Natural Language Processing

1.

1.1 Project Title: Text Summarization from Real Time Speech Recognition

1.2 Team Members:

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1.3 GitHub Link:

https://github.com/PavaniMangugari/NLPProject-9

2. Goals and Objectives:

2.1 Motivation:

Information retrieval is one of the most widely needed use cases these days. The process of extracting the summary of a video lecture while remembering it and manually writing a summary is a time taking and intensive task for humans. There are plenty of text and video material available on the Internet. The process of developing a model for the machine to automatically convert the speech in the video to text would help the students and lectures.

Speech recognition would mean converting the speech to text in the real time scenario i.e., exactly converting the words with means of pronunciation. Text summarization is defined as the process of finding the meanings of difficult words and gets summarized to the shorter version where we can find them easily. So, we plan to develop a model that would take the lecture and interpret and summarize it. Additionally, we are using SR with text summarization to get Question and Answers that would help the students review their knowledge regarding the lecture and automatically check the correctness. We also use Machine Translation to translate the document into another native language.

2.2 Significance:

In this age where remote education and online videos are becoming hugely popular, the need for a model that can convert speech to text is necessary. The model would not only help a lot of users, having problems with understanding the language, it would also help the users with disabilities too. The whole text and lecture are hard to memorize, so having a summary that would brief about the lecture would help the users while revising or just to know the undergoing of the lecture.

With the implementation of additional functionality, it will allow the users to view a few questions based on the lecture so that they can test their understanding in the lecture. This project aims to ease online learning and help users who are struggling whilst listening to these classes and get concise overview of the lecture in their native language.

2.3 Objectives:

We are going to implement this project in 3 steps.

➢ Speech to Text

➢ Text Summarization

➢ Q&A module.

Fig 1

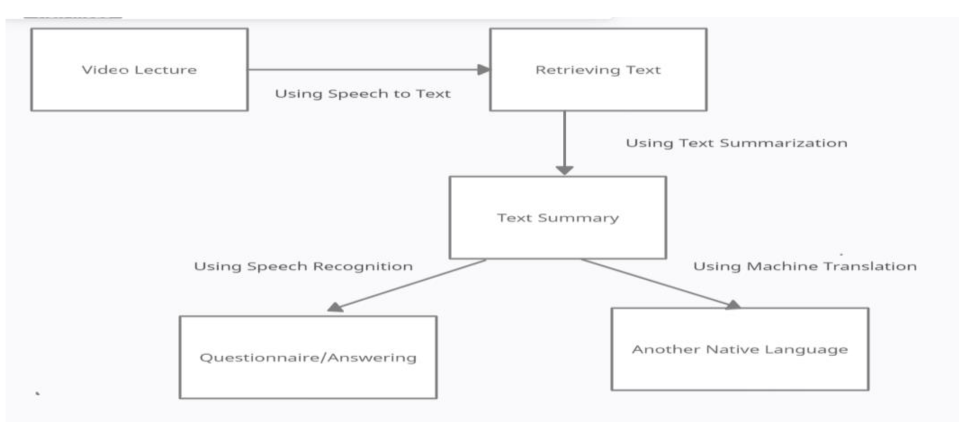


Fig 2

We are planning to do the project using the speech to text, text summarization and other training models. We will use the NLTK, SPACY, Genism, and Hugging Face tools to accomplish our project. We use machine translation for translating the text to another language.

We are at the end of the project planning to achieve an interface that would take the video input that converts it to text summary. In turn it uses this summary to build a Q/A model and Machine Translator for translating it to another language (Spanish and German). The goal of our project is to develop a model that will be accurate and precise in the summarization and processing that would help the users.

2.4 Features:

The video speech is converted into text using the python modules that would allow for the speech to turn into the text. We retrieve the text, perform the text cleaning and processing. We then tokenize the words, perform summarization techniques to get a video summary.

Using the machine translation, we convert the text into German and Spanish. We get the questions and answers from the original text. The user would be allowed to click for a correct answer. The answer would then be evaluated by the machine and returns if the user is right or wrong.

We will be implementing the feature that the user will be selecting an appropriate answer so that the system can check if the answer is correct or not. `

3 Related Work (Background)

Paper-1: They have considered that the system should consider the word by word from multiple speakers at a time so that it can identify the number of speakers. They have used some profiling techniques to reduce the signal-noise ratio by means of normalization and splitting the words so that they can get the ratio of 1:1. They got the accuracy of 71.7%.

Paper-2: In this they have taken the isolated word recognition and continuous phoneme recognition in a cued speech. They have concatenated the lip movement and hand shape for feature fusion and HMM based recognition has been implemented. They got 94% and 89% as accuracy for normal hearing and deaf people hearing.

Paper-3: In this paper they have used Devanagari script for classifying their classes based on phonemes. It converts the speech to phonemes by means of simple operations like zero-crossing and FTT. They did not get satisfactory results as the vowels and other consonants overlap in the same group. They got the accuracy of 75%, which is not satisfactory.

Paper-4: In this they have converted the normal speech to whispered speech by means of signal processing and voice conversion techniques. They have used gaussian mixture model (GMM) and deep neural networks (DNN) to map the features. They have also evaluated the naturalness and the speaker similarity after converting them to whispered speech. However, the model has failed in detecting the gender based on the speaker.

Paper-5: They have taken the double handed Indian sign language and converted them into patterns and converts speech to speech less. For this they have used the clustering techniques which may be useful for classifying the text and minimum eigen value algorithm for conversion. They have used bare hands for sign language rather than gloves. They have converted sign language into both text and speech.

Paper-6: they have taken both speech and object detection for speech recognition. They have taken the cognitive model for object detection based on speech to text recognition. In This they have developed a speech command and given it as input and by that the object is detected. The object is detected within a square box. For speech they have used google speech recognition and for object detection they have used YOLO V3 algorithm for that.

Paper-7: Here they are converting text to speech by mapping the source features. They have proposed a novel architecture used in Deep Learning. By considering the linear constraints, it prevents the input from converting features into unrealistic features. It is done by network-based conversion in a time variant way. It is suitable for multiple frames features.

4. Dataset

In the process of developing the application, we send audio data in the wav format. The application can handle data of a long duration. We tested the dataset of a university lecture about food processing. It is one hour long and has a lecture where there is one speaker.

Using the wave, we find the features of our dataset. We can see that we have 2 channels, with a sample width of 2. The frame rate is 44100 and the number of frames is 175584384.

```
import wave
obj = wave.open('food.wav','r')
print( "Number of channels",obj.getnchannels())
print ( "Sample width",obj.getsampwidth())
print ( "Frame rate.",obj.getframerate())
print ("Number of frames",obj.getnframes())
print ( "parameters:",obj.getparams())
obj.close()
```

```
Number of channels 2
Sample width 2
Frame rate. 44100
Number of frames 175584384
parameters: _wave_params(nchannels=2, sampwidth=2, framerate=44100, nframes=175584384, comptype='NONE', compname='not compressed')
```

