An Online Review Summarization on Abstractive Method Using LSTM

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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DHAKA, BANGLADESH

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APPROVAL

This Project titled **"An Online Review Summarization on Abstractive Method Using LSTM"**, submitted by Md.Lutfur Rahman Razu, ID No: 153-15-597, Sazzad Hossain Sakib, ID: 153-15-592 and Md.Golam Maulla, ID No: 153-15-605 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Bachelor of Science in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 26th November 2019.

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DECLARATION

We hereby declare that, this project has been done by us under the supervision of **Sheikh Abujar, Lecturer, Department of CSE** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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Finally, we must acknowledge with due respect the constant support and patients of our parents.

ABSTRACT

In this modern era online services are increased faster than before. This is because online services reviews are very much effected and thousands of review posted every day. This study makes an online review summarization. Two approaches are broadly use in text summarization i). Extractive. ii) Abstractive. In this study we work on abstractive text summarization and used Deep learning method. our proposed method works on Amazon Food fair service customers' reviews. In this method we execute sequence to sequence model using encoder and decoder architecture. The input and the output length remain same in sequence to sequence model. To solve this problem Encoder and decoder are used where the input and output sequence are of different length. Jointly differing the Recurrent Neural Network(RNNs), Gated Recurrent Neural Network (GRU) or Long Short Term Memory are preeminence as Encoder and Decoder. In this novel study we use LSTM (long short term memory) components. The main difficulties of this paper is training section. this is because most of data are used to train. Finally, this work help user to get a summarized review on Amazon food service.

TABLE OF CONTENTS

LIST OF TABLES

CHAPTER 1

1.1 Introduction

The revelation of modern technology and advance web application brought a numeric change in online services. This development increases online business faster than before. Now a day's people are more interested to take the online services. This is because every day millions of people take the services and post the review on internet. But all the reviews are not possible to read out and find the proper answer. Amazon Food fair services is one of them. People are more interested to give their order on internet and they order by watching the reviews of previous customers. For that reasons we are wasting our time to read the reviews. Only a novel summarized review can help us from time wasting. people give their opinion in very different format but our proposed model give a fix length output of the post.

1.2Motivation

Time consuming is very much needed for all of us. It is very tough for us to give extra time on reading. The use of text summarization is broadly used in many languages in many different platforms as needed. In this study we present a fix length model on online Food services review. For the proposed work we collected 10 years of reviews data form Amazon and use the data to train our model and reviews. The work will be affected for other reaches to completes their project. The next racers will help us to get any online reviews summarization by changing the data set.

CHAPTER 2

Background Study

2.1 Abstractive Text Summarization with Sequence-sequence Modeling

In abstractive summarization process new sentence are produce from the original text. The generate word or sentence might not be found in original text. This process uses many method and model for summarization. Sequence-sequence model is one of the best process among them.in seq2seeq model the out put come in seuential as input. We are proposed text summarizer so out put need to short.

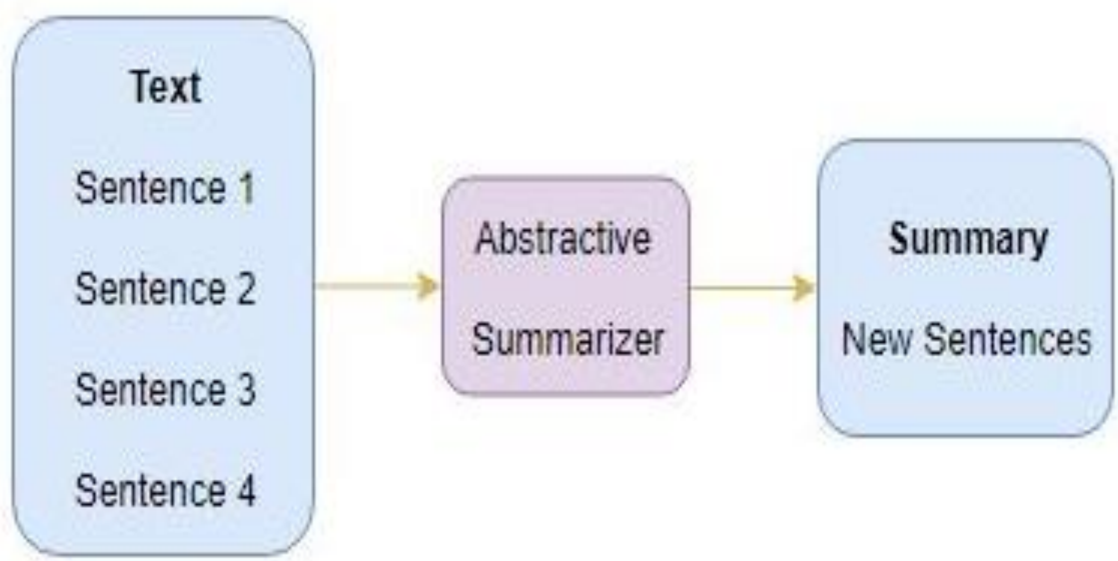

Figure 2.1: Abstractive Summarization Process.

