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Garden of Knowledge and Virtue

KULLIYYAH OF INFORMATION & COMMUNICATION TECHNOLOGY

CSCI 4342 - NATURAL LANGUAGE PROCESSING
SEMESTER 1 - 2021/2022
SECTION 1

TEXT SUMMARIZER

TECHNICAL REPORT

NAME	MATRIC NO
Mohamad Faisal Bin Mohd. Hanafi	1915045
Muhammad Syazmi Bin Suhaidi	1814573
Md. Rakibul Hassan	1720465
Md. Najmul Huda	1627521

LECTURER NAME: Dr. Suriani Bt. Sulaiman

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1. Introduction

Summarization's objective is to extract critical information from enormous amounts of text and present it in a concise, representative, and consistent summary. A well-written summary may greatly lessen the effort required to absorb massive quantities of material on a particular subject. Manually summarizing lengthy text documents is a significant challenge for humans. Text summarizing is the act of spontaneously developing and compressing the format of a given record while preserving its information source into a more compact adaptation of significant length. Text summarization is one of the most important study areas in natural language processing today and is likely to get further interest from NLP researchers in the future.

We demonstrate how to use the spacy library and extractive summarization to the issue of multi-document summarizing in this project. Spacy library and extractive summarization, abbreviated for frequency-inverse document frequency, is a numerical metric used to quantify the value of a word in a document based on its frequency of occurrence in that document and a particular collection of documents. The logic behind this metric is that if a term occurs often in a text, it must be significant, and so deserves a high score. However, if a term occurs in an excessive number of other texts, it is unlikely to be a unique identifier, and hence deserves a lower score. Our tests will demonstrate that optimizing the performance of a state-of-the-art summarizing framework strongly implies the spacy library and extractive summarization are advantageous for this project.

2. Problem Statement

Nowadays, everyone is aware of text summarization and understands how critical it is to their everyday life. When someone attempts to create it manually, it is not a simple process. Utilizing text summarization, you may quickly do a literature review, an analysis, or a paper review. It is a well-established fact that present abstractive text summarization methods often create incorrect data. This may occur at the entity level (new entities are created) or at the entity relation level (the context in which entities occur is incorrectly generated). This article assesses factual consistency exclusively at the entity level, leaving relationship-level consistency to future research. They suggest a metric for quantifying the model's hallucinations, as well as a few measurements and training techniques for improving the model's performance and producing factually true entity-level summaries. Customer testimonials are often lengthy and comprehensive. As you may guess, carefully analyzing these evaluations is somewhat time intensive. This is where natural language processing's genius may be employed to provide a summary for lengthy evaluations.

3. Motivation

Text summarizing (TS) is the process of extracting the most critical information from a document or collection of related documents and expressing it in a fraction of the space (usually by a ratio of five to ten) of the original text. Utilizing the background and related work, it was determined that a critical component of current research and projects was a lecture summarizing service that could be used by students with variable lecture sizes while using the most recent deep learning technology. This finding inspired the creation of the lecture summary service, a cloud-based service that performed inference from the spacy library and extractive summarization model in order to provide dynamically scaled lecture summaries. Several causes for text summarizing include the following:

1. Individuals become informed about international events through listening to the news.
2. Individuals make investing selections based on market updates.
3. Even still, many go to movies primarily based on the reviews they've read.
4. Summaries enable consumers to make more informed judgments in less time.

The goal here is to develop a program that is computationally efficient and automatically generates summaries.

4. Related Work

To contextualize the suggested solution of automated lecture summarizing, it is useful to review prior research, noting the advantages and disadvantages of each technique. Many multimedia apps provided manual summaries for each lecture in the early days of lecture searching. One such example comes from M.I.T.'s lecture processing project, which uploaded a significant number of lectures, complete with transcripts for keyword searching and a synopsis of the course's content (Glass, Hazen, Cyphers, Malioutov, Huynh, & Barzilay, 2007). This strategy may serve for small amounts of material, but as the data becomes larger, the human summary process may become wasteful.

In the mid-2000s, one reason for manual summation was the low quality of extractive summary tools. In 2005, researchers developed a technique for automatically extracting business meeting summaries using basic probabilistic models but rapidly discovered that the output was much inferior to summaries provided by humans (Murray, Renals, & Carletta, 2005). Due to the methodology's poor performance, multiple research articles were written to enhance the procedure.

5. Technical Background

There is a massive amount of textual information available, and it continues to develop every day. In the world of the Internet, where web pages, news articles, status updates, blogs, and so much more. Because the data is unstructured, the best way is to go through and search all the data just to find the results. Therefore, it is a great method to reduce much of this text data to short, focused summaries that capture the key features so that users can explore it more easily and ensure that the larger documents include the information needed. Stated by (Torres-Moreno, 2014), the 6 reasons why the community needs automatic text summarization tools

1. Summarizing reduces reading time.
2. When researching documents, summaries make the selection process easier.
3. Automatic summarization improves the effectiveness of indexing.
4. Automatic summarization algorithms are less biased than human summarizers.
5. Personalized summaries are useful in question-answering systems as they provide personalized information.
6. Using automatic or semi-automatic summarization systems enables commercial abstract services to increase the number of texts they are able to process.

While the world keeps on evolving, text summarization has also been widely used. Deep learning algorithms for text summarization have recently shown promising results. Text summarization has been framed as a sequence-to-sequence (Seq2Seq) algorithm, which has been motivated by the application of deep learning approaches for automatic machine translation.

6. Approach Description

For this project, we decided to use Text Summarization through the use of the spaCy library. SpaCy is a free and open-source advanced natural language Python and Cython. The main reason we used spaCy is that spaCy offers a syntactic analysis that is fast and accurate, as well as named entity recognition and access to word vectors. The spaCy library comes with:

- tokenization,
- sentence boundary detection,
- POS tagging,
- syntactic parsing, integrated word vectors,
- alignment into the original string with accuracy.

