Project Capstone Report

Extractive Summarizer Using BERT/Transformer Model

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Submitted By:

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Koay Seng Tian

Abstract

The goal of this project is to provide an annotation tool to accentuate key points in a corpus of text.

We utilised an extractive summarizer to find representative sentences in a corpus and annotate it. The summarization technique is powered by a Bidirectional Encoder Representations from Transformers (BERT) model.

In this report, we describe our thought process from backend code to the user interface, in addition to discussions on model selection and results evaluation.

Acknowledgement

We would like to thank Timothy Liu and Zhang Sheng from Nvidia Singapore Development Pte Ltd for their technical assistance, advice and guidance throughout the project. Our project supervisor/mentor, Poh Keam has also been extremely supportive in providing the necessary resources and scoping for this project.

Thank you guys! ☺

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1. Background

This project is a collaboration between Nvidia and Republic Polytechnic (RP) as a capstone project for the Tech Immersion and Placement Programme (TIPP) programme by Infocomm Media Development Authority (IMDA). The project aims to provide a real-world work environment for the students to apply artificial intelligence techniques taught in the course. Supervisors in return receive the intellectual property of the final product.

1.1 Goal

The goal of this project is to provide an annotation tool, to differentiate key takeaways in a corpus of text. The summarization technique will be powered by BERT models.

2. Methodology and Design

Project: Extractive Summarizer using BERT transformer model.

i) The main entry to the application is via a webpage where user enters a URL as an input. This BERT model summarizer aims to extract key feature sentences of the main corpus.

ii) These extracted features will then be presented as an annotated form, together with the main corpus as an output document.

iii) Using a client-server model, the web application provides seamless transition between server (Flask), user interface (Streamlit) and the underlying Python code. The software is developed using open-source software, libraries and/or modules.

iv) For evaluation, we will be using the ROUGE (Recall-Oriented Understudy for Gisting Evaluation) scoring system which is optimised to calculate distances/similarities between summarized articles. By using ROUGE and comparing between BERT generated summaries against human generated summaries, we calculate the similarity between the text and recommend ways to further improve the results.

2.1 Software Data Flow

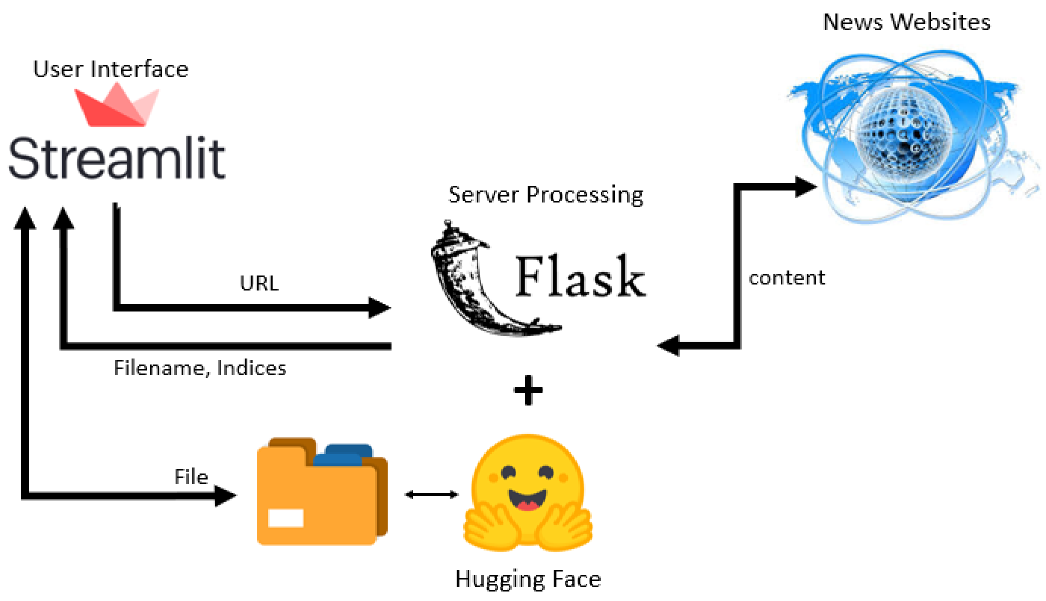


Figure 1. Software Data Flow

The software is developed using available open-source application frameworks (Streamlit, Flask, Newspaper3k etc.) and Hugging Face BERT/Transformer model. Python scripting language is mostly used.

Streamlit architecture is based on mirroring a web application the same way a plain Python script is written and displayed. Streamlit applications have a unique data flow: every time a change is made on the user interface (UI), it triggers an automatic call to the server and trigger an update to the screen (for example, when the application needs to response to a button press), Streamlit will attempt to rerun the entire Python script from top to bottom.

This will pose a challenge for the application/UI developer because it is not implemented as a 'call back', like most web applications. As a remedy, the streamlit community generally recommended modifying the underlying code using streamlit's cache decorator (i.e. streamlit@cache) which allows developers to skip certain costly computations when the application reruns. However, such technique as we have observed, may create stability issues.

2.2 Collecting User Feedback

User can feedback or suggest user-defined summary by checking or unchecking the returned check boxes. Check boxes are used to reflect machine or user selected summary. The original and enhanced summaries can be saved as CSV (Comma Separated Values) files for future model fine tuning and improvements.

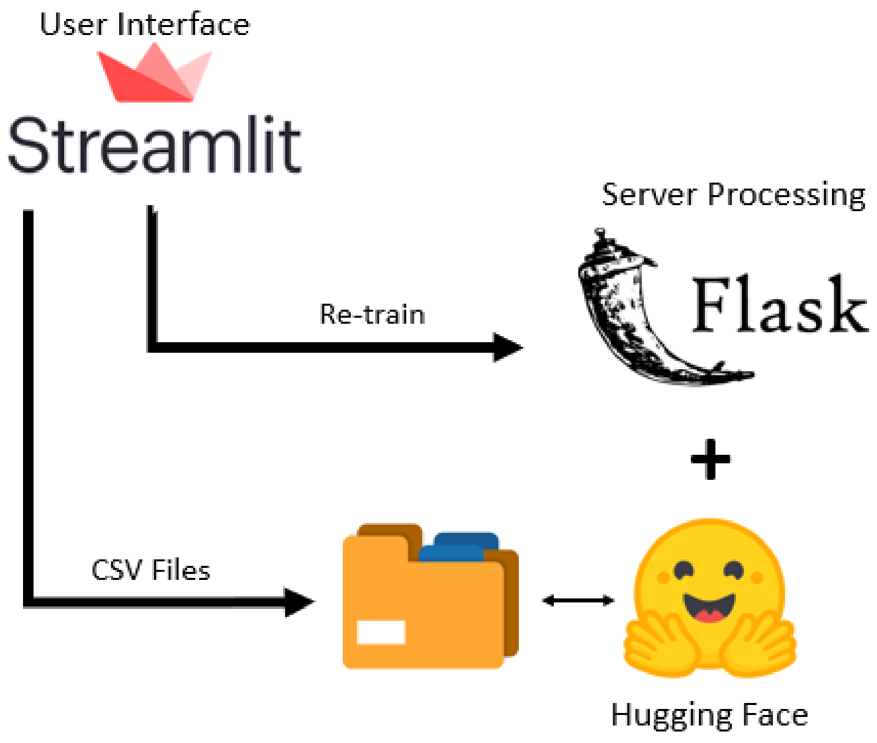


Figure 2. Capturing User Feedbacks

2.3 Scoring and Evaluation System

User can use a ROUGE scoring system to evaluate if the computer-generated annotation is appropriate for the corpus. Scoring results is generated through a Python application, with the CSV file inputs from user feedback and BERT annotations. In terms of output, a recall score, precision score and F1 score will be generated together with a short user description.

3. Findings

3.1 BERT Models Are Not Equal

When we first started the project, we utilised the "stock" BERT model (bert-base-uncased) that was embedded in the summarizer library to run our models. While testing, we quickly realised that we may face some usability issues as the waiting time for the extractive summary to complete took around seventeen (17) seconds to complete.

According to recent research on attention spans, we discovered that our current human attention spans range between eight (8) and twelve (12) seconds. This means that at seventeen (17) seconds, users might find our program "too slow", and may not even use the product even if it was a perfect product. As a matter of fact, seventeen (17) seconds might be long enough for them to read the article themselves! We need to find a compromise between speed and performance.