2.2 Use Encoder and Decoder

The main component of Sequence-sequence model is Encoder and Decoder.t The Encoder-Decoder design is principally accustomed solve the sequence-to-sequence (Seq2Seq) issues wherever the input and output sequences are of various lengths. In this process we use the Long Short-Term Memory (LSTM) as encoder decoder component. this is as a result of its capable of capturing long run dependencies by overcoming the matter of vanishing gradient**.**

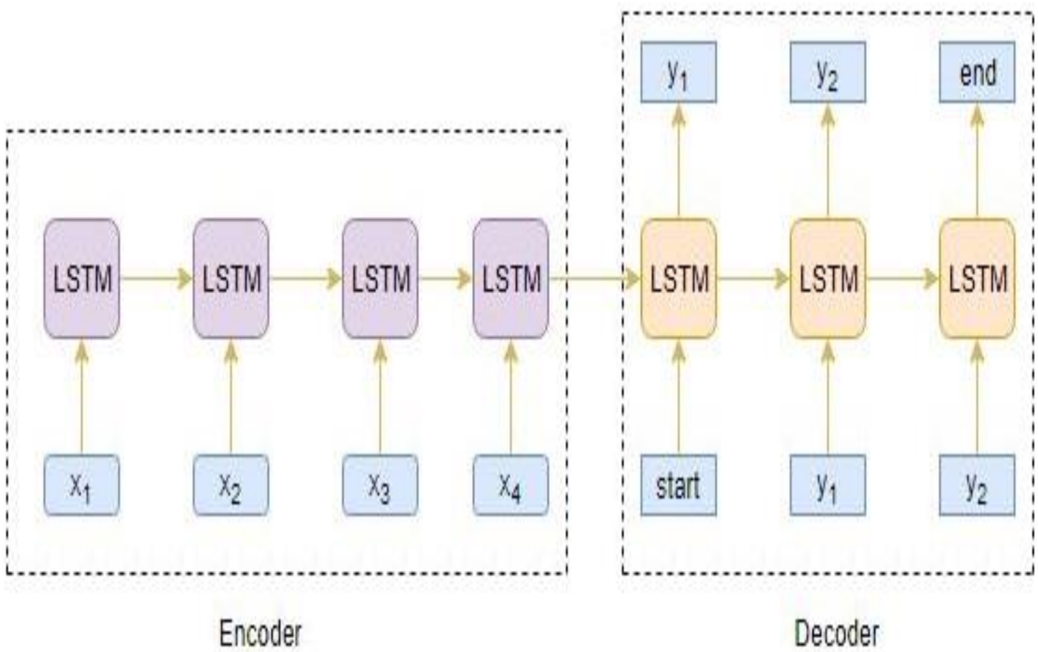

Figure 2.2: Using Encoder & Decoder in Sequence-Sequence Model.

2.3 Familiar Encoder & Decoder with LSTM

For the most part, variations of Recurrent Neural Networks (RNNs), for example Gated Recurrent Neural Network (GRU) or Long Short-Term Memory (LSTM), are favored as the encoder and decoder segments. This is on the grounds that they are fit for catching long haul conditions by conquering the issue of evaporating slope.

We consider the encoder and decoder in two part.

- Training phase
- Inference phase

2.3.1 Training Phase

First of all, we setup the encoder and decoder. Secondly the model is ready for training and expected the target sequence offset by one-time setup.

Encoder:

In this process LSTM read all the input data as sequentially. Then it analyses all the data and process a timestep.it carry all the sensitive information from the input sequence. The most important thing is initialization all the state (hidden state, cell state) for decoder.

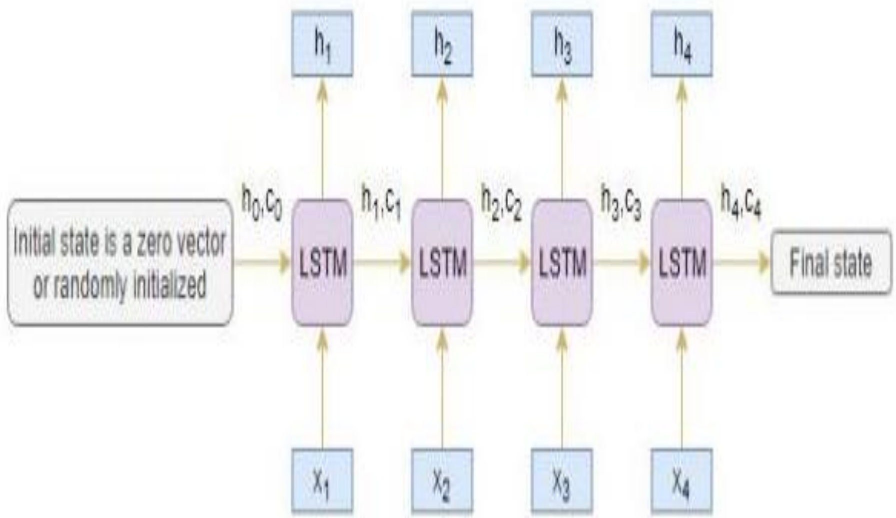

Figure 2.3.1: LSTM in Encoder

Decoder:

