are encoder/decoder (Xu et al., 2017), attention models (See et al., 2017; Cohan et al., 2018) and GANs (Liu et al., 2018).

2.3. Submodular Summarization Models

The approach of Lin and Bilmes (2010, 2011) uses a submodular scoring function, which takes into account the inter-sentence similarity for generating summaries so that there is maximum coverage of important information and redundancy is simultaneously reduced. However, sentence pairwise model in Lin and Bilmes (2010) needs to be manually tuned to get the best inter-sentence similarity measure. The authors of Sipos et al. (2012a) improve upon this technique and propose a supervised approach to learn both the appropriate similarity measure as well as the required trade-off between coverage and redundancy from the training data. This model was further used in Sipos et al. (2012b) for corpus summarization over a time interval.

3. NewsSumm

The NewsSumm toolkit includes all the previous algorithms available in DocSumm (Verma and Lee, 2017). As a part of the toolkit it also provides the capability to truncate summaries to desired length. Because it relies on state-of-the-art NLP techniques for basic tasks such as tokenization and possessives, it is more accurate. In addition to this it provides four additional important avenues of exploration:

• Normalizing Factors: Normalizing is imposed to remove bias from over-valuing a score based purely on length. For example, if a sentence is valued by the sum of its terms, then longer sentences will often receive higher scores. NewsSumm parameterizes three separate score influencing values: sentence length, and both factors of the $tfidf$ (Section 3.1).

• Integer Linear Programming (ILP): The problem of set-cover is a known NP-hard problem. To battle this, NewsSumm incorporates ILP to find optimal set covers (Section 3.2).

• ILP extended: novel ILP formulations that incorporates both a word budget and alternate scoring metrics (Section 3.3).

1. https://www.tools4noobs.com/summarize/
2. https://www.textcompactor.com/
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- Title-driven summarization (Section 3.4): When creating titles, humans try to capture the essence of a document in a single sentence. NewsSumm leverages the title words to drive sentence selection.

### 3.1. Normalizers

A common practice for selecting candidates for a final summary is to rank a sentence by the sum of its terms. Longer sentences would, on average, have higher scores. To offset this bias, “normalization” is used. It modifies a sentence’s score based on the length of the sentence (in words). More specifically, the score of a sentence $s$, $\text{score}(s)$, is normalized by dividing by the length of $s$, $|s|$, the number of words in $s$. 

$$\text{norm}(s) = \frac{\text{score}(s)}{|s|}$$ (1)

Previous research has shown this kind of normalization can over-compensate for bias towards longer sentences (Lin and Bilmes, 2010). NewsSumm parameterizes normalization using the idea of Lin and Bilmes (2010):

$$\frac{\text{score}(s)}{|s|^r}, \text{ with } 0 \leq r \leq 1$$ (2)

The original normalization parameter is Equation 2, where $r = 1$.

A popular scoring heuristic is $\text{tfidf}$. $\text{tfidf}$ is a word score based on its frequency. $\text{tf}$ represents the term frequency in a document. The inverse document frequency $\text{idf}$ is computed as:

$$\text{idf} = \log \left( \frac{N}{df} \right)$$ (3)

Where $N$ is the number of sentences in document and $df$ is the number of sentences that include the term (Sparck Jones, 1972).

Research has shown that the presence/absence of $\text{tf}$ and $\text{idf}$ have different affects on the final summary (Garcia-Hernandez and Ledeneva, 2009). We explore this by also parameterizing the two factors of $\text{tfidf}$. Because $\text{tfidf}$ is the product of two measures, we parameterize the influence of these factors by exponentiating them before the final product.

$$\text{tfidf} = (\text{tf})^a(\text{idf})^b$$ (4)

### 3.2. Integer Linear Programming

Integer linear programming has found promise in solving computationally complex problems (Williams et al., 2009). NewsSumm provides exploration of optimal set covers with ILP, and also a variant of ILP that includes a budget on words. One can easily extend this feature to explore set cover of “important subsets of words” instead of all words (or stemmed words after stopword elimination).

Given a document $D$ with $n$ sentences, the basic ILP formulation has an objective function to minimize the number of sentences, $s_i$. We want to minimize the following function over the vector $\hat{x} = (x_1, x_2, \ldots, x_{n-1}, x_n)$: compression and with

$$\sum_{i=1}^{n} x_i$$ (5)

Each $x_i \in \hat{x}$ is a binary variable that represents inclusion/exclusion of the $i^{th}$ sentence in the summary. Then we add the dot-product constraints:

$$\forall j : \hat{x} \cdot T_j > 0$$ (6)

Here, $T_j$ is the $j$-th row of a term-sentence matrix $T$. These constraints ensure that every word of the document is included in the summary. Note that this set of document words, can be reduced by applying stemming and removing stop words as a preprocessing step.
3.3. Extending ILP

A variant of this ILP is to constrain it based on a budget, \( L \), of the number of words allowed in the final summary. This variant then becomes a maximization problem on number of words covered. Let vector \( \hat{z} = (z_1, z_2, \ldots, z_{m-1}, z_m) \) represent words covered and \( z_j \) be the inclusion/exclusion of the \( j \text{th} \) word. Then the objective function is:

\[
\sum_{j=1}^{m} z_j
\]  

(7)

We need an integrity constraint for each term covered (i.e. if \( z_j \) is included then at least one sentence with \( z_j \) is also included in the summary).

\[
\forall j : (\sum_{i} T_{ji}) - z_j \geq 0
\]  

(8)

With only Equation 8, one may believe that the formulation could allow for a solution where a sentence is included, but a term of that sentence is removed. However, this is a maximization problem, so if a sentence, \( x_i \) is included, then any solution which ignores a specific term will not be the maximum. Therefore, all terms will naturally be selected for inclusion.

The only limiting factor would be the budget constraint. Let \( c_i \) be the associated word count (i.e. cost) for sentence \( i \), then the budget constraint is:

\[
\sum_{i=1}^{n} x_i c_i \leq L
\]  

(9)

This constraint would force the solution summary not to exceed the budget.

