DOI: 10.21917/ijsc.2022.0384

AUTOMATED SUMMARIZATION OF RESTAURANT REVIEWS USING HYBRID APPROACHES

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Abstract

The arena of automatic text summarization incorporates the paramount and relevant information from a large document. This research paper attempts at representing two hybrid models for automatic text summarization. Extractive summarization followed by an abstractive summarization, is the strategy which is adopted in this paper to produce an informative and concise summary. The LexRank algorithm is used for extractive summarization, while BART (Bidirectional and Auto Regressive Transformers) and T5 (Text-To-Text Transfer Transformer) are used for abstractive summarization. BART and T5 are advanced per-trained models based on Transformer. The Transformer-based Per-trained models are causing a stir in the deep learning world. The first hybrid model is constructed using LexRank with BART (LRB) and the second hybrid model is constructed with LexRank with T5 (LRT). This specific approach will result in the generation of the extractive summary using the LexRank algorithm. The resulted output of LexRank is used as the input for BART and T5. The efficiency of two hybrid models is analyzed using qualitative and quantitative methods. The human-generated summary is used to evaluate the quality of the models, while the ROUGE score provides a quantitative assessment of their performance. Thus, this work may be concluded in the precision that, the LRT hybrid model is more effective than LRB hybrid model.

Keywords:

BART, T5, LexRank, ROUGE Score, Extractive Summarization, Abstractive Summarization

1. INTRODUCTION

21st century can be stated as an era with an amalgamation of online services with day-today life. With the advent of digital gadgets and rapid growth in digital technologies, users are provided with digital services to express their feelings in the form of reviews. Opinion Mining and Review Summarization are the key indicators that will help individuals, manufacturers, and organizations make better advancements. The automatic text summarization is one of the major challenges in natural language processing. It automatically extracts the most essential information from a long document [1]. The goal of this approach is to create a condensed representation of a text corpus that captures the original document's core meaning.

Document summarization can be divided into extractive and abstractive approaches [2] [3]. The extractive summarization creates a summary by extracting key sentences from the source document. It chooses sentences based on statistical and linguistic characteristics of natural language [4] [5]. The abstractive summary creates a new text summary that does not include the source material. It is like humans build summaries [6]. By using natural language generation techniques, abstractive summarization uses the semantic content of the original documents to generate new sentences [7].

This work provides an informative and concise summary using the extractive summarization followed by an abstractive summarization. The extractive summarization is performed using the LexRank algorithm. The models upon which the abstractive summarization is applied are: Facebook's BART and Google's T5.

LexRank is an unsupervised graph-based method [8] for constructing informative summaries. It calculates a score for each sentence. The graph representation of sentences is used to compute the importance of sentence based on eigenvector centrality [9]. It first finds the centroid sentence in the document, and then scores each sentence on how similar it is to the centroid. Analyze the score and identify the most central sentences in each cluster that provide relevant and sufficient information. It is often possible to determine a sentence's centrality based on its words, so the TF-IDF (Term Frequency - Inverse Document Frequency) is calculated for each sentence. The Cosine similarity metric is used to calculate how similar sentences are represented by vectors.

BART and T5 are Transformer based Per-trained Models. Transformers is a library of transformer-based architectures for distributing pre-trained models [10]. Researchers at Hugging Face maintain the Transformers project as an ongoing effort. BART is a pre-trained sequence-to-sequence model [11]. This model consists of two parts: an encoder like BERT [12] and a decoder using stacked transformers. The encoder's output is transferred to the decoder. BART is mainly useful for text generation, and it is also effective for comprehension tasks. T5 is a Text-to-Text Transfer Transformer [13] based on transfer learning [14]. Layers of a transformer are encoders and decoders. The encoder layer is responsible for encoding the input into a numeric form, using this information, the decoder layer outputs a summary.

The objective of this work is to create a concise, accurate, and short summary over a large amount of online restaurant reviews. This study presents two hybrid models to provide an informative and concise summary. This work prepares a positive and negative summary of each important aspect in the restaurant review (Food, Service, Staff, Ambience and Price).