The target sequence is read in the decoder in LSTM network.it reads all the target as word by word and train to predict for the next sequence in same time seat and same dataset.in here we use a special token for target the sequence.

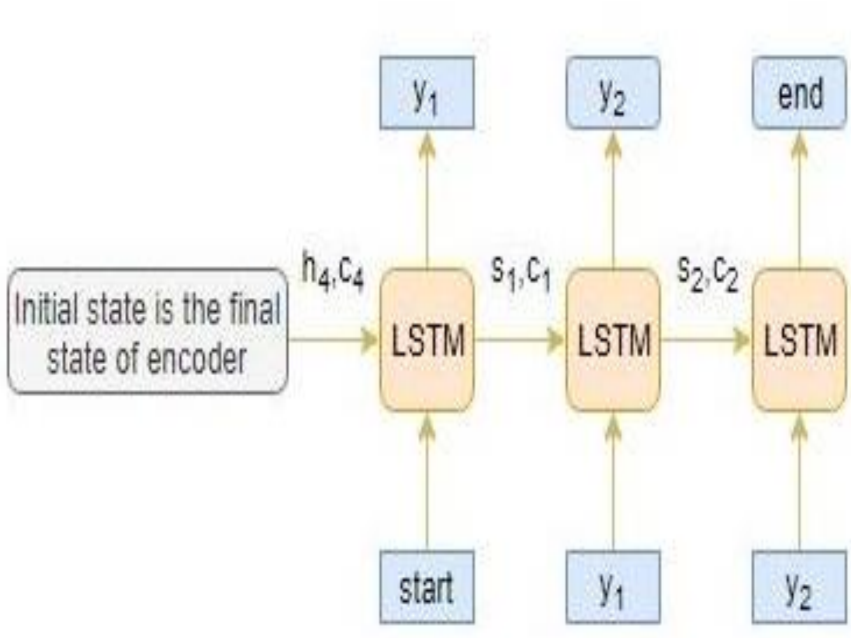

Figure 2.3.2: LSTM in Decoder

2.3.2 Inference Phase:

This process is start work when the training period complete and new model is tested for target sequence. For that reason, target sequence is unknown.

2.4 Limitations of the Work:

The encoder changes over the whole information grouping into a fixed length vector and afterward the decoder predicts the yield succession. This works just for short arrangements since the decoder is taking a gander at the whole information grouping for the expectation

Here comes the issue with long arrangements. It is hard for the encoder to remember long arrangements into a fixed length vector.

CHAPTER 3

Introduced System

3.1 Process of Work:

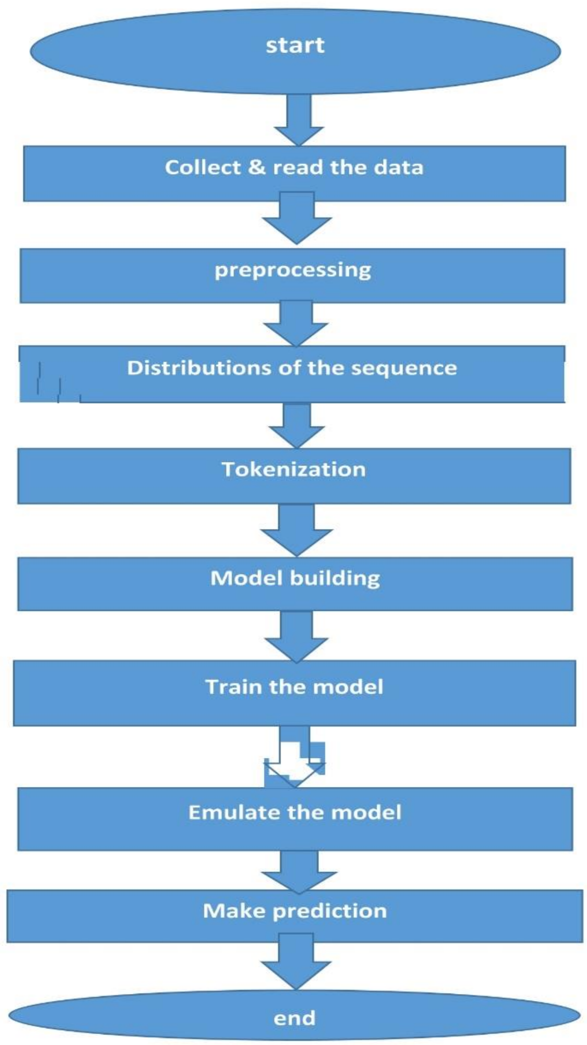

Figure 3.1: Workflow of the Process.