Fig.3

5. Detail design of Features

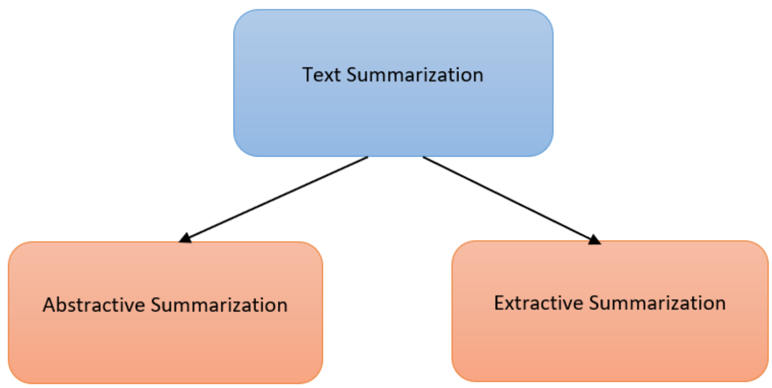


Fig.4

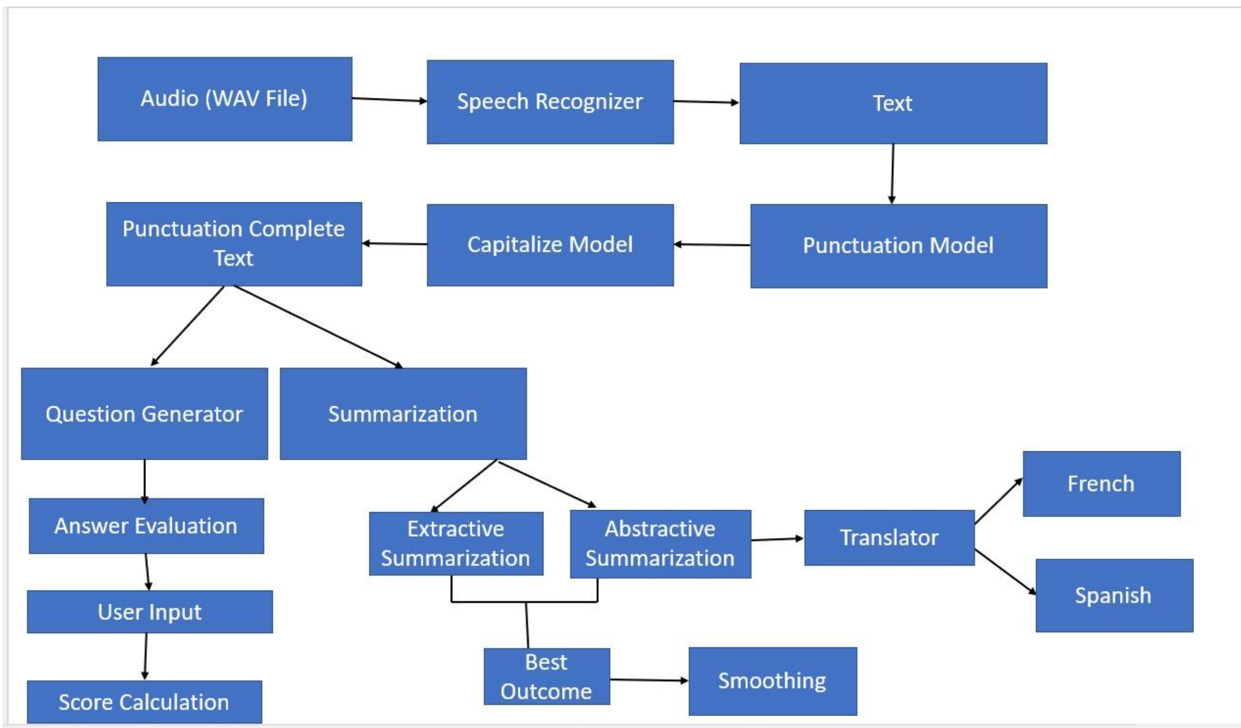


Fig.5

Architecture Diagram.

Our application first takes an audio input as a wav file

|

The audio file is first processed using the wave libraries, the matplotlib and get graphs regarding the audio frequency vs time.

|

Later, we take the text and pass it through a speech recognizer where the speech is converted into the text

|

The processed text is passed through a punctuationModel() where the information that we get from the recognizer.

|

The information that we get from the punctuation model is then sent and we capitalize words using capitalize () method.

|

Now, we get the text from the reformed model and perform text summarization using two different methods

|

We use the bigram model on the summarized text and apply Laplace and interpolation smoothening techniques and find accuracy.

|

Using the original text file, we send the text into an t5 based question-answer based model

|

The model generates question and answer inputs based on a given value of questions.

|

The model also takes an evaluation factor that takes the scores and gives the highest rank answer that is correct by itself.

|

The user is displayed the questions and asked to enter the correct option

|

The system checks if the answer is correct or not and then calculates the score and finally displays the final output score.

The extractive text is taken which we generate from the model and translate it into German and Spanish language.

Workflow diagram with explanation

6. Analysis

In the analysis phase, we try to take the audio input that we have taken and try to analyze it. Later, we also try to analyze the differences in the word count in the original vs the summarized text in the summarizers that we have used.

```
[41] import wave
     obj = wave.open('food.wav','r')
     print( "Number of channels",obj.getnchannels())
     print ( "Sample width",obj.getsampwidth())
     print ( "Frame rate.",obj.getframerate())
     print ("Number of frames",obj.getnframes())
     print ( "parameters:",obj.getparams())
     obj.close()

     Number of channels 2
     Sample width 2
     Frame rate. 44100
     Number of frames 175584384
     parameters: _wave_params(nchannels=2, sampwidth=2, framerate=44100, nframes=175584384, comptype='NONE', compname='not compressed')
```

Fig.6

We first analyze the audio dataset and can see the features of the dataset.

