VIT®

Vellore Institute of Technology

(Deemed to be University under section 3 of UGC Act, 1956)

Programme	:	**M.Tech Software Engineering**	Semester	:	**Fall2020**
Course	:	**Natural Language Processing**	Code	:	**SWE1017**
Faculty	:	**Prof. SHRAVAN KUMAR**	Slot	:	**G1**

NLP FINAL REVIEW DOCUMENT

PROJECT TITLE

TEXT SUMMARIZATION USING TEXT RANKING

BY

P JYOSHNA-17MIS1153

ABSTRACT

Text Summarization is one of those applications of Natural Language Processing (NLP) which is bound to have a huge impact on our lives. The demand for automatic text summarization systems is spiking these days thanks to the availability of large amounts of textual data. In this project we take a dataset with the interview articles of sportspersons and summarize the big articles into small paragraphs.

The algorithm we use is Text Ranking. We use Extractive Summarization, this relies on extracting several parts, such as phrases and sentences, from a piece of text and stack them together to create a summary. Therefore, identifying the right sentences for summarization is of utmost importance in an extractive method.

LITERATURE SURVEY

TECHNIQUES USED FOR TEXT SUMMARIZATION

Text summarization is broadly divided into abstractive and extractive. The brief description about each approach is discussed in following section:

Abstractive Summarization Approach

Summarizations using abstractive techniques are broadly classified into two categories: Structured based approach and Semantic based approach

Structured Based Approach:

Structured based approach encodes most important information from the document through cognitive schemes such as templates, extraction rules and other structures such as tree, ontology, lead and body phrase structure

ABSTARCTIVE TEXT SUMMARIZATIONMETHODS: USING STRUCTURED BASED APPROACHS

Methods	Description	Advantages	Limitation	Author & Year
Tree Based Method	-It uses a dependency tree to represent the text of a document. -It uses either a language generator or an algorithm for generation of summary.	- It walks on units of the given document read and easy to summary.	- It lacks a complete model which would include an abstract representation for content selection.	Barzilay and McKeown (1999, 2005) et al.
Template Based Method	-It uses a template to represent a whole document. Linguistic patterns or extraction rules are matched to identify text snippets that will be mapped into template slots	-It generates summary is highly coherent because it relies on relevant information identified by IE system	Requires designing of templates and generalization of template is to difficult	Harabagiu and Lacatusu (2002)
Ontology Based Method	-Use ontology (knowledge base) to improve the process of summarization. -It exploits fuzzy ontology to handle uncertain data that simple domain ontology cannot	-Drawing relation or context is easy due to ontology - Handles uncertainty at reasonable amount	-This approach is limited to Chinese news only. - Creating Rule based system for handling uncertainty is a complex task.	Lee and Jian (2005) , Meghana viswanath(2006), et al.
Lead and Body Phrase Method	- This method is based on the operations of phrases	-It is good for semantically appropriate revisions for	-Parsing errors degrade sentential completeness	Tanaka and Kinoshita (2009) .

	(insertion and substitution) that have same syntactic head chunk in the lead and body sentences in order to rewrite the lead sentence.	revising a lead sentence.	such as grammaticality and repetition. -It focuses on rewriting techniques, and lacks a complete model which would include an abstract representation for content selection	
Rule Based Method	-Documents to be summarized are represented in terms of categories and a list of aspects.	-It has a potential for creating summaries with greater information density than current state of art.	-The drawback of this methodology is that all the rules and pattern are manually written, which is tedious & time consuming.	Genest and Lapalme (2012)[2]

Semantic Based Approach

In Semantic based approach, semantic representation of document is used to feed into natural language generation (NLG) system. This method focuses on identifying noun phrase and verb phrase by processing linguistic data.

EXTRACTIVE TEXT SUMMARIZATION TECHNIQUES USING SEMANTIC BASED APPROACH

Methods	Description	Advantages	Limitation	Author & Year
Multimodal semantic model	A semantic model, which captures concepts and relationship among concepts, is	-An important advantage of this framework is that it produces abstract summary,	- The limitation of this framework is that it is manually evaluated by humans.	Greenbacker (2011)

	built to represent the contents of multimodal documents	whose coverage is excellent because it includes salient textual and graphical content from the entire document		
Information Item Based Method	-The contents of summary are generated from abstract representation of source documents, rather than from sentences of source documents. - The abstract Representation is Information Item, which is the smallest element of coherent information in a text	-The major strength of this approach is that it produces short, coherent, information rich and less redundant summary	-It rejected due to the difficulty of creating meaningful and grammatical sentences from them. - Linguistic quality of summaries is very low due to incorrect parses	Genest and Lapalme (2011)
Semantic Graph Based Method	-This method is used to summarize a document by creating a semantic graph called Rich Semantic Graph (RSG) for the original document, reducing the generated semantic graph.	- It produces concise, coherent and less redundant and grammatically correct sentences	This method is limited to single document abstractive summarization	Moawad & Aref (2012) et al.

B. Extractive Summarization Techniques

An extractive summarization method consists of selecting important sentences, paragraphs etc. from the original document and concatenating them into shorter form. The importance of sentences is decided based on statistical and linguistic features of sentences

Methods	Description	Author & Year
Term Frequency Inverse Document Frequency Method	-Sentence frequency is defined as the number of sentences in the document that contain that term. -Then this sentence vectors are scored by similarity to the query and the highest scoring sentences are picked to be part of the summary	M.Fachrurrozi, Novi Yusliani, and Rizky Utami Yoanita, (2013) et al.
Graph Theoretic Approach	-Graph theoretic representation of passages provides a method of identification of themes. -After the common pre-processing steps, namely, stemming and stop word removal; sentences in the documents are represented as nodes in an undirected graph	Rada Mihalcea, Niraj Kumar et al.
Text summarization With Neural Networks	This method involves training the neural networks to learn the types of sentences that should be included in the summary. -It uses three- layered Feed Forward neural network	Khosrow Kaikhan(2004), Sarda A.T. and Kulkarni A.R.(2015).
Automatic TS based on fuzzy logic	-This method considers each characteristic of a text such as similarity to title, sentence length and similarity to key word etc. as the input of the fuzzy system.	Ladda Suanmali, Naomie Salim, and Mohammed Salem Binwahlan (2009) et al.
Query Based Extractive Text Summarization	In query based text summarization system, the sentences in a given document are scored based on the frequency counts of terms. -It uses Vector Space Model	Ibrahim Imam, Nihal Nounou, Alaa Hamouda et al.