3.2 Appropriate Use of Data

We collected a dataset of reviews from Amazon fine food. In this dataset more than 500,000 reviews exist and it measures a long time period more than ten-eleven years. Approximately thirty percentages of data are used for training our module to understand the process.in this dataset different types of commends are used. For that reason, we prepressed the noisy or uncleaned data.

3.2 Preprocessing the Data

One of the most important part is cleaning the data where we remove all the unnecessary text, symbols, characters, emoji etc. all the massy and corrupted data can make an issue on expected outcome. In here we used a dictionary to remove the problem and make the text effected.

```
mapping ={"ain't": "is not", "aren't": "are not","can't": "cannot", "'cause": "because", "could've": "could have", "couldn't": "could not",

        "didn't": "did not",  "doesn't": "does not", "don't": "do not", "hadn't": "had not", "hasn't": "has not", "haven't": "have not",

        "he'd": "he would","he'll": "he will", "he's": "he is", "how'd": "how did", "how'd'y": "how do you", "how'll": "how will", "how's": "how is",

        "I'd": "I would", "I'd've": "I would have", "I'll": "I will", "I'll've": "I will have","I'm": "I am", "I've": "I have", "i'd": "i would",

        "i'd've": "i would have", "i'll": "i will",  "i'll've": "i will have","i'm": "i am", "i've": "i have", "isn't": "is not", "it'd": "it would",

        "it'd've": "it would have", "it'll": "it will", "it'll've": "it will have","it's": "it is", "let's": "let us", "ma'am": "madam",

        "mayn't": "may not", "might've": "might have","mightn't": "might not","mightn't've": "might not have", "must've": "must have",

        "mustn't": "must not", "mustn't've": "must not have", "needn't": "need not", "needn't've": "need not have","o'clock": "of the clock",

        "oughtn't": "ought not", "oughtn't've": "ought not have", "shan't": "shall not", "sha'n't": "shall not", "shan't've": "shall not have",

        "she'd": "she would", "she'd've": "she would have", "she'll": "she will", "she'll've": "she will have", "she's": "she is",

        "should've": "should have", "shouldn't": "should not", "shouldn't've": "should not have", "so've": "so have","so's": "so as",

        "this's": "this is","that'd": "that would", "that'd've": "that would have", "that's": "that is", "there'd": "there would",

        "there'd've": "there would have", "there's": "there is", "here's": "here is","they'd": "they would", "they'd've": "they would have",
```

Figure 3.2: Dictionary Used Expanding Constructions.

3.2.1 Text Cleaning

In this part we work on

- First of all, convert all the character in lowercase
- HTML tags need to omit
- Stop word & short word both are remove
- Reduce the (‘s)
- Especial characters and punctuation are also removed in hear.

```
0    I have bought several of the Vitality canned dog food products and have found them all to be of good quality. The product look
s more like a stew than a processed meat and it smells better. My Labr...
1            Product arrived labeled as Jumbo Salted Peanuts...the peanuts were actually small sized unsalted. Not sure if this wa
s an error or if the vendor intended to represent the product as "Jumbo".
2    This is a confection that has been around a few centuries.  It is a light, pillowy citrus gelatin with nuts - in this case Fil
berts. And it is cut into tiny squares and then liberally coated with ...
3    If you are looking for the secret ingredient in Robitussin I believe I have found it.  I got this in addition to the Root Beer
Extract I ordered (which was good) and made some cherry soda.  The fl...
4                                                       Great taffy at a great price.  There was a wide assortment of yummy
taffy.  Delivery was very quick.  If your a taffy lover, this is a deal.
5    I got a wild hair for taffy and ordered this five pound bag. The taffy was all very enjoyable with many flavors: watermelon, r
oot beer, melon, peppermint, grape, etc. My only complaint is there wa...
6    This saltwater taffy had great flavors and was very soft and chewy.  Each candy was individually wrapped well.  None of the ca
ndies were stuck together, which did happen in the expensive version, ...
7                                                       This taffy is so good.  It is very soft and chewy.  The flavors are
amazing.  I would definitely recommend you buying it.  Very satisfying!!
8                                                              Right now I'm mostly just sprouting this so my cats can ea
t the grass. They love it. I rotate it around with Wheatgrass and Rye too
9                                                         This is a very healthy dog food. Good for their digestion. Also
good for small puppies. My dog eats her required amount at every feeding.
Name: Text, dtype: object
```

Figure 3.2.1: Text Cleaning

3.2.2 Summary Cleaning

In this part we add The Start and End special token for summary.

```
0                           Good Quality Dog Food
1                              Not as Advertised
2                           "Delight" says it all
3                                 Cough Medicine
4                                    Great taffy
5                                     Nice Taffy
6    Great!  Just as good as the expensive brands!
7                         Wonderful, tasty taffy
8                                     Yay Barley
9                              Healthy Dog Food
Name: Summary, dtype: object
```

Figure 3.2.2: Output After Summery Cleaning.