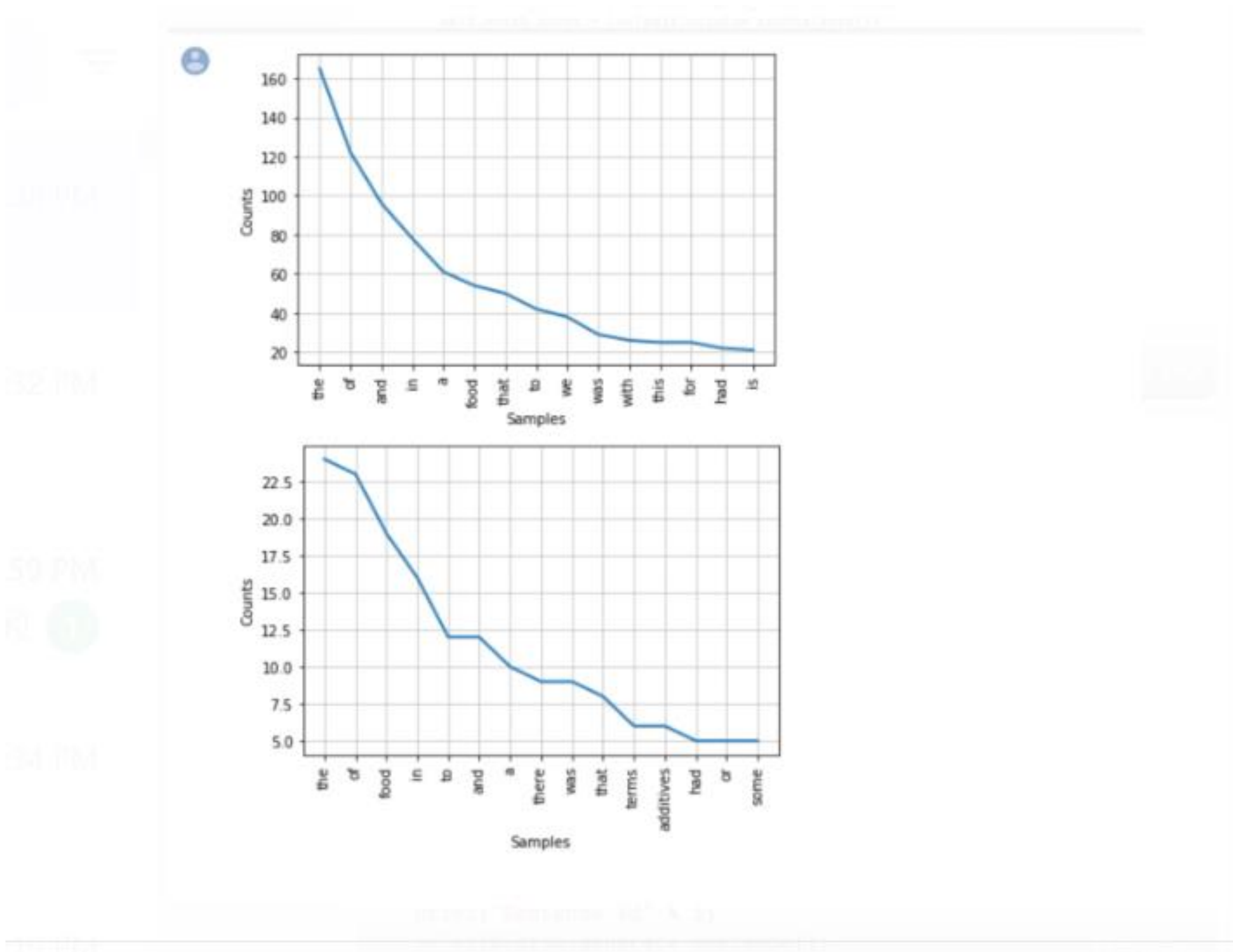


Fig.7

Difference between the counts in the abstractive summarizer vs the original text

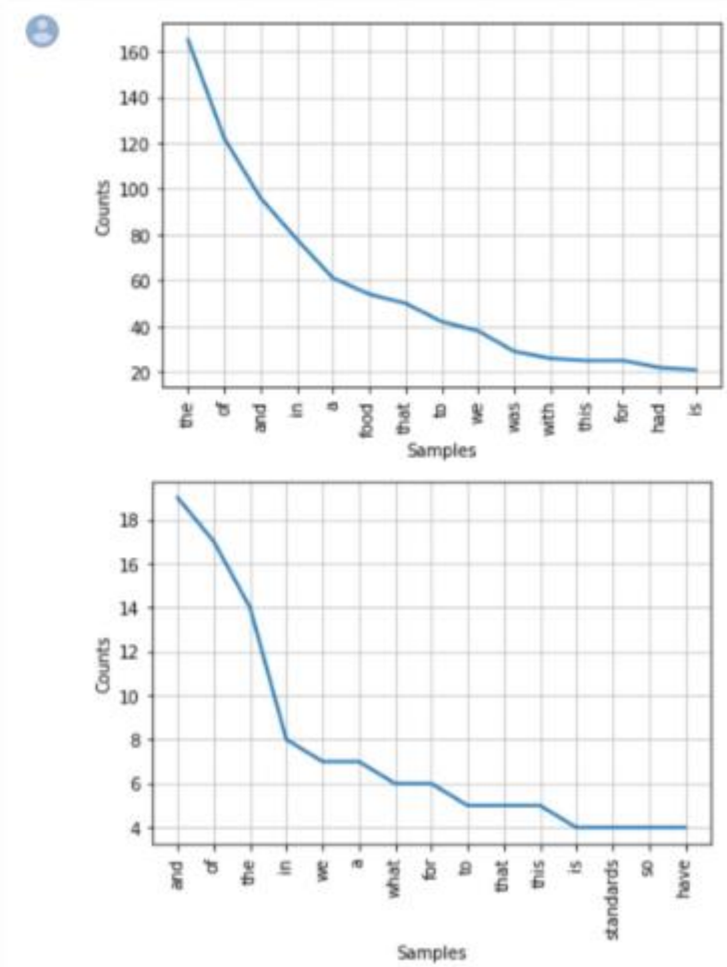


Fig.8

Difference between the counts in the extractive summarizer vs the original text.

```python
#opening the file using wave
raw = wave.open("food.wav")
  #reading the signal of 300000 frames
signal = raw.readframes(300000)
signal = np.frombuffer(signal, dtype ="int16")
  # gets the frame rate
f_rate = raw.getframerate()
  #for plotting the time, we divide the len of the signal with the frame rate.
time = np.linspace(
  0, # start
  len(signal) / f_rate,
  num = len(signal)
)
  #using matplotlib for the plot
plt.figure(1)
plt.title("Sound Wave")
plt.xlabel("Time")
plt.plot(time, signal)
plt.show()
```

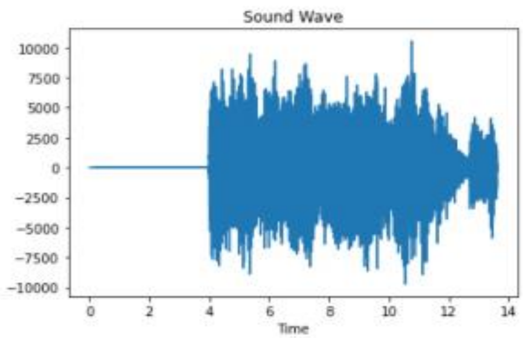


Fig. 9

Drawing a graph between the time and signal of the audio source.

```python
#using the librosa library and plot the wave file for time and sample rate for the provided wav file.
plt.figure(figsize=(15,4))
data1,sample_rate1 = librosa.load('food.wav', sr=44100, mono=True, offset=0.0, duration=900, res_type='kaiser_best')
librosa.display.waveplot(data1,sr=sample_rate1, max_points=50000.0,x_axis='time', offset=0.0, max_sr=1000)
```

```
<matplotlib.collections.PolyCollection at 0x7f5aa4d41710>
```

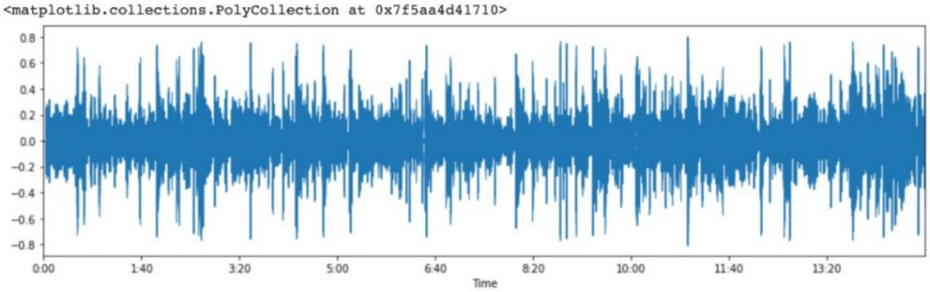


Fig. 10

A graph between the time duration and the energy involved which is the sampling rate and the signal.

```
#using the wav file to plot the energry vs sample rate and time vs frequency graphs

signal_wave = wave.open("food.wav", 'r')
sig = np.frombuffer(signal_wave.readframes(16000), dtype=np.int16)
plt.figure(1)


plot_b = plt.subplot(212)
plot_b.specgram(sig, NFFT=1024, Fs=16000, noverlap=900)
plot_b.set_xlabel('Time')
plot_b.set_ylabel('Frequency')

plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/matplotlib/axes/_axes.py:7592: RuntimeWarning: divide by zero encountered in log10
  Z = 10. * np.log10(spec)
```

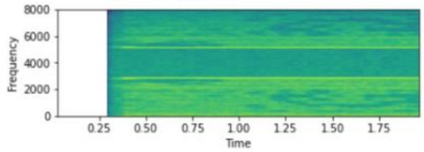


Fig. 11

The analysis between the time and the frequency of the audio wav file.

7. Implementation

```
pip install SpeechRecognition

Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: SpeechRecognition in /usr/local/lib/python3.7/dist-packages (3.8.1)

[4] import os
    import speech_recognition as sr

[5] r = sr.Recognizer()
    audio = sr.AudioFile('food.wav')
```

Fig. 12

Using the speech recognizer module for reading the audio file.