To achieve this, we started to explore different BERT models available in the market. We eliminated the "large" BERT models at first cut, because they contain more parameters which will intuitively mean longer processing time. This narrows our focus to the base BERT model. To quickly evaluate the performance of different BERT models, we run a loop test, controlling all parameters except for a model swap. In this experiment, we recorded the performance in the form of processing time and text length.

At this point, we are using just quantitative measures, such as (1) processing speed and (2) text length as our selection criteria.

Within the BERT models, we chose DistillBERT as our default model as its processing speed falls within the sweet spot between eight (8) and twelve (12) seconds while the summarized text length seems reasonable.

To artificially improve on the run time, we also created a time illusion (to make time seem to pass faster), by inserting a "loading animation" to stimulate an active program during the processing runtime.

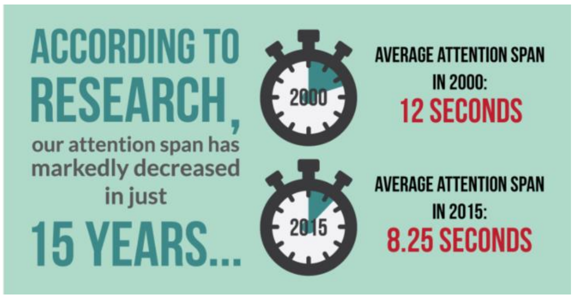
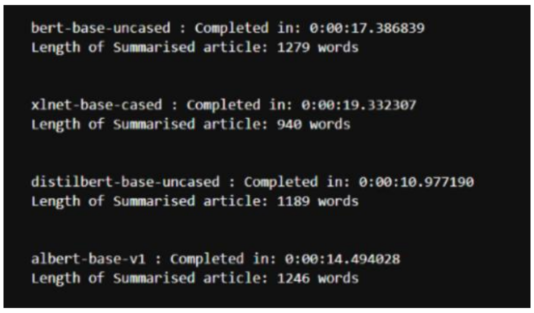

ACCORDING TO RESEARCH,
our attention span has markedly decreased in just
15 YEARS...
2000
AVERAGE ATTENTION SPAN IN 2000:
12 SECONDS
2015
AVERAGE ATTENTION SPAN IN 2015:
8.25 SECONDS

Figure 3. Human Attention Span Infographics (digital information world)



```
bert-base-uncased : Completed in: 0:00:17.386839
Length of Summarised article: 1279 words


xlnet-base-cased : Completed in: 0:00:19.332307
Length of Summarised article: 940 words


distilbert-base-uncased : Completed in: 0:00:10.977190
Length of Summarised article: 1189 words


albert-base-v1 : Completed in: 0:00:14.494028
Length of Summarised article: 1246 words
```

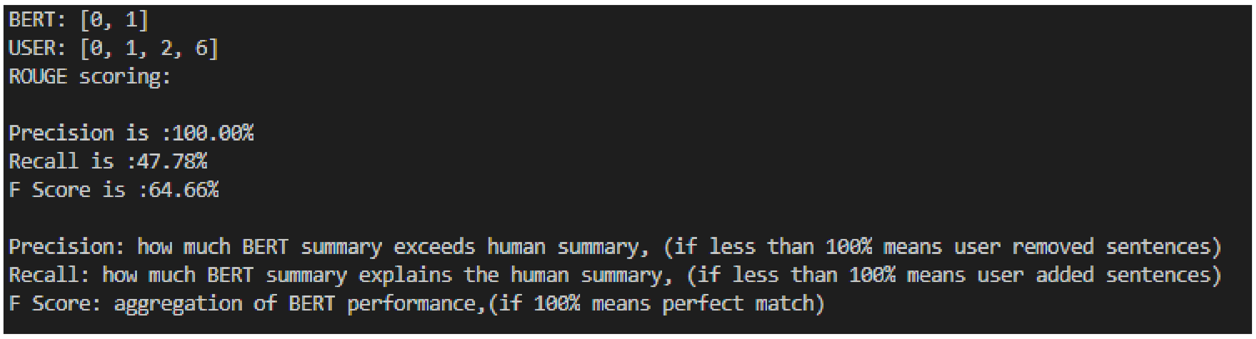
Figure 4. Human Attention Span Infographics (digital information world)

3.2 ROUGE and not BLEU

We selected ROUGE as our main technique to measure model accuracy. The main reason is because ROUGE provides more granularity insights into the scoring mechanism than BLEU (Bilingual Evaluation Understudy). During our project, one of the difficulties is to find a way to evaluate whether a summary is good or bad, and a quick way to locate areas to improve. We find that ROUGE fits our requirements.

In ROUGE, the precision and recall scores are also generated. Using a low precision or recall score, we can find out whether the machine generated text, is too short or too long, or is it not relevant. With this knowledge, we could either tweak the parameters correctly, or if the summary is bad, we can fine-tune it by training the model on a longer relevant corpus. As compared to BLEU, another popular scoring technique, only the final BLEU score (between 0 and 1) is generated; however, this gives us no clear direction on how to improve our model.

ROUGE and BLEU are both popular methods in summaries evaluation. They use similar calculation methods surrounding n-grams and variations of recall and precision. When implementing, we discovered that BLEU does not seem to work very well when there are differences in corpus length (between BERT and human generated). This could be due to the brevity penalty effect or an input restriction. This was acknowledged in the BLEU documentation, which recommended a smoothing technique to overcome this issue. However, even with the adjustments, we did not find the value to be as intuitively accurate as ROUGE. Therefore, rating the techniques in terms of usability, we decided to choose ROUGE.



```
BERT: [0, 1]
USER: [0, 1, 2, 6]
ROUGE scoring:

Precision is :100.00%
Recall is :47.78%
F Score is :64.66%

Precision: how much BERT summary exceeds human summary, (if less than 100% means user removed sentences)
Recall: how much BERT summary explains the human summary, (if less than 100% means user added sentences)
F Score: aggregation of BERT performance,(if 100% means perfect match)
```

Figure 5. Rouge Score (Python)

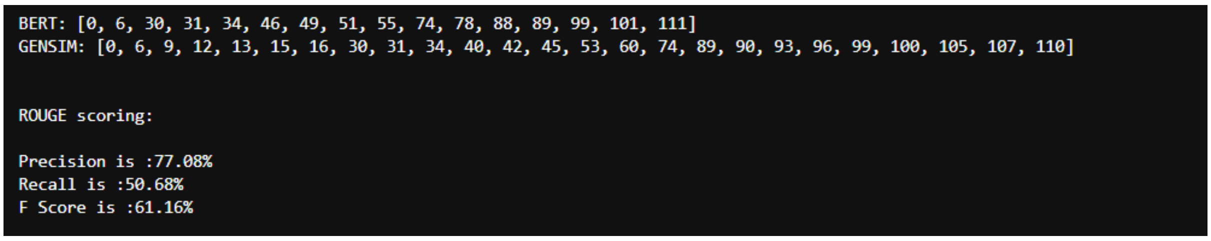
3.3 Update: Comparing BERT model against TextRank (gensim) summarisers (feedback from project presentation)

We compared BERT models against traditional NLP TextRank summarisers found in popular NLP libraries in gensim and NLTK. Unlike BERT models that focus on headers, attention and parameters, TextRank uses a graph-based extractive summarization algorithm. This means that it does not use an underlying pre-train model to derive its summaries.

Passing both BERT and TextRank summariser text results (and standardizing the hyper-parameters) through our ROUGE scoring system, we are able to share the following findings. The test article we are using is PM Lee Hsien Loong’s speech on COVID-19.