We can also further modify the ILP maximization function generalizing the term-sentence matrix, \( T \), into a score matrix. Rather than, each entry being a binary 0/1, we can let them be a score that represents the value of a terms inclusion in the summary. Then the goal of the ILP is to maximize this score, rather than a word count. So instead of Equation 7 we would maximize the terms, \( t_{ji} \) of \( T \). Let \( A \) be a matrix of 0/1 values such that \( a_{ji} \) means inclusion of \( t_{ji} \). The Equation 10 follows as the new maximization objective function.

\[
\sum_{i=0}^{n} \sum_{j=0}^{m} (A \circ T)_{ji}
\]  

(10)

Also, note that each term, \( t_{ji} \) is unique. Meaning the same word can potentially have different scores based on the sentence they appear in. It follows that the integrity constraint will change to:

\[
\forall i, j : a_{ji} - x_j = 0
\]  

(11)

This constraint enforces the conditions that a sentence is selected if and only if all the words are selected.

3.4. Title Driven Summarization

The goal of automatic summarization is to quickly distill the important parts of a document into a short grouping of words (or sentences). The authors of documents try to capture the essence of a document with an attention-seeking title. NewsSumm tries to leverage the authors’ title, which we can think of as a pithy summary of the document, with an unsupervised title-driven summarization algorithm as shown in Algorithm 1. In essence, a tree \( T \) with sentences as nodes is created using a greedy strategy. At the root is the title sentence. It will have an edge to any sentence that overlaps with the root. The next level consists of sentences that overlap with any sentence of the previous level. Here we use a greedy strategy to connect a child sentence with the first parent sentence with which it overlaps. This algorithm continues until: (1) all the sentences are used or (2) there are no more sentences that overlap with the tree nodes.

The tree structure is implicit in Algorithm 1 because all we need for our title-driven summarization is the information about the level of a sentence in the tree hierarchy.
Algorithm 1 *TitleDrivenReduction*(doc, title)

1: Let $G$ be ordered list of lists, where $G[i]$ represents set of sentences at $i^{th}$ level
2: $D \leftarrow$ set of sentences, each sentence a set of words.
3: $T \leftarrow$ set of words of title
4: $T_{next} \leftarrow \emptyset$
5: $i \leftarrow 0$
6: while $D \neq \emptyset$ do
7:     $G[i] \leftarrow \emptyset$
8:     for all $S \in D$ do
9:         if $T \cap S \neq \emptyset$ then
10:             $G[i] \leftarrow G[i] \cup S$
11:             $T_{next} \leftarrow T_{next} \cup (S - T)$
12:         end if
13:     end for
14:     if $T_{next} = \emptyset$ then
15:         break
16:     end if
17:     $T \leftarrow T_{next}$
18:     $T_{next} \leftarrow \emptyset$
19:     $i \leftarrow i + 1$
20: end while

We can then order the sentences based on traversing the tree in a breadth-first search manner. This will give a new ordering of the original document, as well as potentially reducing the original document size. We believe this ordering helps to prioritize sentence ordering with the title in mind. Because of the greedy strategy implemented in NewsSumm, there is an inherent preference to sentences visited earlier. In our title-driven summarization algorithm, we will work with the reduced set of sentences from the document, the sentences from the *TitleDrivenReduction* tree. All the scoring algorithms will work fine, but, of course, some of the scores of the words will change, e.g. $tfidf$.

The *TitleDrivenReduction* also has a depth parameter. This parameter will prematurely truncate the tree at a certain depth, i.e. $depth = 1$ includes title and direct children, $depth = 2$ would also include grandchildren. This version can produce a summary without using any scoring metric. It would simply create a document with sentences up to the specified depth and then truncate to summary size.

One kind of title-driven summary is to just use the *TitleDrivenReduction* tree sentences. Another option is to run the NewsSumm algorithms on the reduced set of sentences. We explore both options below.

4. Experiments

The experiments were designed to explore novel approaches to single-document extractive summarization. We begin with the datasets (Section 4.1), pre-processing (Section 4.2) and the ROUGE evaluation metric (Section 4.3). Next we look at the experiment design for “Parameterization,” “Integer Linear Programming,” and “Title Driven.” We close the section with a brief description of baselines used for comparison.

4.1. Datasets

For demonstration of NewsSumm we will use datasets from Document Understanding Conferences in 2001 and 2002. These conferences began in 2001. After 2002, NIST discontinued the single document extractive summarization task, because no automatic system could beat a baseline consisting of the first 100 words for news articles in a statistically significant way.

Table 1 gives a brief overview of the datasets used. It is important to note that DUC02 has 34 duplicate documents, which could bias the results. Many previous works have ignored this issue and used all 567 documents. We have taken care to remove all duplicate documents from DUC02.

- DUC01: These are the documents of the Document Understanding Conference (DUC). It is the test set used in 2001 (NIST, 2014a). There are 305 documents, each with a single summary. The original set of documents had a duplicate document with a different name. So this document was removed.
Table 1 Description of datasets used in all experiments.

| Dataset Name | Number of Documents | Summaries Per Document | Words Per Document |
|--------------|---------------------|------------------------|-------------------|
| DUC01        | 305                 | 1                      | 98.35             |
| DUC02        | 533                 | 1 to 5                 | 568.21            |
| TITLE02      | 526                 | 1 to 5                 | 562.89            |

- **DUC02**: DUC documents used in test set of 2002, the last year of single-document summarization task (NIST, 2014b). It is a collection of 533 unique news articles.

- **TITLE02**: We also create a subset of DUC02. This dataset is the set of documents which include legitimate titles. DUC02 contains seven articles that do not have valid headlines. So these articles were excluded for the title-driven experiments (see Appendix A).

### 4.2. Pre-processing

To ensure comparable results across the methods, all documents are pre-processed in the same manner. The goal of pre-processing is to find the informative words for word scoring. We now present the pre-processing steps.

- **Stemming.** Stemming removes morphological changes so that words like ‘musical’ and ‘music’ are the same. It also removes common verb endings to words (e.g. jump, jumps, jumped, and jumping).

- **Stopword Removal.** Words like ‘the’ and ‘on’ provide little informational content relative to main idea of a document. So a precompiled list of stopwords is removed from the document. Our software uses NLTK’s English stopword list.

- **Punctuation.** Tokenization separates punctuation marks from the word such that they are standalone tokens. These punctuation tokens are removed from the document.

- **Lowercase Letters.** In all word comparisons, we always convert uppercase letters to their lowercase counterparts.

