# Part 1: Preprocessing the Data

```
!pip install -q transformers datasets rouge-score
```

```
#install spacy large language model
!python -m spacy download en_core_web_sm
```

```
import tensorflow_datasets as tfds
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import spacy
from tqdm.notebook import tqdm

import tensorflow_hub as hub
from tensorflow import keras
import tensorflow as tf
from IPython.display import Image
import matplotlib.pyplot as plt
```

```
nlp = spacy.load('en_core_web_sm')
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.m
```

```
cnn_ds = pd.read_csv('/content/drive/MyDrive/PlakshaNLP/Project/test.csv')
```

```
cnn_ds
```

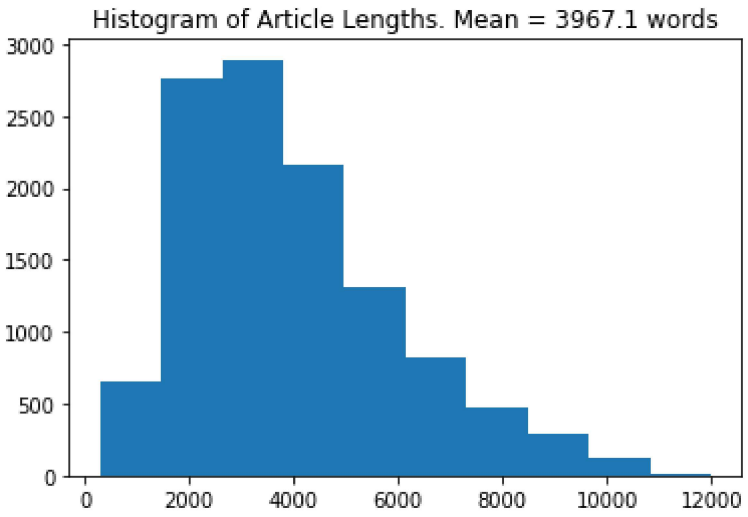
```
x='there was a man. there was a dear. the maker is dead'
```

```
import nltk
nltk.download('punkt')
from nltk.tokenize import sent_tokenize
```

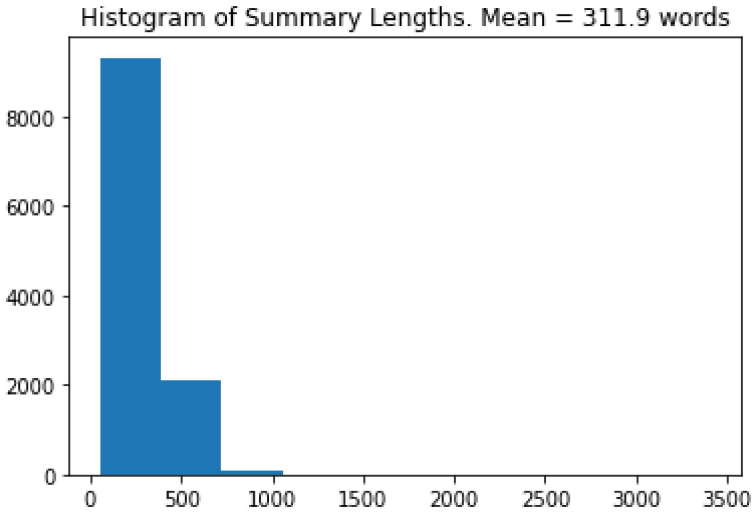
```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
```

```
cnn_df = pd.DataFrame(cnn_ds)
#cnn_df.highlights = cnn_df.highlights.apply(lambda x: x.decode('utf-8'))
cnn_df["summary"] = cnn_df.highlights.apply(lambda x: "".join(x.split("\n")) )
#cnn_df.article = cnn_df.article.apply(lambda x: x.decode('utf-8'))
```