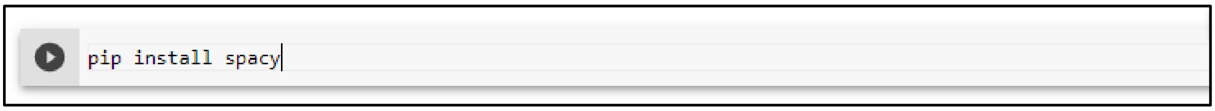
Usually, projects of text summarization can largely be divided into two categories: **Extractive Summarization** and **Abstractive Summarization.** We have decided to approach our project with Extractive Summarization. These methods rely on extracting numerous components from a piece of text, such as phrases and sentences, and stacking them together to form a summary. As a result, in an extractive technique, identifying the appropriate sentences for summary is essential.

7. Experimental Setup

I. System Development

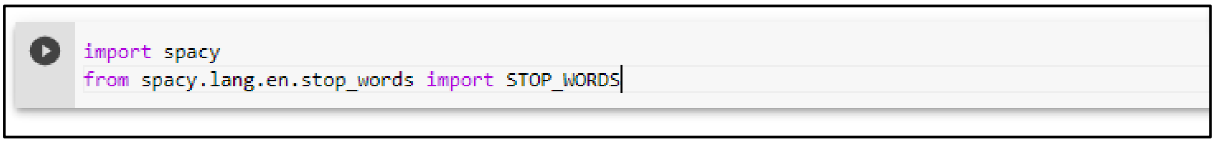
The tools that we decided to use for this project are Google Colab or Jupyter Notebook. These two are original web applications for creating and sharing computational documents. Both websites allow anybody to write and execute arbitrary python code through the browser and are especially well suited to data analysis.

To kick off the project the first thing is to install the spaCy Library.



```
pip install spacy
```

After completing the installation process of the spaCy make sure to import the library and also import stop words



```
import spacy
from spacy.lang.en.stop_words import STOP_WORDS
```

II. Article Selection

We believed that in the pursuit of producing a good model the utilization of high-quality data is essential in the training and testing phase. For this process, we had obtained six different literatures in terms of the type, genre, complexity, size, and the source which are all obtained from. Here are the differences of the article:

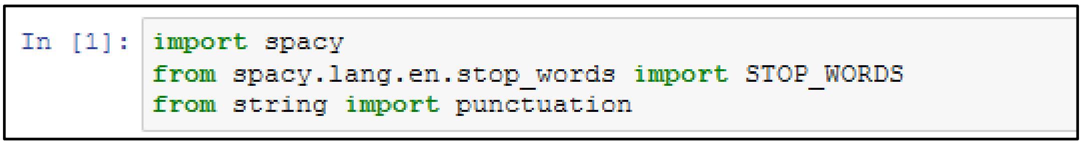
Title	Type	Complexity	Genre	Size	Source
Automatic text summarization techniques & methods	Web Article	Medium	Education	1545 words	https://www.sciencedirect.com/science/article/pii/S1319157820303712
Who are the best up-and-Coming Coaches in European Football?	Blog	Low	Sport	3209 words	https://www.sportsblog.com/uksoccer/who-are-the-best-up-and-coming-coaches-in-european-football/
History of light novel	Encyclopedia	Medium	Fiction	7797 words	https://en.wikipedia.org/wiki/Light_novel
'Janet Jackson' tells the singer's story, but it's clear who's in control	News Article	Low	Entertainment	3217 words	https://edition.cnn.com/2022/01/28/entertainment/janet-jackson-documentary-review/index.html
Classification of Ice in Lutzow-Holm Bay	Journal Article	High	Education	13214 words	https://www.mdpi.com/2072-4292/12/19/3179
State and local public policies	Research Paper	High	Education	15326 words	https://ivypanda.com/essays/state-and-local-public-policies/

Table 1: Articles Difference

8. Experimental Implementation

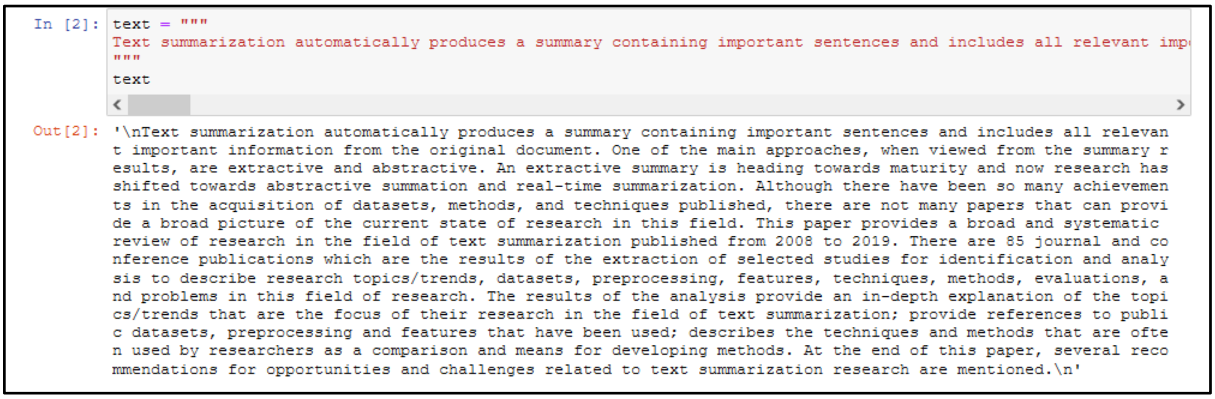
I. Data Cleaning

The first step is to import the library that will be utilized, in this case, we will be importing the spaCy library.



