Contrastive Opinion Summarization: A Survey

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***Abstract* - Today, abundant amount of opinionated data is found on web. Opinionated text generally contains both the positive and negative opinions about a topic which makes a challenging task for user to efficiently digest all the opinions. Referring all the positive and negative opinions regarding a topic is also a tedious job. Contrastive Opinion Summarization (COS) is an automatically generated summary that aids user to understand mixed opinions. It is a summary consisting of contrasting pair of sentences on same aspect. This Summary presents a clear picture of both positive and negative opinions about same topic in one frame allowing users to decide whether to opt for that product or not. This study presents a comprehensive overview concerning the computation techniques, models and algorithms for Contrastive Opinion Summarization.**

***Keywords* - Contrastive opinion summarization, Contradictory opinion, Opinion summarization**

I. INTRODUCTION

Opinions emerge in all aspects of our activities and thus influence our behavior, our observation of reality and affect how we see and evaluate things around us. This is the reason why we often seek the opinions of others, especially when we are about to make a decision. With the advancement in web technologies, people can easily convey their opinions on variety of topic using platforms such as blogs, forums and other dedicated opinion websites. Since large amount of opinions are available about a topic, it makes difficult for users to assimilate all the opinions. An attempt was made by generating a concise and digestible summary for large number of opinions which is called opinion summarization.

Traditional opinion summarization techniques separate positive and negative opinion on some specified topic. Now the question arises is what more can be done after separating positive and negative opinions for more clear understanding of user. A Contrastive summary is an approach where user can view both the side of coin together and decide according to his/her convinces. For example, some customer may say positive things about the phone X such as "the phone is exceptionally good for a technical person" but others might say "the phone operating system is not easy to understand, not happy to use." So it can be seen that both the opinions are contradictory but are on same topic i.e. phone X but both the opinions are made under different conditions. When there are many such contrastive pairs of sentences about same aspect user would need to understand how to interpret those types of sentences. So instead of referring thousands of opinions COS highlights the most contrastive and representative sentence pairs in form of summary. From the summary for above mentioned example one can conclude that if a user is a technical person phone is best for him otherwise not.

From the sets of positive and negative opinions which is generally the output of an opinion summarizer, COS aims to extract most representative sentences from the set of opinions and compute a summary consisting set of contrastive sentence pairs.

This paper is structured as follow: Section II describes the classification of opinion summarization framework, section III type of contrasting pairs in text; section IV contains literature review of different research papers related contrastive opinion summarization and at last section V holds the limitation of current system and future scope in the contrastive opinion summarization.

II. CLASSIFICATION OF OPINION SUMMARIZATION FRAMEWORK

Opinion summarization is classified in two ways as follows:

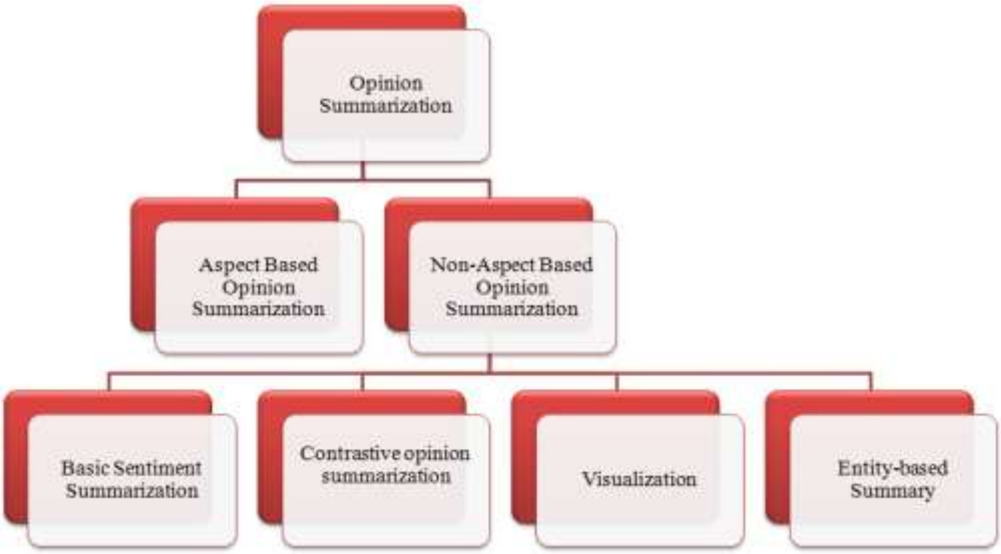

Fig 1. Classification of Opinion Summarization

Aspect Based Opinion Summarization: The most common type of opinion summarization is Aspect Based Opinion Summarization which generates a summary based on particular aspects/features of an entity. This type of opinion summarization includes mainly three distinct steps – aspect/feature identification, sentiment predictions and summary generation.

Non Aspect Based Opinion Summarization: This type of opinion summarization is generates a summary without considering the aspects/features of an entity. They are not bound by feature based format and put forward different formats for opinion summarization. There are various proposed methods for generation of non aspect based summary as follows basic sentiment summarization, advanced text summarization techniques which include contrastive opinion summarization, visualization and entity based methods.

III. TYPES OF CONTRASTIVE PAIRS OF TEXT

Type	Examples of opinions	
Antonym	Time magazine is interesting for business concerned people.	I found time magazine boring being a student.
Numeric	100 people were killed in tsunami.	120 people were found almost dead, some are reported to be still alive.
Factive	The terrorist didn't enter through the main gate of screen 1 in the theatre.	Terrorist entered the theatre through the exit gate of screen 1.
Structure	John bought shoes from bob the shoe world store.	Bob bought shoes from her friend John
Linguistic	In the election he said about 24x7 water services availability.	He said 24x7 water service will not be available for more than a year.
World Knowledge	Apple company was found in 1976.	1n 1977 Apple was renamed.

Fig 2: Various types of contradictions

IV. LITERATURE REVIEW

In this paper [1] the limitation of traditional contrastive opinion summarization (COS) is improved by integrating expert opinions with the ordinary opinions. The author proposed a technique called Expert Guided COS (ECOS) for controversial issues where semi supervised Probabilistic Latent Semantic Analysis (PLSA) is used to extract topic/arguments from opinions. ECOS model aims to select most contrastive argument pairs for controversial topics. Sentence selection strategy has two parts aligned and non aligned cluster. As ECOS model is semi supervised most clusters are aligned and for free clusters, two sentence selection strategies are proposed. Clustering result can be improved using other supervised models.

The authors in this paper [2] provided a new method namely Contrastive Max-Sum Opinion Summarization (CMSOS) which considers representativeness and contrastiveness in parallel. The method creates a list of pairs of the most representative sentences related to given aspect/topic. In CMSOS model for sentence similarity Cosine Similarity measure is used with Term Frequency (TF) and Inverse Term Frequency (TF-IDF). Better result is obtained with the combination of Cosine and TF-IDF methods. The authors have also created a new Turkish dataset for the Contrastive Opinion Summarization purposes.

In this paper [3] the author presents a study of a problem called contrastive opinion summarization. The aim of COS is to extract the most comparable sentences containing contrastive pair of opinions. The author proposed two general methods based on similarity measures i.e. content similarity measures and contrastive similarity measures. Content similarity measures the content or sentences in group of opinions while contrastive similarity measure the content or sentences lying in two different groups of opinions. The two algorithm proposed in this paper are Representativeness-First (R-F) algorithm and Contrastiveness-First (C-F) algorithm. C-F method gives better result in terms of precision and aspect coverage. Use of advanced semantic based similarity measures can be used for better results.