(https://www.channelnewsasia.com/news/singapore/coronavirus-covid-19-lee-hsien-loong-update-address-nation-tv-12606328):

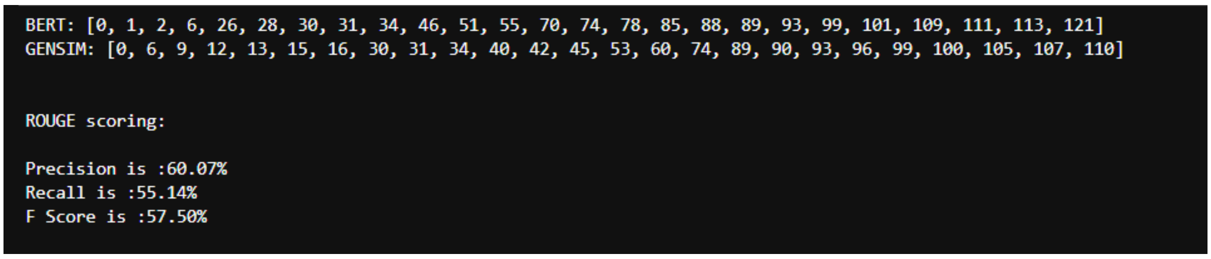
1) Generally BERT summaries are more concise than TextRank because it tends to ignore sentences that are too short and deem it as less important. TextRank, on the other hand, does not discriminate. Thus, despite setting both summaries to be 20% of the original text, we get 15% in the BERT output, as compared to TextRank, where we get 20%. Looking at the precision score and F-score, we can conclude that BERT and TextRank have similar overlapping annotated sentences. However, TextRank given that is has more output, gives more information about the article.



```
BERT: [0, 6, 30, 31, 34, 46, 49, 51, 55, 74, 78, 88, 89, 99, 101, 111]
GENSIM: [0, 6, 9, 12, 13, 15, 16, 30, 31, 34, 40, 42, 45, 53, 60, 74, 89, 90, 93, 96, 99, 100, 105, 107, 110]


ROUGE scoring:

Precision is :77.08%
Recall is :50.68%
F Score is :61.16%
```

Figure 6. Comparing BERT (20% summary) against TextRank models (20%)

2) To adjust for part 1, (where we discovered BERT tends to filter out short sentences), we increase the BERT summary output from 20% to 30% to create a more balanced output. Despite this adjustment, we do not see any significant improvements on the score. Precision, recall and F-score range around 60%, suggesting that there is strong similarity in the summarised output.



```
BERT: [0, 1, 2, 6, 26, 28, 30, 31, 34, 46, 51, 55, 70, 74, 78, 85, 88, 89, 93, 99, 101, 109, 111, 113, 121]
GENSIM: [0, 6, 9, 12, 13, 15, 16, 30, 31, 34, 40, 42, 45, 53, 60, 74, 89, 90, 93, 96, 99, 100, 105, 107, 110]


ROUGE scoring:

Precision is :60.07%
Recall is :55.14%
F Score is :57.50%
```

Figure 7. Comparing BERT (30% summary) against TextRank models (20%)

3) Given that both are computer generated results, we cannot decide which has better real world performance. However, given that there are overlaps in the results, a method that combines both of them might work best. As an extension, we could test both models against more test sets evaluate further.

4. Evaluation and Analysis

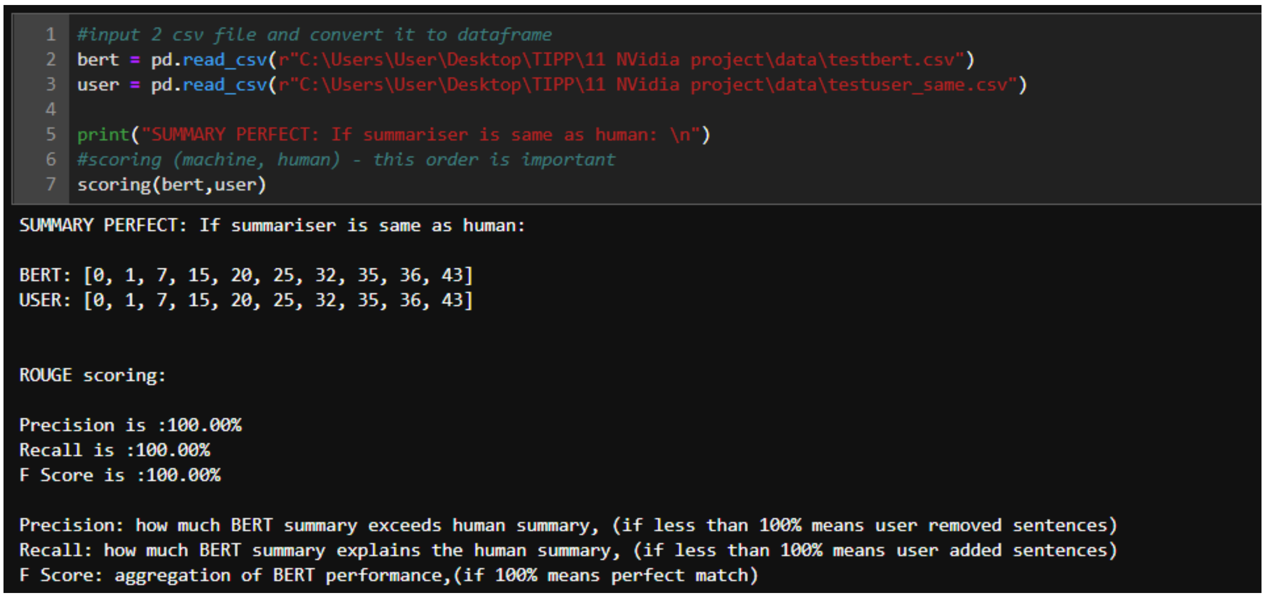
4.1 ROUGE Scoring Model

To evaluate our summarizer model, we use a ROUGE scoring model.

Using the annotated corpus derived from previous steps, we will be able to fit it into our ROUGE scoring model for scoring.

Three scenarios were considered: (1) When the translation is perfect, (2) when the translation is not perfect, and user highlighted more sentences, (3) translation is not perfect and user deleted sentence.

i) *SUMMARY IS PERFECT: Summary is equal to user annotation*



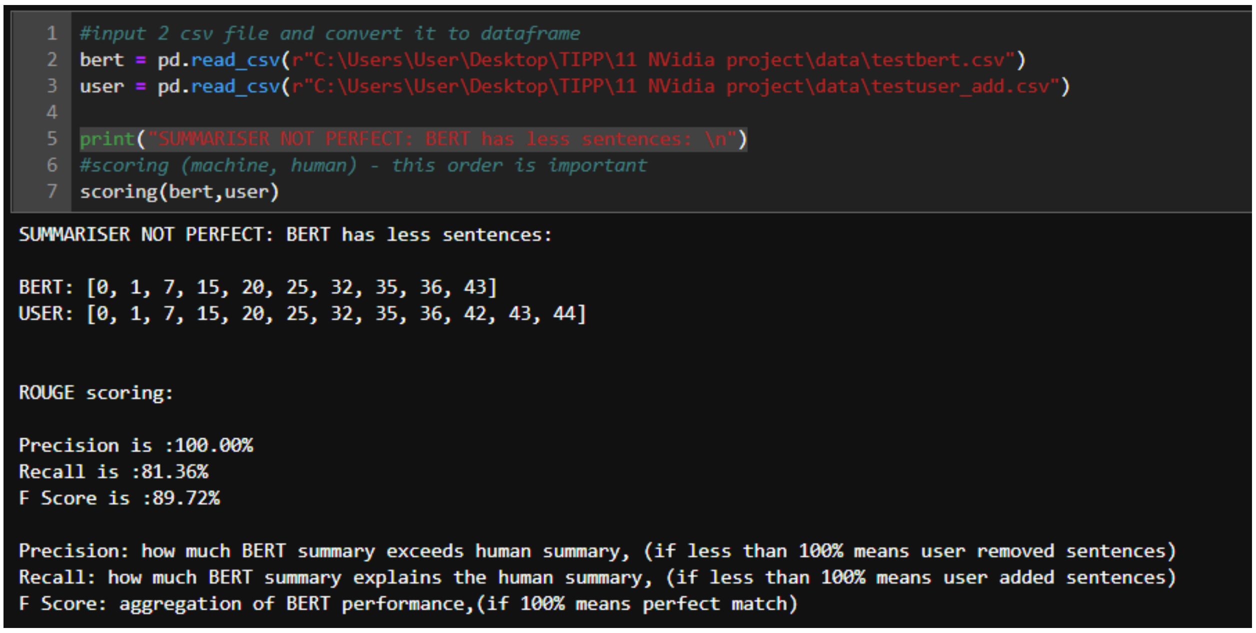
```
#input 2 csv file and convert it to dataframe
bert = pd.read_csv(r"C:\Users\User\Desktop\TIPP\11 NVidia project\data\testbert.csv")
user = pd.read_csv(r"C:\Users\User\Desktop\TIPP\11 NVidia project\data\testuser_same.csv")

print("SUMMARY PERFECT: If summariser is same as human: \n")
#scoring (machine, human) - this order is important
scoring(bert,user)
```

```
SUMMARY PERFECT: If summariser is same as human:

BERT: [0, 1, 7, 15, 20, 25, 32, 35, 36, 43]
USER: [0, 1, 7, 15, 20, 25, 32, 35, 36, 43]


ROUGE scoring:

Precision is :100.00%
Recall is :100.00%
F Score is :100.00%

Precision: how much BERT summary exceeds human summary, (if less than 100% means user removed sentences)
Recall: how much BERT summary explains the human summary, (if less than 100% means user added sentences)
F Score: aggregation of BERT performance,(if 100% means perfect match)
```