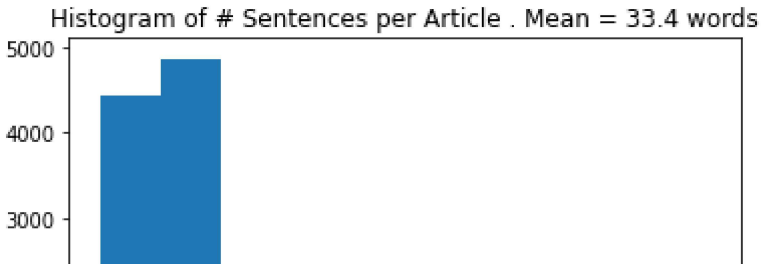
```
cnn_df["art_sents"] = cnn_df.article.apply(lambda x: len([x for x in sent_tokenize(x)]))
#x = cnn_df.article.apply(lambda x: len([x for x in sent_tokenize(x)]))
cnn_df


art_lengths = [ len(x) for x in cnn_df.article]
plt.hist(art_lengths);
plt.title("Histogram of Article Lengths. Mean = " + str(round(sum(art_lengths)/ len(art_le
```




```
sum_lengths = [ len(x) for x in cnn_df.highlights]
plt.hist(sum_lengths);
plt.title("Histogram of Summary Lengths. Mean = " + str(round(sum(sum_lengths)/ len(sum_le
```




```
# art_lengths = [ len(x) for x in cnn_df.article]
plt.hist(cnn_df.art_sents);
plt.title("Histogram of # Sentences per Article . Mean = " + str(round(sum(cnn_df.art_sent
```




## Exporting the Data for future reuse

This will ensure that we dont have to download the data everytime we run this code.

```
import os


train_df = pd.read_csv('/content/drive/MyDrive/PlakshaNLP/Project/test.csv')
test_df = pd.read_csv('/content/drive/MyDrive/PlakshaNLP/Project/validation.csv')


test_df


train_df = train_df.drop(['id'], axis = 1)
test_df = test_df.drop(['id'], axis = 1)
test_df.shape, train_df.shape
```

```
((13368, 2), (11490, 2))
```

```
#os.makedirs("data/", exist_ok=True)
#os.makedirs("data/test", exist_ok=True)
#os.makedirs("data/train", exist_ok=True)

#test_df.to_json("data/test/test.json")
#train_df.to_json("data/train/train.json")
```

## Preprocessing using Spacy library

```
def get_dicts(df, folder="test"):
  sents_dict = {}
  doc_dict = { i: {"article": df.article[i], "highlight": df.highlights[i]} for i in df.in
  raw_docs = [ doc_dict[k]["article"] for k in doc_dict.keys()]

  doc_sents = {}
  sents_list = []
  raw_sents = []
  i = 0
  min_sent_length = 14
  for k in tqdm(doc_dict.keys()):
    article = doc_dict[k]["article"]
    highlight = doc_dict[k]["highlight"]
    sents = sent_tokenize(article)
```

```
    doc_sent_ids = []
    for sent in sents:
      if (len(sent)) > min_sent_length:
        sents_dict[i] = {"docid":k, "text": str(sent)}
        sents_list.append({"sentid":i, "docid":k, "text": str(sent) })
        raw_sents.append(str(sent))
        i += 1

  return doc_dict, sents_list

test_doc_dict, test_sents_list = get_dicts(test_df)
train_doc_dict, train_sents_list = get_dicts(train_df)
```

```
100%  13368/13368 [00:14<00:00, 925.56it/s]
100%  11490/11490 [00:12<00:00, 900.83it/s]
```