This research paper divides the area into six sections. Section 2 describes the literature on the subject which is discussed on. Section 3 deals with the methodology of the research. Section 4 is allotted for the performance evaluations. Section 5 discuss the results of the experiment. Conclusions and findings are summarized in the final section.

2. RELATED WORK

Many authors have contributed in the realm of extractive and abstractive text summarization recently. This area specifically focuses upon such reviews in order to emphasize the necessity of the same. Iwasaki et al. [15] used a neural network to build and analyses abstractive summarization technique in Japanese. This method uses the BERT approach to produce an aspect-based input vector of sentences and a transformer-based decoder is used to generate a summary. This analysis has been conducted with the help of the dataset; Live door News. The work also uses a repeat block and WordPiece to handle repeated sentences and unknown words.

Farahani et al. [16] propose two methods of multilingual T5 and an encoder-decoder version of the ParsBERT for abstractive summarization. This work summarizes the document in Persian. They created and released a new dataset called pn-summary particularly for this work. The ROUGE metrics is used in order to emulate the efficiency of the model.

Liu and Lapata [17] introduce a comprehensive approach for both extractive and abstractive summarization. They present a unique BERT-based document-level encoder. This work first constructs an extractive model on top of this encoder. A two-staged fine-tuning approach was adopted in this method to improve the quality of the generated summaries. Kale and Rastogi [18] use a T5 framework to construct a summarization model with the help of the transfer learning process. The T5 model is compared to the BERT and GPT-2 in this study, and the results show that T5 outperforms the others.

3. METHODOLOGY

The methodology construct two hybrid text summarization models. The proposed models include the extractive and abstractive summarization. LexRank algorithm is used for extractive summarization and for abstractive summarization; BART of Facebook and T5 of Google are used.

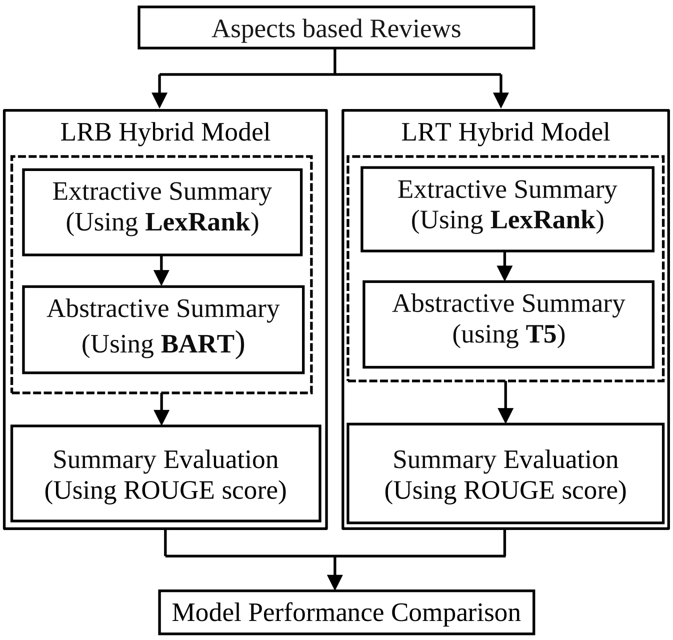

Fig.1. Methodology

The LRB hybrid model is constructed using LexRank with BART and the LRT hybrid model is constructed using LexRank with T5. This strategy generates the extractive summary using the LexRank algorithm and the output of the LexRank is chose to be the input of BART and T5. The effectiveness of two hybrid models is evaluated against human generated summary. The performance of the model is analyzed using the ROUGE (Recall-Oriented Understudy for Gisting Evaluation) score. The Fig.1 shows the methodology diagram.

3.1 INPUT DATASET

Nowadays, choosing a restaurant is often based solely on its online reputation. TripAdvisor [19] offers reviews and information on hotels, attractions, restaurants, and other travel-related subjects. Restaurant reviews may provide details about a user's experience, which can be useful to the consumer in making a decision. Restaurant review dataset is the dataset that is relied upon for this analysis. Web crawlers are used to extract the reviews. There was a total of 10,089 reviews taken, out of which 26,059 sentences were available for the analysis. The aspects regarding Food, Service, Staff, Ambience and Price are extracts from the dataset using the topic modeling techniques NMF (Non-Negative Matrix Factorization) and by the literature study. An ensemble technique is applied for opinion mining and the results are stored as the positive and as well as the negative opinion for each aspect in separate csv files. This csv file is structures as the dataset for this work.