Figure 8. SUMMARY IS PERFECT: Summary is equal to user annotation

In this case, no adjustment is needed.

ii) SUMMARY IS NOT PERFECT: BERT has less sentences



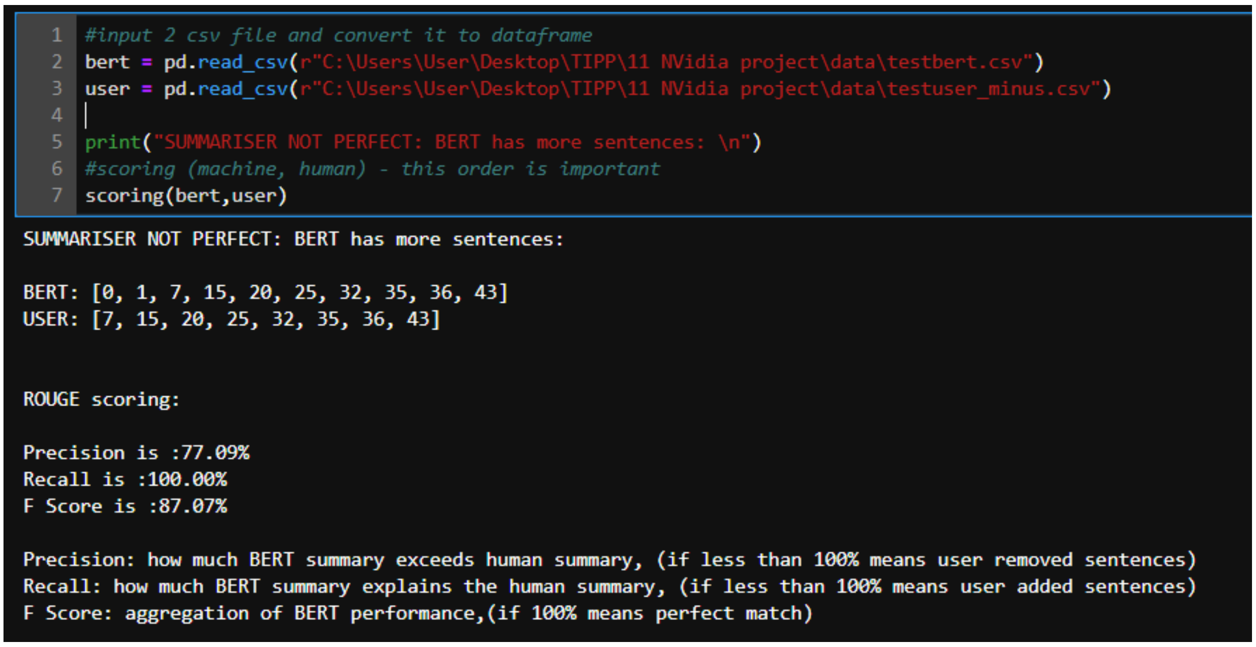
```
#input 2 csv file and convert it to dataframe
bert = pd.read_csv(r"C:\Users\User\Desktop\TIPP\11 NVidia project\data\testbert.csv")
user = pd.read_csv(r"C:\Users\User\Desktop\TIPP\11 NVidia project\data\testuser_add.csv")

print("SUMMARISER NOT PERFECT: BERT has less sentences: \n")
#scoring (machine, human) - this order is important
scoring(bert,user)
```

```
SUMMARISER NOT PERFECT: BERT has less sentences:

BERT: [0, 1, 7, 15, 20, 25, 32, 35, 36, 43]
USER: [0, 1, 7, 15, 20, 25, 32, 35, 36, 42, 43, 44]


ROUGE scoring:

Precision is :100.00%
Recall is :81.36%
F Score is :89.72%

Precision: how much BERT summary exceeds human summary, (if less than 100% means user removed sentences)
Recall: how much BERT summary explains the human summary, (if less than 100% means user added sentences)
F Score: aggregation of BERT performance,(if 100% means perfect match)
```

Figure 9. SUMMARY IS NOT PERFECT: BERT has less sentences

In this case, we can adjust the model to allow for more summarized results.

iii) SUMMARY IS NOT PERFECT: BERT has more sentences



```
#input 2 csv file and convert it to dataframe
bert = pd.read_csv(r"C:\Users\User\Desktop\TIPP\11 NVidia project\data\testbert.csv")
user = pd.read_csv(r"C:\Users\User\Desktop\TIPP\11 NVidia project\data\testuser_minus.csv")

print("SUMMARISER NOT PERFECT: BERT has more sentences: \n")
#scoring (machine, human) - this order is important
scoring(bert,user)
```

```
SUMMARISER NOT PERFECT: BERT has more sentences:

BERT: [0, 1, 7, 15, 20, 25, 32, 35, 36, 43]
USER: [7, 15, 20, 25, 32, 35, 36, 43]


ROUGE scoring:

Precision is :77.09%
Recall is :100.00%
F Score is :87.07%

Precision: how much BERT summary exceeds human summary, (if less than 100% means user removed sentences)
Recall: how much BERT summary explains the human summary, (if less than 100% means user added sentences)
F Score: aggregation of BERT performance,(if 100% means perfect match)
```

Figure 10. SUMMARY IS NOT PERFECT: BERT has more sentences

In this case, we may consider reducing the amount of summarizer results, or more fine-tuning.

5. Results

We successfully created and deployed a web application that allows a user to (1) enter a Uniform Resource Locator (URL) and received a full text with annotated key points, (2) user can provide feedback, which can be used to provide a quantitative scoring and (3) we could improve the BERT model based on the scoring.

Our average runtime for the model is between eight (8) and ten (10) seconds.

Project managers from Nvidia are extremely satisfied with the progress we made.

6. Conclusion

We concluded that the DistillBERT model is the optimal BERT model for a general news extractive summarizer. A ROUGE scoring model is the most appropriate scoring system as it provides more feedback. Using a modular coding style, a user could swop out and replace individual parts of the summarizer with minimum effort.

7. Recommendations

Given that the code is designed to be modular based and robust, the engineer will be able to switch out part of the code and further customised it to his project. For example, as our parser is optimised for newspaper articles, it may not work as well for PDF documents. In which case, the engineer could switch in a PDF parser instead. This instruction is similar should the engineer wants to switch a different BERT model.

The Streamlit application works perfectly for a proof-of-concept user interface; to quickly unlock the power of the underlying model and test out concept feasibility. However, the UI content has some limitations such as lack of feedback functionality (like a HTML application), and limited fine-tuning options, which limits our ability to improve the product. As an improvement, the user can migrate to a full-fletch web development environment, probably using Javascript, HTML5, Bootstrap, jQuery, for example.

In Natural Language Processing (NLP) literature, the computer-generated summary is always compared against a “gold standard” summary to determine its accuracy. However, in our case, the BERT summary is compared against to a random user feedback. This user may have its own biasness and may have an inconsistent proficiency of the subject. This could affect our evaluation score of the model. To avoid this issue, it might be useful to collect an aggregation of user responses, before tweaking the model.