The existed works on this topic and how they solved:
For text summarization they used many methods like tree , template , ontology , lead and body phrase , and rule based methods in structured based approach but they lacks in different ways like lack in model for content selection , designing and generalization of template is difficult and some are time consuming etc same for semantic based approach. In extractive summarization technique they solved by using methods like graph theoretic approach , with neural networks ,term-frequency inverse document method, automatic TS based on fuzzy logic, query based here also they lack like in TF-IDF which may be slow for large vocabularies. , measures are fundamentally limited in GTA , for NN in text summarization requires a lot of computational power, and some doesn't have the correct sense to summarize so these are all the methods used and solved.

The proposed method to solve the problem:
We use text ranking algorithm for text extraction, in this number of common words measure the sentences similarity , it gives the most informative document or summary also used in order to find the most relevant sentences in text and also to find most relevant keywords

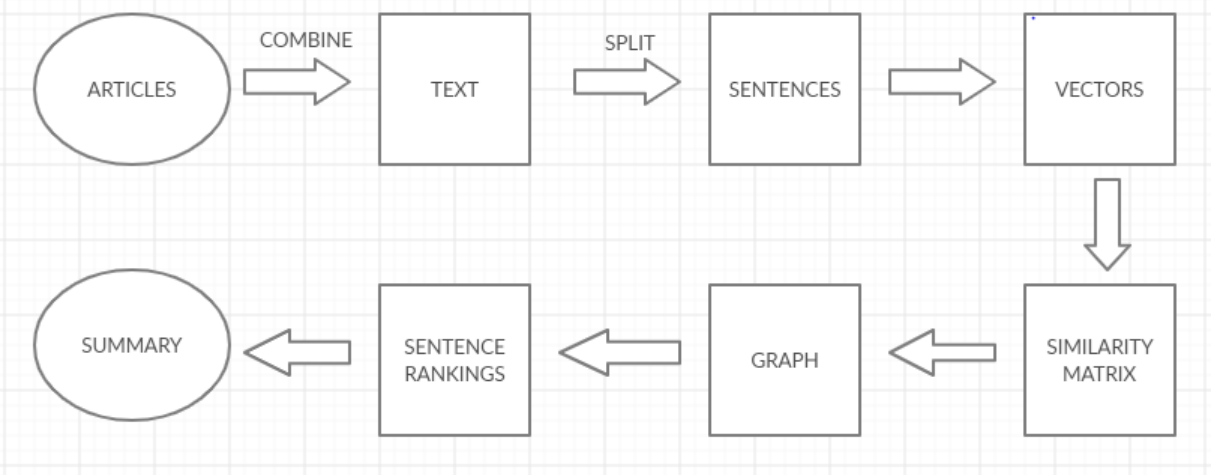
ALGORITHM

Text Rank Algorithm

Let's understand the Text Rank algorithm, now that we have a grasp on PageRank. I have listed the similarities between these two algorithms below:

- In place of web pages, we use sentences
- Similarity between any two sentences is used as an equivalent to the web page transition probability
- The similarity scores are stored in a square matrix, similar to the matrix M used for PageRank

Text Rank is an extractive and unsupervised text summarization technique. Let's take a look at the flow of the Text Rank algorithm that we will be following:



- The first step would be to concatenate all the text contained in the articles
- Then split the text into individual sentences
- In the next step, we will find vector representation (word embeddings) for each and every sentence
- Similarities between sentence vectors are then calculated and stored in a matrix
- The similarity matrix is then converted into a graph, with sentences as vertices and similarity scores as edges, for sentence rank calculation
- Finally, a certain number of top-ranked sentences form the final summary