3.2 LRB HYBRID MODEL

LexRank and BART are used to construct the LRB hybrid model. The summary which is generated through LexRank algorithm, as an extractive summary is passed on to BART. From this extractive summary BART generate an abstractive summary. LexRank is a graph-based unsupervised approach for generating relevant summaries [20]. Initially, this method generates a graph containing all the sentences in the corpus. Each sentence in the corpus is represented by a node, and the edges represent similarity relationships between sentences. LexRank calculates a sentence's relevance based on its eigenvector centrality [21]. The Cosine similarity metric is used to determine how similar sentences are represented by vectors.

LexRank Scores is calculate using the following algorithm:

Input: Array S of N sentences; Cosine threshold T

Output: An array L of LexRank scores

Step 1: Initialize the Cosine matrix, Degree, and Eigen Values.

Array Cosine Matrix [N][N];

Array Degree [N];

Array L [N];

Step 2: Matrix is initialized by TFIDF modified values for each review sentence

For i = 1 to N

For j = 1 to N

Cosine Matrix [i] [j] = IDF-modified-cosine(S[i], S[j]);

Step 3: Create TF-IDT matrix

If Cosine Matrix [i] [j] > T then

Cosine Matrix [i] [j] = 1;

Degree [i]++;

End if

Else

Cosine Matrix [i] [j] = 0;

End

End For

End for

Step 4: Divide each value of the cosine matrix by the Degree of centrality (degree of each node).

For i = 1 to N

For j = 1 to N

Cosine Matrix [i] [j] = Cosine Matrix [i] [j]/Degree [i];

End For

End For

Step 5: Calculate the final score using the Power iteration method

L = PowerMethod(Cosine Matrix, N, ϱ);

Return L;

The BART combines a Bidirectional Encoder with an Autoregressive Decoder [22]. This method first alters the text with an arbitrary nosing function and then learn a model to reconstruct the original text [23]. The BART Pre-Training model is prepared by the following steps [24]:

Step 1: **Masking Tokens**: Samples of random tokens are selected and are masked with mask tokens.

Step 2: **Deletion of Tokens**: The model samples and deletes random tokens, and adds a new token in their place.

Step 3: **Infilling of Tokens**: Poisson's distribution is used to draw a number of spans and replace each span with a masked token.

Step 4: **Permutations of Sentences**: Sentences of documents are shuffled randomly

Step 5: **Rotation of Documents**: Using a random token, a document is rotated so that the chosen token appears at the beginning. In this task, the model is trained to determine where the document begins.

3.3 LRT HYBRID MODEL

The LRT hybrid model is built using LexRank and T5 (Text-To-Text Transfer Transformer). The extractive summary generated by LexRank is the input of T5 then T5 generates an abstractive summary. T5 is an end-to-end transformer model that is trained with text as input and updated text as output [25]. The transformer consists of encoder and decoder. An encoder layer converts long sequences into numerical form, while a decoder layer uses the encoded data to generate a summary. Based on the following idea, T5 generates the abstractive summary [26].

- On the unlabeled review document, pre-train a Transformer Encoder-Decoder model.
- Pose natural language processing (NLP) task as text to text.
- Fine-tune each downstream task separately and simultaneously.

4. PERFORMANCE EVALUATION

The effectiveness of two hybrid models is evaluated using both the qualitative and quantitative analysis. With the help of the human-generated summary the quality of the models is evaluated and the ROUGE score is used as the quantitative metrics to measure the performance of the models. The ROUGE compares the content coverage of the summaries generated by the model against the human summary. The scores are determined by comparing n-grams between the system-generated and reference summaries [27]. This work employed ROUGE-1, ROUGE-2, and ROUGE-L to analyze the suggested summarization model. ROUGE tool measures the efficiency based on precision, recall and F-score.