8. Appendices

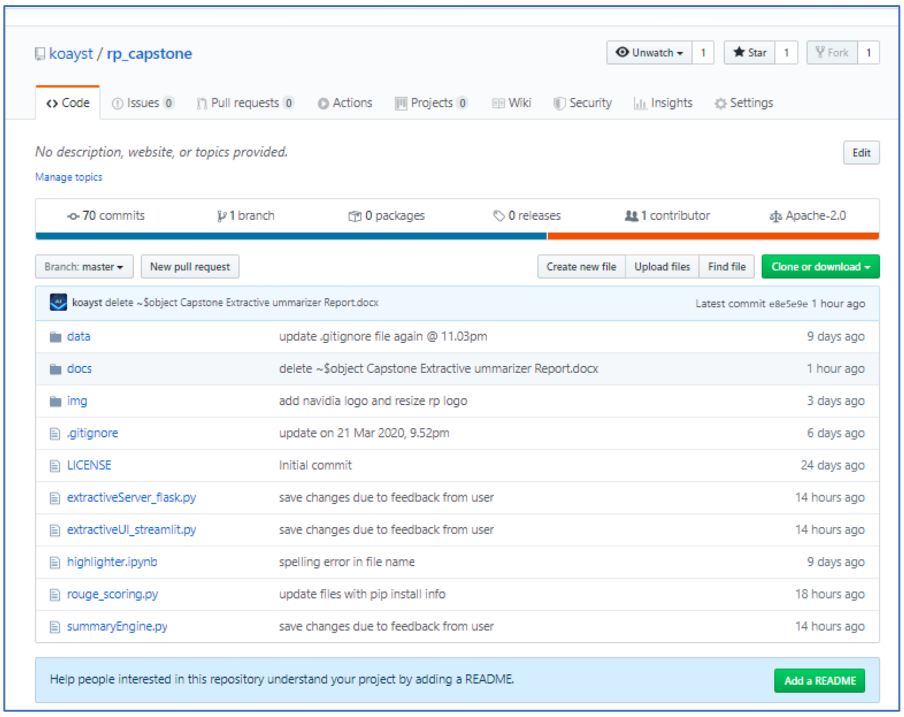
8.1 GitHub

The source codes, documentation and the test data for the project are hosted in Github.

Repository URL: https://github.com/koayst/rp_capstone

If you have issue accessing the GitHub, please contact any one of us.

Github uses Git as an open-source version control system. The purpose is to keep the revisions straight, storing modification in a central repository. This allows us, as a developer, to easily collaborate, as we can download a new version of the software, make changes and upload the newest version, after we make the modifications.



No description, website, or topics provided.

koayst delete ~$object Capstone Extractive ummarizer Report.docx — Latest commit e8e5e9e 1 hour ago

data	update .gitignore file again @ 11.03pm	9 days ago
docs	delete ~$object Capstone Extractive ummarizer Report.docx	1 hour ago
img	add navidia logo and resize rp logo	3 days ago
.gitignore	update on 21 Mar 2020, 9.52pm	6 days ago
LICENSE	Initial commit	24 days ago
extractiveServer_flask.py	save changes due to feedback from user	14 hours ago
extractiveUI_streamlit.py	save changes due to feedback from user	14 hours ago
highlighter.ipynb	spelling error in file name	9 days ago
rouge_scoring.py	update files with pip install info	18 hours ago
summaryEngine.py	save changes due to feedback from user	14 hours ago

Help people interested in this repository understand your project by adding a README.

Figure 11. GitHub Repository Screen Shot

8.2 Development Environment

We are using Microsoft Windows Operating System (Windows 10 and Windows 8) as our development environment.

Anaconda Individual Edition (2019-10) was installed and then relevant modules are installed/updated as required by the project.

8.3 Extractive Summarizer

To run the system, it is advised to create a separate virtual environment. Use Git to download the source codes by cloning it from GitHub.

Install the required, Python, Python libraries and modules.

Open two terminals on a local machine (command prompt for Windows OS) i.e. one to run the Flask server and the other one to run the Streamlit webapp server.

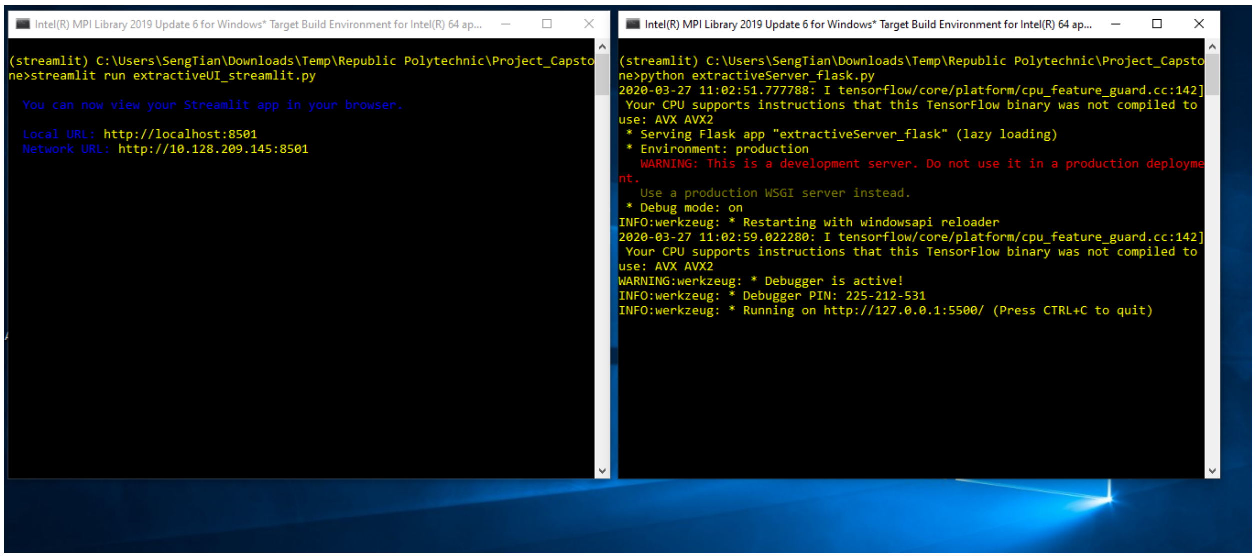
- Flask server: *python extractiveServer_flask.py*
  - Running on http://127.0.0.1:5500/ (Press CTRL+C to quit)
- Streamlit: *streamlit run extractiveUI_streamlit.py*
  - Local URL: http://localhost:8501

To run the ROUGE scoring application, open another terminal to run it.

- Rouge Scoring: python rouge_scording.py data\testbert.csv data\testuser.csv
  - testbert.csv is the output from the summarizer engine
  - testuser.csv is the output after user feedback

Once Streamlit is running, you will notice the webapp is running in your browser. If the Streamlit web app is not running in your browser, you can bring up the Streamlit web app by issuing this URL: 'http://localhost:8501'.

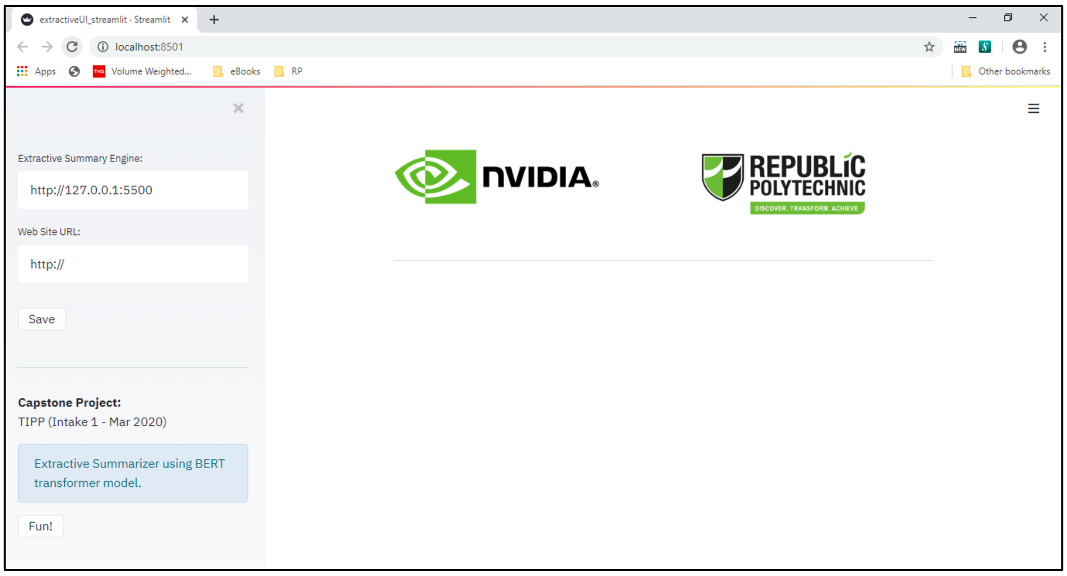
We are using Chrome browser for development and testing.