PROGRAM CODE

```
import numpy as np import

pandas as pd import nltk

from keras import backend as K from

matplotlib import pyplot

nltk.download('punkt') # one time execution import re

df = pd.read_csv("/Users/DELL/Desktop/tennis_articles_v4.csv") df.head()
```

```
df['article_text'][0]

df['article_text'][1]

df['article_text'][2]

from nltk.tokenize import sent_tokenize

sentences = []

for s in df['article_text']:sentences.append(sent_tokenize(s))

sentences = [y for x in sentences for y in x] # flatten list

sentences[:5]

!wget http://nlp.stanford.edu/data/glove.6B.zip

!unzip glove*.zip

# Extract word vectors

word_embeddings = {}

f = open('glove.6B.100d.txt', encoding='utf-8')

for line in f:values = line.split()

word = values[0]

coefs = np.asarray(values[1:], dtype='float32')

word_embeddings[word] = coefs

f.close()

len(word_embeddings)

# remove punctuations, numbers and special characters

clean_sentences = pd.Series(sentences).str.replace("[^a-zA-Z]", " ")
```

```
# make alphabets lowercase

clean_sentences = [s.lower() for s in clean_sentences]

nltk.download('stopwords')

from nltk.corpus import stopwords

stop_words = stopwords.words('english')

# function to remove stopwords

def remove_stopwords(sen):sen_new = " ".join([i for i in sen if i not in stop_words])

returnsen_new

# removestopwords from the sentences

clean_sentences = [remove_stopwords(r.split()) for r in clean_sentences]

# Extract word vectors

word_embeddings = {}

f = open('glove.6B.100d.txt', encoding='utf-8')

for line in f:values = line.split()

word = values[0]

coefs = np.asarray(values[1:], dtype='float32')

word_embeddings[word] = coefs

f.close()

sentence_vectors = []

for i in clean_sentences:

    if len(i) != 0:v = sum([word_embeddings.get(w, np.zeros((100,))) for w in i.split ()])/(len(i.split())+0.001)

else:v = np.zeros((100,))
```

```
sentence_vectors.append(v)

# similarity matrix

sim_mat = np.zeros([len(sentences), len(sentences)])

from sklearn.metrics.pairwise import cosine_similarity

for i in range(len(sentences)):

        for j in range(len(sentences)):

                if i != j:sim_mat[i][j] = cosine_similarity(sentence_vectors[i].reshape(1,100
),sentence_vectors[j].reshape(1,100))[0,0]

import networkx as nx

nx_graph = nx.from_numpy_array(sim_mat)

scores = nx.pagerank(nx_graph)

ranked_sentences = sorted(((scores[i],s) for i,s in enumerate(sentences)), reverse=Tr ue)

# Extract top 10 sentences as the summary

for i in range(10):print(ranked_sentences[i][1])

#model building

K.clear_session()

latent_dim = 500

encoder_inputs = Input(shape=(max_len_text,))

enc_emb = Embedding(x_voc_size, latent_dim,trainable=True)(encoder_inputs)

encoder_lstm1 = LSTM(latent_dim,return_sequences=True,return_state=True)

encoder_output1, state_h1, state_c1 = encoder_lstm1(enc_emb)

encoder_lstm2 = LSTM(latent_dim,return_sequences=True,return_state=True)
```

```
encoder_output2, state_h2, state_c2 = encoder_lstm2(encoder_output1)

decoder_inputs = Input(shape=(None,))

dec_emb_layer = Embedding(y_voc_size, latent_dim,trainable=True)

dec_emb = dec_emb_layer(decoder_inputs)

decoder_lstm = LSTM(latent_dim, return_sequences=True, return_state=True)

decoder_outputs,decoder_fwd_state, decoder_back_state = decoder_lstm(dec_emb,initial_ state=[state_h,
state_c])

Attention layer attn_layer = AttentionLayer(name='attention_layer')

attn_out, attn_states = attn_layer([encoder_outputs, decoder_outputs])

decoder_concat_input = Concatenate(axis=-1, name='concat_layer')([decoder_outputs, at tn_out])

decoder_dense = TimeDistributed(Dense(y_voc_size, activation='softmax'))

decoder_outputs = decoder_dense(decoder_concat_input)

# Define the model

model = Model([encoder_inputs, decoder_inputs], decoder_outputs)

model.summary()

model.compile(optimizer='rmsprop', loss='sparse_categorical_crossentropy')

history=model.fit([x_tr,y_tr[:,:-1]], y_tr.reshape(y_tr.shape[0],y_tr.shape[1], 1)[:,
1:] ,epochs=50,callbacks=[es],batch_size=512, validation_data=([x_val,y_val[:,:-1]],
y_val.reshape(y_val.shape[0],y_val.shape[1], 1)[:,1:]))

pyplot.plot(history.history['loss'], label='train')

pyplot.plot(history.history['val_loss'], label='test')

pyplot.legend() pyplot.show()
```

```
def seq2summary(input_seq):
```

```
    newString=''
    for i in input_seq:
        if((i!=0 and i!=target_word_index['start']) and i!=target_word_index['end']):
            newString=newString+reverse_target_word_index[i]+' '
    return newString


def seq2text(input_seq):
    newString=''
    for i in input_seq:
        if(i!=0):
            newString=newString+reverse_source_word_index[i]+' '
    return newString
for i in range(len(x_val)):
    print("Review:",seq2text(x_val[i]))
    print("Original summary:",seq2summary(y_val[i]))
    print("Predicted summary:",decode_sequence(x_val[i].reshape(1,max_len_text)))
    print("\n")
```

SUMMARIZED OUTPUT

When I'm on the courts or when I'm on the court playing, I'm a competitor and I want to beat every single person whether they're in the locker room or across the net.So I 'm not the one to strike up a conversation about the weather and know that in the next few minutes I have to go and try to win a tennis ma tch.

Major players feel that a big event in late November combined with one in January bef ore the Australian Open will mean too much tennis and too little rest.

Speaking at the Swiss Indoors tournament where he will play in Sundays final against Romanian qualifier Marius Copil, the world number three said that given the impossibl y short time frame to make a decision, he opted out of any commitment.

"I felt like the best weeks that I had to get to know players when I was playing were the Fed Cup weeks or the Olympic weeks, not necessarily during the tournaments.

Currently in ninth place, Nishikori with a win could move to within 125 points of the cut for the eight-man event in London next month.

He used his first break point to close out the first set before going up 3-0 in the s econd and wrapping up the win on his first match point.

The Spaniard broke Anderson twice in the second but didn't get another chance on the South African's serve in the final set.

"We also had the impression that at this stage it might be better to play matches tha n to train.

The competition is set to feature 18 countries in the November 18-24 finals in Madrid next year, and will replace the classic home-and-away ties played four times per year for decades.

Federer said earlier this month in Shanghai in that his chances of playing the Davis Cup were all but non-existent.

The top 10 sentences are selected and displayed as summary of the article

OUTPUT SCREENSHOTS

In[1]:

```
importnumpyas npimport
pandas as pdimport nltk

nltk.download('punkt') # one time execution
```

```
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\dell\AppData\Roaming\nltk_data...
[nltk_data]   Package punktis alreadyup-to-date!
```

In[2]:

```
df= pd.read_csv("tennis_articles_v4.csv")
```

In[3]:

```
df.head()
```

Out[3]:

	article_id	article_text	source
0	1	Maria Sharapova has basically no friends aste...	https://www.tennisworldusa.org/tennis/news/Mar...
1	2	BASEL, Switzerland (AP), Roger Federer advance...	http://www.tennis.com/pro-game/2018/10/copil-s...
2	3	Roger Federer has revealed thatorganisersof...	https://scroll.in/field/899938/tennis-roger-fe...
4	5	Federer, 37, first broke through on tour over ...	https://www.express.co.uk/sport/tennis/1036101...
3	4	Kei Nishikoriwill try to end his long losing...	http://www.tennis.com/pro-game/2018/10/nishiko...