### 4.3. Evaluation

We use the ROUGE metric to evaluate all summaries. Given gold-standard summaries, it is an automated metric that has been shown to have high correlation with more expensive human-based metrics (Lin and Hovy, 2003). Recent research also reveals that of the many different configurations, ROUGE-2 (bigram) correlates the best (Owczarzak et al., 2012; Graham, 2015) for differentiating automatic summarizers. In Owczarzak et al. (2012), researchers show that ROUGE-2 recall has high correlation with Pyramid scores for differentiating automatic summarizers. They also show that ROUGE-1 has higher correlation with Pyramid scores for differentiating automatic versus a human summary.

However, Graham (2015) recommends reporting scores with ROUGE-2 precision because it had the highest correlation with human assessments of automatic systems and it was not significantly out-performed by other evaluation techniques.

For many of our experiments, we report the ROUGE-1 and also ROUGE-2 F-1 scores. Unless otherwise specified all scores are F-1 scores. Some of the ROUGE-2 figures can be found in the Appendix C. For reference we have also included ROUGE-3, ROUGE-4 and ROUGE-L (longest common subsequence) in select tables. All ROUGE evaluations were run with the parameters listed in Table 2. All summaries are truncated to 100 words before ROUGE evaluations.

### 4.4. Optimal Parameters

NewsSumm’s normalizing factors are compared across four preprocessing parameters. Verma and Lee (2017) reports \( tf id f \) option as the best performing greedy scoring metric, so we report results on \( tf id f \). A variant of \( tf id f \) is \( stf id f \), which counts the term frequency per sentence rather than the whole document. The four relevant binary parameters used are stemming (S), stopword removal (W), distinctness (D) and update on-the-fly (U).

We first look at finding the optimal \( r \)-values over all combinations of preprocessing options. We do a similar search for optimal \( \alpha \) and \( \beta \). As a final experiment a cube search over different \( r \), \( \alpha \) and \( \beta \) values.
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| Param | Setting | Detail |
|-------|---------|--------|
| -c    | 95      | Confidence interval |
| -r    | 1000    | Number samples for bootstrapping |
| -l    | 100     | Upper limit on number of words in summaries |
| -m    | Set     | Use stemming |
| -n    | 4       | ROUGE n-gram for 1-gram to 4-gram |
| -x    | Unset   | If set, ROUGE-L is not computed |

Table 2
Parameters used for ROUGE evaluation in all experiments.

4.5. Integer Linear Programming

Integer Linear Programming lends itself to many different hard problems. NewsSumm explores different formulations to approach the automatic summarization problem (Section 3.2 and Section 3.3). We experiment with the following variations on ILP:

1. Budget Constraint: Forcing output to be no longer than a set threshold on number of words (e.g., 100).
2. Slack Parameter: Allowing ILP to solve with a larger budget and then truncating the result to meet the budget constraint.
3. ILP with score matrix (score\_ilp): Giving words a score based on tfidf values. We did experiment with a variation of tfidf called stfidf (Verma and Lee, 2017), but this gave us inferior results, so we rarely show these results.
4. Normalization: Varying $r$, $a$ and $\beta$.

4.6. Title Driven as Documents and Summaries

Since title driven summaries require a title, we had to go back to the original XML version of the articles. This process came with its own set of hurdles:

1. One XML (WSJ870220-0106) had an ill-formed body (used ‘&’ instead of ‘&amp;’) and needed to be manually corrected.
2. Three documents (see Appendix A) did not contain any headings to start with.
3. Another four documents (see Appendix A) seemed to contain internal communications between editors and journalists in the headings. As such they did not contain relevant headings.
4. A final issue was that four document titles had no overlap with the body (see Appendix B). This means that the words of the title are not mentioned anywhere in the body text. For these, we implemented a failsafe where the first sentence is considered the title. This sentence along with all overlapping sentences would then be the reduced document.

First, TitleDrivenReduction was applied to the dataset to reduce documents to sentences that have direct/indirect overlap with the title. These documents were compared with the whole documents as summaries to get a sense of how much information, if any, was lost.

We also explore different ways to produce summaries using TitleDrivenReduction:

- **TITLE+DEPTH**: TitleDrivenReduction applied with $depth = 1$, then truncated to 100 words if needed.
- **TITLE+BFS**: TitleDrivenReduction tree is traversed in breadth-first manner, and stopped after 100 words.
- **TITLE+FILTER**: TitleDrivenReduction as a filter in a pipeline that also uses score\_ilp.

4.7. Baselines

We use several baselines, both supervised and unsupervised, to compare our work.
4.7.1. **Supervised Submodular**

Optimization of submodular set function has been previously used as a technique for automated summarization by Sipos and Joachims (2013), Lin and Bilmes (2010), Zhang et al. (2016) and Li et al. (2012). While generating a single document summary, the submodular scoring function is used to select sentences from the document taking into account maximum term coverage while penalizing redundant sentences in the generated summary (Sipos and Joachims, 2013; Lin and Bilmes, 2010). Sipos and Joachims (2013) use trained Support Vector Machines (supervised learning system), instead of the unsupervised optimization technique proposed in Lin and Bilmes (2010), to learn the sentence similarity as well as the word weights. Since the proposed summarization system was available only for multi-document summarization, we modify the system to be used for single document summarization.

Therefore, we used the submodular function proposed by Sipos et al. (2012a). This measure uses supervised learning to learn the best possible similarity value as well as coverage/redundancy trade-off from the training data that is fed into it. This supervised system proposed learns a ‘parameterized monotone submodular scoring’ function from the dataset of news articles and their summaries when given to it.

We also integrate the supervised submodular approach with our title-driven algorithms. For direct comparison, we report all results only on the TITLE02 data and with five-fold cross-validation. We bin the 526 documents of TITLE02 into bins of size 105, 105, 105, 105 and 106. Following is a list of experiments done with submodular approach:

- Using supervised submodular approach by itself. This provides a simple baseline for comparison.
- First using *TitleDrivenReduction* on each document to reduce number of sentences for each document. Then applying the supervised submodular approach.
- Using *TitleDrivenReduction* with depth = 1, followed by the supervised submodular approach.