## Getting labels and balanced dataset

```
from rouge_score import rouge_scorer
scorer = rouge_scorer.RougeScorer(['rouge1', 'rougeL'], use_stemmer=True)

def get_rougue_score(text, highlights, metric="rougeL"):
  max_score = 0
  for h_text in highlights:
    score =  scorer.score(text, h_text)[metric].fmeasure
    # print(score, text, "\n \t" , h_text)
    if score > max_score:
      max_score = score
  return max_score


def get_label(sent, doc_dict,  score_threshold = 0.55):
  sent_id, doc_id, sentence = sent["sentid"], sent["docid"], sent["text"]
  highlights = doc_dict[doc_id]["highlight"].split("\n")
  doc = doc_dict[doc_id]["article"]

  label_score = get_rougue_score(sentence, highlights)
  # Normalize label to 0/1 based on rogue score threshold
  label_score = 0 if label_score < score_threshold else 1
  return (sentence, doc, label_score)

def sub_sample(sents_batch, doc_dict, neg_multiplier=2):
  # get labels
  vals = [get_label(x, doc_dict)  for x in sents_batch]

  # construct arrays of sentences, corresponding documents and labels
  sents, docs, y = [], [], []
  for row in vals:
    sents.append(row[0])
    docs.append(row[1])
    y.append(row[2])
```

```
  # get balanced number of positive and negative
  sub_df = pd.DataFrame.from_dict({"sents":sents, "docs":docs, "y":y})
  pos_df = sub_df[sub_df.y == 1]
  neg_df = sub_df[sub_df.y == 0]

  print("Negative sample size:", len(neg_df))
  print("Positive sample size:", len(pos_df))

  sub_neg_df = neg_df.sample(len(pos_df)*neg_multiplier)
  balanced_df = pos_df.append(sub_neg_df)

  return balanced_df


train_bdf = sub_sample(train_sents_list, train_doc_dict)
test_bdf = sub_sample(test_sents_list, test_doc_dict)
```

```
Negative sample size: 363977
Positive sample size: 12120
Negative sample size: 415393
Positive sample size: 15155
```

```
train_bdf.to_json("/content/drive/MyDrive/PlakshaNLP/Project/train_bdf.json")
test_bdf.to_json("/content/drive/MyDrive/PlakshaNLP/Project/test_bdf.json")
```

```
!gsutil cp -r data $sum_dir
```

```
CommandException: Wrong number of arguments for "cp" command.
```

```
#define a directory to save data
sum_dir = "/content/drive/MyDrive/PlakshaNLP/Project/"
!gsutil cp -r data $sum_dir
```

```
CommandException: No URLs matched: data
```

# Part 2: Building the Model

```
!pip install -q transformers  rouge-score
```

```
import os
os.environ['CUDA_LAUNCH_BLOCKING'] = "1"

import torch
import torch.nn as nn
import torch.nn.functional as F
import numpy as np
```

```
import pandas as pd
import transformers
from torch.utils.data import Dataset, DataLoader


from transformers import AutoTokenizer, AutoModel
sentenc_model_name = "sentence-transformers/paraphrase-MiniLM-L3-v2"
tokenizer = AutoTokenizer.from_pretrained(sentenc_model_name)
```

```
Downloading: 100%  314/314 [00:00<00:00, 12.6kB/s]
Downloading: 100%  629/629 [00:00<00:00, 25.2kB/s]
Downloading: 100%  226k/226k [00:00<00:00, 295kB/s]
Downloading: 100%  455k/455k [00:01<00:00, 538kB/s]
Downloading: 100%  112/112 [00:00<00:00, 4.70kB/s]
```

```
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
from tqdm.notebook import tqdm

import os
# location to store and load models
sum_dir = "/content/drive/MyDrive/PlakshaNLP/Project/"


MAX_LEN = 512
TRAIN_BATCH_SIZE = 4
VALID_BATCH_SIZE = 4
EPOCHS = 1
LEARNING_RATE = 1e-05

# Loading Preprocessed samples from CNN/Dailymail Dataset
train_df = pd.read_json(sum_dir + "train_bdf.json")
test_df = pd.read_json(sum_dir +"test_bdf.json")
print( "Train, Test shape", train_df.shape, test_df.shape)
```

```
Train, Test shape (36360, 3) (45465, 3)
```