In [4]:

```
df['article_text'][0]
```

Out[4]:

```
"MariaSharapovahasbasicallynofriendsastennisplayersontheWTATour.TheRussianplayerh
asnoproblemsinopenlyspeakingaboutitandinarecentinterviewshesaid:'Idon'treallyhi
deanyfeelingstoomuch.Ithinkeveryoneknowsthisismyjobhere.WhenI'monthecourtsorw
henI'monthecourtplaying,I'macompetitorandIwanttobeateverysinglepersonwhetherthe
y'reinthelockerroomoracrossthenet.SoI'mnottheonetostrikeupaconversationaboutth
eweatherandknowthatinthenextfewminutesIhavetogoandtrytowinatennismatch.I'ma pretty
competitive girl. I say my hellos, but I'm not sending any players flowers as well. Uhm,
I'mnotreallyfriendlyorclosetomanyplayers.Ihavenotalotoffriendsawayfromthecourt
s.'Whenshesaidsheisnotreallyclosetoalotofplayers,isthatsomethingstrategicthats
heisdoing?Isitdifferentonthemen'stourthanthewomen'stour?'No,notatall.Ithinkjustbecauseyou'rei
nthesamesportdoesn'tmeanthatyouhavetobefriendswitheveryonejustb
ecauseyou'recategorized,you'reatennisplayer,soyou'regoingtogetalongwithtennisplayers.Ithinkev
erypersonhasdifferentinterests.Ihavefriendsthathavecompletelydifferentj
obsandinterests,andI'vemettheminverydifferentpartsofmylife.Ithinkeveryonejustthinksbecausewe'
retennisplayersweshouldbethegreatestoffriends.Butultimatelytennisis
justaverysmallpartofwhatwedo.Therearesomanyotherthingsthatwe'reinterestedin,th at wedo.'"
```

In [5]:

```
df['article_text'][1]
```

Out[5]:

```
"BASEL,Switzerland(AP),RogerFedereradvancedtothe14thSwissIndoorsfinalofhiscareerby
```

```
beatingseventh-seededDaniilMedvedev6-1,6-
4onSaturday.Seekinganinthtitleathishometownevent,anda99thoverall,Federerwillplay93th-
rankedMariusCopilonSunday.Federerdominatedthe20th-rankedMedvedevandhadhisfirstmatch-
pointchancetobreakserveagainat5-1.He
thendroppedhisservetolove,andletanothermatchpointslipinMedvedev'snextservicegame
bynettingabackhand.Heclinchedonhisfourthchancewhen Medvedevnettedfromthebaseline.C
opilupsetexpectationsofaFedererfinalagainstAlexanderZverevina6-3,6-7(6),6-4winoverthefifth-
rankedGermanintheearliersemifinal.TheRomanianaimsforafirsttitleafterarrivingatBaselwithoutaca
reerwinoveratop-10opponent.Copilhastwoafteralsobeating No.
6MarinCilicinthesecondround.Copilfired26acespastZverevandneverdroppedserve,clinchingafter21/2
hourswithaforehandvolleywinnertobreakZverevforthesecondtimeinthes
emifinal.Hecamethroughtworoundsofqualifyinglastweekendtoreachthe Baselmaindraw,includingbeatin
gZverev'solderbrother,Mischa.Federerhadaneasiertimethaninhisonlypreviousmatchagainst Medvedev,
athree-setteratShanghaitwoweeksago."
```

In[6]:

```
##SPLITTING INTO SENTENES

fromnltk.tokenizeimport sent_tokenize sentences = []

fors in df['article_text']:

  sentences.append(sent_tokenize(s))
```

In[7]:

```
sentences[:5]
```

Out[7]:

```
['Maria Sharapovahas basically no friends as tennis players on the WTATour.',
 "TheRussianplayerhasnoproblemsinopenlyspeakingaboutitandinarecentinterviewshesaid: 'I don't
really hide any feelings toomuch.",
 'I think everyone knows this is my jobhere.',
 "WhenI'monthecourtsorwhenI'monthecourtplaying,I'macompetitorandIwanttobeateverysingleperson
whetherthey'reinthelockerroomoracrossthenet.SoI'mnottheonetostrikeupaconversationabouttheweat
herandknowthatinthenextfewminutesIhavetogoandtry to win a tennismatch.",
 "I'm a pretty competitive girl."]
```

In[8]:

```
#FROM GLOVE WORD EMBEDDINGS

# Extract word vectors

word_embeddings= {}
f = open('glove.6B.100d.txt', encoding='utf-8')
forline in f:

    values= line.split()
```

In[9]:

```
len(word_embeddings)
```

Out[9]:

```
400000
```

In[10]:

```
#TEXT PROCESSING

# remove punctuations, numbers and special characters

clean_sentences= pd.Series(sentences).str.replace("[^a-zA-Z]", " ")
```

In[11]:

```
nltk.download('stopwords')
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\dell\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwordsis alreadyup-to-date!
```

Out[11]:

```
True
```

In[13]:

```
fromnltk.corpusimport stopwordsstop_words=
stopwords.words('english')
```

In[14]:

```
## define a function to remove these stopwordsfrom our dataset. # functionto remove stopwords

defremove_stopwords(sen):
    sen_new= " ".join([i for i in seni f i not in stop_words])

    returnsen_new
```

In[15]:

```
#Vector Representation of Sentences # Extract word
vectors word_embeddings= {}

f = open('glove.6B.100d.txt', encoding='utf-8')
forline in f:

    values= line.split()
    word = values[0]
    coefs= np.asarray(values[1:], dtype='float32')
    word_embeddings[word] = coefs
```

In[16]:

```
sentence_vectors= []
fori in clean_sentences:

  iflen(i) != 0:
    v = sum([word_embeddings.get(w, np.zeros((100,))) for w in i.split()])/(len(i.split())+0.001)
  else:
```

