Review Summarization Using Deep Learning

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Abstract: In the present days, online shopping has become the most popular way for buying the things. People are also showing most interest in buying the products online. While, buying those products we'll arise so many doubts like whether the product is good or not.To solve those doubts we get into the reviews which were given by previous customers who already bought the product. But it is troublesome to read massive amounts of reviews given by different customers and obtain useful information from it and it is also a lot of time consuming because the customer reviews will be typically in a very informal way[1]. Thus, summarizing the reviews helps to understand about the product in a very less time and helps the customer to find the quick answer. In our model we read the review and then preprocess it and later we apply tokenization LSTM(Long Short-Term Memory) algorithm and Sequence to Sequence model to generate the summarized review for the customer[2].

Keywords: Review Summary, LSTM algorithm, Sequence to Sequence model, Deep Learning, Attention Layer.

1 Introduction

Now a days the amount of customer reviews from different platforms grow rapidly. It is difficult to people to go through large number of reviews and to gain valid information about a certain product. Hence, summarizing the reviews of customers is helpful for identifying the useful details which helps the users in getting the valid facts.By providing the previous review summarization of a product ,the customers can easily understand the features of the product and sellers can learn actual need of the customers[3].

Basically, summarization is classified into two types which are, Abstractive and Extractive methods. Abstractive summarization helps in generating the short text. In both abstractive and extractive methods encoder and decoder are used. But when it comes to extractive method attention mechanism will also be applied.[12]

However, when we regard a certain way a extremely large amount of reviews from many services for individual result or goods created, it will be very troublesome for some new services to take the place of all these reviews, and it will exist troublesome to equate beneficial reviews that determine a real content and those that happen not beneficent and hold nothing. So, it happens very influential to study specific reviews and break down to components ruling class so that understand information the helpful comments expected urged to new services, the one give like to visualize that result or goods created and pass away[4].

Clearly, prior consumer reviews are very valuable to new buyer of goods. Such response plays a big part in judging products and growing the portion of sales of that product, exceptionally to customers the one connects the purchase of some products accompanying the reviews of the product.

Since the e-shopping sites admit buyer of goods to judge a product following in position or time validate the purchase, Amazon's buyer of goods can rate the product of five degrees/stars in this manner: starting from individual star that refers to "I hated it", two stars concern "I didn't like it", three stars concern "It was OK", four stars concern "I liked it", and five stars concern "I loved it". After that judgment, the buyer of goods should write a review of the result or goods created display his/her experience and expressing his/her opinion about that result or goods created and reason he/she is giving that rating.[14]

2 Literature Review

The reviews from customer are rapidly increasing due to the increase of various online platforms. The review may be small or large text based on the customer experience and opinion. Many customers find it's hard to read the complete review for each and every product. We have many ways to generate a review summary from customer review using different Algorithms.

In Topic Detection and Summarization of User Reviews. (Pengyuan Li, Lei Huang, Guang Jie Ren),They summarize the user summary was generated by analyzing the review using their model[15]. The model collects input and then preprocess the text to segment them, based on their sentiments, where the summary contains information of the reviews. Their method attained 15.43% over Amazon dataset.[1] .

In Deep Learning Based Abstractive Text Summarization (Dima Suleiman, Arafat Awajan) ,we know the different approaches for summarizing the text through the deep learning. Here we considered the data sets , approaches, evaluation, measures present in deep learning . these all are used to develop a model based on different algorithms[2].

InAbstract Summarization Neural Network based Sequence to Sequence Model (Pramod Kumar, Akhil Khare) , we can generate a new text from original text in less number lines. We summarize the text using neural network and have generate model using ROUGE 1, ROUGE 2, ROUGE 3 has a performance 35.5, 13.3 and 32.7[4].