4.7.2. **PKUSUMSUM**

For comparison, we have run PKUSUMSUM on DUC02. The tool implements several previous works on summarization. The five methods we have run are as follows:

- **Lead** is a baseline method that uses initial sentences of the document as summary.
- **Centroid** Radev et al. (2004) scores sentences using a centroid. The centroid is a pseudo-sentence to represent a group of documents. Sentences are scored based on similarity to this centroid, sentence position and similarity to first sentence of a document.
- **TextRank** Mihalcea and Tarau (2004b) is a graph based method that has sentences as vertexes and edge weights based on overlap. Random walk is used to determine sentence ranks.
- **LexPageRank** Erkan and Radev (2004) is also a graph based method. Like TextRank its vertexes are the sentences. However, the edges are based on cosine similarity. Page rank is run on this graph and the node values are the “LexPageRank” values used for a greedy choice.
- **Unsupervised Submodular** Uses algorithms in Lin and Bilmes (2010); Li et al. (2012). These are unsupervised methods based on submodular set functions in mathematics.

5. **Results and Discussion**

We now present the results of our experiments and discuss their significance.

5.1. **Importance of R-Normalization**

Table 3 reports the best $r$-value found for all combinations of binary parameters for the *tfidf* metric. For all three datasets, the optimal value is never $r = 0$ or $r = 1$. Even with a simple metric like *tfidf*, we see the value of parameterizing the sentence normalization. These findings are in line with (Lin and Bilmes, 2010). The value of normalization based on size is not always beneficial, but by adjusting the influence of the normalization (i.e. $r$-value), the results show that the benefits of normalization can always be leveraged.

[^3]: [http://www.cs.cornell.edu/~rs/sfour/](http://www.cs.cornell.edu/~rs/sfour/)
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| Params Used | DUC01 | DUC01 | TITL02 | TITL02 |
|-------------|-------|-------|-------|-------|
| S W D U     | r-Value Ends | Best | ROUGE-1 | r-Value Ends | Best | R-1 | r-Value Ends | Best | R-1 |
| 0.0 1.0     | 0.4030 0.4065 0.7 | 0.4122 | 0.4255 0.4242 0.7 | 0.4291 | 0.4260 0.4242 0.7 | 0.4291 |
| X           | 0.4022 0.4116 0.8 | 0.4201 | 0.4274 0.4267 0.7 | 0.4321 | 0.4278 0.4269 0.7 | 0.4322 |
| X           | 0.4105 0.3980 0.5 | 0.4146 | 0.4360 0.4162 0.5 | 0.4375 | 0.4370 0.4170 0.5 | 0.4382 |
| X           | 0.4110 0.3934 0.7 | 0.4160 | 0.4330 0.4173 0.6 | 0.4444 | 0.4338 0.4177 0.6 | 0.4451 |
| X           | 0.3918 0.3996 0.6 | 0.4007 | 0.4238 0.4213 0.0 | 0.4238 | 0.4239 0.4216 0.0 | 0.4239 |
| X           | 0.4111 0.4012 0.5 | 0.4186 | 0.4366 0.4192 0.4 | 0.4393 | 0.4376 0.4199 0.4 | 0.4398 |
| X           | 0.4145 0.3988 0.7 | 0.4195 | 0.4346 0.4204 0.6 | 0.4478 | 0.4350 0.4208 0.6 | 0.4481 |
| X           | 0.3935 0.4010 0.8 | 0.4029 | 0.4219 0.4228 0.2 | 0.4239 | 0.4219 0.4232 0.2 | 0.4240 |
| X           | 0.4144 0.4022 0.5 | 0.4219 | 0.4407 0.4228 0.4 | 0.4446 | 0.4412 0.4234 0.5 | 0.4453 |
| X           | 0.3991 0.3926 0.5 | 0.4017 | 0.4228 0.4192 0.2 | 0.4238 | 0.4232 0.4198 0.2 | 0.4244 |
| X           | 0.3962 0.3966 0.8 | 0.4029 | 0.4261 0.4209 0.5 | 0.4310 | 0.4258 0.4212 0.5 | 0.4313 |
| X           | 0.4161 0.4054 0.6 | 0.4248 | 0.4428 0.4266 0.5 | 0.4474 | 0.4436 0.4273 0.5 | 0.4479 |
| X           | 0.3974 0.3958 0.5 | 0.4006 | 0.4250 0.4223 0.5 | 0.4261 | 0.4257 0.4229 0.5 | 0.4268 |
| X           | 0.3986 0.3965 0.6 | 0.4041 | 0.4259 0.4214 0.6 | 0.4293 | 0.4255 0.4217 0.6 | 0.4296 |
| X           | 0.4002 0.3986 0.4 | 0.4082 | 0.4295 0.4289 0.4 | 0.4325 | 0.4301 0.4294 0.4 | 0.4329 |
| X           | 0.3985 0.3980 0.5 | 0.4084 | 0.4318 0.4277 0.5 | 0.4374 | 0.4325 0.4284 0.5 | 0.4383 |

Table 3
Best r-values for each set of parameters (explained in Section 4.4) using tfidf Greedy Heuristic on DUC02. Best overall ROUGE-1 F-1 scores for each dataset are marked in bold italics.

| ROUGE METRIC | Threshold |
|--------------|-----------|
|              | ROUGE-1   | ROUGE-2 | ROUGE-L |
| 100          | 0.4083    | 0.1512  | 0.3430  |
| 110          | 0.4125    | 0.1557  | 0.3475  |
| 120          | 0.4129    | 0.1586  | 0.3492  |
| 130          | 0.4143    | 0.1592  | 0.3500  |
| 140          | 0.4172    | 0.1629  | 0.3531  |
| 150          | 0.4197    | 0.1646  | 0.3558  |
| ...          | ...       | ...     | ...     |
| 950          | 0.4764    | 0.2244  | 0.4123  |

Table 4
Threshold effect on budget_ilp on DUC02 with truncation.

5.2. ILP with Budget Constraint

This algorithm also incorporates a budget in the search for best coverage. In those experiments the algorithm preprocessed the input text with stemming and stopword removal. The scores show that ILP fails to overcome the ROUGE scores of tfidf based greedy heuristic on DUC02.

A possibility is that a 100 word initial threshold is over-constraining the search for good set covers. So further runs were done with increasing amounts of budget (called threshold in the table) and then a truncation to 100 words before measuring the ROUGE scores. All these results are reported in Table 5. Interestingly, adding more and more slack to Budget-ILP keeps improving the scores, until it matches the ROUGE-1 F-1 score of the Lead baseline of PKUSUMSUM (compare with Table 11). We expect it to match the ROUGE-2 and ROUGE-L scores as well if the slack is increased further.