In[17]:

```
# similarity matrix

#We will use Cosine Similarity to compute the similarity between a pair of sentences.
```

In[18]:

```
# initialize the matrix with cosine similarity scores.

fori in range(len(sentences)):

   forj in range(len(sentences)):
```

In[19]:

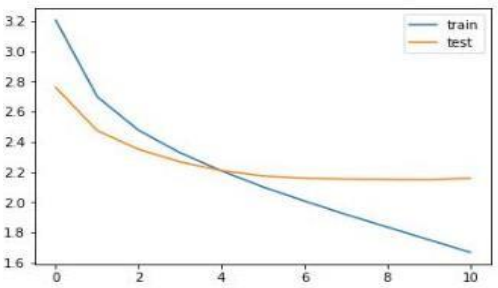
```
#Applying PageRank Algorithm

importnetworkxas nx
```

In[21]:

```
#Summary Extraction

ranked_sentences= sorted(((scores[i],s) for i,sin enumerate(sentences)),reverse=True)
# Extract top 10 sentences as the summary
```

```
WhenI'monthecourtsorwhenI'monthecourtplaying,I'macompetitorandIwanttobeatever
ysinglepersonwhetherthey'reinthelockerroomoracrossthenet.SoI'mnottheonetostrike
upaconversationabouttheweatherandknowthatinthenextfewminutesIhavetogoandtryto         win      a
tennismatch.
MajorplayersfeelthatabigeventinlateNovembercombinedwithoneinJanuarybeforetheAustralianOpenwil
lmeantoomuchtennisandtoolittlerest.
SpeakingattheSwissIndoorstournamentwherehewillplayinSundaysfinalagainstRomanianqua
lifierMariusCopil,theworldnumberthreesaidthatgiventheimpossiblyshorttimeframetoma       ke     a
decision, he opted out ofany commitment.
"IfeltlikethebestweeksthatIhadtogettoknowplayerswhenIwasplayingweretheFedCup  weeks  or  the
Olympic weeks, not necessarily during thetournaments.
Currentlyinninthplace,Nishikoriwithawincouldmovetowithin125pointsofthecutforthe        eight-man
event in London nextmonth.
```

```
Layer (type)                 Output Shape              Param #   Connected to
==================================================================================================
input_1 (InputLayer)         (None, 80)                0
--------------------------------------------------------------------------------------------------
embedding (Embedding)        (None, 80, 500)           25785500  input_1[0][0]
--------------------------------------------------------------------------------------------------
lstm (LSTM)                  [(None, 80, 500), (N 2002000     embedding[0][0]
--------------------------------------------------------------------------------------------------
input_2 (InputLayer)         (None, None)              0
--------------------------------------------------------------------------------------------------
lstm_1 (LSTM)                [(None, 80, 500), (N 2002000     lstm[0][0]
--------------------------------------------------------------------------------------------------
embedding_1 (Embedding)      (None, None, 500)         7048000   input_2[0][0]
--------------------------------------------------------------------------------------------------
lstm_2 (LSTM)                [(None, 80, 500), (N 2002000     lstm_1[0][0]
--------------------------------------------------------------------------------------------------
lstm_3 (LSTM)                [(None, None, 500),  2002000     embedding_1[0][0]
                                                              lstm_2[0][1]
                                                              lstm_2[0][2]
--------------------------------------------------------------------------------------------------
attention_layer (AttentionLayer [(None, None, 500),  500500      lstm_2[0][0]
                                                              lstm_3[0][0]
--------------------------------------------------------------------------------------------------
concat_layer (Concatenate)   (None, None, 1000)   0           lstm_3[0][0]
                                                              attention_layer[0][0]
--------------------------------------------------------------------------------------------------
time_distributed (TimeDistribut (None, None, 14096)  14110096    concat_layer[0][0]
==================================================================================================
Total params: 55,452,096
Trainable params: 55,452,096
Non-trainable params: 0
```




```
Predicted output: ['Maria Sharapova has basically no friends as tennis players on the
WTA Tour.', "The Russian player has no problem sino penly speaking about it and in a recent interviewsh
e said: 'I don't really hide any feelings too much.", 'I think everyone knows this is my
job here.', "When I'm on the court or when I'm on the court playing, I'm a competitor and I want to be a te
very single person whether they're in the locker room or across the net. So I'm not the one to strike up a
conversation about the weather and know that in the next few minutes I have to go and try to win a
tennis match.", "I'm a pretty competitive girl."]
```

RESULT

The text summarization of the article was done efficiently by the text ranking algorithm.

This algorithm finds plays an important role in summarization and is used in various application.

And as well as the LSTM model also able to perform and evaluate efficiently.

Statistical Summarization

Iris DataSet :

sepal_length	sepal_width	petal_length	petal_width	Species
5.1	3.5	1.4	0.2	Setosa
4.9	3	1.4	0.2	Setosa
4.7	3.2	1.3	0.2	Setosa
4.6	3.1	1.5	0.2	Setosa
5	3.6	1.4	0.2	Setosa
5.4	3.9	1.7	0.4	Setosa
4.6	3.4	1.4	0.3	Setosa
5	3.4	1.5	0.2	Setosa
4.4	2.9	1.4	0.2	Setosa
4.9	3.1	1.5	0.1	Setosa
5.4	3.7	1.5	0.2	Setosa
4.8	3.4	1.6	0.2	Setosa
4.8	3	1.4	0.1	Setosa
4.3	3	1.1	0.1	Setosa
5.8	4	1.2	0.2	Setosa
5.7	4.4	1.5	0.4	Setosa
5.4	3.9	1.3	0.4	Setosa
5.1	3.5	1.4	0.3	Setosa
5.7	3.8	1.7	0.3	Setosa
5.1	3.8	1.5	0.3	Setosa
5.4	3.4	1.7	0.2	Setosa
5.1	3.7	1.5	0.4	Setosa
4.6	3.6	1	0.2	Setosa
5.1	3.3	1.7	0.5	Setosa
4.8	3.4	1.9	0.2	Setosa
5	3	1.6	0.2	Setosa
5	3.4	1.6	0.4	Setosa
5.2	3.5	1.5	0.2	Setosa
5.2	3.4	1.4	0.2	Setosa
4.7	3.2	1.6	0.2	Setosa
4.8	3.1	1.6	0.2	Setosa
5.4	3.4	1.5	0.4	Setosa
5.2	4.1	1.5	0.1	Setosa
5.5	4.2	1.4	0.2	Setosa
4.9	3.1	1.5	0.2	Setosa
5	3.2	1.2	0.2	Setosa
5.5	3.5	1.3	0.2	Setosa
4.9	3.6	1.4	0.1	Setosa
4.4	3	1.3	0.2	Setosa
5.1	3.4	1.5	0.2	Setosa
5	3.5	1.3	0.3	Setosa
4.5	2.3	1.3	0.3	Setosa