In this research paper [4] the author focuses on extractive summarization especially contrastive opinion summarization. The main challenge found is evaluation of summaries. Recall-Oriented Understanding for Gisting Evaluation (ROUGE) is for automatic evaluation of summaries but it lacks to take into consideration semantic of words, despite this author explored this issue and compute document similarity using four frequency semantic models such as Latent Semantic Analysis (LSA) , Latent Dirichlet Allocation (LDA) , Doc2vec, Word2vec and one term frequency model i.e. Term Frequency- Inverse Document Frequency (TF-IDF). Results of all these four models are compared with ROUGE score. The main aims to find a model that best imitate the human generated summary. Doc2vec model gives high quality document vectors and scores better than other all mentioned models.

In research paper [5] the author tried to sum up their work done in the area of comparative opinion summarization. The aim of this paper is analysis of input documents and creation of summaries which depict the most significant differences between them. Two well known methods – Latent Semantic Analysis and Latent Dirichlet Allocation are used to obtain latent topic of documents.

In this paper [6] the author presented a two-stage approach for summarizing multiple contrastive viewpoints in opinionated text. In the first stage, an unsupervised probabilistic approach to extract multiple viewpoints in text is used. In the second stage, Comparative LexRank, a novel random walk formulation is used to score sentences and pair of sentences from opposite viewpoints based on both representativeness and contrastiveness with each other. They have shown that accuracy of clustering documents by viewpoints can be enhanced using simple but rich dependency features. They have introduced Comparative LexRank, an extension of LexRank algorithm that aims to generate contrastive summaries both at the macro and micro level.

In this paper [7] the authors presented an approach to select pairs of snippets from reviews in a way that creates a summarizing product comparison. They have proposed a submodular objective function that aligns the snippet into pairs. Here snippets are selected from the product reviews due to their easy availability. Using a supervised learning approach they have achieved generalization across different product pairs by using user feedback on the given pairs.

In research paper [8] the author introduces classification of contradictions. There are basically seven types of contradiction for e.g. anatomy, negation, numeric mismatches and more. Anatomies are the words with opposite meanings such words when used in opinion give rise to a contradiction when used to describe same topic. Negation type contradictions can be seen explicitly with the use of word "not". Numeric mismatch type contradictions are the one in which two opinion contradict in terms of numeric value used in the opinions. The other types of contradictions seen like factual, world knowledge and linguistic are comparatively tough to detect. The contradiction detection system follows same steps as Recognizing Textual Entailment (RTE) system that contains three stages such as linguistic preprocessing, alignment of words and finally extracting of entailment features. In contradiction detection one more stage is added before feature extraction for event coherence recognization.

In this paper [9] the authors described a new framework for recognizing contradictions between multiple text sources using three forms of linguistic information such as negation, antonymy and semantic information. This proposed framework combines techniques for the processing of negation, the recognition of contrasts and the automatic detection of antonymy in order to identify instances of contradictions.

In this research paper [10] the author evaluated various existing text similarity measures which are used to calculate similarity score between sentences in many text applications. The sentence similarity measures evaluated in this paper are Word Overlap Measures, TF-IDF Measures and Linguistic Measures. The word overlap measures are based on the number of words shared by two sentences. TF-IDF measures sentence similarity on bases of frequency of term used. Linguistic Measure uses the semantic relation between words.

In the paper [11] the author addresses the task of identifying controversial events using Twitter. Three models are proposed for this task such as Direct model, Two-step pipeline model and Two-step blended model. In Direct model the controversy score is calculated based on regression methods. Two-step pipeline model is used for event detection while two-step blended model uses the result of pipeline model and gives the controversial event based on the snapshots from twitter.

V. CONCLUSION

This paper aimed to sum up work done in contrastive opinion summarization. Contrastive summaries help used to understand mixed opinions on a topic. Different models and algorithms are used for generating contrastive summaries are explored in this paper. Contrastive opinion summarization is upcoming research topic. This paper gives a brief idea of various types of contradictions found in an opinion. Contrastive summaries can be improved by using advanced sentence similarity measures. Contrastive opinion summarization is required for large size of data.

VI. REFERENCES

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