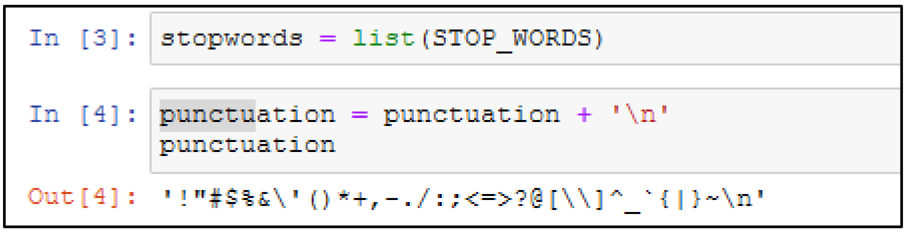
```
In [1]: import spacy
        from spacy.lang.en.stop_words import STOP_WORDS
        from string import punctuation
```

Next, we will be storing the text that will be summarized later into a variable, for this we had chosen to name the variable as "text" variable.



```
In [2]: text = """
        Text summarization automatically produces a summary containing important sentences and includes all relevant imp
        """
        text

Out[2]: '\nText summarization automatically produces a summary containing important sentences and includes all relevan
        t important information from the original document. One of the main approaches, when viewed from the summary r
        esults, are extractive and abstractive. An extractive summary is heading towards maturity and now research has
        shifted towards abstractive summation and real-time summarization. Although there have been so many achievemen
        ts in the acquisition of datasets, methods, and techniques published, there are not many papers that can provi
        de a broad picture of the current state of research in this field. This paper provides a broad and systematic
        review of research in the field of text summarization published from 2008 to 2019. There are 85 journal and co
        nference publications which are the results of the extraction of selected studies for identification and analy
        sis to describe research topics/trends, datasets, preprocessing, features, techniques, methods, evaluations, a
        nd problems in this field of research. The results of the analysis provide an in-depth explanation of the topi
        cs/trends that are the focus of their research in the field of text summarization; provide references to publi
        c datasets, preprocessing and features that have been used; describes the techniques and methods that are ofte
        n used by researchers as a comparison and means for developing methods. At the end of this paper, several reco
        mmendations for opportunities and challenges related to text summarization research are mentioned.\n'
```

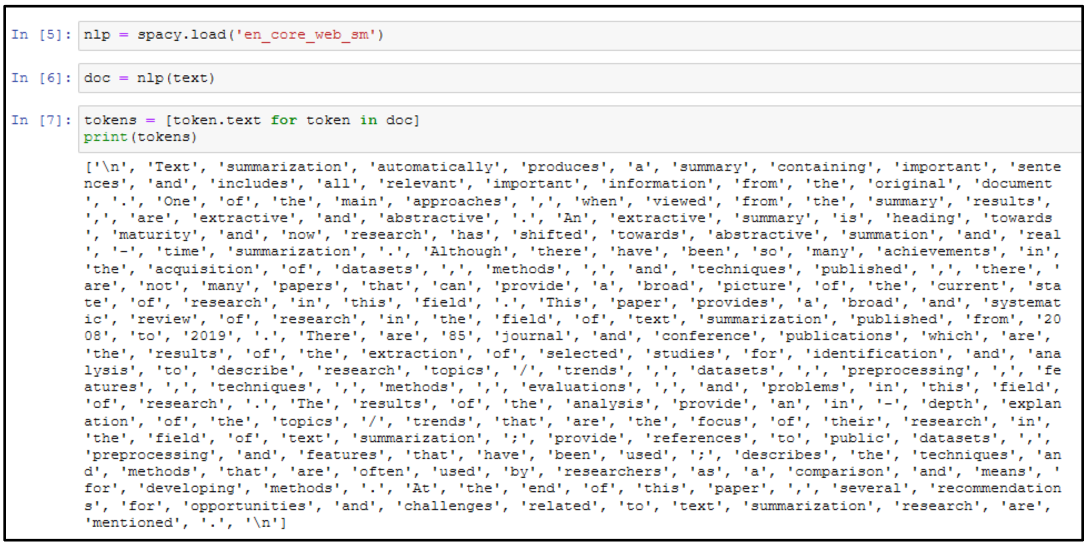
Then, we will import the punctuation marks from the string and also add the additional next line tag into it.



```
In [3]: stopwords = list(STOP_WORDS)

In [4]: punctuation = punctuation + '\n'
        punctuation

Out[4]: '!"#$%&\'()*+,-./:;<=>?@[\\]^_`{|}~\n'
```

II. Initialize Tokenization

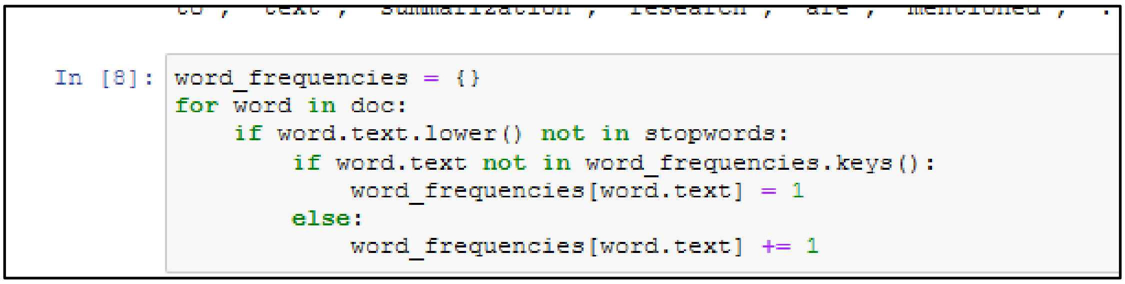
We will then start the tokenization process by tokenizing the words from the sentences in the "text" variable.



```
In [5]: nlp = spacy.load('en_core_web_sm')

In [6]: doc = nlp(text)

In [7]: tokens = [token.text for token in doc]
        print(tokens)

        ['\n', 'Text', 'summarization', 'automatically', 'produces', 'a', 'summary', 'containing', 'important', 'sente
        nces', 'and', 'includes', 'all', 'relevant', 'important', 'information', 'from', 'the', 'original', 'document
        ', '.', 'One', 'of', 'the', 'main', 'approaches', ',', 'when', 'viewed', 'from', 'the', 'summary', 'results',
        ',', 'are', 'extractive', 'and', 'abstractive', '.', 'An', 'extractive', 'summary', 'is', 'heading', 'towards
        ', 'maturity', 'and', 'now', 'research', 'has', 'shifted', 'towards', 'abstractive', 'summation', 'and', 'real
        ', '-', 'time', 'summarization', '.', 'Although', 'there', 'have', 'been', 'so', 'many', 'achievements', 'in',
        'the', 'acquisition', 'of', 'datasets', ',', 'methods', ',', 'and', 'techniques', 'published', ',', 'there', '
        are', 'not', 'many', 'papers', 'that', 'can', 'provide', 'a', 'broad', 'picture', 'of', 'the', 'current', 'sta
        te', 'of', 'research', 'in', 'this', 'field', '.', 'This', 'paper', 'provides', 'a', 'broad', 'and', 'systemat
        ic', 'review', 'of', 'research', 'in', 'the', 'field', 'of', 'text', 'summarization', 'published', 'from', '20
        08', 'to', '2019', '.', 'There', 'are', '85', 'journal', 'and', 'conference', 'publications', 'which', 'are',
        'the', 'results', 'of', 'the', 'extraction', 'of', 'selected', 'studies', 'for', 'identification', 'and', 'ana
        lysis', 'to', 'describe', 'research', 'topics', '/', 'trends', ',', 'datasets', ',', 'preprocessing', ',', 'fe
        atures', ',', 'techniques', ',', 'methods', ',', 'evaluations', ',', 'and', 'problems', 'in', 'this', 'field',
        'of', 'research', '.', 'The', 'results', 'of', 'the', 'analysis', 'provide', 'an', 'in', '-', 'depth', 'explan
        ation', 'of', 'the', 'topics', '/', 'trends', 'that', 'are', 'the', 'focus', 'of', 'their', 'research', 'in',
        'the', 'field', 'of', 'text', 'summarization', ';', 'provide', 'references', 'to', 'public', 'datasets', ',',
        'preprocessing', 'and', 'features', 'that', 'have', 'been', 'used', ';', 'describes', 'the', 'techniques', 'an
        d', 'methods', 'that', 'are', 'often', 'used', 'by', 'researchers', 'as', 'a', 'comparison', 'and', 'means', '
        for', 'developing', 'methods', '.', 'At', 'the', 'end', 'of', 'this', 'paper', ',', 'several', 'recommendation
        s', 'for', 'opportunities', 'and', 'challenges', 'related', 'to', 'text', 'summarization', 'research', 'are',
        'mentioned', '.', '\n']
```