4.4	3.2	1.3	0.2	Setosa
5	3.5	1.6	0.6	Setosa
5.1	3.8	1.9	0.4	Setosa
4.8	3	1.4	0.3	Setosa
5.1	3.8	1.6	0.2	Setosa
4.6	3.2	1.4	0.2	Setosa
5.3	3.7	1.5	0.2	Setosa
5	3.3	1.4	0.2	Setosa
7	3.2	4.7	1.4	Versicolor
6.4	3.2	4.5	1.5	Versicolor
6.9	3.1	4.9	1.5	Versicolor
5.5	2.3	4	1.3	Versicolor
6.5	2.8	4.6	1.5	Versicolor
5.7	2.8	4.5	1.3	Versicolor
6.3	3.3	4.7	1.6	Versicolor
4.9	2.4	3.3	1	Versicolor
6.6	2.9	4.6	1.3	Versicolor
5.2	2.7	3.9	1.4	Versicolor
5	2	3.5	1	Versicolor
5.9	3	4.2	1.5	Versicolor
6	2.2	4	1	Versicolor
6.1	2.9	4.7	1.4	Versicolor
5.6	2.9	3.6	1.3	Versicolor
6.7	3.1	4.4	1.4	Versicolor
5.6	3	4.5	1.5	Versicolor
5.8	2.7	4.1	1	Versicolor
6.2	2.2	4.5	1.5	Versicolor
5.6	2.5	3.9	1.1	Versicolor
5.9	3.2	4.8	1.8	Versicolor
6.1	2.8	4	1.3	Versicolor
6.3	2.5	4.9	1.5	Versicolor
6.1	2.8	4.7	1.2	Versicolor
6.4	2.9	4.3	1.3	Versicolor
6.6	3	4.4	1.4	Versicolor
6.8	2.8	4.8	1.4	Versicolor
6.7	3	5	1.7	Versicolor
6	2.9	4.5	1.5	Versicolor
5.7	2.6	3.5	1	Versicolor
5.5	2.4	3.8	1.1	Versicolor
5.5	2.4	3.7	1	Versicolor
5.8	2.7	3.9	1.2	Versicolor
6	2.7	5.1	1.6	Versicolor
5.4	3	4.5	1.5	Versicolor

6	3.4	4.5	1.6	Versicolor
6.7	3.1	4.7	1.5	Versicolor
6.3	2.3	4.4	1.3	Versicolor
5.6	3	4.1	1.3	Versicolor
5.5	2.5	4	1.3	Versicolor
5.5	2.6	4.4	1.2	Versicolor
6.1	3	4.6	1.4	Versicolor
5.8	2.6	4	1.2	Versicolor
5	2.3	3.3	1	Versicolor
5.6	2.7	4.2	1.3	Versicolor
5.7	3	4.2	1.2	Versicolor
5.7	2.9	4.2	1.3	Versicolor
6.2	2.9	4.3	1.3	Versicolor
5.1	2.5	3	1.1	Versicolor
5.7	2.8	4.1	1.3	Versicolor
6.3	3.3	6	2.5	Virginica
5.8	2.7	5.1	1.9	Virginica
7.1	3	5.9	2.1	Virginica
6.3	2.9	5.6	1.8	Virginica
6.5	3	5.8	2.2	Virginica
7.6	3	6.6	2.1	Virginica
4.9	2.5	4.5	1.7	Virginica
7.3	2.9	6.3	1.8	Virginica
6.7	2.5	5.8	1.8	Virginica
7.2	3.6	6.1	2.5	Virginica
6.5	3.2	5.1	2	Virginica
6.4	2.7	5.3	1.9	Virginica
6.8	3	5.5	2.1	Virginica
5.7	2.5	5	2	Virginica
5.8	2.8	5.1	2.4	Virginica
6.4	3.2	5.3	2.3	Virginica
6.5	3	5.5	1.8	Virginica
7.7	3.8	6.7	2.2	Virginica
7.7	2.6	6.9	2.3	Virginica
6	2.2	5	1.5	Virginica
6.9	3.2	5.7	2.3	Virginica
5.6	2.8	4.9	2	Virginica
7.7	2.8	6.7	2	Virginica
6.3	2.7	4.9	1.8	Virginica
6.7	3.3	5.7	2.1	Virginica
7.2	3.2	6	1.8	Virginica
6.2	2.8	4.8	1.8	Virginica
6.1	3	4.9	1.8	Virginica

6.4	2.8	5.6	2.1	Virginica
7.2	3	5.8	1.6	Virginica
7.4	2.8	6.1	1.9	Virginica
7.9	3.8	6.4	2	Virginica
6.4	2.8	5.6	2.2	Virginica
6.3	2.8	5.1	1.5	Virginica
6.1	2.6	5.6	1.4	Virginica
7.7	3	6.1	2.3	Virginica
6.3	3.4	5.6	2.4	Virginica
6.4	3.1	5.5	1.8	Virginica
6	3	4.8	1.8	Virginica
6.9	3.1	5.4	2.1	Virginica
6.7	3.1	5.6	2.4	Virginica
6.9	3.1	5.1	2.3	Virginica
5.8	2.7	5.1	1.9	Virginica
6.8	3.2	5.9	2.3	Virginica
6.7	3.3	5.7	2.5	Virginica
6.7	3	5.2	2.3	Virginica
6.3	2.5	5	1.9	Virginica
6.5	3	5.2	2	Virginica
6.2	3.4	5.4	2.3	Virginica
5.9	3	5.1	1.8	Virginica

