Performance of Opinion Summarization towards Extractive Summarization

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***Abstract*—Opinion summarization summarizes opinion in texts while extractive summarization summarizes texts without considering opinion in the texts. Can opinion summarization be used to produce a better extractive summary? This paper proposes to determine the effectiveness of opinion summarization generation against extractive text summarization. Sentiment that includes emotion which indicates whether a sentence may be positive, negative or neutral is considered. Sentences that have strong sentiment, either positive or negative are deemed important in text summarization to capture the sentiments in a story text. Thus, a comparative study is conducted on two types of summarizations; opinion summarization using the proposed method, which uses two different sentiment lexicons: VADER and SentiWordNet against extractive summarization using established methods: Luhn, Latent Semantic Analysis (LSA) and LexRank. An experiment was performed on 20 news stories, comparing summaries generated by the proposed opinion summarization method against the summaries generated by established extractive summarization methods. From the experiment, the VADER sentiment analyzer produced the best score of 0.51 when evaluated against the LSA method using ROUGE-1 metric. This implies that opinion summarization converges with extractive summarization.**

***Index Terms*—Extractive summarization; opinion summarization; LexRank method; LSA method; Luhn method.**

I. INTRODUCTION

The abundance of opinions on the Web has inspired the research of opinion summarization in the last few years. Opinion summary is the outcome of sentiment analysis which summarizes opinions in texts. The objective of opinion summary is to assist the reader to understand the huge collection of opinions in an efficient way [1]. This summarization approach involves text clustering, sentiment analysis, text mining and natural language processing (NLP). Nevertheless, it is unlike common text summarization because opinion summarization emphasizes on the opinionated parts while the common extractive summarization emphasizes on extracting informative parts and redundancy removal.

Sentiment analysis is part of opinion summarization. It has been a popular platform in gauging sentiments on the Web and social media. Sentiment analysis distinguishes and extracts subjective or emotion information in texts by using NLP, text analysis and computational linguistics [2]. It focuses on the expressed opinion of a text, disregarding the topic of the text itself. There are three levels in sentiment analysis; document level, sentence level and phrase level. Document level sentiment analysis determines whether the whole document gives a positive, negative or neutral sentiment. The advantage of this level of analysis is the ability to determine the overall text sentiment classification. As for sentence level sentiment analysis, it classifies whether each sentence indicates a positive, negative or neutral opinion [3]. Phrase level is also known as feature based sentiment analysis in which sentiment is directly assigned to the features.

With the growth in the number of digital documents, there is an important need for text summarization. When reading a text, a reader usually tends to skim through the text for the first time to grab the general idea of the text. Text summarization can generally be described as the process of forming a summary out of the textual elements of a text narrative. A summary is defined as a text that is generated from one or more texts, that delivers important information in the original text, and that is no longer than half of the original text [2]. The original text can be very long and this may put the casual reader off. Thus, automatic text summarization (ATS) can aid the reader to understand the gist of the text in just a fraction of time by providing a concise summary. ATS is helpful when a useful summary is needed from a very lengthy text.

The question that remains to be answered is how does opinion summarization correlate with extractive summarization? This study was undertaken to compare the result of the proposed opinion summarization method against the result of established text summarization methods: Luhn, LSA and LexRank. The metric used for evaluation is ROUGE-N, looking for overlapping fragments of text.

II. RELATED WORKS

The scene of text summarization research had evolved over the years. The earliest works on summarization largely made use of statistical-based techniques based on word frequency [4, 5] and sentence position [5]. These techniques form the foundation of feature extraction in text summarization and are still largely adopted in most text summarization approaches. Subsequently, machine learning and NLP techniques for text summarization followed. Machine learning techniques are used for selecting the best feature to extract in text summarization [6-8] while NLP techniques allow elements of the natural language such as text structure, concepts in documents [6] and lexical chains [7] to be exploited for text summarization. The major approaches to text summarization are also summarized in [8], highlighting the literature for summarization through extraction and abstraction.

More recent approaches to text summarization looks at sentence ordering [9, 10], extracting salient sentences in given document(s) by modeling text summarization as an optimization problem [11], constraint-driven models [12],