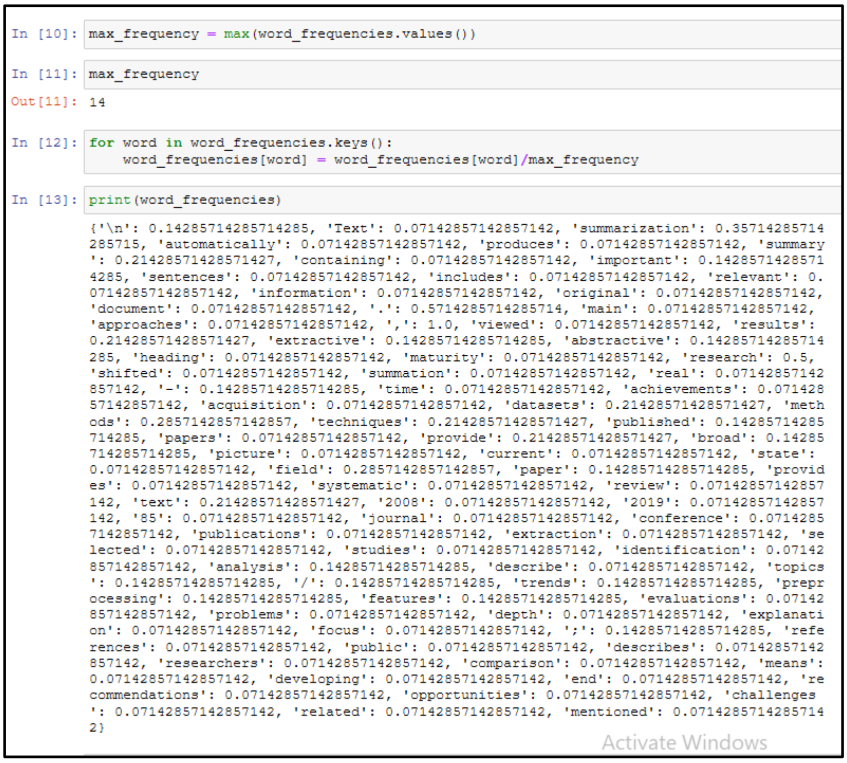
III. Word Frequency Table

Next, we will calculate the word frequencies from the text after removing stop words and punctuations.



```
            'to', 'text', 'summarization', 'research', 'are', 'mentioned', '.

In [8]: word_frequencies = {}
        for word in doc:
            if word.text.lower() not in stopwords:
                if word.text not in word_frequencies.keys():
                    word_frequencies[word.text] = 1
                else:
                    word_frequencies[word.text] += 1
```

We will print the word frequencies to know the important words in the text.