3 Research Methodology

3.1 Proposed Solution

Sharing the opinions of customers in a review will help other customers to decide whether to buy that particular product or not. In those reviews many of them are in informal form or there will be repeated data about the product, these reviews might also contain the unnecessary data which will be troublesome to other customers who are viewing the reviews and also it takes more time consumption for the user[5].If we have a review which is of more words, then by using this model we can summarize that into three to five words.So, the customer will easily understand about the product by looking at summarized reviews in a relatively short time compared to the non-summarized review.In this system we'll pass the non-summarized review as input, it was then pre-processed and later it cleans the data i.e., removes repeated, unnecessary data.Then the cleaned data will be tokenized and later we implement sequence to sequence model and LSTM algorithm to summarize the review.

3.2 Model and Algorithm

- **Sequence 2 sequence Model**

A general seq2seq modelling architecture consists of an encoder and decoder for the abstractive level summarization of the data or text.[3] The work of encoder is to read the input data or the input document, which are denoted by considering a variable x and that $x=(x_1,x_2....x_n)$ and this gets transformed into some fixed number of hidden states.Now the work of the decoder is to output a summary, which are represented by $y=(y_1, y,y_3,......y_t)$.And the decoder considers the context from the hidden states as its input. The length of the data or the document can be represented by N and T respectively. The encoder and decoder can be of either CNN or RNN. [3]The Long Short Term Memory algorithm and the Gated Recurrent Unit algorithm are some special forms of RNN architecture which are most widely used ones as the encoders and decoders.[3] The LSTM based encoder and decoder forms as the base for the Neural Abstractive Summarization.[4] As for the encoder it takes a sequence of tokens as input x and starts producing sequences of hidden states. The decoder considers its input from the encoded representations of the base document and then it gives the summary in a sequence of output y. The hidden states of the decoder are initialized with the encoded vectors.[11]

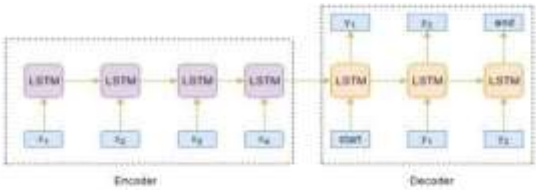

Fig 3.2 a.Seq 2 Seq Model

- **LSTM Algorithm**

The recurring unit of the LSTM algorithm holds a input or read state, memory or update state, forget and the output gate. These 4 gates share the data and the information with each other and hence a flow of information exists between them for a long period of time. [2]

Input/Read gate, The foremost step includes a input vector that is generated randomly. Moving ahead towards the subsequent steps the input of the working step is the output of the preceding step. In every case the input gets subjected to the element wise multiplication with that of the output obtained at the forget gate. The result of the multiplication gets added to the output obtained at the memory gate.

Forget gate, it can be defined as a Neural network with a layer and a function of Sigmond activation. The value obtained by this Sigmond function determines whether the information of previous state should be kept or not. If the value obtained is 1, then the information is remembered or if the value is 0 it is removed. The input for the forget gate includes the input vector, remembered value, bias and the output from preceding block.

Memory gate, the function of memory gate is to control the effect of remembered information on the latest information. The memory gate holds two neural networks in which the initial network has the structure same to that of forget gate but holds different bias. And the second has a tan h activation network and can be used to produce new data.

Output gate, this final gate controls the amount of information that gets to the next unit of LSTM. The output gate is also a neural network with a Sigmond activation function, that accepts the input vector, the previous hidden states, the bias and the new information.[4]

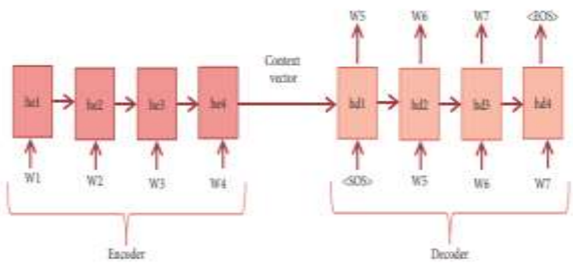

Fig 3.2b. Sequence-to-sequence; the last hidden state of the encoder is fed as input to the decoder with the symbol EOS.