ROUGE-1: It analyses unigrams of the machine-generated summary against the manually generated summary. ROUGE-1 has two metrics: recall and precision. ROUGE-1 calculates the F-score separately based on recall and precision.

ROUGE-2: Rouge-2 measures the bi-grams between a machine-generated summary and the summary generated by a human. ROUGE-2 has separate recall and precision, and calculates the F-score based on these.

ROUGE-L: Rouge-L examines each summary as a sequence of words and looks for the longest common subsequence (LCS). In ROUGE-L, the precision is the ratio between the length of LCS and the word count of the generated summary.

Precision: It shows how many relevant data items were selected. In other words, it determines the number of actual positive observations out of all those predicted by the algorithm. The Eq. (1) is used to calculate the precision. The precision is the result of dividing the number of true positives by the sum of true positives and false positives.

Recall: A recall measure is used to determine how many real positive cases were recognized by the algorithm out of all the real positive cases. The Eq. (2) is used to calculate the recall. It is calculated by dividing a true positive count by the sum of a true positive and false negative count.

F-score: The F1-score metric evaluates the performance of an algorithm by considering precision and recall. The Eq. (3) is used to calculate the F-score.

$$Precision=TP/(TP+FP) \tag{1}$$

$$Recall=TP/(TP+FN) \tag{2}$$

$$\text{F-}score=(2*Precision*Recall)/(Precision+Recall) \tag{3}$$

TP refers to the correctly retrieved sentence, while TN represents the incorrectly retrieved sentence, FP refers to the valid sentences that were not retrieved, and FN corresponds to the invalid sentences that were not retrieved in the summary.

5. RESULTS AND DISCUSSION

This research work focuses upon the customer opinion reviews about restaurants. The positive and negative reviews for each aspect (that include Food, Service, Staff, Ambience and Price) are stored in separate csv files. These ten csv files are used as the dataset for analytical research. This study then prepares a positive and negative summary of each aspect. Hybrid summarization is presented in these models. LexRank is used to generate the extractive summary; the output of LexRank is converted as the input into BART and T5. The LRB hybrid model and the LRT hybrid models are constructed with this specific approach. Qualitative and quantitative are the methods that employed to evaluate the effectiveness of the models that in which the experiment is carried out.

Table.1. LRB hybrid model summary of positive and negative opinions on each aspect

Positive Aspects Summary	Negative Aspects Summary
Food Amazing food!! The food was very good, and service was on time. Staff behaviour very good. Food was delicious and tasty.', 'Delicious Food The food served was good. The fish and biryani was nice', 'Good Value and Great Food I have been to this place more than four times in the last six months and did enjoy the food always. Service could be better though sometimes	**Food** Good food but highly overpriced Good quality of food is being served but that doesn't mean people will just come in and expect nothing other than food. No Air conditioning and no proper service, mostly it is self service, i don't want to call it a restaurant as per the...More", 'Too costly for the quantity The quality of the food is good. But, the price is too high for the food. Not worth for the money you pay
Service Shridhar It's nice place to visit. Good food and excellent service. Good option for travelers. The buffet is the best ablot of options. The service staff is very helpful and makes you comfortable. A perfect place to spend a special evening with friends and family. Prices are very reasonable.	**Service** One of the worst service I have ever seen We had planned to go for sea food restaurant and a guy from office recommended Trishna. I have to say that the food was good as told but the service was so pathetic that I would not go there again just for the bad service....More', 'Decent Food but lack Ambience and Service
Staff Good food and Service The buffet breakfast is nice with many choices. The staff are very friendly and helpful. Well done to Rahul and Abhishik. More', 'Excellent Service and Friendly Staff Fantastic food at this restaurant, great attentive service and the staff are really friendly' The staff Sweety and Jyoti show us how to make a Indian tea.	**Staff** Good food bad staff its not that the food was awfull or the staff was ignorant or bad mannered. its a 5 star and lets let it be that. though the staff were very un aware and a lot of mis understandings occurred during our dinner. The food was...More','staff is rude food is good but pricey, staff is a bit rude surprisingly have been to Saravana Bhavan Restaurant in many locations but i didnt like this one
Price Excellent place for Indian Food This the one of the best restaurant in this area. very nice food with good price and good value. Saravana Bhavan was our great savoir, during our last visit to Chennai. This chain of restaurant have good variety of south Indian food.	**Price** Too costly for the quantity The quality of the food is good. But, the price is too high for the food. Not worth for the money you pay' 'Good south indian food chain restaurant I think now they are only cashing the name sarvana bhavan because the quality of food is not good and you are able to eat good south indi food any other restaurant in chennai in less price
Ambience Nice food and Ambience We visited this restaurant for the first time and the food was amazing along with ambience. We had a great breakfast buffet and the quality of the food and service is great. The menu is varied and the staff very pleasing and prompt. A nice place to enjoy a relaxed...More	**Ambience** Decent Food but lack Ambience and Service went to this place for a family lunch with very high expectation. 'Good food, but costly & very rude staff Place is known for the sea food. We had fish and chicken. They were out of mutton. The ambience is average but the staff is very rude