5.3. ILP with Score

ILP with a strict budget constraint fails to do better then greedy tfidf heuristic. We believe this is because the formulation is giving equal weight to all words. To investigate this further, we apply a score to each term. Rather than giving equal value to all words, we introduce a scoring matrix. When the ILP is run using tfidf values for the scoring metric it comes closer to the best pure greedy tfidf run, with a ROUGE-1 score of 0.4266 on DUC02. Using the tfidf score for each term proves to be the best scoring metric for this version of ILP. This is competitive with the
state-of-the-art in unsupervised extractive summarization. We also add r-normalization and found that this detracted from the scores. These are seen in the values of $r > 0$ in Figure 1. Initially, the experiments only looked at values in the range $[0.0, 1.0]$; Figure 1 shows there is a trend of increasing scores as $r$ tends to 0.0. Hence, we generated summaries using negative $r$-values and found that it does improve the ROUGE-1 scores.

We believe an explanation can be found in the formulation of $tfidf$. The $tfidf$ includes a form of normalization, by penalizing a word that appears often through a corpus. Because r-normalization serves a similar goal, it is over penalizing words. A negative $r$-value serves to remove this over-penalizing by crediting scores that come from longer sentences. Figure 1 shows that negative $r$-values indeed improve the score. The $stfidf$ scores in Figure 1 suggest that more improvement can be found beyond an $r$-val of $-1.0$. However, additional experiments in that range did not improve, and instead showed a steady decline. The best score is seen with $tfidf$ on DUC02 with an F-1 score of 0.4385 found at $r = -0.8$.

Since normalization influences the contribution of sentence length to the score of a sentence, negative $r$-values would favor longer sentences. We plotted the average sentence length along with standard deviation for all the summaries at different $r$ values. The trend can be seen in Figure 2 and Figure 3 for DUC01 and DUC02, respectively. However, the standard deviation depicted by the bands show that as the average sentence length decreases so does the standard deviation. This means that although negative $r$-values produce summaries that include longer sentences, the algorithm does not exclusively choose longer sentences. Another interesting point is the similar shape of the sentence length curve and the F-score curve. We computed the Pearson Correlation as 0.939. Expressed differently, it means there is a strong correlation between higher ROUGE scores and longer sentences.

Next we look at the influence of the two factors of $tfidf$, namely $tf$ and $idf$. For the initial experiment, we fixed $r$-value at $-0.4$ (the best ROUGE-1 from previous experiment) and ran $score_{ilp}$ with varying $\alpha$ values from $-1.0$ to $1.0$ in increments of 0.1. The best $\alpha$ was found to be at 1.0. The scores showed an increasing trend so an additional experiment was done to search in range between 1.0 and 2.0. Here we found that the score continues to improve until $\alpha = 1.1$, after which there is a quick decline. We then fix $\alpha = 1.1$ and vary $\beta$ in same range of values, we see that

| Threshold | ROUGE METRIC |
|-----------|--------------|
|           | ROUGE-1 | ROUGE-2 | ROUGE-L |
| 100       | 0.4391  | 0.1870  | 0.3782  |
| 110       | 0.4414  | 0.1888  | 0.3793  |
| 120       | 0.4463  | 0.1936  | 0.3836  |
| 130       | 0.4540  | 0.2007  | 0.3912  |
| 140       | 0.4541  | 0.2021  | 0.3919  |
| 150       | 0.4548  | 0.2002  | 0.3920  |
| ...       | ...     | ...     | ...     |
| 900       | 0.4780  | 0.2260  | 0.4139  |
| 910       | 0.4780  | 0.2259  | 0.4138  |
| 920       | 0.4782  | 0.2260  | 0.4141  |
| 930       | 0.4781  | 0.2260  | 0.4139  |
| 940       | 0.4779  | 0.2259  | 0.4137  |
| 950       | 0.4776  | 0.2256  | 0.4133  |
| 960       | 0.4779  | 0.2258  | 0.4137  |
| 970       | 0.4779  | 0.2257  | 0.4136  |
| 980       | 0.4778  | 0.2257  | 0.4135  |
| 990       | 0.4778  | 0.2258  | 0.4135  |
| 1000      | 0.4779  | 0.2286  | 0.4136  |
| 1010      | 0.4779  | 0.2257  | 0.4136  |
| 1020      | 0.4776  | 0.2257  | 0.4134  |
| 1030      | 0.4775  | 0.2257  | 0.4133  |
| 1040      | 0.4775  | 0.2256  | 0.4133  |
| 1050      | 0.4775  | 0.2255  | 0.4133  |
| ...       | ...     | ...     | ...     |
| 2350      | 0.4771  | 0.2231  | 0.4129  |

Table 5
Threshold effect on $score_{ilp}$ with $tfidf$ on DUC02 with truncation. Bolding shows highest scores in each column.
the best $\beta$ is $\beta = 1.1$ with a ROUGE-1 F-score of 0.4539 (Figure 4). Effectively, this means that $\beta$ does not induce a better solution. We investigate this in following experiment.

Because of the local max found at $\beta = 0.7$, there is reason to believe that different combinations of $\alpha$ and $\beta$ may produce superior summaries. To further explore this we do three separate experiments:

1. Only vary $\alpha$ ($\beta = 1$, $r = 0$) (Figure 5).
2. Only vary $\beta$ ($\alpha = 1$ and $r = 0$) (Figure 6).
3. A cube search across the $r$-value, $\alpha$ and $\beta$. We show the three dimensional plot for the best $r$-value (Figure 7).

Note that default values for $\alpha$ and $\beta$ are 1.0, because they are part of the tfidf metric. This basically leaves them in a neutral state with regards to the tfidf metric, i.e. when the studied parameter is also 1.0 we should see the result as if the tfidf score was untouched.

Varying $\alpha$ and $\beta$ individually does affect the ROUGE scores. The best $\alpha$ is at 1.1 and $\beta$ at 1.1.