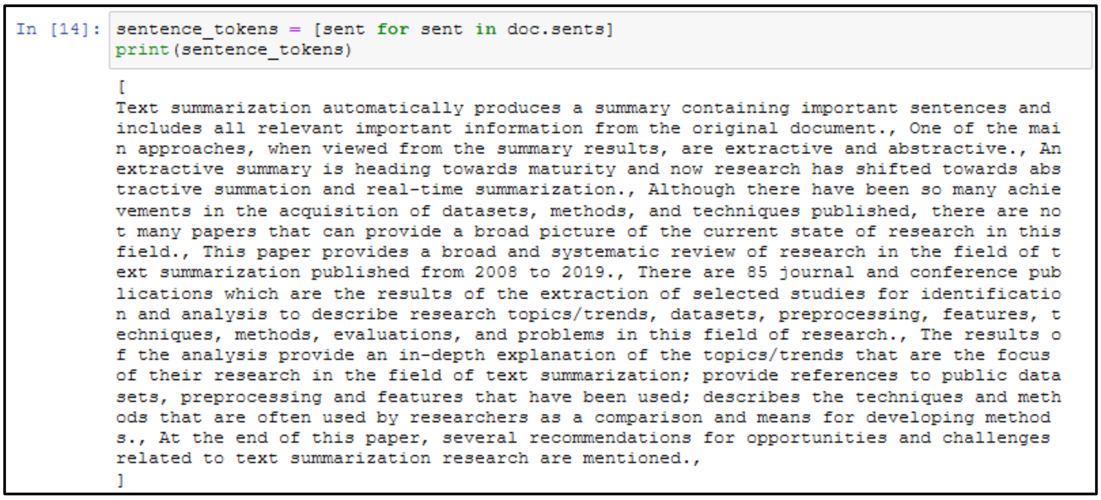


```
In [10]: max_frequency = max(word_frequencies.values())

In [11]: max_frequency

Out[11]: 14

In [12]: for word in word_frequencies.keys():
             word_frequencies[word] = word_frequencies[word]/max_frequency

In [13]: print(word_frequencies)

         {'\n': 0.14285714285714285, 'Text': 0.07142857142857142, 'summarization': 0.35714285714
         285715, 'automatically': 0.07142857142857142, 'produces': 0.07142857142857142, 'summary
         ': 0.21428571428571427, 'containing': 0.07142857142857142, 'important': 0.1428571428571
         4285, 'sentences': 0.07142857142857142, 'includes': 0.07142857142857142, 'relevant': 0.
         07142857142857142, 'information': 0.07142857142857142, 'original': 0.07142857142857142,
         'document': 0.07142857142857142, '.': 0.5714285714285714, 'main': 0.07142857142857142,
         'approaches': 0.07142857142857142, ',': 1.0, 'viewed': 0.07142857142857142, 'results':
         0.21428571428571427, 'extractive': 0.14285714285714285, 'abstractive': 0.14285714285714
         285, 'heading': 0.07142857142857142, 'maturity': 0.07142857142857142, 'research': 0.5,
         'shifted': 0.07142857142857142, 'summation': 0.07142857142857142, 'real': 0.07142857142
         857142, '-': 0.14285714285714285, 'time': 0.07142857142857142, 'achievements': 0.071428
         57142857142, 'acquisition': 0.07142857142857142, 'datasets': 0.21428571428571427, 'meth
         ods': 0.2857142857142857, 'techniques': 0.21428571428571427, 'published': 0.14285714285
         714285, 'papers': 0.07142857142857142, 'provide': 0.21428571428571427, 'broad': 0.14285
         714285714285, 'picture': 0.07142857142857142, 'current': 0.07142857142857142, 'state':
         0.07142857142857142, 'field': 0.2857142857142857, 'paper': 0.14285714285714285, 'provid
         es': 0.07142857142857142, 'systematic': 0.07142857142857142, 'review': 0.07142857142857
         142, 'text': 0.21428571428571427, '2008': 0.07142857142857142, '2019': 0.07142857142857
         142, '85': 0.07142857142857142, 'journal': 0.07142857142857142, 'conference': 0.0714285
         7142857142, 'publications': 0.07142857142857142, 'extraction': 0.07142857142857142, 'se
         lected': 0.07142857142857142, 'studies': 0.07142857142857142, 'identification': 0.07142
         857142857142, 'analysis': 0.14285714285714285, 'describe': 0.07142857142857142, 'topics
         ': 0.14285714285714285, '/': 0.14285714285714285, 'trends': 0.14285714285714285, 'prepr
         ocessing': 0.14285714285714285, 'features': 0.14285714285714285, 'evaluations': 0.07142
         857142857142, 'problems': 0.07142857142857142, 'depth': 0.07142857142857142, 'explanati
         on': 0.07142857142857142, 'focus': 0.07142857142857142, ';': 0.14285714285714285, 'refe
         rences': 0.07142857142857142, 'public': 0.07142857142857142, 'describes': 0.07142857142
         857142, 'researchers': 0.07142857142857142, 'comparison': 0.07142857142857142, 'means':
         0.07142857142857142, 'developing': 0.07142857142857142, 'end': 0.07142857142857142, 're
         commendations': 0.07142857142857142, 'opportunities': 0.07142857142857142, 'challenges
         ': 0.07142857142857142, 'related': 0.07142857142857142, 'mentioned': 0.071428571428571
         42}
```

Activate Windows

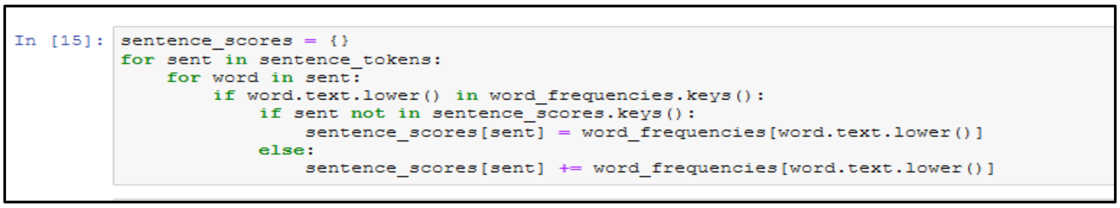
IV. Sentence Tokenization

After knowing the important words in the text, we will get the sentence tokens in the text.



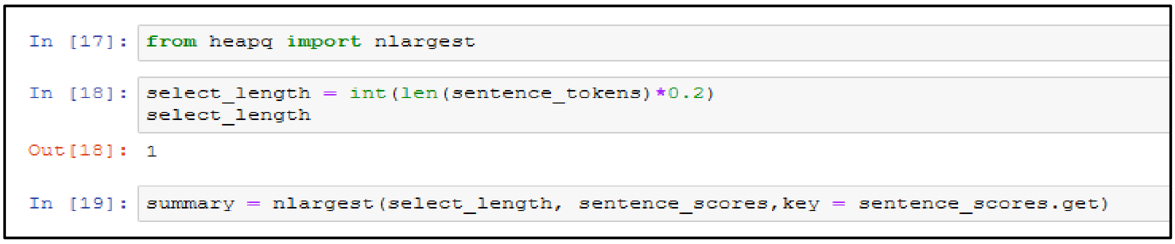
```
In [14]: sentence_tokens = [sent for sent in doc.sents]
         print(sentence_tokens)

         [
         Text summarization automatically produces a summary containing important sentences and
         includes all relevant important information from the original document., One of the mai
         n approaches, when viewed from the summary results, are extractive and abstractive., An
         extractive summary is heading towards maturity and now research has shifted towards abs
         tractive summation and real-time summarization., Although there have been so many achie
         vements in the acquisition of datasets, methods, and techniques published, there are no
         t many papers that can provide a broad picture of the current state of research in this
         field., This paper provides a broad and systematic review of research in the field of t
         ext summarization published from 2008 to 2019., There are 85 journal and conference pub
         lications which are the results of the extraction of selected studies for identificatio
         n and analysis to describe research topics/trends, datasets, preprocessing, features, t
         echniques, methods, evaluations, and problems in this field of research., The results o
         f the analysis provide an in-depth explanation of the topics/trends that are the focus
         of their research in the field of text summarization; provide references to public data
         sets, preprocessing and features that have been used; describes the techniques and meth
         ods that are often used by researchers as a comparison and means for developing method
         s., At the end of this paper, several recommendations for opportunities and challenges
         related to text summarization research are mentioned.,
         ]
```