Speech to Text

```
#intializing text to empty first
finalText=""
#the intial offset is 0
offset=0
#i in the range of for the duration offset, we repeat the conversion
for i in range(10):
  #using the recogniser to find the text from the audio
  r = sr.Recognizer()
  audio = sr.AudioFile('food.wav')
  with audio as source:
    audio = r.record(source, duration=300,offset=offset)
  # set offset as 300
  offset=offset+300
  text=r.recognize_google(audio)
  finalText=finalText+text ## recognizing the speech and converting into text
print(finalText)
```

```
hello my name is food toxicology would like to welcome back once again today the subject of the lecture is going to be the history of us food regulation and
```

Fig. 13

Using the speech recognition model, we get converted text

```
from deepmultilingualpunctuation import PunctuationModel
!pip install transformers

model = PunctuationModel()
text = text1
clean_text=model.preprocess(text)
labeled_words=model.predict(clean_text)
result = model.restore_punctuation(text)
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: transformers in /usr/local/lib/python3.7/dist-packages (4.24.0)
Requirement already satisfied: regex!=2019.12.17 in /usr/local/lib/python3.7/dist-packages (from transformers) (2022.6.2)
Requirement already satisfied: huggingface-hub<1.0,>=0.10.0 in /usr/local/lib/python3.7/dist-packages (from transformers) (0.10.1)
Requirement already satisfied: importlib-metadata in /usr/local/lib/python3.7/dist-packages (from transformers) (4.13.0)
Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.7/dist-packages (from transformers) (1.21.6)
Requirement already satisfied: requests in /usr/local/lib/python3.7/dist-packages (from transformers) (2.23.0)
Requirement already satisfied: tqdm>=4.27 in /usr/local/lib/python3.7/dist-packages (from transformers) (4.64.1)
Requirement already satisfied: filelock in /usr/local/lib/python3.7/dist-packages (from transformers) (3.8.0)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.7/dist-packages (from transformers) (21.3)
Requirement already satisfied: tokenizers!=0.11.3,<0.14,>=0.11.1 in /usr/local/lib/python3.7/dist-packages (from transformers) (0.13.1)
Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.7/dist-packages (from transformers) (6.0)
Requirement already satisfied: typing-extensions>=3.7.4.3 in /usr/local/lib/python3.7/dist-packages (from huggingface-hub<1.0,>=0.10.0->transformers) (4.1.1)
Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in /usr/local/lib/python3.7/dist-packages (from packaging>=20.0->transformers) (3.0.9)
Requirement already satisfied: zipp>=0.5 in /usr/local/lib/python3.7/dist-packages (from importlib-metadata->transformers) (3.10.0)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in /usr/local/lib/python3.7/dist-packages (from requests->transformers) (1.25.11)
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.7/dist-packages (from requests->transformers) (3.0.4)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.7/dist-packages (from requests->transformers) (2022.9.24)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/dist-packages (from requests->transformers) (2.10)
/usr/local/lib/python3.7/dist-packages/transformers/pipelines/token_classification.py:136: UserWarning: `grouped_entities` is deprecated and will be removed
  "`grouped_entities` is deprecated and will be removed in version v5.0.0, defaulted to"
```

```
#predicted accuracy
print(labeled_words)
```

```
[['hello', ',', 0.89068866], ['my', '0', 0.9999896], ['name', '0', 0.9998072], ['is', '0', 0.9979177], ['food', '0', 0.9322935], ['toxicology', '0', 0.555714
```

Fig. 14

Using the word punctuation model, we get the converted text with punctuations

Capitalizing Text

```
[ ] def capitalizng_sentence(data):
      sent_tokenizer = nltk.data.load('tokenizers/punkt/english.pickle')
      sentences_from_summary = sent_tokenizer.tokenize(data)
      corrected_sentences = [sentence.capitalize() for sentence in sentences_from_summary]
      print(' '.join(corrected_sentences))
```

```
[ ] capitalizedres=capitalizng_sentence(result)
    print(capitalizedres)

    Hello, my name is food toxicology would like to welcome back once again. Today. The subject of the lecture is going to be the history of us food regulation,
    None
```

Fig. 15

Using the capitalizing text, we capitalize each sentence.

```
def summarize(text, per):
    nlp = spacy.load('en_core_web_sm')
    doc= nlp(text)
    tokens=[token.text for token in doc]
    word_frequencies={}
    for word in doc:
        if word.text.lower() not in list(STOP_WORDS):
            if word.text.lower() not in punctuation:
                if word.text not in word_frequencies.keys():
                    word_frequencies[word.text] = 1
                else:
                    word_frequencies[word.text] += 1
    max_frequency=max(word_frequencies.values())
    for word in word_frequencies.keys():
        word_frequencies[word]=word_frequencies[word]/max_frequency
    sentence_tokens= [sent for sent in doc.sents]
    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()]
    select_length=int(len(sentence_tokens)*per)
    summary=nlargest(select_length, sentence_scores,key=sentence_scores.get)
    final_summary=[word.text for word in summary]
    summary=''.join(final_summary)
    return summary
```

```
[ ] text2=summarize(text1, 0.07)
    print(text2)

    so in fact they had to prove certain health benefits and so the whole idea of patent or quack medicines went away fairly rapidly after that or at least had t
```

Fig. 16

We summarize text using the abstractive summarization

Text Summarization(Extractive)

```
!pip install -q bert-extractive-summarizer
!pip install -q spacy
!pip install -q transformers
!pip install -q neuralcoref
```

```
from summarizer import Summarizer
from pprint import pprint
```

```
model = Summarizer()
```

```
Some weights of the model checkpoint at bert-large-uncased were not used when initializing BertModel: ['cls.predictions.transform.LayerNorm.bias', 'cls.predi
- This IS expected if you are initializing BertModel from the checkpoint of a model trained on another task or with another architecture (e.g. initializing a
- This IS NOT expected if you are initializing BertModel from the checkpoint of a model that you expect to be exactly identical (initializing a BertForSequen
```

```
full=""
res = model(result)
full = ''.join(res)
```

```
print(full)
```

```
hello, my name is food toxicology would like to welcome back once again. one of the answers, one of the responses is to establish standards of behavior, stan
```

Fig. 17

Using extractive summarization, we get the summarized text.

Bigram model and smoothening

```
from collections import defaultdict
from collections import Counter
from numpy.random import choice
from tqdm import tqdm

class Bigram():
    def __init__(self):
        self.bigram_counts = defaultdict(Counter)
        self.unigram_counts = Counter()
        self.context = defaultdict(Counter)
        self.start_count = 0
        self.token_count = 0
        self.vocab_count = 0

    def convert_sentence(self, sentence):
        return ["<s>"] + [w.lower() for w in sentence] + ["</s>"]

    def get_counts(self, sentences):
        # collect unigram counts
        for sentence in sentences:
            sentence = self.convert_sentence(sentence)

            for word in sentence[1:]:  # from 1, because we don't need the <s> token
                self.unigram_counts[word] += 1

            self.start_count += 1
```

Fig. 18

```
        # collect bigram counts
        for sentence in sentences:
            sentence = self.convert_sentence(sentence)
            bigram_list = zip(sentence[:-1], sentence[1:])
            for bigram in bigram_list:
                self.bigram_counts[bigram[0]][bigram[1]] += 1
                self.context[bigram[1]][bigram[0]] += 1
        self.token_count = sum(self.unigram_counts.values())
        self.vocab_count = len(self.unigram_counts.keys())

    def generate_sentence(self):
        current_word = "<s>"
        sentence = [current_word]
        while current_word != "</s>":
            prev_word = current_word
            prev_word_counts = self.bigram_counts[prev_word]
            # obtain bigram probability distribution given the previous word
            bigram_probs = []
            total_counts = float(sum(prev_word_counts.values()))
            for word in prev_word_counts:
                bigram_probs.append(prev_word_counts[word] / total_counts)
            # sample the next word
            current_word = choice(list(prev_word_counts.keys()), p=bigram_probs)
            sentence.append(current_word)

        sentence = " ".join(sentence[1:-1])
        return sentence
```

Fig. 19

```
import nltk
from nltk.tokenize import sent_tokenize
##from nltk.corpus import brown
nltk.download('punkt')
s=sent_tokenize(result)
l=[]
for i in s:
  l1=list(i.split(' '))
  l.append(l1)

print(l)
bigram = Bigram()
bigram.get_counts(l)
for i in range(len(l)):
    print("Sentence %d" % i)
    print(bigram.generate_sentence())
```