## DataLoader

```
class CNNDailyMailData(Dataset):
    def __init__(self, dataframe, tokenizer, max_len):
        self.len = len(dataframe)
        self.data = dataframe
        self.tokenizer = tokenizer
        self.max_len = max_len

    def __getitem__(self, index):
```

```
        sentence = str(self.data.iloc[index].sents)
        sentence = " ".join(sentence.split())

        document = str(self.data.iloc[index].docs)
        document = " ".join(document.split())

        inputs = self.tokenizer.batch_encode_plus(
            [sentence, document],
            add_special_tokens=True,
            max_length=self.max_len,
            padding="max_length",
            return_token_type_ids=True,
            truncation=True
        )
        ids = inputs['input_ids']
        mask = inputs['attention_mask']

        return {
            'sent_ids': torch.tensor(ids[0], dtype=torch.long),
            'doc_ids': torch.tensor(ids[1], dtype=torch.long),
            'sent_mask': torch.tensor(mask[0], dtype=torch.long),
            'doc_mask': torch.tensor(mask[1], dtype=torch.long),
            'targets': torch.tensor([self.data.iloc[index].y], dtype=torch.long)
        }

    def __len__(self):
        return self.len


training_set = CNNDailyMailData(train_df, tokenizer, MAX_LEN)
testing_set = CNNDailyMailData(test_df, tokenizer, MAX_LEN)

train_params = {'batch_size': TRAIN_BATCH_SIZE,
                'shuffle': True,
                'num_workers': 0
                }

test_params = {'batch_size': VALID_BATCH_SIZE,
                'shuffle': True,
                'num_workers': 0
                }

training_loader = DataLoader(training_set, **train_params)
testing_loader = DataLoader(testing_set, **test_params)
```