The cube search showed that the maximum ROUGE-1 scores occurred at $r = -0.4$. So, Figure 7 shows a 3D surface plot with this $r$ value. The maximum ROUGE-1 score of 0.4540 is found at $\alpha = 1.2$ and $\beta = 1.2$. This is different from before, so the cube search did find higher ROUGE scores. Similar results were found when the cube search was done on TITLE02, its results can be found in Appendix C (Figures 17, 18 and 19).

Using the best results found in the cube search, we now revisit the effect of threshold on score_{ilp}. Like, the budget_{ilp}, Table 5 reveals that score_{ilp} also gradually improves in score. However, we see that it begins to do...
better than the lead method. And furthermore, we also see that it peaks at a threshold amount of 960, giving a score of 0.4779.

5.4. Title Driven as Documents and Summaries

NewsSumm uses the TitleDrivenReduction algorithm to reduce a document to sentences that are indirectly or directly overlapping with the title of the document. To evaluate the benefit of this, we first run all the non-ILP algorithms on the reduced dataset, TITLE02 (results in Table 3). Nearly all the scores were boosted and the best result was a ROUGE-1 F-1 Score of 0.4483.

Limit on ROUGE Recall. In addition to this experiment we also look at how these reduced documents do when viewed as a summary themselves. ROUGE evaluates by finding the word overlap between the model summary and generated summary. Because the model summary were created by human annotators, they are abstractive and will...
often make use of words not in the actual article. This puts an inherent limit to the highest achievable score, when the summary can only include words from the document (extractive summaries). To find this limit we run the ROUGE on the documents themselves as summaries evaluation against the human summaries. Of course the precision will be very low, but the recall will show the maximum coverage possible of the human summary as evaluated by ROUGE. That result is presented in Table 6. In Verma and Lee (2017), researchers report the ROUGE-1 Recall as 0.907 for full documents as summaries, and we see that title driven summaries do not detract much from that limit.

**TITLE+DEPTH.** *TitleDrivenReduction* by itself is used to create a summary. This is done by simply looking only at the sentences that are directly overlapping with the title (i.e. $depth = 1$). If these sentences go over the 100 word budget, then the summary is truncated to fit. The results are in Table 7. We see that this produces a competitive ROUGE score with $score_{ilp}$ with $tfidf$ with an F-1 score of 0.4745. This further confirms that the title holds salient information with respect to a summary.

**TITLE+BFS.** We can also produce summaries by traversing the full *TitleDrivenReduction* tree and then truncating at 100 words. Those results are reported in Table 8. Notice that this approach improves the F-1 score to 0.4751. The main reason for this is due to the ordering of sentences at each level. Since, they are placed in document sentence order, this comes close to the strong *Lead* method.

**TITLE+FILTER.** As a final experiment, we use the title-driven process as a preprocessing step for our ILP formulations:

1. Use traditional techniques of stemming and stopword removal.

2. Apply Algorithm 1 to reduce set of input sentences.
Figure 4: DUC02 ROUGE-1 F-1 scores for varying $\beta$ after finding best $\alpha$ (= 1.1) when $r = -0.4$ (Uses $score_{ilp}$.)

### Table 7
Title Driven based summaries at $depth = 1$ with truncation.

| Metric    | Recall | Precision | F-Score |
|-----------|--------|-----------|---------|
| ROUGE-1   | 0.4719 | 0.4778    | 0.4745  |
| ROUGE-2   | 0.2201 | 0.2228    | 0.2213  |
| ROUGE-3   | 0.1439 | 0.1457    | 0.1447  |
| ROUGE-4   | 0.1058 | 0.1072    | 0.1064  |
| ROUGE-L   | 0.4091 | 0.4143    | 0.4114  |

3. Apply $score_{ilp}$ with $t f i d f$ on reduced set of sentences.

The best result found in the cubesearch was ROUGE-1 F-1 score of 0.4548 with $r = -0.4$, $\alpha = 1.2$ and $\beta = 1.2$. This does not beat the breadth-first traversal of TitleDrivenReduction.

**TITLE+FILTER+SLACK** Because giving slack improves results, we also perform two experiments using the best parameter values for score ILP with **TITLE+FILTER**. After step (3) we will then explore different amounts of slack, as we did for the Table 5 experiment. For comparison, we do the same experiments without the **TitleDrivenReduction**. The experiments show that filtering and then using slack is the best performing unsupervised method (Figure 8). Without the **TitleDrivenReduction** using $score_{ilp}$ with slack of 920 gives a ROUGE-1 F-1 score 0.4782. And when **TitleDrivenReduction** is used as a filter, the unsupervised highest ROUGE-1 F-1 score of 0.4787 (slack = 920) is achieved. We see a similar trend for ROUGE-L with scores of 0.4155 and 0.4142, with and without the filter, respec-
Figure 5: Effect of $\alpha (\beta = 1, r = 0)$ on ROUGE F-1 score on DUC02 using score.ilp.

| Metric   | Recall | Precision | F-Score |
|----------|--------|-----------|---------|
| ROUGE-1  | 0.4687 | 0.4821    | 0.4751  |
| ROUGE-2  | 0.2178 | 0.2239    | 0.2207  |
| ROUGE-3  | 0.1424 | 0.1464    | 0.1443  |
| ROUGE-4  | 0.1045 | 0.1075    | 0.1060  |
| ROUGE-L  | 0.4075 | 0.4192    | 0.4131  |

Table 8
Title Driven based summaries with breadth-first search and truncation.

tively (Appendix C Figure 20. However, for ROUGE-2 we see that applying a filter actually hurts the performance (Figure 9). We see the peak for ROUGE-2 is still at slack = 920, but this changes when the filter is applied. Here the peak moves to slack = 950 and the score is 0.2235. This leads to an intriguing new hypothesis that the more interesting bigrams in DUC02 dataset are in the sentences that do not directly overlap with the title. There could be deeper reasons behind this. We leave this investigation for future work.

5.5. Baseline 1 - Supervised Submodular

While this system was designed for multi-document summarization, we adapted the system to be used for single document summarization. For the supervised submodular summarization algorithm, average ROUGE-1 F-1 score across five folds was .5854 on DUC02 dataset. For DUC01 it was .5977.

While the system was available for multi-document summarization, we tuned the system to be used for single
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Figure 6: Effect of $\beta (\alpha = 1, r = 0)$ on ROUGE F-1 score on DUC02 using score_ilp.