3.3 Construct a Model building & distribution of the sequence

The length of the reviews and summary is very much important. The length of the project is fixed. The final outcome will come in fixed length. We constructed a final model. To make the model about 90% of data are used as training data and keep the other data for judgment the answer of summary as holdout set of data.

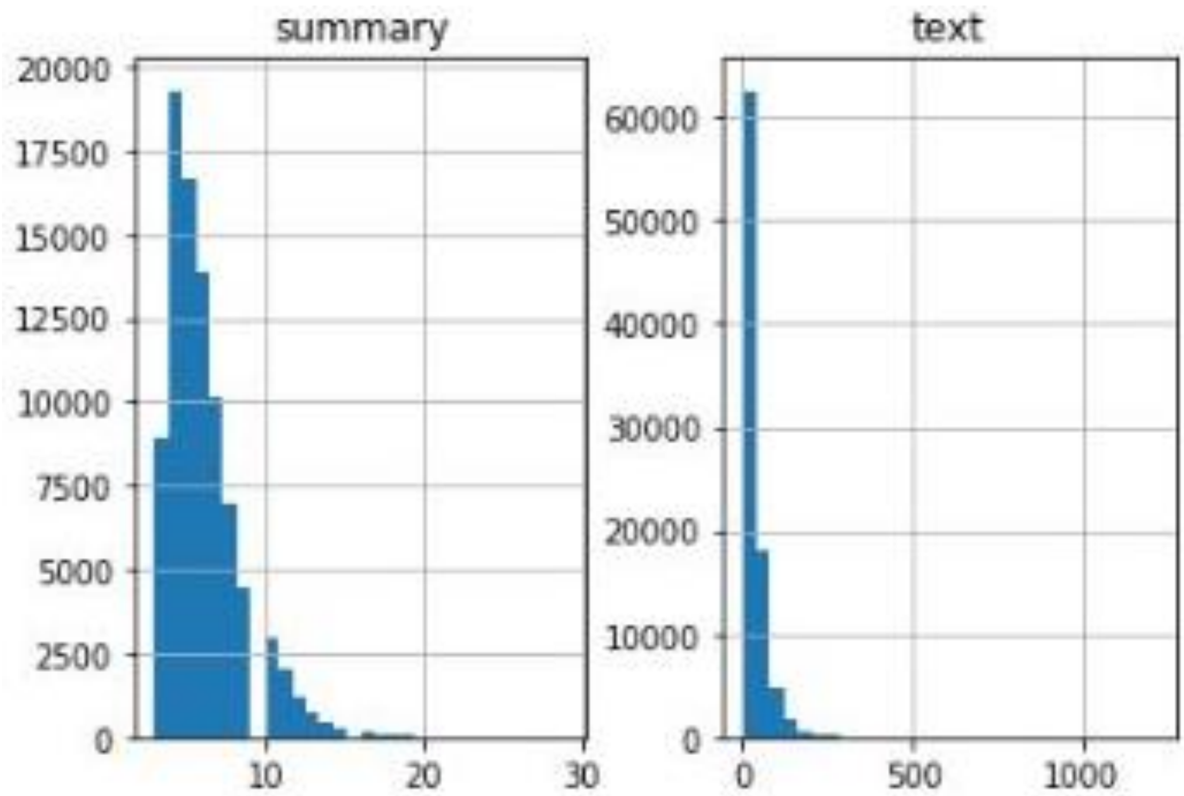

Figure 3.3: Fix Length Chart.

According to the chart after fixed the length the output become shorter. Now we build a final model here we build a LSTM encoder. In the modeling part all the hidden state, cell state and overall all the process are in work. The final model gives us the expected outcome.

3.4 Setting up the Tokenizer

A tokenizer fabricates the jargon and changes over a word grouping to a whole number arrangement. Feel free to fabricate tokenizers for content and rundown:

- Text tokenizer
- Summary tokenizer

Model Construction:

We are at last at the model structure part. In any case, before we do that, we have to acquaint ourselves with a couple of terms which are required preceding structure the model.