Fig. 20

We used the bigram model to generate the sentence from the summarized text.

```
[ ] !pip install sentencepiece
    !pip install transformers[sentencepiece]

    Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
    Collecting sentencepiece
      Downloading sentencepiece-0.1.97-cp37-cp37m-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (1.3 MB)
         ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 1.3/1.3 MB 58.6 MB/s eta 0:00:00
    Installing collected packages: sentencepiece
    Successfully installed sentencepiece-0.1.97
    WARNING: Running pip as the 'root' user can result in broken permissions and conflicting behaviour with the system package manager. It is recommended t
    Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
    Requirement already satisfied: transformers[sentencepiece] in /usr/local/lib/python3.7/dist-packages (4.24.0)
    Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.7/dist-packages (from transformers[sentencepiece]) (21.3)
    Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.7/dist-packages (from transformers[sentencepiece]) (6.0)
    Requirement already satisfied: huggingface-hub<1.0,>=0.10.0 in /usr/local/lib/python3.7/dist-packages (from transformers[sentencepiece]) (0.11.1)
    Requirement already satisfied: filelock in /usr/local/lib/python3.7/dist-packages (from transformers[sentencepiece]) (3.8.0)
    Requirement already satisfied: tokenizers!=0.11.3,<0.14,>=0.11.1 in /usr/local/lib/python3.7/dist-packages (from transformers[sentencepiece]) (0.13.2)
    Requirement already satisfied: requests in /usr/local/lib/python3.7/dist-packages (from transformers[sentencepiece]) (2.23.0)
    Requirement already satisfied: tqdm>=4.27 in /usr/local/lib/python3.7/dist-packages (from transformers[sentencepiece]) (4.64.1)
    Requirement already satisfied: importlib-metadata in /usr/local/lib/python3.7/dist-packages (from transformers[sentencepiece]) (4.13.0)
    Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.7/dist-packages (from transformers[sentencepiece]) (1.21.6)
    Requirement already satisfied: regex!=2019.12.17 in /usr/local/lib/python3.7/dist-packages (from transformers[sentencepiece]) (2022.6.2)
    Requirement already satisfied: protobuf<=3.20.2 in /usr/local/lib/python3.7/dist-packages (from transformers[sentencepiece]) (3.19.6)
    Requirement already satisfied: sentencepiece!=0.1.92,>=0.1.91 in /usr/local/lib/python3.7/dist-packages (from transformers[sentencepiece]) (0.1.97)
    Requirement already satisfied: typing-extensions>=3.7.4.3 in /usr/local/lib/python3.7/dist-packages (from huggingface-hub<1.0,>=0.10.0->transformers[se
    Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in /usr/local/lib/python3.7/dist-packages (from packaging>=20.0->transformers[sentencepiece]) (
```

Fig. 21

Installing the required libraries.

```
[ ] import en_core_web_sm
    import json
    import numpy as np
    import random
    import re
    import torch
    from transformers import (
        AutoTokenizer,
        AutoModelForSeq2SeqLM,
        AutoModelForSequenceClassification,
    )
    from typing import Any, List, Mapping, Tuple


    class QuestionGenerator:
        def __init__(self) -> None:

            QG_PRETRAINED = "iarfmoose/t5-base-question-generator"
            self.ANSWER_TOKEN = "<answer>"
            self.CONTEXT_TOKEN = "<context>"
            self.SEQ_LENGTH = 512

            self.device = torch.device(
                "cuda" if torch.cuda.is_available() else "cpu")

            self.qg_tokenizer = AutoTokenizer.from_pretrained(
                QG_PRETRAINED, use_fast=False)
            self.qg_model = AutoModelForSeq2SeqLM.from_pretrained(QG_PRETRAINED)
            self.qg_model.to(self.device)
            self.qg_model.eval()

            self.qa_evaluator = QAEvaluator()

        def generate(
            self,
            article: str,
            num_questions: bool = None,
        ) -> List:
            print("Loading questions:\n")
            qg_inputs, qg_answers = self.generate_qg_inputs(article)
            generated_questions = self.generate_questions_from_inputs(qg_inputs)
            encoded_qa_pairs = self.qa_evaluator.encode_qa_pairs(
                generated_questions, qg_answers
            )
            scores = self.qa_evaluator.get_scores(encoded_qa_pairs)
            if num_questions:
                qa_list = self._get_ranked_qa_pairs(
                    generated_questions, qg_answers, scores, num_questions
                )
            else:
                qa_list = self._get_ranked_qa_pairs(
                    generated_questions, qg_answers, scores
                )
            return qa_list

        def generate_qg_inputs(self, text: str) -> Tuple[List[str], List[str]]:
            inputs = []
```

Fig.22

The question generator file

```
            if show_answers:
                print(
                    f"{space}A: 1. {answer[0]['answer']} "
                    f"{np.where(answer[0]['correct'], '(correct)', '')}"
                )
                for j in range(1, len(answer)):
                    print(
                        f"{space + '   '}{j + 1}. {answer[j]['answer']} "
                        f"{np.where(answer[j]['correct']==True,'(correct)', '')}"
                    )

            else:

                answerRight = -1
                print(f"{space}A: 1. {answer[0]['answer']}")
                for j in range(1, len(answer)):
                    print(f"{space + '   '}{j + 1}. {answer[j]['answer']}")
                    if(answer[j]['correct']==True):
                      answerRight = j+1
                print("Enter the correct option:")
                s=int(input(" "))
                if(s==answerRight):
                  print("Correct answer")
                  score = score+1
                else:
                  print("Wrong answer")
            print("")
        else:
            if show_answers:
                print(f"{space}A: {answer}\n")
    print("Your total score is ",score)
```

```
[ ] import torch
    device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
    assert device == torch.device('cuda'), "Not using CUDA. Set: Runtime > Change runtime type > Hardware Accelerator: GPU"
```

```
[ ] !pip install sentencepiece
```

Fig.23

The question evaluator file which takes the score and tells the correct answer for a question.

Translating the summarized text

```
[ ] with open('summarized_text.txt','r') as t:
      sum_text= t.read()
```

```
!pip install translator

Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: translator in /usr/local/lib/python3.7/dist-packages (0.0.9)
Requirement already satisfied: beautifulsoup4>=4.0 in /usr/local/lib/python3.7/dist-packages (from translator) (4.11.1)
Requirement already satisfied: soupsieve>1.2 in /usr/local/lib/python3.7/dist-packages (from beautifulsoup4>=4.0->translator) (2.3.2.post1)
```

```
[ ] !pip install deep_translator

Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: deep_translator in /usr/local/lib/python3.7/dist-packages (1.9.1)
Requirement already satisfied: beautifulsoup4<5.0.0,>=4.9.1 in /usr/local/lib/python3.7/dist-packages (from deep_translator) (4.11.1)
Requirement already satisfied: requests<3.0.0,>=2.23.0 in /usr/local/lib/python3.7/dist-packages (from deep_translator) (2.23.0)
Requirement already satisfied: soupsieve>1.2 in /usr/local/lib/python3.7/dist-packages (from beautifulsoup4<5.0.0,>=4.9.1->deep_translator) (2.3.2.post1)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.7/dist-packages (from requests<3.0.0,>=2.23.0->deep_translator) (2022.9.24)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in /usr/local/lib/python3.7/dist-packages (from requests<3.0.0,>=2.23.0->deep_translat
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.7/dist-packages (from requests<3.0.0,>=2.23.0->deep_translator) (3.0.4)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/dist-packages (from requests<3.0.0,>=2.23.0->deep_translator) (2.10)
```

```
[ ] print(sum_text)

hello, my name is food toxicology would like to welcome back once again. one of the answers, one of the responses is to establish standards of behavior, stan
```