Table 9
F-1 scores, on TITLE02, Submodular Five Folds. R-X above denotes ROUGE-X metric for X=1, 2, 3, 4, and L.

| Metric | Fold 1 | Fold 2 | Fold 3 | Fold 4 | Fold 5 |
|--------|--------|--------|--------|--------|--------|
| R-1    | 0.8083 | 0.6863 | 0.5797 | 0.5252 | 0.3881 |
| R-2    | 0.6178 | 0.4950 | 0.3415 | 0.2653 | 0.1005 |
| R-3    | 0.4974 | 0.4100 | 0.2562 | 0.1753 | 0.0305 |
| R-4    | 0.3850 | 0.3434 | 0.1692 | 0.1354 | 0.0103 |
| R-L    | 0.7979 | 0.6667 | 0.5314 | 0.4849 | 0.2886 |

document summarization. The submodular system was trained on the DUC02 using five-fold cross validation method. The training took a total of 49 minutes and 29 seconds on a machine with 64-bit Intel Core i7 Processor with 16GB RAM. The ROUGE evaluation results for the system have been presented in Table 9.

We see that at the cost of more training time and the requirement of annotated data, we can get better results on summarization. We have included those results as a comparison to our unsupervised approach. For NewsSumm, there is no training time and producing summaries for the DUC02 dataset takes only 27 seconds. Since, the summaries can be quickly generated, it makes NewsSumm a strong candidate for preprocessing for the more expensive supervised methods.

Experiments were run to test the viability of preprocessing with NewsSumm. These experiments involve the TitleDrivenReduction algorithm, the best algorithm in NewsSumm. Table 10 shows how different parameters affect the results of submodular. It reports the average ROUGE-1 F-1 Score, average summary length (in number of words),
total training time, and extra time for running the algorithm. Running \textit{TitleDrivenReduction} produces smaller input files and allows submodular to decrease training time by 5 minutes and 44 seconds at the cost of only 55 seconds. All together, if preprocessing included as a part of training, it is a decrease of nearly 10%. Not only this, the Average ROUGE-1 F-1 score improves as well. In addition, NewsSumm's \textit{TitleDrivenReduction} with depth $= 1$ can dramatically decrease the training time. Again for a small preprocessing time of 53 seconds, there is a reduction of 58.3%. There is a minor performance hit, but often the cost of training time can outweigh the gain in performance.

5.6. Baseline 2 - PKUSUMSUM

PKUSUMSUM offers several different unsupervised methods in their tool. We take a look at the summaries created by PKUSUMSUM.\footnote{We contacted author’s for their system parameters, but have not received a response at the time of writing.}
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Figure 8: ROUGE-1 F-1 scores for different slack amounts using TITLE+FILTER (TitleDrivenReduction then score_ilp) and TITLE (only score_ilp) on TITLE02 dataset.

![Figure 8: ROUGE-1 F-1 scores for different slack amounts using TITLE+FILTER (TitleDrivenReduction then score_ilp) and TITLE (only score_ilp) on TITLE02 dataset.](image)

Table 11

| Alg.         | ROUGE-1 | ROUGE-2 | ROUGE-L |
|--------------|---------|---------|---------|
| Centroid     | 0.4585  | 0.2135  | 0.4210  |
| Lead         | 0.4764  | 0.2248  | 0.4407  |
| LexPgRnk     | 0.3954  | 0.1326  | 0.3613  |
| Unsupervised | 0.4524  | 0.1805  | 0.4114  |
| Submodular   |         |         |         |
| TxtRnk       | 0.4296  | 0.1662  | 0.3871  |

Table 11
PKUSUMSUM ROUGE F-1 values on DUC02 dataset

We see in Table 11 that in PKUSUMSUM the Lead method is the best for news article summarization with Centroid second.

5.7. Summary Sizes

Since the baselines, Supervised Submodular and PKUSUMSUM, are not implemented by us, we check the summary lengths for all top performing methods next. Table 12 reports the average summary lengths, along with standard deviations, on the DUC02 dataset. We see that the Lead method summaries of PKUSUMSUM are the longest on the average and Supervised Submodular summaries are second longest. NewsSumm summaries are slightly short of the ideal and Centroid has the shortest average summary length. Moreover, NewsSumm also has the smallest standard
Figure 9: ROUGE-2 F-1 scores for different slack amounts using TITLE+FILTER (TitleDrivenReduction then score_ilp) and TITLE (only score_ilp) on TITLE02 dataset.

| Summarizer                | Average Summary Length | Standard Deviation |
|---------------------------|------------------------|--------------------|
| Score_ILP (NewsSumm)      | 97.9                   | 2.68               |
| Supervised Submodular     | 104.0                  | 6.98               |
| Lead (PKUSUMSUM)          | 105.5                  | 15.33              |
| Centroid (PKUSUMSUM)      | 81.8                   | 7.31               |
| Human (DUC02 dataset)     | 101.1                  | 4.20               |

Table 12
Average Summary Length and Standard Deviation (in words) of Top Summarizers on DUC02 dataset.

deviation. Thus, NewsSumm scores are achieved without the potential “extra boost” provided by longer summaries.

For comparison, we report the results of the Baseline, which is also the first 100-word summary, from Barrera and Verma (2011). They reported a ROUGE-1 F-1 score of 0.4617. SynSem’s highest ROUGE-1 F-1 score from Barrera and Verma (2011) is 0.4655 and S28’s, the best system at DUC 02 competition, ROUGE-1 F-1 score is 0.4673. However, they do not report average summary length and standard deviations. Since the organizers of DUC02 truncated summaries to 100 words, we expect that S28 summaries should be in a narrow band around that number as well.
5.8. Limit on Recall

In Verma and Lee (2017), we showed that there is a limit on ROUGE-1 $F_1$ score of 0.907 for extractive summarizers on DUC02 dataset, and, as mentioned above, the limit is 0.9027 on TITLE02 dataset, so we see that the best extractive unsupervised summarizers are achieving about 52.7% ($score_{ilp}$) of that limit for DUC02 and 53.0% (TITLE+FILTER+SLACK) for TITLE02 dataset. With supervised training we are able to improve to 64.5% and 58.3% on DUC02 and TITLE02, respectively.

5.9. Qualitative Evaluation

A word cloud is a visual representation of a document that highlights the frequency counts of the words in the document. The relative differences in word frequencies can be represented through font size and/or colors. We use them here to give a qualitative analysis of the types of summaries being generated. We look specifically at one document set as defined by the organizers of DUC 2002.