Program Code :

Statistical Summarization

```
import pandas as pd
import numpy as np
from scipy import stats
import matplotlib.pyplot as plt
%matplotlib inline

# read dataset
df = pd.read_csv("C:\\Users\\DELL\\Desktop\\iris.csv")

def histo():
    # create histogram
    bin_edges = np.arange(0, df['sepal_length'].max() + 1, 0.5)
    fig = plt.hist(df['sepal_length'], bins=bin_edges)

    # add plot labels
    plt.xlabel('count')
    plt.ylabel('sepal length')

histo()
plt.show()

x = df['sepal_length'].values
x.dtype # dtype means type to use in computing the SD. for array of integers,the defualt is float64.
```

Sample Mean:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^n = x_i$$

```
sum(i for i in x) / len(x)
```

```
x_mean = np.mean(x)
x_mean
```

```
histo()
plt.axvline(x_mean, color='darkorange')
plt.show()
```

Sample Variance:

$$Var_x = \frac{1}{n-1}\sum_{i=1}^n (x_i - \bar{x})^2$$

```
sum([(i - x_mean)**2 for i in x]) / (len(x) - 1)
```

```
var = np.var(x, ddof=1) #ddof means delta degree of freedom. by default ddof =0
var
```

```
df['sepal_length'].var()
```

```
histo()
```

```
plt.axvline(x_mean + var, color='darkorange')
plt.axvline(x_mean - var, color='darkorange')
plt.show()
```

Sample Standard Deviation:

$$Std_x = \sqrt{\frac{1}{n-1}{\sum_{i=1}^n (x_i - \bar{x})^2}}$$

```
(sum([(i - x_mean)**2 for i in x]) / (len(x) - 1))**0.5
```

```
np.sqrt(np.var(x, ddof=1))
```

```
std = np.std(x, ddof=1)
std
```

```
df['sepal_length'].std() # note that Bessel's correction+ is the default
```

```
histo()
plt.axvline(x_mean + std, color='darkorange')
plt.axvline(x_mean - std, color='darkorange')
plt.show()
```

Min/Max:

```
np.min(x)
```

```
np.max(x)
```

Mode:

```
lst = list(x)
mode = max(set(lst), key=lst.count)
mode
```

```
lst.count(mode)
```

```
stats.mode(x)
```

25th and 75th Percentile:

```
y = np.sort(x)
percentile_25th = y[round(0.25 * y.shape[0]) + 1]
percentile_25th
```

```
percentile_75th = y[round(0.75 * y.shape[0]) - 1]
percentile_75th
```

```
np.percentile(x, q=[25, 75], interpolation='lower')
```

```
df['sepal_length'].quantile(0.25, interpolation='lower')
```

```
df['sepal_length'].quantile(0.75, interpolation='lower')

histo()
plt.axvline(percentile_75th, color='darkorange')
plt.axvline(percentile_25th - var, color='darkorange')
plt.show()

### Median (50th Percentile):

x = np.sort(x)

tmp = round(0.5 * x.shape[0])

if x.shape[0] % 2:
    median = x[tmp - 1]
else:
    median = x[tmp - 1] + (x[tmp] - x[tmp - 1]) / 2.

median

np.median(x)

histo()
plt.axvline(median, color='darkorange')
```

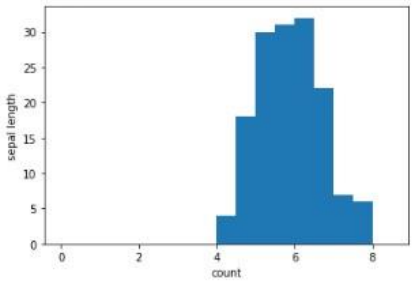
plt.show()

OUTPUT SCREENSHOTS

Statistical Summarization

In [95]:
```
import pandas as pd
import numpy as np
from scipy import stats
import matplotlib.pyplot as plt
%matplotlib inline
```

In [96]:
```
# read dataset
df = pd.read_csv("C:\\Users\\DELL\\Desktop\\iris.csv")

def histo():
    # create histogram
    bin_edges = np.arange(0, df['sepal_length'].max() + 1, 0.5)
    fig = plt.hist(df['sepal_length'], bins=bin_edges)

    # add plot labels
    plt.xlabel('count')
    plt.ylabel('sepal length')


histo()
plt.show()
```



In [97]:
```
x = df['sepal_length'].values
x.dtype # dtype means type to use in computing the SD. for array of integers,the defualt is  float64.
```

Out[97]:
```
dtype('float64')
```

Sample Mean:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} = x_i$$

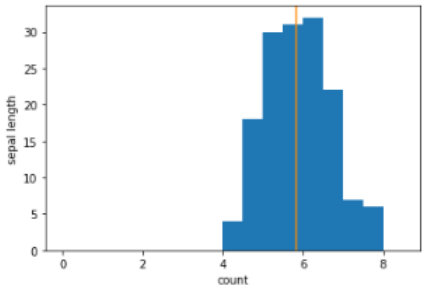
In [98]:
```
sum(i for i in x) / len(x)
```

Out[98]:
```
5.843333333333335
```

In [70]:
```
x_mean = np.mean(x)
x_mean
```

Out[70]:
```
5.843333333333334
```

In [99]:
```
histo()
plt.axvline(x_mean, color='darkorange')
plt.show()
```



Sample Variance:

$$Var_x = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2$$

In [100]:
```
sum([(i - x_mean)**2 for i in x]) / (len(x) - 1)
```

Out[100]:
```
0.6856935123042504
```

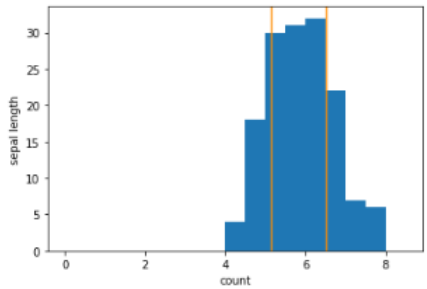
In [101]:
```
var = np.var(x, ddof=1) #ddof means delta degree of freedom. by default ddof =0
var
```