Intel(R) MPI Library 2019 Update 6 for Windows* Target Build Environment for Intel(R) 64 ap...
Intel(R) MPI Library 2019 Update 6 for Windows* Target Build Environment for Intel(R) 64 ap...

```
(streamlit) C:\Users\SengTian\Downloads\Temp\Republic Polytechnic\Project_Capsto
ne>streamlit run extractiveUI_streamlit.py

  You can now view your Streamlit app in your browser.

  Local URL: http://localhost:8501
  Network URL: http://10.128.209.145:8501
```

```
(streamlit) C:\Users\SengTian\Downloads\Temp\Republic Polytechnic\Project_Capsto
ne>python extractiveServer_flask.py
2020-03-27 11:02:51.777788: I tensorflow/core/platform/cpu_feature_guard.cc:142]
 Your CPU supports instructions that this TensorFlow binary was not compiled to
use: AVX AVX2
 * Serving Flask app "extractiveServer_flask" (lazy loading)
 * Environment: production
   WARNING: This is a development server. Do not use it in a production deployme
nt.
   Use a production WSGI server instead.
 * Debug mode: on
INFO:werkzeug: * Restarting with windowsapi reloader
2020-03-27 11:02:59.022280: I tensorflow/core/platform/cpu_feature_guard.cc:142]
 Your CPU supports instructions that this TensorFlow binary was not compiled to
use: AVX AVX2
WARNING:werkzeug: * Debugger is active!
INFO:werkzeug: * Debugger PIN: 225-212-531
INFO:werkzeug: * Running on http://127.0.0.1:5500/ (Press CTRL+C to quit)
```

Figure 12. Screen shots for running the summarizer



Extractive Summary Engine: http://127.0.0.1:5500

Web Site URL: http://

Capstone Project:
TIPP (Intake 1 - Mar 2020)

Extractive Summarizer using BERT transformer model.

Figure 13. Streamlit webapp screen shot

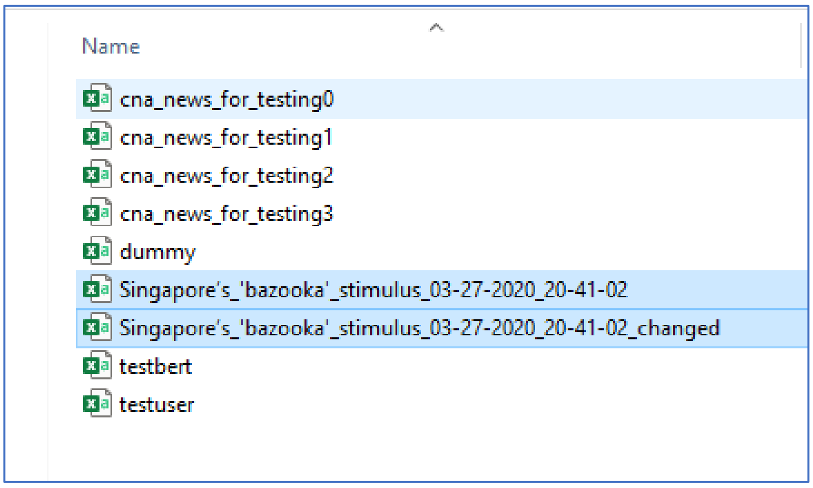
8.4 Running the Summarizer

To test, go to a sample webpage, Channel News Asia Site (https://www.channelnewsasia.com/) and select a news article you want to summarize. Copy the URL and paste it to the Streamlit webapp. Press 'Enter' to start the summarizer engine.

The output will show as a list of checkboxes. User can enhance the modelling by checking and unchecking the checkboxes.

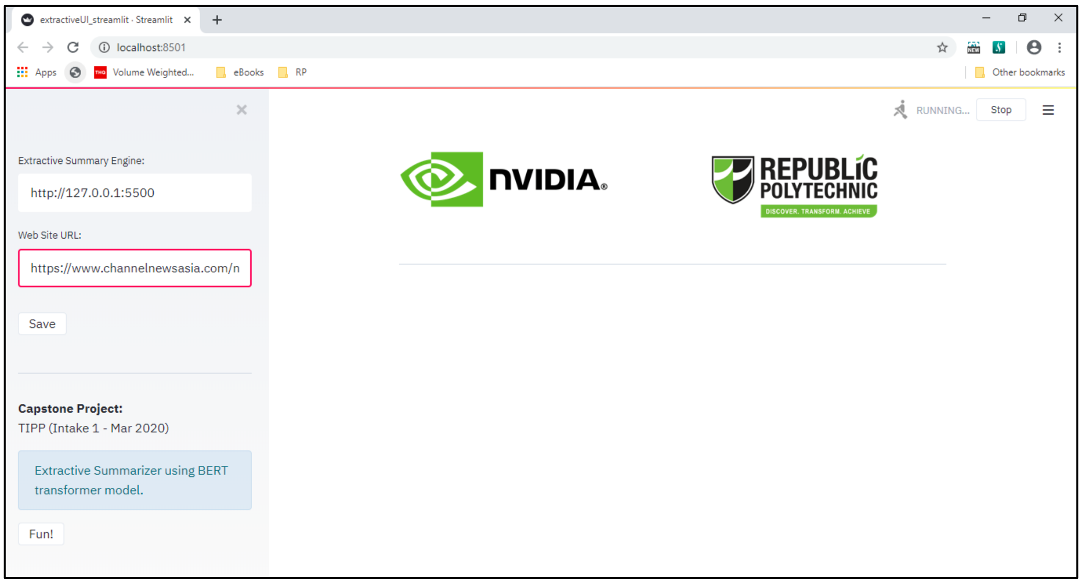
User's feedback can be saved by clicking the 'Save' button.

Two CSV (Comma-Separated Values) files are stored in the data directory. It is highlighted as shown below



Name
cna_news_for_testing0
cna_news_for_testing1
cna_news_for_testing2
cna_news_for_testing3
dummy
Singapore's_'bazooka'_stimulus_03-27-2020_20-41-02
Singapore's_'bazooka'_stimulus_03-27-2020_20-41-02_changed
testbert
testuser

Figure 14. The CSV files needed (2 files)



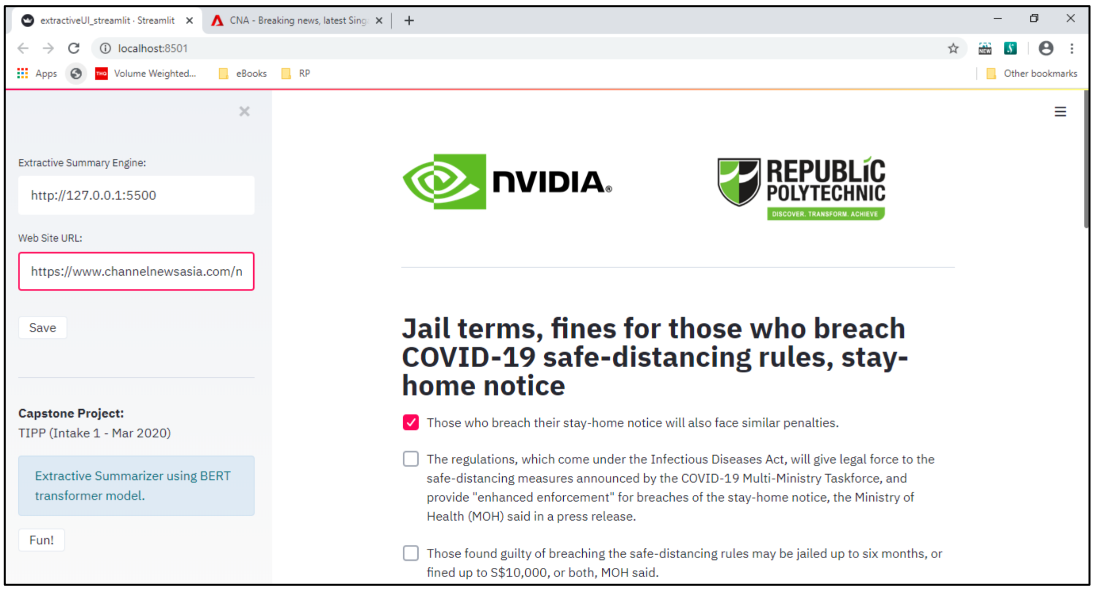
Extractive Summary Engine: http://127.0.0.1:5500

Web Site URL: https://www.channelnewsasia.com/n

Capstone Project:
TIPP (Intake 1 - Mar 2020)

Extractive Summarizer using BERT transformer model.

Figure 15. Input URL and Press ‘Enter’


extractiveUI_streamlit · Streamlit
CNA - Breaking news, latest Sing
localhost:8501
Apps
Volume Weighted...
eBooks
RP
Other bookmarks
NVIDIA
REPUBLIC POLYTECHNIC
DISCOVER. TRANSFORM. ACHIEVE
Save
Fun!