- **Return Sequences** = True: When the arrival arrangements parameter is set to True, LSTM produces the shrouded state and cell state for each time step

- **Return State** = True: When return state = True, LSTM produces the concealed state and cell condition of the last time step as it were

- **Starting State:** This is utilized to instate the inside conditions of the LSTM for the first time step

- **Stacked LSTM:** Stacked LSTM has various layers of LSTM stacked over one another. This prompts a superior portrayal of the arrangement. I urge you to explore different avenues regarding the various layers of the LSTM stacked over one another (it's an incredible method to become familiar with this)

```
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input_1 (InputLayer)            (None, 30)           0
__________________________________________________________________________________________________
embedding (Embedding)           (None, 30, 100)      844000      input_1[0][0]
__________________________________________________________________________________________________
lstm (LSTM)                     [(None, 30, 300), (N 481200      embedding[0][0]
__________________________________________________________________________________________________
input_2 (InputLayer)            (None, None)         0
__________________________________________________________________________________________________
lstm_1 (LSTM)                   [(None, 30, 300), (N 721200      lstm[0][0]
__________________________________________________________________________________________________
embedding_1 (Embedding)         (None, None, 100)    198900      input_2[0][0]
__________________________________________________________________________________________________
lstm_2 (LSTM)                   [(None, 30, 300), (N 721200      lstm_1[0][0]
__________________________________________________________________________________________________
lstm_3 (LSTM)                   [(None, None, 300),  481200      embedding_1[0][0]
                                                                 lstm_2[0][1]
                                                                 lstm_2[0][2]
__________________________________________________________________________________________________
attention_layer (AttentionLayer [(None, None, 300),  180300      lstm_2[0][0]
                                                                 lstm_3[0][0]
__________________________________________________________________________________________________
concat_layer (Concatenate)      (None, None, 600)    0           lstm_3[0][0]
                                                                 attention_layer[0][0]
__________________________________________________________________________________________________
time_distributed (TimeDistribut (None, None, 1989)   1195389     concat_layer[0][0]
==================================================================================================
Total params: 4,823,389
Trainable params: 4,823,389
Non-trainable params: 0
```

Figure 3.4: 3 Staked LSTM Module

3.4 Train Model:

After build the model structure now it's time to train the model. We build a three stacked LSTM for the encoder. utilizing scanty clear-cut cross-entropy as the misfortune work since it changes over the number grouping to a one-hot vector on the fly. This defeats any memory issues. it is utilized to quit preparing the neural system at the correct time by checking a client indicated metric. Here, we checking the approval misfortune (val_loss). Our model will quit preparing once the approval misfortune increments. The batch size is 128.

```
Train on 41346 samples, validate on 4588 samples
WARNING:tensorflow:From /opt/conda/lib/python3.6/site-packages/tensorflow/python/ops/math_ops.py:3066: to_
int32 (from tensorflow.python.ops.math_ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.cast instead.
Epoch 1/50
41346/41346 [==============================] - 85s 2ms/sample - loss: 2.8152 - val_loss: 2.5780
Epoch 2/50
41346/41346 [==============================] - 79s 2ms/sample - loss: 2.4859 - val_loss: 2.4072
Epoch 3/50
41346/41346 [==============================] - 81s 2ms/sample - loss: 2.3259 - val_loss: 2.3232
Epoch 4/50
41346/41346 [==============================] - 80s 2ms/sample - loss: 2.2281 - val_loss: 2.2534
Epoch 5/50
41346/41346 [==============================] - 79s 2ms/sample - loss: 2.1604 - val_loss: 2.1862
Epoch 6/50
41346/41346 [==============================] - 80s 2ms/sample - loss: 2.1065 - val_loss: 2.1549
Epoch 7/50
41346/41346 [==============================] - 80s 2ms/sample - loss: 2.0616 - val_loss: 2.1177
Epoch 8/50
41346/41346 [==============================] - 80s 2ms/sample - loss: 2.0202 - val_loss: 2.0992
Epoch 9/50
41346/41346 [==============================] - 79s 2ms/sample - loss: 1.9835 - val_loss: 2.0822
Epoch 10/50
41346/41346 [==============================] - 80s 2ms/sample - loss: 1.9476 - val_loss: 2.0636
Epoch 11/50
41346/41346 [==============================] - 80s 2ms/sample - loss: 1.9145 - val_loss: 2.0606
Epoch 12/50
41346/41346 [==============================] - 79s 2ms/sample - loss: 1.8826 - val_loss: 2.0672
Epoch 13/50
41346/41346 [==============================] - 79s 2ms/sample - loss: 1.8553 - val_loss: 2.0444
Epoch 14/50
41346/41346 [==============================] - 80s 2ms/sample - loss: 1.8267 - val_loss: 2.0422
Epoch 15/50
41346/41346 [==============================] - 80s 2ms/sample - loss: 1.7980 - val_loss: 2.0456
Epoch 16/50
41346/41346 [==============================] - 79s 2ms/sample - loss: 1.7745 - val_loss: 2.0409
Epoch 17/50
41346/41346 [==============================] - 79s 2ms/sample - loss: 1.7518 - val_loss: 2.0374
Epoch 18/50
41346/41346 [==============================] - 80s 2ms/sample - loss: 1.7299 - val_loss: 2.0434
Epoch 19/50
41346/41346 [==============================] - 80s 2ms/sample - loss: 1.7070 - val_loss: 2.0398
Epoch 00019: early stopping
```

Figure 3.4: Training Model with Data Set.