Fig.24

Taking the summarized text and installing the required libraries.

```
from deep_translator import GoogleTranslator
translated = GoogleTranslator(source='english', target='spanish').translate_file('summarized_text.txt')
print(translated)
```

```
hola, mi nombre es toxicología alimentaria me gustaría darle la bienvenida una vez más. una de las respuestas, una de las respuestas es establecer estándares
```

```
from deep_translator import GoogleTranslator
translated = GoogleTranslator(source='english', target='german').translate_file('summarized_text.txt')
print(translated)
```

```
hallo, mein name ist lebensmitteltoxikologie möchte mich wieder einmal herzlich willkommen heißen. Eine der Antworten, eine der Antworten ist, Verhaltensstan
```

Fig.25

The summarized text in Spanish and English languages.

```
epochs = 10

transformer.summary()
transformer.compile(
    "rmsprop", loss="sparse_categorical_crossentropy", metrics=["accuracy"]
)
transformer.fit(train_ds, epochs=epochs, validation_data=val_ds)
```

```
Model: "transformer"
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==================================================================================================
 encoder_inputs (InputLayer)    [(None, None)]       0           []

 positional_embedding (Position  (None, None, 256)   3845120     ['encoder_inputs[0][0]']
 alEmbedding)

 decoder_inputs (InputLayer)    [(None, None)]       0           []

 transformer_encoder (Transform  (None, None, 256)   3155456     ['positional_embedding[0][0]']
 erEncoder)

 model_1 (Functional)           (None, None, 15000)  12959640    ['decoder_inputs[0][0]',
                                                                  'transformer_encoder[0][0]']

==================================================================================================
Total params: 19,960,216
Trainable params: 19,960,216
Non-trainable params: 0
__________________________________________________________________________________________________
Epoch 1/10
```

Fig.26

While training the translator model, we use 10 epochs and get the final predictions.

8. Results

```
#intializing text to empty first
finalText=""
#the intial offset is 0
offset=0
#i in the range of for the duration offset, we repeat the conversion
for i in range(10):
  #using the recogniser to find the text from the audio
  r = sr.Recognizer()
  audio = sr.AudioFile('food.wav')
  with audio as source:
    audio = r.record(source, duration=300,offset=offset)
  # set offset as 300
  offset=offset+300
  text=r.recognize_google(audio)
  finalText=finalText+text ## recognizing the speech and converting into text
print(finalText)
```

```
hello my name is food toxicology would like to welcome back once again today the subject of the lecture is going to be the history of us food regulation and
```

Fig. 27

First, we get the text from converting the speech which is wav file.

```
[ ] print(result)

hello, my name is food toxicology would like to welcome back once again. today. the subject of the lecture is going to be the history of us food regulation,
```

Fig. 28

Second, we add punctuation to the text.

```
[ ] capitalizedres=capitalizng_sentence(result)
    print(capitalizedres)

Hello, my name is food toxicology would like to welcome back once again. Today. The subject of the lecture is going to be the history of us food regulation,
None
```

Fig. 29

Then, we capitalize each sentence after adding punctuation.

```python
def interpolation(text2, bigram, lambdas):
    bigram_lambda = lambdas[0]
    unigram_lambda = lambdas[1]
    zerogram_lambda = 1 - lambdas[0] - lambdas[1]

    sentence = bigram.convert_sentence(text2)
    bigram_list = zip(sentence[:-1], sentence[1:])
    prob = 0

    for prev_word, word in bigram_list:
        # bigram probability
        sm_bigram_counts = bigram.bigram_counts[prev_word][word]
        if sm_bigram_counts == 0: interp_bigram_counts = 0
        else:
            if prev_word == "<s>": u_counts = bigram.start_count
            else: u_counts = bigram.unigram_counts[prev_word]
            interp_bigram_counts = sm_bigram_counts / float(u_counts) * bigram_lambda

        # unigram probability
        interp_unigram_counts = (bigram.unigram_counts[word] / bigram.token_count) * unigram_lambda

        # "zerogram" probability: this is to account for out-of-vocabulary words, this is just 1 / |V|
        vocab_size = len(bigram.unigram_counts)
        interp_zerogram_counts = (1 / float(vocab_size)) * zerogram_lambda

        prob += math.log(interp_bigram_counts + interp_unigram_counts + interp_zerogram_counts)
    return prob

bigram_interpolation = Bigram()
bigram_interpolation.get_counts(training_set)
plex_interpolation = calculate_perplexity(test_set, bigram_interpolation, interpolation, (0.8, 0.19))
print(plex_interpolation)
```

```
100%|██████████| 19/19 [00:00<00:00, 4788.31it/s]1070.463080935843
```

Fig. 30

```python
import numpy as np
import matplotlib.pyplot as plt

data={'Laplacian': 250.587,'Interpolation':1070.463}
ST=list(data.keys())
perp=list(data.values())

fig=plt.figure(figsize=(10,5))

plt.bar(ST,perp, color='blue', width=0.4)

plt.xlabel("Smoothing techniuge")
plt.ylabel("perplexity")
plt.show()
```

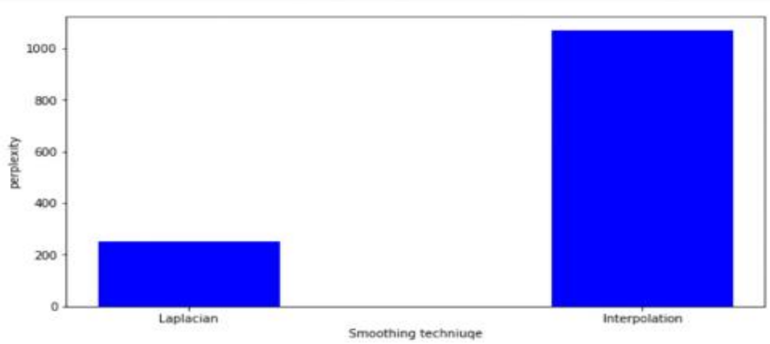


Fig. 31

Using the two models i.e., Laplacian and interpolation, we got the perplexities as shown below.

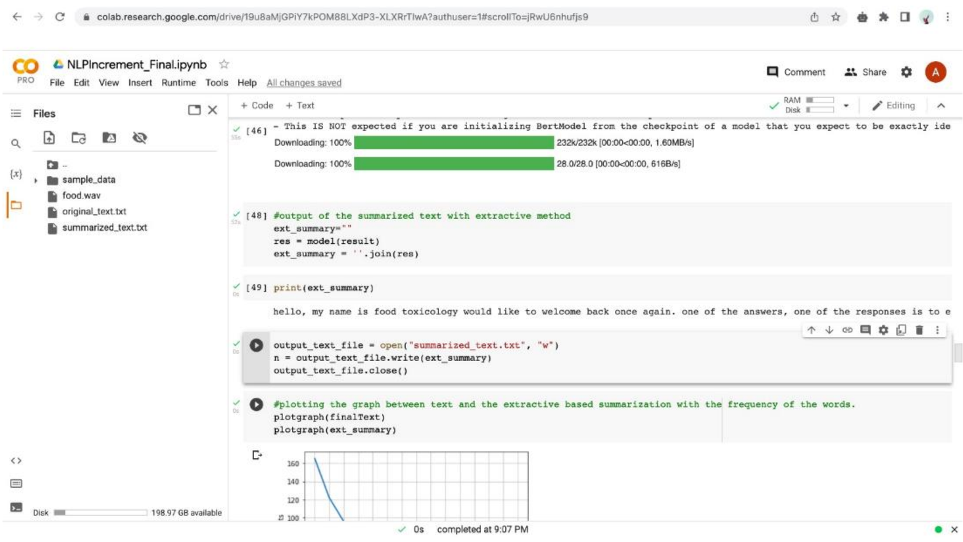
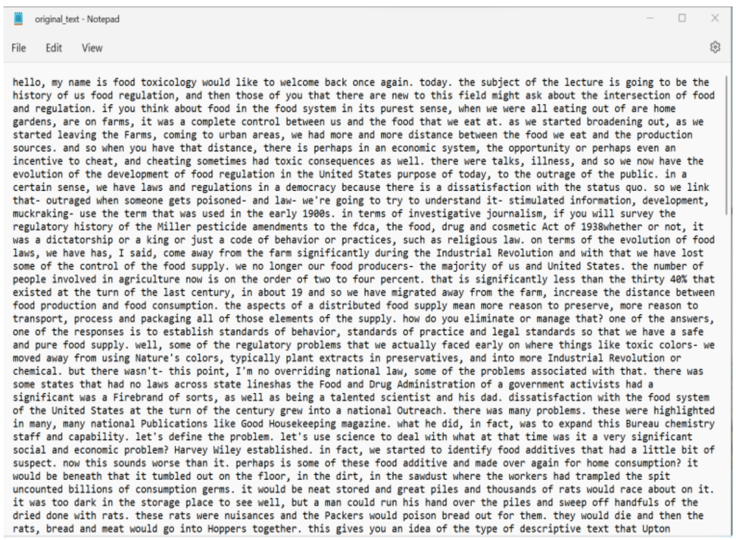


Fig. 32

The two files of the original and summarized text are downloaded.