Out[101]:
```
0.6856935123042507
```

In [74]:
```
df['sepal_length'].var()
```

Out[74]:
```
0.6856935123042505
```

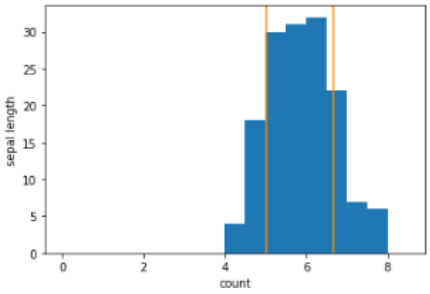
In [102]:
```
histo()
plt.axvline(x_mean + var, color='darkorange')
plt.axvline(x_mean - var, color='darkorange')
plt.show()
```



Sample Standard Deviation:

$$Std_x = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

```
In [103]: (sum([(i - x_mean)**2 for i in x]) / (len(x) - 1))**0.5
Out[103]: 0.8280661279778628

In [104]: np.sqrt(np.var(x, ddof=1))
Out[104]: 0.828066127977863

In [105]: std = np.std(x, ddof=1)
          std
Out[105]: 0.828066127977863

In [106]: df['sepal_length'].std() # note that Bessel's correction+ is the default
Out[106]: 0.8280661279778629

In [107]: histo()
          plt.axvline(x_mean + std, color='darkorange')
          plt.axvline(x_mean - std, color='darkorange')
          plt.show()
```



Min/Max:

```
In [108]: np.min(x)
Out[108]: 4.3

In [109]: np.max(x)
Out[109]: 7.9
```

Mode:

```
In [110]: lst = list(x)
          mode = max(set(lst), key=lst.count)
          mode
Out[110]: 5.0

In [111]: lst.count(mode)
Out[111]: 10

In [112]: stats.mode(x)
Out[112]: ModeResult(mode=array([5.]), count=array([10]))
```

25th and 75th Percentile:

In [113]:
```
y = np.sort(x)
percentile_25th = y[round(0.25 * y.shape[0]) + 1]
percentile_25th
```

Out[113]: 5.1

In [114]:
```
percentile_75th = y[round(0.75 * y.shape[0]) - 1]
percentile_75th
```

Out[114]: 6.4

In [115]:
```
np.percentile(x, q=[25, 75], interpolation='lower')
```

Out[115]: array([5.1, 6.4])

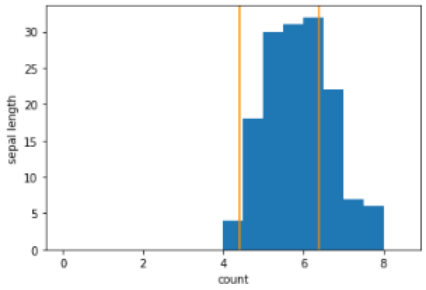
In [116]:
```
df['sepal_length'].quantile(0.25, interpolation='lower')
```

Out[116]: 5.1

In [117]:
```
df['sepal_length'].quantile(0.75, interpolation='lower')
```

Out[117]: 6.4

In [118]:
```
histo()
plt.axvline(percentile_75th, color='darkorange')
plt.axvline(percentile_25th - var, color='darkorange')
plt.show()
```



Median (50th Percentile):

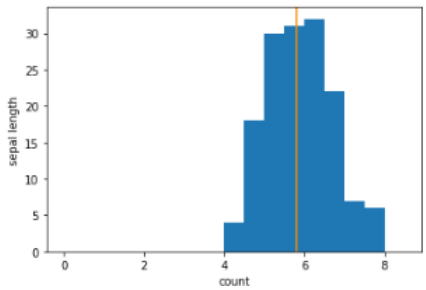
In [119]:
```
x = np.sort(x)

tmp = round(0.5 * x.shape[0])

if x.shape[0] % 2:
    median = x[tmp - 1]
else:
    median = x[tmp - 1] + (x[tmp] - x[tmp - 1]) / 2.

median
```

Out[119]: 5.8

In [120]:
```
np.median(x)
```

Out[120]: 5.8

In [121]:
```
histo()
plt.axvline(median, color='darkorange')
plt.show()
```



CONCLUSION

Automatic Text Summarization is a hot topic of research .Text Summarization is one of those applications of Natural Language Processing (NLP) which is bound to have a huge impact on our lives. With growing digital media and ever growing publishing – who has the time to go through entire articles / documents / books to decide whether they are useful or not.so here we are using text ranking algorithm which gives the best summarization and also gives us efficient prediction.

FUTURE WORK

Coming to future work, we will explore the abstractive text summarization technique. In addition, we can also look into the following summarization tasks: Problem specific-Multiple domain text summarization, Single document summarization. Algorithm-specific: Text summarization using Reinforcement Learning.

REFERENCES

[1] Dazhi Yang_ and Allan N. Zhang Singapore Institute of Manufacturing Technology "Title of the paper Performing literature review using text mining, Part III: Summarizing articles using Text Rank".

[2] Ali Toofanzadeh Mozhdehi, Mohamad Abdolahi and Shohreh Rad Rahimi title " Overview of extractive text summarization" .

[3] Wengen Li and Jiabao Zhao School of management and engineering title "Text Rank algorithm by exploiting Wikipedia for short text keywords extraction."

[4] Sonya Rapinta Manalu, Willy School of Computer Science title "Stop Words in Review Summarization Using Text Rank ".

[5] Blog Vidhya Analytics https://www.analyticsvidhya.com/blog/2018/11/introduct ion-text-summarization-textrank-python/