Next, we can calculate the most important sentences by adding the word frequencies in each sentence in the "text" variable.



```
In [15]: sentence_scores = {}
         for sent in sentence_tokens:
             for word in sent:
                 if word.text.lower() in word_frequencies.keys():
                     if sent not in sentence_scores.keys():
                         sentence_scores[sent] = word_frequencies[word.text.lower()]
                     else:
                         sentence_scores[sent] += word_frequencies[word.text.lower()]
```

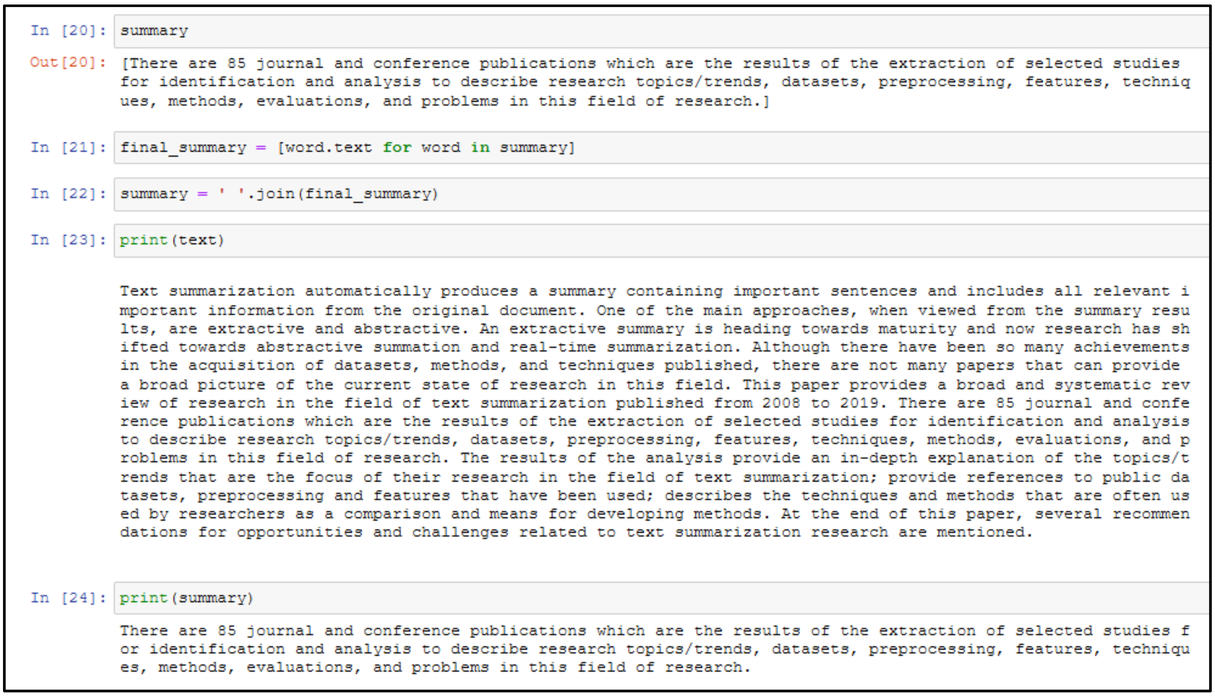
Then, by utilizing nlargest that had been obtained from heapq library, we can calculate the nlargest and calculate 20% of text with maximum score. For your information, after some testing it is recorded that 20% is the lowest that we can summarize this specific text, we believe if the text is longer, sub-20% may be achievable.



```
In [17]: from heapq import nlargest

In [18]: select_length = int(len(sentence_tokens)*0.2)
         select_length

Out[18]: 1

In [19]: summary = nlargest(select_length, sentence_scores,key = sentence_scores.get)
```

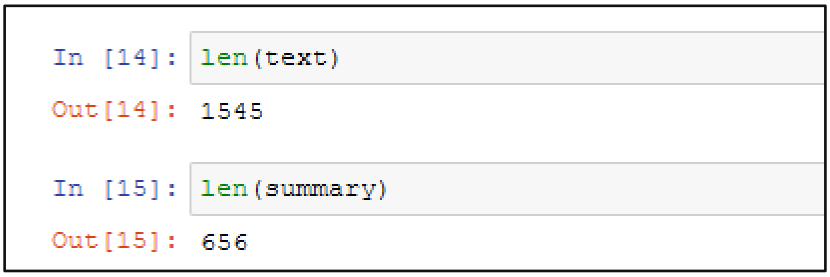
V. *Summarization*

Finally, we can get the summary of the text.



```
In [20]: summary
Out[20]: [There are 85 journal and conference publications which are the results of the extraction of selected studies
          for identification and analysis to describe research topics/trends, datasets, preprocessing, features, techniq
          ues, methods, evaluations, and problems in this field of research.]

In [21]: final_summary = [word.text for word in summary]

In [22]: summary = ' '.join(final_summary)

In [23]: print(text)

          Text summarization automatically produces a summary containing important sentences and includes all relevant i
          mportant information from the original document. One of the main approaches, when viewed from the summary resu
          lts, are extractive and abstractive. An extractive summary is heading towards maturity and now research has sh
          ifted towards abstractive summation and real-time summarization. Although there have been so many achievements
          in the acquisition of datasets, methods, and techniques published, there are not many papers that can provide
          a broad picture of the current state of research in this field. This paper provides a broad and systematic rev
          iew of research in the field of text summarization published from 2008 to 2019. There are 85 journal and confe
          rence publications which are the results of the extraction of selected studies for identification and analysis
          to describe research topics/trends, datasets, preprocessing, features, techniques, methods, evaluations, and p
          roblems in this field of research. The results of the analysis provide an in-depth explanation of the topics/t
          rends that are the focus of their research in the field of text summarization; provide references to public da
          tasets, preprocessing and features that have been used; describes the techniques and methods that are often us
          ed by researchers as a comparison and means for developing methods. At the end of this paper, several recommen
          dations for opportunities and challenges related to text summarization research are mentioned.

In [24]: print(summary)
          There are 85 journal and conference publications which are the results of the extraction of selected studies f
          or identification and analysis to describe research topics/trends, datasets, preprocessing, features, techniqu
          es, methods, evaluations, and problems in this field of research.
```

