# **Ling 573 Summarization Presentation**

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### **Abstract**

TODO: fill out

1 Introduction

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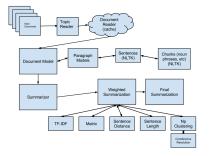
# 2 System Overview Diagram

TODO: fill out

# 3 Approach

## 3.1 System Architecture

Figure 1: System Architecture



### 3.2 Content Selection

We used a variety of methods initially to help with content selection. First, we the average tf-idf score of every non-stop word for every sentence to help rank the highest sentences.

Next, we implemented a simple graph based metric, in which a dense undirected graph of sentences is constructed with edge weights set to the cosine similarity of the sentences. The most connected sentence is iteratively selected, and the weights of the edges of the previously selected sentences are set to be negative to discourage redundancy.

We also implemented a noun phrase clustering algorithm where we used co-reference resolution to resolve pronouns to their most likely antecedent, and then compared each sentence's noun phrases to each other sentence.

## 3.3 Information Ordering

Each method had its own ordering criteria.

Tf-idf selection was ordered by the highest sum sentences.

Np-clustering selection was ordered by the number of matches each sentence had to every other sentence.

Simple graph selection was ranked by the most connected sentences.

The highest sentence selection technique was ordered by the longest sentences.

The sentence position technique was ordered by the sentences nearest to the beginning.

## 3.4 Content Realization

Our realization was simple, the highest ranking sentences were realized into the summary. We used a weighted summarization class to look at every technique, given a defined weight, and selected the top sentences (with a one hundred character limit) to be realized for the summary.

## 3.5 Best Technique

The best technique we found was tf-idf enhanced with simple graph similarity.

## 4 Results

**ROUGE-4** 

Our best score was tf-idf enhanced with matrix similarity:

Rouge Technique	Recall	Precision	F-Score		
ROUGE-1	0.54107	0.57388	0.55580		
ROUGE-2	0.42822	0.45443	0.43997		
ROUGE-3	0.36791	0.39088	0.37819		
ROUGE-4	0.31867	0.33882	0.32767		
Followed by simple graph similarity by itself:					
Rouge Technique	Recall	Precision	F-Score		
ROUGE-1	0.55024	0.52418	0.53571		
ROUGE-2	0.44809	0.42604	0.43580		
ROUGE-3	0.38723	0.36788	0.37643		

0.33438

0.31742

0.32490

The score for just the np-clustering technique was:

Rouge Technique	Recall	Precision	F-Score
ROUGE-1	0.45691	0.53378	0.49056
ROUGE-2	0.33306	0.39053	0.35813
ROUGE-3	0.28221	0.33196	0.30386
ROUGE-4	0.24758	0.29237	0.26700

The score for just the matrix clustering technique was:

Rouge Technique	Recall	Precision	F-Score
ROUGE-1	0.48228	0.56860	0.52048
ROUGE-2	0.36821	0.43541	0.39787
ROUGE-3	0.31484	0.37348	0.34065
ROUGE-4	0.27465	0.32683	0.29757

## 4.1 Error Analysis

There are many things to still tweak with both npclustering and the matrix comparison. For example, we could do better normalization with other co-referents rather than just pronouns. We will be experimenting with these techniques further.

#### 5 Discussion

TODO: fill out

#### 6 Conclusion

Conclusions have been made as can be seen from the following Nenkova, Radev, and Jones (Nenkova et al., 2007) (Jones, 2007) (Radev et al., 2001). We used co-referenced based off ideas from (Cardie and Wagstaff, 1999).

## References

C. Cardie and K. Wagstaff. 1999. Noun phrase coreference as clustering. *Proceedings of the Joint Conference on Empirical Methods in Natural Language Processing and Very Large Corpora*, 1001:82–89.

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Dragomir R Radev, Sasha Blair-Goldensohn, and Zhu Zhang. 2001. Experiments in single and multi-document summarization using mead. *Ann Arbor*, 1001:48109.