Extractive Summary Engine: http://127.0.0.1:5500

Web Site URL: https://www.channelnewsasia.com/n

Capstone Project:
TIPP (Intake 1 - Mar 2020)

Extractive Summarizer using BERT transformer model.

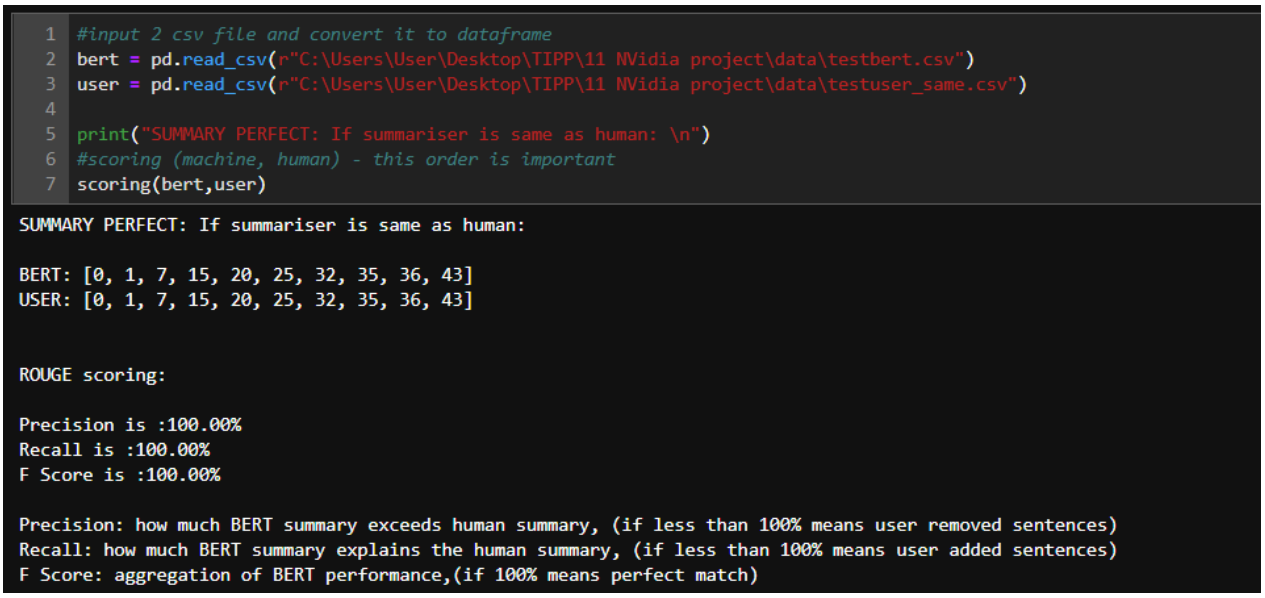
Jail terms, fines for those who breach COVID-19 safe-distancing rules, stay-home notice

- [x] Those who breach their stay-home notice will also face similar penalties.
- [ ] The regulations, which come under the Infectious Diseases Act, will give legal force to the safe-distancing measures announced by the COVID-19 Multi-Ministry Taskforce, and provide "enhanced enforcement" for breaches of the stay-home notice, the Ministry of Health (MOH) said in a press release.
- [ ] Those found guilty of breaching the safe-distancing rules may be jailed up to six months, or fined up to S$10,000, or both, MOH said.

Figure 16. Output of Summarizer

8.5 ROUGE Scoring Model

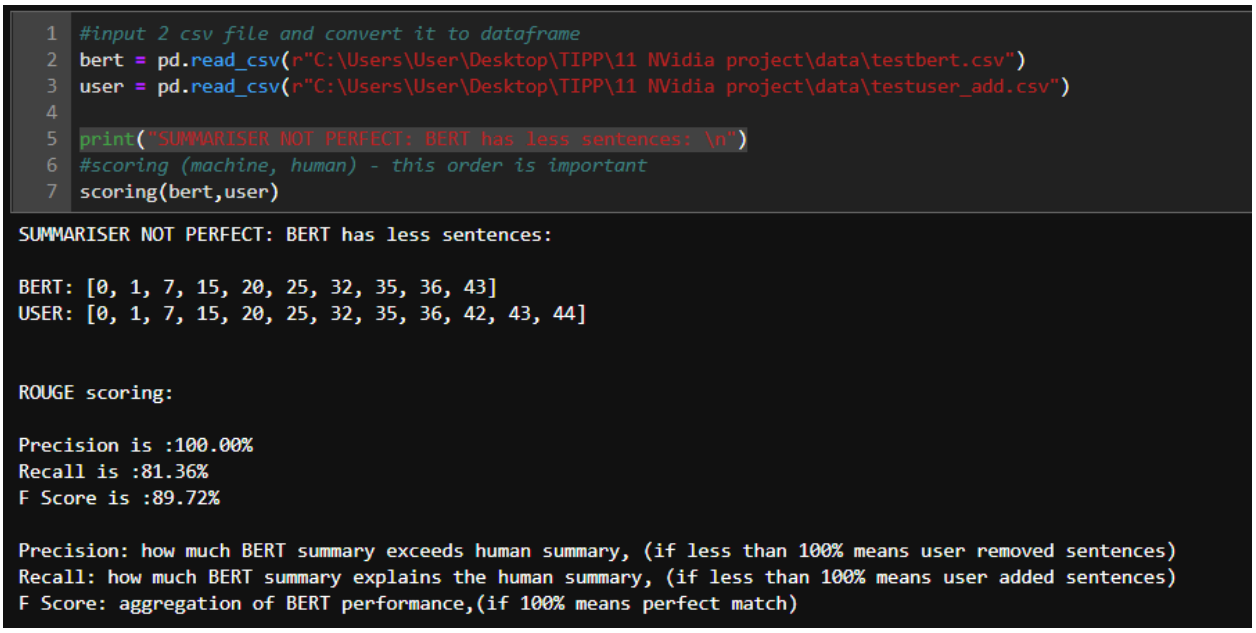
From the files generated above, we will be able to fit it into our ROUGE scoring model for scoring. We display 3 scenarios: (1) When the translation is perfect, (2) when the translation is not perfect, and user highlighted more sentence, (3) translation is not perfect and user deleted sentence.



```
#input 2 csv file and convert it to dataframe
bert = pd.read_csv(r"C:\Users\User\Desktop\TIPP\11 NVidia project\data\testbert.csv")
user = pd.read_csv(r"C:\Users\User\Desktop\TIPP\11 NVidia project\data\testuser_same.csv")

print("SUMMARY PERFECT: If summariser is same as human: \n")
#scoring (machine, human) - this order is important
scoring(bert,user)
```

```
SUMMARY PERFECT: If summariser is same as human:

BERT: [0, 1, 7, 15, 20, 25, 32, 35, 36, 43]
USER: [0, 1, 7, 15, 20, 25, 32, 35, 36, 43]


ROUGE scoring:

Precision is :100.00%
Recall is :100.00%
F Score is :100.00%

Precision: how much BERT summary exceeds human summary, (if less than 100% means user removed sentences)
Recall: how much BERT summary explains the human summary, (if less than 100% means user added sentences)
F Score: aggregation of BERT performance,(if 100% means perfect match)
```