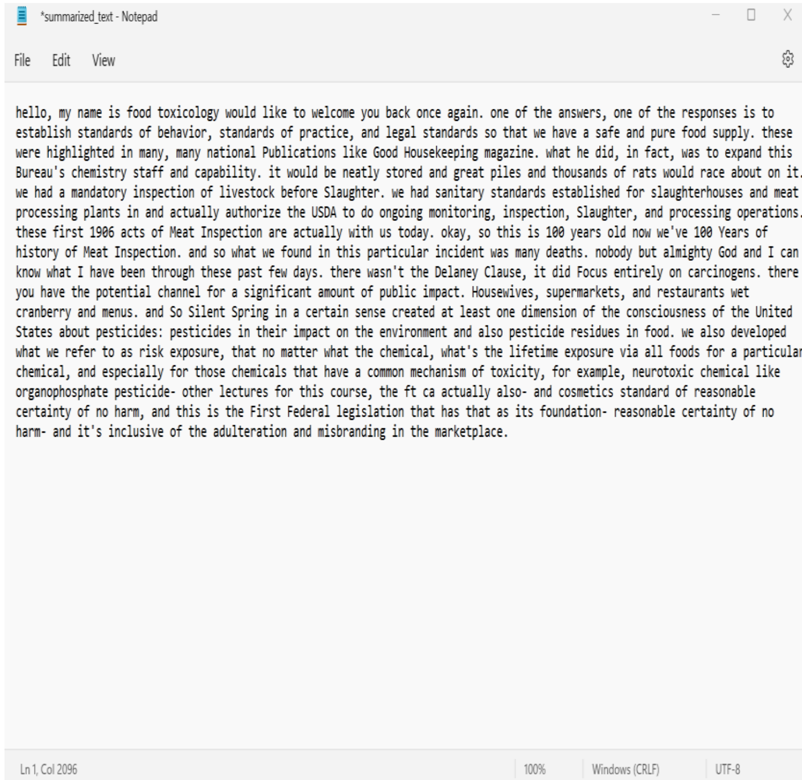


original_text - Notepad

File Edit View

hello, my name is food toxicology would like to welcome back once again. today. the subject of the lecture is going to be the history of us food regulation, and then those of you that there are new to this field might ask about the intersection of food and regulation. if you think about food in the food system in its purest sense, when we were all eating out of are home gardens, are on farms, it was a complete control between us and the food that we eat at. as we started broadening out, as we started leaving the Farms, coming to urban areas, we had more and more distance between the food we eat and the production sources. and so when you have that distance, there is perhaps in an economic system, the opportunity or perhaps even an incentive to cheat, and cheating sometimes had toxic consequences as well. there were talks, illness, and so we now have the evolution of the development of food regulation in the United States purpose of today, to the outrage of the public. in a certain sense, we have laws and regulations in a democracy because there is a dissatisfaction with the status quo. so we link that- outraged when someone gets poisoned- and law- we're going to try to understand it- stimulated information, development, muckraking- use the term that was used in the early 1900s. in terms of investigative journalism, if you will survey the regulatory history of the Miller pesticide amendments to the fdca, the food, drug and cosmetic Act of 1938whether or not, it was a dictatorship or a king or just a code of behavior or practices, such as religious law. on terms of the evolution of food laws, we have has, I said, come away from the farm significantly during the Industrial Revolution and with that we have lost some of the control of the food supply. we no longer our food producers- the majority of us and United States. the number of people involved in agriculture now is on the order of two to four percent. that is significantly less than the thirty 40% that existed at the turn of the last century, in about 19 and so we have migrated away from the farm, increase the distance between food production and food consumption. the aspects of a distributed food supply mean more reason to preserve, more reason to transport, process and packaging all of those elements of the supply. how do you eliminate or manage that? one of the answers, one of the responses is to establish standards of behavior, standards of practice and legal standards so that we have a safe and pure food supply. well, some of the regulatory problems that we actually faced early on where things like toxic colors- we moved away from using Nature's colors, typically plant extracts in preservatives, and into more Industrial Revolution or chemical. but there wasn't- this point, I'm no overriding national law, some of the problems associated with that. there was some states that had no laws across state lineshas the Food and Drug Administration of a government activists had a significant was a Firebrand of sorts, as well as being a talented scientist and his dad. dissatisfaction with the food system of the United States at the turn of the century grew into a national Outreach. there was many problems. these were highlighted in many, many national Publications like Good Housekeeping magazine. what he did, in fact, was to expand this Bureau chemistry staff and capability. let's define the problem. let's use science to deal with what at that time was it a very significant social and economic problem? Harvey Wiley established. in fact, we started to identify food additives that had a little bit of suspect. now this sounds worse than it. perhaps is some of these food additive and made over again for home consumption? it would be beneath that it tumbled out on the floor, in the dirt, in the sawdust where the workers had trampled the spit uncounted billions of consumption germs. it would be neat stored and great piles and thousands of rats would race about on it. it was too dark in the storage place to see well, but a man could run his hand over the piles and sweep off handfuls of the dried done with rats. these rats were nuisances and the Packers would poison bread out for them. they would die and then the rats, bread and meat would go into Hoppers together. this gives you an idea of the type of descriptive text that Upton

Fig.33



*summarized_text - Notepad

File Edit View

hello, my name is food toxicology would like to welcome you back once again. one of the answers, one of the responses is to establish standards of behavior, standards of practice, and legal standards so that we have a safe and pure food supply. these were highlighted in many, many national Publications like Good Housekeeping magazine. what he did, in fact, was to expand this Bureau's chemistry staff and capability. it would be neatly stored and great piles and thousands of rats would race about on it. we had a mandatory inspection of livestock before Slaughter. we had sanitary standards established for slaughterhouses and meat processing plants in and actually authorize the USDA to do ongoing monitoring, inspection, Slaughter, and processing operations. these first 1906 acts of Meat Inspection are actually with us today. okay, so this is 100 years old now we've 100 Years of history of Meat Inspection. and so what we found in this particular incident was many deaths. nobody but almighty God and I can know what I have been through these past few days. there wasn't the Delaney Clause, it did Focus entirely on carcinogens. there you have the potential channel for a significant amount of public impact. Housewives, supermarkets, and restaurants wet cranberry and menus. and So Silent Spring in a certain sense created at least one dimension of the consciousness of the United States about pesticides: pesticides in their impact on the environment and also pesticide residues in food. we also developed what we refer to as risk exposure, that no matter what the chemical, what's the lifetime exposure via all foods for a particular chemical, and especially for those chemicals that have a common mechanism of toxicity, for example, neurotoxic chemical like organophosphate pesticide- other lectures for this course, the ft ca actually also- and cosmetics standard of reasonable certainty of no harm, and this is the First Federal legislation that has that as its foundation- reasonable certainty of no harm- and it's inclusive of the adulteration and misbranding in the marketplace.