Finally, we can also calculate the length of the summary from the original text.



```
In [14]: len(text)
Out[14]: 1545

In [15]: len(summary)
Out[15]: 656
```

9. Result

In this section, in order to evaluate the model's capabilities, we tested it with three different articles, each of which came from three diversely different genres from each other, and all of the articles had different ranges of words with three different length of summary. Here are the results:

	Title					
Length of Summary	Automatic text summarization techniques & methods	'Janet Jackson' tells the singer's story, but it's clear who's in control	Who are the best up-and-Coming Coaches in European Football?	History of light novel	Classification of Ice in Lutzow-Holm Bay	State and local public policies
Original	1545	3217	3209	7797	13214	15326
10%	NA	141	412	1167	2071	2491
20%	289	646	838	2499	3848	4499
30%	656	1039	1370	3573	5902	6293
40%	879	1461	1709	4681	7382	8065

Table 2: Model's results

10. Error Analysis

For this section, we will evaluate the result obtained from the model by comparing the predicted value of the summary with the actual output, hence with it, we can calculate the accuracy of each summary's length, with the result, we can acknowledge the length of summary with lowest accuracies as the most accurate summary that can produce the most accurate result. Here are the results:

I. 10% length of summary

	Length of Summary		
Title	10% (Predicted)	10% (Actual)	Difference (Predicted/Actual)
Automatic text summarization techniques & methods	155	NA	0%
'Janet Jackson' tells the singer's story, but it's clear who's in control	322	251	128.3%
Who are the best up-and-Coming Coaches in European Football?	322	412	78.2%
History of light novel	778	1167	66.7%
Classification of Ice in Lutzow-Holm Bay	1321	2071	63.8%
State and local public policies	1533	2491	61.5%
Average Accuracy	66.4%		

Table 3: 10% length of summary accuracies

II. 20% length of summary

	Length of Summary		
Title	10% (Predicted)	10% (Actual)	Difference (Predicted/Actual)
Automatic text summarization techniques & methods	309	289	106.9%
'Janet Jackson' tells the singer's story, but it's clear who's in control	643	646	99.5%

Who are the best up-and-Coming Coaches in European Football?	641	838	76.5%
History of light novel	1559	2499	62.4%
Classification of Ice in Lutzow-Holm Bay	2642	3848	68.7%
State and local public policies	3065	4499	68.1%
Average Accuracy	80.4%		

Table 4: 20% length of summary accuracies

III. 30% length of summary

	Length of Summary		
Title	10% (Predicted)	10% (Actual)	Difference (Predicted/Actual)
Automatic text summarization techniques & methods	464	656	70.7%
‘Janet Jackson’ tells the singer's story, but it's clear who's in control	965	1039	92.9%
Who are the best up-and-Coming Coaches in European Football?	963	1370	70.3%
History of light novel	2339	3573	65.5%
Classification of Ice in Lutzow-Holm Bay	3964	5902	67.2%
State and local public policies	4598	6293	73.1%
Average Accuracy	73.3%		

Table 5: 30% length of summary accuracies

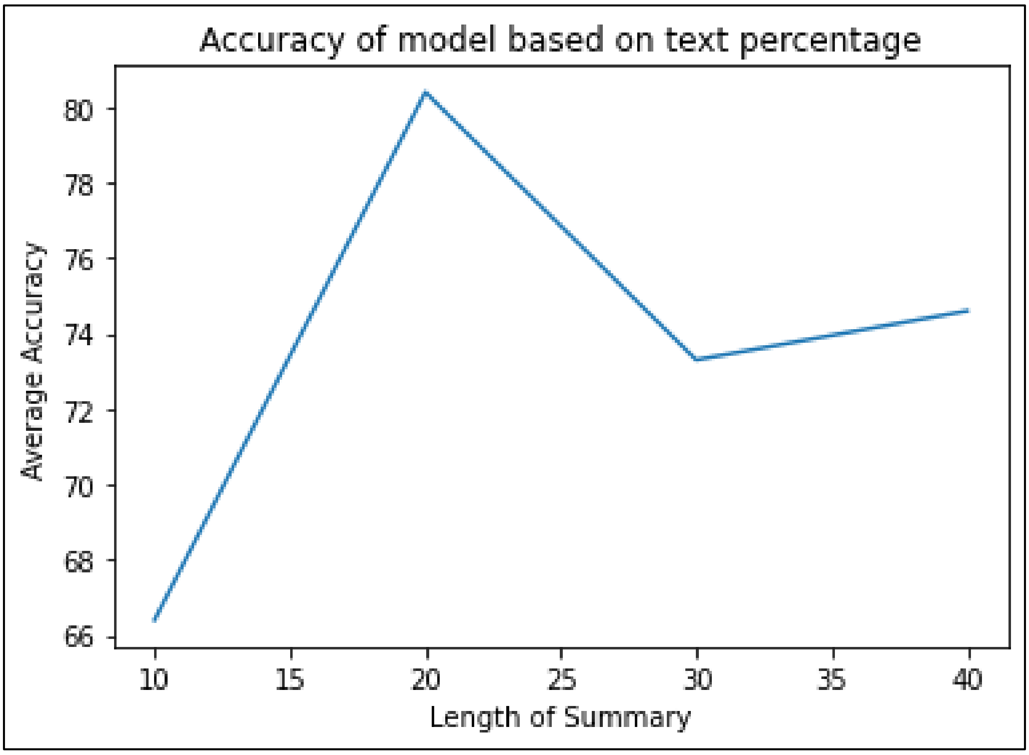
IV. 40% length of summary

	Length of Summary		
Title	10% (Predicted)	10% (Actual)	Difference (Predicted/Actual)
Automatic text summarization techniques & methods	618	879	70.3%
‘Janet Jackson’ tells the singer's story, but it's clear who's in control	1287	1461	88.1%

Who are the best up-and-Coming Coaches in European Football?	1284	1709	75.1%
History of light novel	3119	4681	66.6%
Classification of Ice in Lutzow-Holm Bay	5285	7382	71.6%
State and local public policies	6130	8065	76.0%
Average Accuracy	74.6%		

Table 6: 40% length of summary accuracies

We also prepare the summary of the error analysis in the graph, here is:



Graph 1: Result accuracies

To conclude, based on the graph above, the best way to produce an accurate summary is to utilize only 20% of the text percentage.