Understanding the Diagnostic Plot:

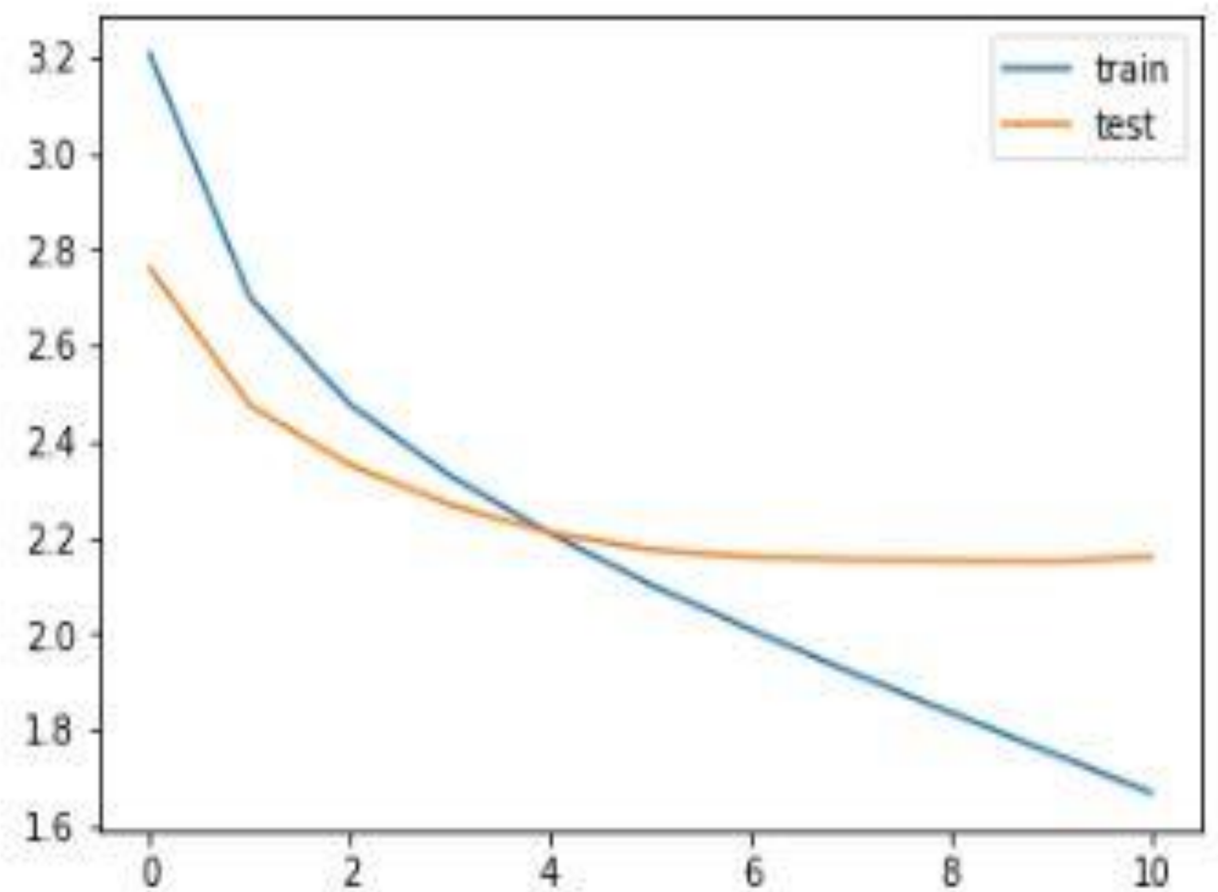

Figure 3.4: Training Diagnostic Graph.

This graph illustrates that a there is a validation lose after ten epochs .so we have to stop the training model where we found the epoch. It describes the module behavior also.

CHAPTER 4

Results

In this section we found the final outcome of your work and show the summarized views of the review. Our summarizer gives a fixed length of review. We construct a model and train the model with 10% of our data. We stop training the neural network in time by observing when the user-specified metric come. Our model generates a similar review as human but the terms of word are different. The output length is eight.