Ln 1, Col 2096 | 100% | Windows (CRLF) | UTF-8

Fig. 34

The two files of the original and summarized text are shown.

```
[ ] ques_gen = QuestionGenerator()

[ ] with open('original_text.txt','r') as t:
      original_text=t.read()

[ ] questions = ques_gen.generate(
        original_text,
        num_questions=10,
    )
    print_qa(questions,False)

    Loading questions:

    /usr/local/lib/python3.7/dist-packages/transformers/generation_utils.py:1364: UserWarning: Neither `max_length` nor `max_new_tokens` has been set, `max_length` will default to 20 (`self.config.max_length`). Controlling `max_length` via the config is deprecated and `max_length` will be removed from the config in
      UserWarning,
    1) Q: where did you receive your MD?
       A: 1. Tulane University School of Medicine
          2. Meat Inspection
          3. Focus
          4. Cover
    Enter the correct option:
     1
    Wrong answer

    2) Q: Who is now allowed to use a one in million standard for carcinogens?
       A: 1. Bureau
          2. the Food and Drug Administration
          3. Time Magazine
          4. Target
    Enter the correct option:
     1
    Wrong answer

    3) Q: how long before Thanksgiving?
       A: 1. the early 1900s
          2. 1911
          3. 1900
          4. 17 days
    Enter the correct option:
     1
    Wrong answer

    4) Q: when did muckraking come into being?
       A: 1. 100 years old
          2. more than a quarter-century
          3. the early 1900s
          4. the 1960s
    Enter the correct option:
     1
    Wrong answer

    5) Q: How long has a doctor been practicing?
       A: 1. 4 years
          2. years
          3. more than a quarter-century
          4. the early 1900s
    Enter the correct option:
     1
    Wrong answer
```

Fig.35

The Command line code where the user is given some questions from the summary, and he can choose the correct answer. From this, we can see that the user can select options and based on a evaluator it will automatically generate if the answer is right or not and finally, the user is given a score.

```python
import matplotlib.pyplot as plt
epochValues = [i+1 for i in range(4)]
epoch_accuracies = [0.5431,0.5904,0.6206,0.6371]
epoch_loses = [1.3149,1.1628,1.0816,1.0450]
plt.plot(epochValues, epoch_accuracies)
plt.title('Accuracy in epochs')
plt.xlabel('epochs')
plt.ylabel('accuracy')
plt.show()
```

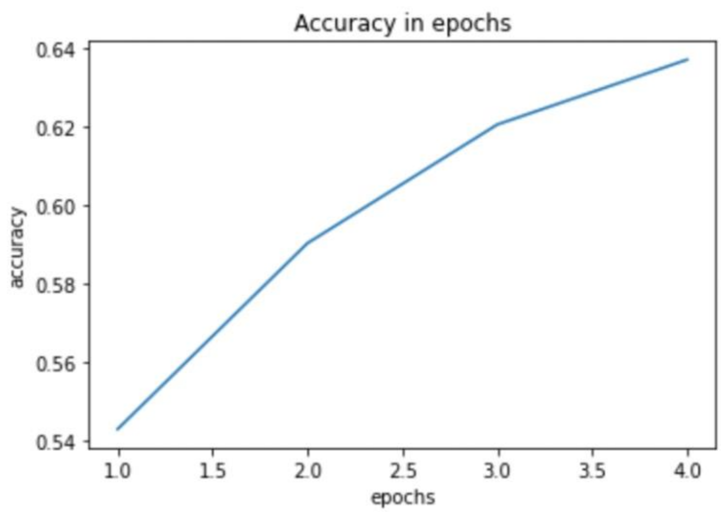


Fig.36

When we are translating the text from English to Spanish we plot the accuracy vs epochs graph.

```python
import matplotlib.pyplot as plt
epochValues = [i+1 for i in range(4)]
epoch_accuracies = [0.5431,0.5904,0.6206,0.6371]
epoch_loses = [1.3149,1.1628,1.0816,1.0450]
plt.plot(epochValues, epoch_loses)
plt.title('losses in epochs')
plt.xlabel('epochs')
plt.ylabel('losses')
plt.show()
```

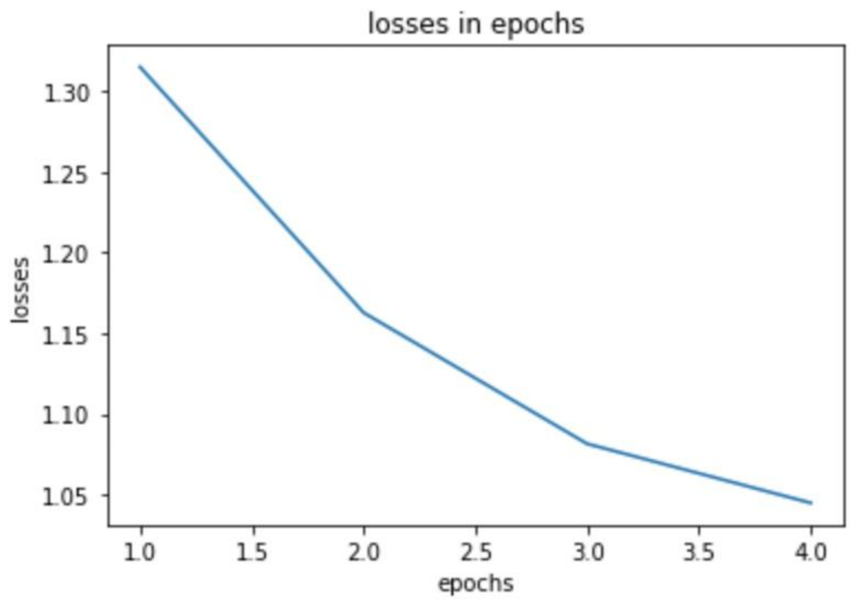


Fig.37

When we are translating the text from English to Spanish, we plot the losses vs epochs graph. We can see the accuracies of the model and the language losses and how they decrease with time. The accuracy increases after each epoch.

9. Project Management

Getting the best outcomes as well as directing the project with all the available resources is a crucial task. We have incorporated users' and participants' perspectives into this application's data gathering and analysis.

The objective of the project is to deliver a finished product that meets the requirements of the outcome. The project's objective is frequently to modify that to be more effectively achieve the project's goals.

9.1 Implementation Status Report

9.1.1 **Work Completed:**

We have worked on the speech to text, Q/A module, text translation and the smoothening techniques.

- **Responsibility and contributions:**

S.no	**Person**	**Task description**	**Contributions**
1.	Achala Samudrala	Converted Speech-text recognizer. Q&A module	24%
2.	Pavani Mangugari	Applied Smoothing techniques. Q&A module	26%
3.	Tharun Puri	Added punctuation to the recognized text. Text translation	26%
4.	Venkata Sai Preetham B	Summarized text from recognized text. Text translation	24%

- **Issues/Concerns:**

Difficulty in overcoming the errors faced by the summarizer and speech to text recognition and Q/A module. We went through lot of online sources and worked on resolving errors.

It became hard for us to communicate as we have different class schedules. However, we have managed the schedules so that we can communicate among ourselves.

10. References/Bibliography:

https://ieeexplore.ieee.org/document/9622156

https://paperswithcode.com/paper/predicting-subjective-features-from-questions

https://paperswithcode.com/paper/iit-uhh-at-semeval-2017-task-3-exploring

https://paperswithcode.com/paper/qdee-question-difficulty-and-expertise

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https://paperswithcode.com/paper/predicting-subjective-features-from-questions

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https://paperswithcode.com/paper/qdee-question-difficulty-and-expertise

https://ieeexplore.ieee.org/document/8465680

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https://ieeexplore.ieee.org/document/9315985

https://ieeexplore.ieee.org/document/8282216