11. Manual Evaluation

For this last section, we will be manually evaluating the summaries by scoring them on a range of one to five (1-5) in term of its summarization's accuracy with 1 being the most inaccurate and 5 being the most accurate summarization. However, for the sake of ease of understanding, we will evaluate it by utilizing a table per article. Here are the tables:

I. Automatic text summarization techniques & methods summary

	Evaluator			
Length of Summary	Faisal	Syazmi	Rakibul	Najmul
10%	2	3	2	2
20%	4	3	3	4
30%	3	3	4	3
40%	3	4	4	4

Table 7: Manual Evaluation Article 1

II. 'Janet Jackson' tells the singer's story, but it's clear who's in control

	Evaluator			
Summary	Faisal	Syazmi	Rakibul	Najmul
10%	2	3	2	3
20%	3	4	4	4
30%	3	3	3	3
40%	3	4	3	3

Table 8: Manual Evaluation Article 2

III. Who are the best up-and-Coming Coaches in European Football?

	Evaluator			
Summary	Faisal	Syazmi	Rakibul	Najmul
10%	2	3	3	2
20%	4	4	3	4
30%	4	3	4	3
40%	3	3	4	2

Table 9: Manual Evaluation Article 3

IV. History of light novel

	Evaluator			
Summary	Faisal	Syazmi	Rakibul	Najmul
10%	2	3	3	4
20%	4	4	4	4
30%	3	4	4	2
40%	4	4	3	2

Table 10: Manual Evaluation Article 4

V. Classification of Ice in Lutzow-Holm Bay

	Evaluator			
Summary	Faisal	Syazmi	Rakibul	Najmul
10%	1	2	2	3
20%	4	5	3	3
30%	3	4	4	3
40%	3	2	2	3

Table 11: Manual Evaluation Article 5

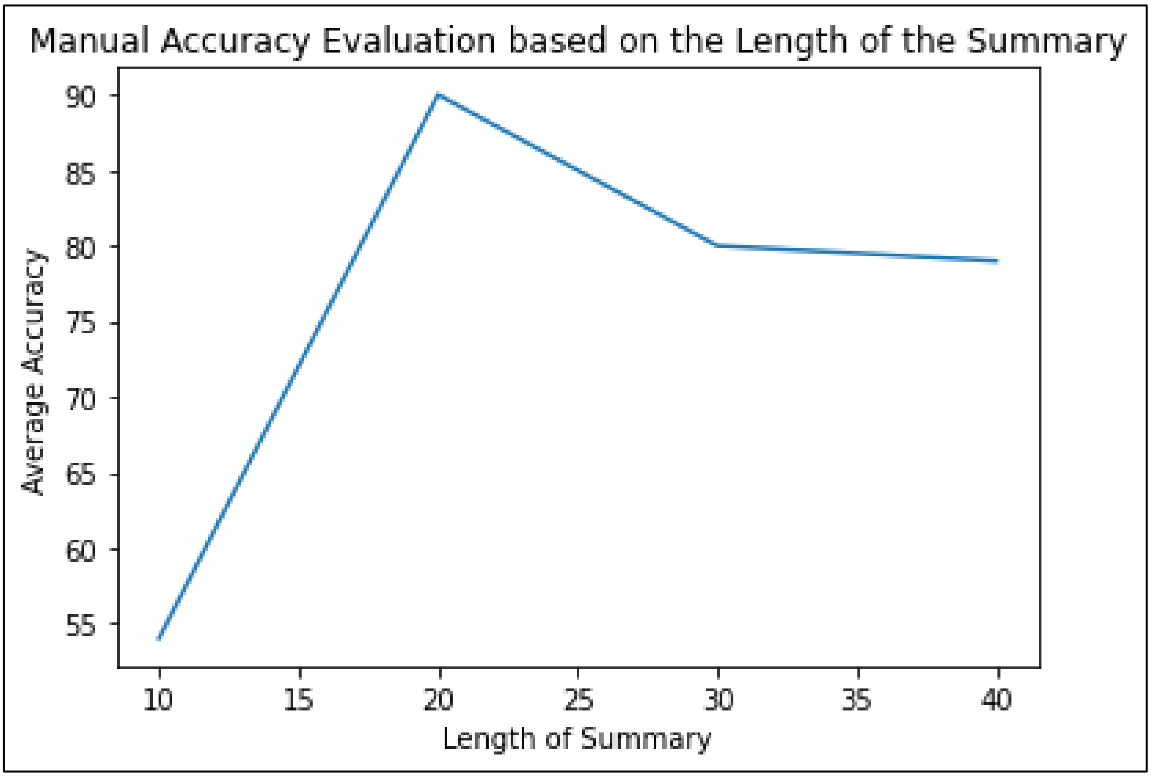
VI. State and local public policies summary

	Evaluator			
Summary	Faisal	Syazmi	Rakibul	Najmul
10%	2	2	2	1
20%	4	4	3	4
30%	4	4	3	3
40%	3	4	4	5

Table 12: Manual Evaluation Article 6

Final Evaluation

After the result of the manual evaluation is produced, we can now calculate the best length for a summary to be understood the most by calculating the average of the summaries by length, similarly like what we had done in the error analysis section. Here is the result:



Graph 2: Average Manual Evaluation

In conclusion, there are two main observations found, the first is that based on the manual evaluation tables above, it is found that the manual evaluators do not prefer the 10% length of summary in articles that contained a huge number in the size section. Finally, based on the result on the graph above, we can make the same conclusion as in the previous section as our second finding, that is the fact that 20% is still found to be the best length of a summary by both human and computer evaluation.

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