4.1 Noise Free Clean Output:

In summarization clean output is very much important. To find a noise free output we remove all the symbols, tags, special sign, html tags and so on. This process helps us to find a better outcome of the result.

```
0    I have bought several of the Vitality canned dog food products and have found them all to be of good quality. The product look
s more like a stew than a processed meat and it smells better. My Labr...
1            Product arrived labeled as Jumbo Salted Peanuts...the peanuts were actually small sized unsalted. Not sure if this wa
s an error or if the vendor intended to represent the product as "Jumbo".
2    This is a confection that has been around a few centuries.  It is a light, pillowy citrus gelatin with nuts - in this case Fil
berts. And it is cut into tiny squares and then liberally coated with ...
3    If you are looking for the secret ingredient in Robitussin I believe I have found it.  I got this in addition to the Root Beer
Extract I ordered (which was good) and made some cherry soda.  The fl...
4                                                    Great taffy at a great price.  There was a wide assortment of yummy
taffy.  Delivery was very quick.  If your a taffy lover, this is a deal.
5    I got a wild hair for taffy and ordered this five pound bag. The taffy was all very enjoyable with many flavors: watermelon, r
oot beer, melon, peppermint, grape, etc. My only complaint is there wa...
6    This saltwater taffy had great flavors and was very soft and chewy.  Each candy was individually wrapped well.  None of the ca
ndies were stuck together, which did happen in the expensive version, ...
7                                                    This taffy is so good.  It is very soft and chewy.  The flavors are
amazing.  I would definitely recommend you buying it.  Very satisfying!!
8                                                           Right now I'm mostly just sprouting this so my cats can ea
t the grass. They love it. I rotate it around with Wheatgrass and Rye too
9                                                     This is a very healthy dog food. Good for their digestion. Also
good for small puppies. My dog eats her required amount at every feeding.
Name: Text, dtype: object
```

Figure 4.1: Reviews of Clean Output

Comparing with Human Result:

We compare our result with human generate result. The result is different in the terms of words. But the summarized result is very much similar in meaning.

```
Review: daughter drinking since months old months old still loves snack time healthy delicious great addit
ion menu
Original summary: great snack
Predicted summary:  great snack


Review: live guinea africa order products delivered boat every months sometimes disappointed time zero cal
ories zero carbs taste great price zero delivery costs prime ordered different flavors one favorite love
Original summary: love it
Predicted summary:  great product


Review: purchased larger size love size perfect keep purse snack especially times others dessert snack can
not eat must gluten free spouse touch diet food loves
Original summary: cannot get enough
Predicted summary:  great snack


Review: always house drink favorite mix sprite oh good every day mind larger bottles use much bring
Original summary: am an adult still love this
Predicted summary:  great taste


Review: ginger snaps overpowering ginger go great milk really enjoyed house great buy affordable compared
alternative diet foods last least week store well
Original summary: you can eat ginger again
Predicted summary:  ginger


Review: give squid one star use might thoroughly disappointed quite possibly call crazy
Original summary: can for your
Predicted summary:  good stuff


Review: quality seeds excellent begin germinate hours days ready use never sprouted seeds results good eas
ily recommend sprouter whether human consumption four legged friends
Original summary: wheat grass seeds
Predicted summary:  great product
```

Figure 4.2: Human Generate Vs Predicted Summary

CHAPTER 5

Discussion

Automatically generating review summarization adds an extra dimension in online marketing, online hotel booking, online tourism and overall online services. We are working on online food service reviews where food item, food order, prizing etc. are under consideration. So it is handful for both customers and the vendors. It is important for future work in analyzing other data with this project. We used LSTM method of seq2seq modeling in the project to generate summery. LSTM works as encoder & decoder in the model. Though the LSTM method look difficult, it is very much effective for text summarization, voice recognition and so on.

We created a fixed length review model that will take input of 80 characters and will generate output of 8 characters. The model will skip space character. Thus the model will show a reduced form of a review on the website.

The advantage of our model is if we train it using other site's dataset it can automatically adapt to that environment and generate review on that purpose.

CHAPTER 6

Conclusion

This is truly cool stuff. Despite the fact that the real rundown and the synopsis created by our model don't coordinate as far as words, the two are passing on a similar importance. Our model can produce a neat synopsis dependent on the setting present in the content.

This project helps people to save their time and get a proper idea on online service. It is just the beginning and can be used in future work and we can go far more with this work in future. Our model can create a clear outline dependent on the setting present in the content.

Our model work doesn't stop here, anyone can play around and experiment with the model by increasing the training dataset. The speculation capacity of a deep learning model upgrades with an expansion in the preparation dataset size. Executing Bi-Directional LSTM which is equipped for catching the setting from both the directions and results in a superior context vector.

This is the manner by which we can perform content rundown utilizing profound learning ideas in Python.

References:

1. https://github.com/aravindpai/How-to-build-own-text-summarizer-using-deep-learning/blob/master/How_to_build_own_text_summarizer_using_deep_learning.ipynb

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