Table.2. LRT Hybrid model summary of positive and negative opinions on each aspect

Positive Aspects Summary	Negative Aspects Summary
Food amazing food!! The food was very good, and service was on time. Staff behavior very good. Food was delicious and tasty.', 'Delicious Food The food served was good. The fish and briyani was nice. The place is small, congested but the food here is very good	**Food** too costly for the quantity The quality of the food is good. But, the price is too high for the food. Not worth for the money you pay', 'reputed name but overall OK food I visited this restaurant many times before. But this time not satisfied. Quality of food is not good. Better luck next time
Service Shridhar It's nice place to visit.It is a good Restaurant Great quality service and food. Hospitality is awesome, warm staff. Specially Mr Nandan he has given us a great and special service. Really touched with his kind nature and service. my all friends are happy with...More', 'fantastic ambiance, food, service one of the most peaceful and Mind-blowing view at night... Food was great	**Service** service was so pathetic that I would not go there again just for the bad service. food was decent but the ambience and the service was not that great. Good bengali food but need for depth in ambience and service to qualify as a fine dining place.
Staff good food and service The buffet breakfast is nice with many choices . the staff are very helpful and friendly. The staff Sweety	**Staff** 'the food was good but pricey, staff is a bit rude surprisingly have been to Saravana Bhavan Restaurant in many locations but i didnt like this

and Jyoti show us how to make a Indian tea ;) highly recommend ;)’	one’ ‘arrogant staff who treat the customer like dirt, tasty but extremely over priced food. Not worth the money spent’
Price good local delicacy at affordable price Saravana Bhavan was our great savoir, during our last visit to Chennai. ‘Good place for food items. This is the hotel with very good taste and memorable to eat again and again. the cost of the food item is bit high...at the same time quality is very good.	**Price** Too costly for the quantity The quality of the food is good. But, the price is too high for the food. Not worth for the money you pay’, ‘good south indian food chain restaurant I think now they are only cashing the name sarvana bhavan because the quality of food is not good
Ambience Great food! This restaurant serves excellent variety of cuisines along with great food. Really good service. Highly recommend this place’, ‘great food! My first visit to this restaurant. Awesome ambience and variety of food. Service is a bit slow. And the staff also may come across as a. bit indifferent. Overall a good place to dine.	**Ambience** The food was decent but the ambience and the service was not that great. ‘the prices were exhorbitant vis-à-vis the quality of food and service. Would not like to go again’.