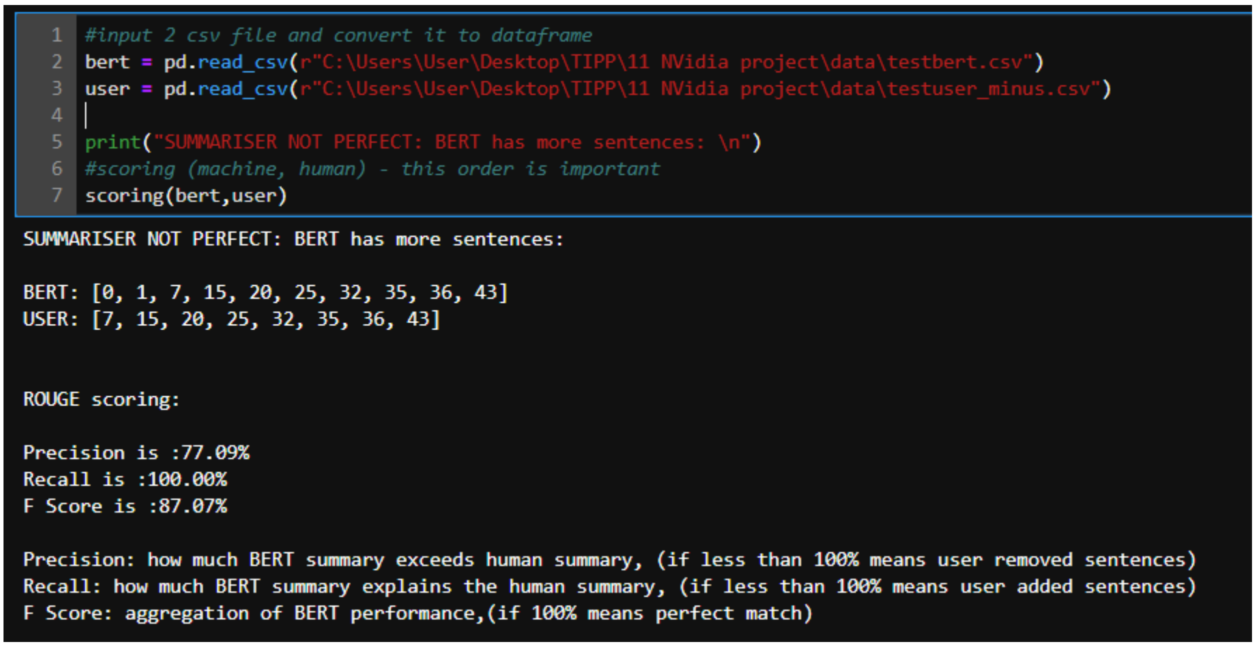
Figure 17. SUMMARY IS PERFECT: Summary is equal to user annotation



```
#input 2 csv file and convert it to dataframe
bert = pd.read_csv(r"C:\Users\User\Desktop\TIPP\11 NVidia project\data\testbert.csv")
user = pd.read_csv(r"C:\Users\User\Desktop\TIPP\11 NVidia project\data\testuser_add.csv")

print("SUMMARISER NOT PERFECT: BERT has less sentences: \n")
#scoring (machine, human) - this order is important
scoring(bert,user)
```

```
SUMMARISER NOT PERFECT: BERT has less sentences:

BERT: [0, 1, 7, 15, 20, 25, 32, 35, 36, 43]
USER: [0, 1, 7, 15, 20, 25, 32, 35, 36, 42, 43, 44]


ROUGE scoring:

Precision is :100.00%
Recall is :81.36%
F Score is :89.72%

Precision: how much BERT summary exceeds human summary, (if less than 100% means user removed sentences)
Recall: how much BERT summary explains the human summary, (if less than 100% means user added sentences)
F Score: aggregation of BERT performance,(if 100% means perfect match)
```

Figure 18. SUMMARY IS NOT PERFECT: BERT has less sentences



```
#input 2 csv file and convert it to dataframe
bert = pd.read_csv(r"C:\Users\User\Desktop\TIPP\11 NVidia project\data\testbert.csv")
user = pd.read_csv(r"C:\Users\User\Desktop\TIPP\11 NVidia project\data\testuser_minus.csv")

print("SUMMARISER NOT PERFECT: BERT has more sentences: \n")
#scoring (machine, human) - this order is important
scoring(bert,user)
```

```
SUMMARISER NOT PERFECT: BERT has more sentences:

BERT: [0, 1, 7, 15, 20, 25, 32, 35, 36, 43]
USER: [7, 15, 20, 25, 32, 35, 36, 43]


ROUGE scoring:

Precision is :77.09%
Recall is :100.00%
F Score is :87.07%

Precision: how much BERT summary exceeds human summary, (if less than 100% means user removed sentences)
Recall: how much BERT summary explains the human summary, (if less than 100% means user added sentences)
F Score: aggregation of BERT performance,(if 100% means perfect match)
```

Figure 19. SUMMARY IS NOT PERFECT: BERT has more sentences

8.6 Library Versions

Name	Version
Python	3.7.6
Flask	1.1.1
Keras-applications	1.0.8
Keras-preprocessing	1.1.0
Matplotlib	3.1.3
Newspaper3k	0.2.8
Numpy	1.18.1
Pandas	1.0.1
Pytorch	1.4.0
Regex	2020.2.20
Request	2.23.0
Rouge	1.0.0
Streamlit	0.56.0
Tensorflow	2.0.0
Tokenizers	0.5.2
Torchvision	0.5.0
Transformers	2.2.0
Urllib3	1.2.58

9. References

9.1 Main Modules/Libraries

This project was implemented using Flask Python. Flask is a popular Python web framework for developing web application.

- Flask - https://flask.palletsprojects.com

Streamlit is a recent new tool that allows engineers to quickly build interactive web application around the data.

- Streamlit – https://www.streamlit.io

9.2 Reading and Research List

No.	Articles	Summary	Done By	Type	URL
1	Unsupervised Text Summarisation using Sentence Embeddings	Flow of a text summarisation process	EL	Web link	https://towardsdatascience.com/a-quick-introduction-to-text-summarization-in-machine-learning-3d27ccf18a9f
2	Awesome NLP	A linkful of NLP code examples	EL	github	https://github.com/keon/awesome-nlp
3	Pytorch Tutorial	Get a quick basic tutorial on Pytorch. Not sure whether to learn Pytorch in deep.	ST	Web link	https://pytorch.org/tutorials/
4	Pytorch Guide	A Beginner-Friendly Guide to PyTorch	ST	Web link	https://www.analyticsvidhya.com/blog/2019/09/introduction-to-pytorch-from-scratch/
5	Scrape and Summarize News Articles in 5 Lines of Python Code	Module: newspaper3k scraping	EL	Web link	https://towardsdatascience.com/scrape-and-summarize-news-articles-in-5-lines-of-python-code-175f0e5c7dfc
6	Mark.js	Highlighting JavaScript	ST	Web link	https://markjs.io/
7	Stools	JavaScript to highlight web text	ST	Web link	https://www.nsftools.com/misc/SearchAndHighlight.htm
8	Newspaper article scraping	How did I scrape news article using Python ?	ST	Web link	https://medium.com/@ankurjain_79625/how-did-i-scrape-news-article-using-python-6eff936b3c8c
9	Bert based summarizer notes	Extractive (we need) and abstractive summarization	EL	Web link	https://medium.com/lsc-psd/a-bert-based-summarization-model-bertsum-88b1fc1b3177
10	BERT based extractive summarizer	Extractive summarizer	EL	Web link	https://pypi.org/project/bert-extractive-summarizer/

11	List soup	How to compare lists	EL	Web link	https://www.techbeamers.com/program-python-list-contains-elements/
12	incipits	A Python based HTML to text conversion library	ST	Library	https://pypi.org/project/inscriptis/
13	distillBERT	a light BERT, released recently	EL	Web link	https://github.com/huggingface/transformers/tree/master/examples/distillation
14	Transformer library	Shows all the BERT model, use this to optimise	EL	github	https://github.com/huggingface/transformers
15	NLP - The Age of Transformers	1-Building a machine reading comprehension system using the latest advances in deep learning for NLP.	ST	Web link	https://blog.scaleway.com/2019/building-a-machine-reading-comprehension-system-using-the-latest-advances-in-deep-learning-for-nlp/
16	Understanding text with BERT	2-Building a machine reading comprehension system using the latest advances in deep learning for NLP	ST	Web link	https://blog.scaleway.com/2019/understanding-text-with-bert/
17	BERT Research	BERT Concept - #1	ST	YouTube	https://www.youtube.com/watch?v=FKlPCK1uFrc
18	Wordpiece model and Tokenizer	BERT Concept - #2	ST	YouTube	https://www.youtube.com/watch?v=zJW57aCBCTk&pbjreload=10
19	Fine Tuning	BERT Concept - #3	ST	YouTube	https://www.youtube.com/watch?v=Hnvb9b7a_Ps
20	Blog site for the above		ST	Web link	http://mccormickml.com/2019/11/11/bert-research-ep-1-key-concepts-and-sources/
21	Summarizer	Documentation	EL	github	https://github.com/icoxfog417/awesome-text-summarization
22	Fast Bert	Bert models with potential retraining	EL	Web link	https://pypi.org/project/fast-bert/
23	Fast Bert	Overview	EL	Web link	https://medium.com/huggingface/introducing-fastbert-a-simple-deep-learning-library-for-bert-models-89ff763ad384
24	ROUGE scoring	Evaluation method	EL	weblink	https://en.wikipedia.org/wiki/ROUGE_(metric)
25	ROUGE explanation	Interpreting rouge scoring	EL	weblink	https://stats.stackexchange.com/questions/301626/interpreting-rouge-scores