The document set we consider is $d069f$: a collection of 14 documents all considered relevant to a common topic. We compare the summaries generated by humans as well as four automatically generated summaries: lead method, PKUSUMSUM’s centroid method, NewsSumm’s best performing $score_{ilp}$ method and Supervised Submodular with TitleReduction. For each word cloud, we create a document that combines all the documents. In addition, we remove all punctuation and change all letters to lowercase. This is then given as input to an online word cloud generator. The top 100 most frequent words are selected to produce the final image.

Figure 10a represents the word cloud of document set $d069f$. Simply looking at the representation we can see clearly the content of the articles are on the reunification of Germany. The brighter red color and larger relevant size show words like “germany” and “reunification” are quite frequent in the document set.

For comparison we can look at the word cloud of the human summaries in Figure 10b. Notice that “german,” “germany,” “reunification,” “west,” and “east.” are the most frequent in both human summaries and actual documents. To give a sense of what is not included in the summaries, we compare each summarizer with the original documents. We remove any words that are common to both the generated summaries and the original documents.

We also look at the quality of the different summarizers by comparing unused words of the original documents. To be more specific, we compare words used in the summarizer and remove any occurrence of these words in the original documents. We then create a word cloud based on the frequencies of the remaining words. These can be seen in Figure 11. For comparison we also included the original documents without the words used by human summaries (Figure 11e).

The lead method and PKUSUMSUM’s Centroid method are missing similar words (e.g. “all” and “democratic”). Figure 11c shows NewsSumm misses words different from lead and PKUSUMSUM’s Centroid methods. The content of NewsSumm summaries seem to be complementary to those of the lead method. And finally we see that the supervised submodular method captures a lot of the content in the original documents (evidenced by the lack of red-colored words). Also the remaining words in Figure 11d do not give a clear sense of what the documents are talking about. Like the supervised submodular method, we see that the human summaries are also including most of the indicative words.\footnote{https://worditout.com/word-cloud/create}

\footnote{The “adn” in wordcloud 11e is not a misspelt “and,” but the Agency ADN.}
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(a) Lead method.
(b) PKUSUMSUM Centroid.
(c) NewsSumm $\text{score}_{\text{ilp}}$
(d) Supervised Submodular with Title Reduction.
(e) Human summaries. ("adn" is not a typo but a news agency organization of Germany.)

Figure 11: Each figure represents the remaining words of document set $d_{069f}$ after the words of the generated summaries are removed.

6. Conclusion

NewsSumm provides several avenues of experimentation for unsupervised document summarization. And although the algorithms do not out-perform supervised models, we show that we get competitive results in a trade-off for faster training times. Furthermore, this quick processing lends NewsSumm to be part of a larger pipeline.

Deep learning models are currently dominating in machine learning tasks. Some researchers have moved on to more difficult tasks like abstract summarization or sentiment analysis. However, what is often overlooked is the training time. In this work we show that we can get good results at a fraction of the training time in the order of two magnitudes.

We have made use of third-party software (e.g. IBM (2012)) and improved on this with novel algorithms. Continued research in unsupervised methods can be a step towards more robust solutions. NewsSumm is a step forward for
quick implementation of unsupervised methods.

NewsSumm is a flexible tool for single-document summarization that provides the user several algorithms and options in a single, modular and easily-extensible framework. Even though its algorithms are not finely-tuned for any dataset, on ROUGE-2 and ROUGE-LCS metrics, it is already ahead of other finely-tuned systems on DUC datasets. We believe that researchers in summarization will benefit from having access to NewsSumm and it could also be deployed for customized filtering of the text flood confronting people. Extending NewsSumm for multi-document summarization is an interesting and useful task that we leave for the future.

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A. Bad or no headlines

Some of the original XMLs used the “<HEAD>” field to signal the article was a follow-up to a previous article (e.g. “With BC-APN-Oscars”). Others seemed like internal communications between editors and journalists (e.g. “Eds: To update with Bush attending service, adds new graf after 4th previous, The Iowa”). The remaining did not include any title. The following articles contained no valid headline:

- AP880720-0262 (no title),
- AP900328-0128 (no title),

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• AP880712-0250 (no title),
• AP880328-0206 (internal messaging),
• AP890420-0176 (internal messaging),
• AP891116-0191 (internal messaging),
• and AP890119-0221 (internal messaging)

B. No Overlapping Title
Following are a list of documents where the title did not overlap with any body text. We have included the title of those documents as well for reference:

• AP900210-0106: “Thousands Demonstrate for Unification”
• LA080290-0037: “HOW THE CONFLICT DEVELOPED”
• LA102089-0177: “THE BAY AREA QUAKE; WHAT NEXT?; PONDERING THE LESSONS, HEALING THE SCARS”
• LA111289-0035: “ROGER SIMON: A STRATEGY THAT BEARS REPEATING”

C. Supplementary Figures
These figures provide ROUGE-2 F-1 scores for comparison.
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**Figure 12:** Plot of average length of summaries across different $r$-values.

**Figure 13:** ROUGE-2 F-scores on DUC02 and DUC01 at different $r$-values.

**Figure 14:** Effect of $\alpha$ ($\beta = 1$) on DUC02 ROUGE-2 F-1 scores using $tfidf$ and $score_{ilp}$. 
Figure 15: Effect of $\beta (\alpha = 1)$ on DUC02 ROUGE-2 F-1 scores using $tfidf$ and $score$.

Figure 16: ROUGE-2 F-scores on DUC02 for varying $\beta$ with $r = -0.4$ and $\alpha = 1.1$

Figure 17: ROUGE-2 F-score on DUC02 varying $\alpha$ and $\beta$ and $r$-value fixed at $-0.4$. 
Figure 18: ROUGE-1 F-score on TITLE02 varying $\alpha$ and $\beta$ and $r$-value fixed at $-0.4$.

Figure 19: ROUGE-2 F-score on TITLE02 varying $\alpha$ and $\beta$ and $r$-value fixed at $-0.4$.

Figure 20: ROUGE-L F-1 scores for different slack amounts using TITLE+FILTER (TitleDrivenReduction then score-ilp) and TITLE (only score_ilp) on TITLE02 dataset.