Table 3. ROUGE Scores of LRB hybrid model

Aspect	Rouge-1			Rouge-2			Rouge-L		
	Precision	**Recall**	**F1 - Score**	**Precision**	**Recall**	**F1 - Score**	**Precision**	**Recall**	**F1 - Score**
Food - Positive	0.39	0.49	0.40	0.20	0.32	0.25	0.30	0.43	0.35
Food - Negative	0.70	0.60	0.65	0.65	0.53	0.58	0.70	0.60	0.65
Service - Positive	0.18	0.25	0.21	0.02	0.03	0.02	0.18	0.25	0.21
Service - Negative	0.39	0.39	0.33	0.08	0.05	0.07	0.33	0.24	0.28
Staff - Positive	0.17	0.42	0.25	0.04	0.11	0.05	0.13	0.32	0.19
Staff - Negative	0.30	0.36	0.33	0.11	0.13	0.12	0.29	0.34	0.31
Price - Positive	0.86	0.56	0.63	0.50	0.27	0.35	0.85	0.56	0.63
Price - Negative	0.79	0.97	0.87	0.71	0.98	0.82	0.79	0.97	0.87
Ambience - Positive	0.65	0.43	0.51	0.40	0.22	0.28	0.65	0.43	0.51
Ambience - Negative	0.40	0.36	0.34	0.19	0.15	0.22	0.35	0.32	0.31

Table 4. ROUGE Scores of LRT hybrid model

Aspect	Rouge-1			Rouge-2			Rouge-L		
	Precision	**Recall**	**F1 - Score**	**Precision**	**Recall**	**F1 - Score**	**Precision**	**Recall**	**F1 - Score**
Food – Positive	0.53	0.46	0.49	0.30	0.32	0.30	0.53	0.46	0.49
Food – Negative	0.87	0.56	0.68	0.82	0.55	0.67	0.87	0.56	0.68
Service - Positive	0.22	0.43	0.29	0.63	0.11	0.08	0.29	0.43	0.29
Service - Negative	0.58	0.26	0.36	0.32	0.14	0.20	0.52	0.24	0.33
Staff – Positive	0.19	0.32	0.24	0.29	0.53	0.04	0.16	0.26	0.20
Staff – Negative	0.44	0.36	0.4	0.22	0.16	0.19	0.41	0.64	0.38
Price – Positive	0.95	0.61	0.74	0.85	0.54	0.66	0.93	0.59	0.72
Price - Negative	0.92	0.89	0.91	0.89	0.89	0.89	0.92	0.89	0.91
Ambience - Positive	0.70	0.51	0.59	0.45	0.26	0.33	0.70	0.51	0.59
Ambience - Negative	0.52	0.26	0.34	0.37	0.16	0.22	0.48	0.23	0.31

5.1 QUALITATIVE ANALYSIS

With the aid of human generated summary, the effectiveness of two hybrid models is compared. The abstractive summary of positive and negative opinions on each aspect is provided in Table.1 as the output of the LRB Hybrid model.

The Table.2 presents the results of the LRT Hybrid model, which is an abstractive summary of positive and negative opinions on each aspect. When comparing the abstractive summaries generated by the two hybrid models with the human summary, the LRT hybrid model is more closely matched with the human summary.

5.2 QUANTITATIVE ANALYSIS

The ROUGE score is used to evaluate the models' performance. The proposed summarization model was analyzed using ROUGE-1, ROUGE-2, and ROUGE-L. Based on precision, recall, and F-score, the ROUGE tool measures efficiency. Table 3 shows the similarity of LRB hybrid model with the human generated summary for each aspect. A comparison between LRT hybrid model and the human-generated summary is given in Table 4. When Table.3 and Table.4 are compared, LRT hybrid model outperforms LRB hybrid model.

6. CONCLUSION

This analysis is carried upon the most relevant and precise summaries of restaurant reviews based on five aspects (food, service, staff, ambience, and price). The dataset consists of 10 csv files that contain positive and negative opinions on each aspect. For this research a positive and negative summary for each aspect is prepared. Automatic text summarization is carried out through two hybrid models. The work intends to employ extractive summarization followed by abstractive summarization. The extractive summarization performed with the support of LexRank algorithm, whereas abstractive summarization performed with the support of BART and T5. The extractive summary generated by LexRank algorithm is passed to BART and T5. LexRank has been combined with BART in LRB hybrid model, and then LexRank has been combined with T5 in LRT hybrid model. Both these models were assessed with the support of human generated summary and the ROUGE score is used to evaluate the models' performance. Analysis led to the conclusion that the LRT hybrid model outperforms LRB hybrid model.

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