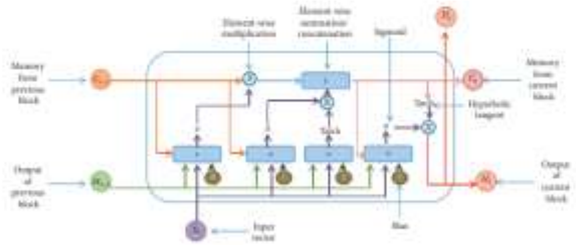

Fig 3.2c. LSTM unit architecture

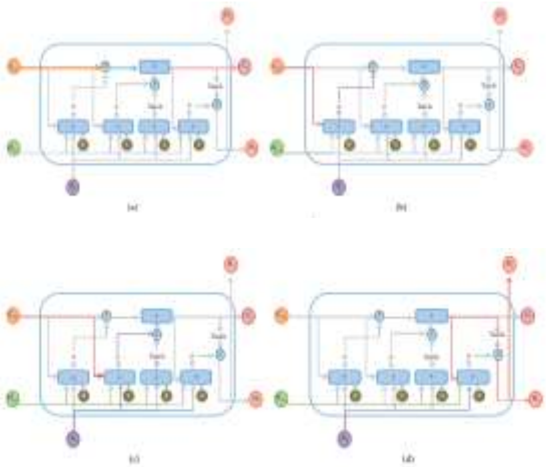

Fig. 3.3 d LSTM unit gates: (a) input gate; (b) forget gate; (c) memory gate; (d) output gate.

4 Results

In the fig you can see the user interface and passing review to the model. Here we can pass data in two formats, as paragraph and another as text document. The summary is displayed in one to five words. The Accuracy of this model 75%.

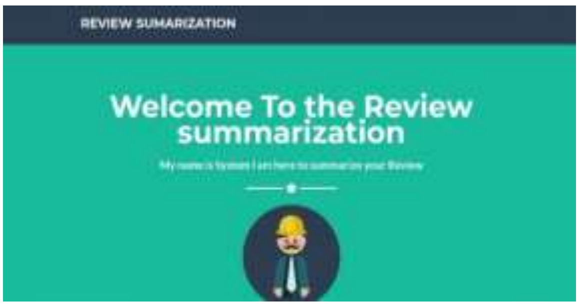

Fig4a. User Interface

Fig 4b. Passage form of Input

Fig 4c. Output for the given passage

Fig 4d. File form of Input

Fig 4e. Given Input File

Fig 4f. Output for given file

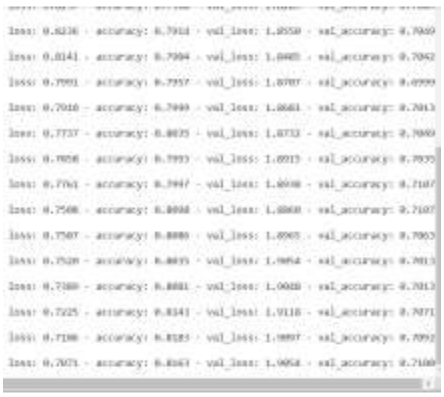

Fig 4g. Loss and Accuracy values

5 Discussion

In this paper we have discussed about how to develop a model using LSTM and Sequence to Sequence model. we can increase the training dataset size and then build a model. By increasing dataset, it increases the capability of model and gives more accurate and reliable data. This can also be implemented using Bi-directional LSTM which can capture the input from both directions. We can perform greedy approach instead of using another strategy like beam search strategy in decoding.This summarization can also be implemented with pointer-generated networks and coverage mechanism.

6 Conclusion

In the present society, we have more than one platform to use the review system. These reviews play an important role in a decision making for customers. The reviews must be understandable to every person. If the reviews are not understandable then it'll be difficult to other customers to know exactly how the product is. For these reasons, review summarization is useful to customers to understand about the product easily and it also helps the sales in the market. Even the people who are less educated can also understand the review about a particular product easily. In this we preprocess the data and perform cleaning and later we perform tokenization. In this paper we collect the reviews and train a model using sequence to sequence model and LSTM algorithm. This model can be used to summarize the review and display the result as output.

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