## Model Architecture

```
# get mean pooling for sentence bert models
# ref https://www.sbert.net/examples/applications/computing-embeddings/README.html#sentenc
def mean_pooling(model_output, attention_mask):
    token_embeddings = model_output[0] #First element of model_output contains all token e
    input_mask_expanded = attention_mask.unsqueeze(-1).expand(token_embeddings.size()).flo
```

```
        sum_embeddings = torch.sum(token_embeddings * input_mask_expanded, 1)
        sum_mask = torch.clamp(input_mask_expanded.sum(1), min=1e-9)
        return sum_embeddings / sum_mask


    # Creating the customized model, by adding a drop out and a dense layer on top of distil b
    # Note that different sentence transformer models may have different in_feature sizes
    class SentenceBertClass(torch.nn.Module):
        def __init__(self, model_name="sentence-transformers/paraphrase-MiniLM-L3-v2", in_feat
            super(SentenceBertClass, self).__init__()
            self.l1 = AutoModel.from_pretrained(model_name)
            self.pre_classifier = torch.nn.Linear(in_features*3, 768)
            self.dropout = torch.nn.Dropout(0.3)
            self.classifier = torch.nn.Linear(768, 1)
            self.classifierSigmoid = torch.nn.Sigmoid()

        def forward(self, sent_ids, doc_ids, sent_mask, doc_mask):

            sent_output = self.l1(input_ids=sent_ids, attention_mask=sent_mask)
            sentence_embeddings = mean_pooling(sent_output, sent_mask)

            doc_output = self.l1(input_ids=doc_ids, attention_mask=doc_mask)
            doc_embeddings = mean_pooling(doc_output, doc_mask)

            # elementwise product of sentence embs and doc embs
            combined_features = sentence_embeddings * doc_embeddings

            # Concatenate input features and their elementwise product
            concat_features = torch.cat((sentence_embeddings, doc_embeddings, combined_feature

            pooler = self.pre_classifier(concat_features)
            pooler = torch.nn.ReLU()(pooler)
            pooler = self.dropout(pooler)
            output = self.classifier(pooler)
            output = self.classifierSigmoid(output)

            return output


    from torch import cuda
    device = 'cuda' if cuda.is_available() else 'cpu'

    model = SentenceBertClass(model_name=sentenc_model_name)
    model.to(device);

    #Defining Loss Function and Optimizer
    loss_function = torch.nn.BCELoss()
    optimizer = torch.optim.Adam(params =  model.parameters(), lr=LEARNING_RATE)
```

```
Downloading:                                                    66.4M/66.4M [00:01<00:00,
100%                                                            60.4MB/s]
```

```
    # Defining the training function on the 80% of the dataset for tuning the distilbert model
    print_n_steps = 1000
```

```
EPOCHS = 3
acc_step_holder, loss_step_holder = [], []


def train(epoch):
    tr_loss = 0
    n_correct = 0
    nb_tr_steps = 0
    nb_tr_examples = 0
    model.train()
    for _,data in tqdm(enumerate(training_loader, 0)):
        sent_ids = data['sent_ids'].to(device, dtype = torch.long)
        doc_ids = data['doc_ids'].to(device, dtype = torch.long)
        sent_mask = data['sent_mask'].to(device, dtype = torch.long)
        doc_mask = data['doc_mask'].to(device, dtype = torch.long)
        targets = data['targets'].to(device, dtype = torch.float)

        outputs = model(sent_ids, doc_ids, sent_mask, doc_mask)
        loss = loss_function(outputs, targets)
        tr_loss += loss.item()
        n_correct += torch.count_nonzero(targets == (outputs > 0.5)).item()

        nb_tr_steps += 1
        nb_tr_examples+=targets.size(0)

        if _%print_n_steps==0:
            loss_step = tr_loss/nb_tr_steps
            accu_step = (n_correct*100)/nb_tr_examples
            print(str(_* train_params["batch_size"]) + "/" + str(len(train_df)) + " - Step
            acc_step_holder.append(accu_step), loss_step_holder.append(loss_step)
        optimizer.zero_grad()
        loss.backward()
        # # When using GPU
        optimizer.step()

    print(f'The Total Accuracy for Epoch {epoch}: {(n_correct*100)/nb_tr_examples}')
    epoch_loss = tr_loss/nb_tr_steps
    epoch_accu = (n_correct*100)/nb_tr_examples
    print(f"Training Loss Epoch: {epoch_loss}")
    print(f"Training Accuracy Epoch: {epoch_accu}")

    return

for epoch in range(EPOCHS):
    train(epoch)
```

```
9090/? [19:27<00:00, 7.87it/s]

0/36360 - Steps. Acc -> 25.0 Loss -> 0.7080827951431274
4000/36360 - Steps. Acc -> 67.38261738261738 Loss -> 0.6062356807313837
8000/36360 - Steps. Acc -> 68.2783608195902 Loss -> 0.5858562649309129
12000/36360 - Steps. Acc -> 68.9686771076308 Loss -> 0.5779726249313243
16000/36360 - Steps. Acc -> 69.2451887028243 Loss -> 0.5738538883568733
20000/36360 - Steps. Acc -> 69.4361127774445 Loss -> 0.5711713526677284
24000/36360 - Steps. Acc -> 69.85502416263957 Loss -> 0.5654657068892809
28000/36360 - Steps. Acc -> 70.2578203113841 Loss -> 0.5595857731432867
32000/36360 - Steps. Acc -> 70.44744406949131 Loss -> 0.557208480028704
36000/36360 - Steps. Acc -> 70.73658482390846 Loss -> 0.5532658475740574
The Total Accuracy for Epoch 0: 70.71507150715071
Training Loss Epoch: 0.5532537191028413
Training Accuracy Epoch: 70.71507150715071

9090/? [19:13<00:00, 8.06it/s]

0/36360 - Steps. Acc -> 100.0 Loss -> 0.31165727972984314
4000/36360 - Steps. Acc -> 75.7992007992008 Loss -> 0.4944355990719069
8000/36360 - Steps. Acc -> 74.38780609695152 Loss -> 0.5065030841950862
12000/36360 - Steps. Acc -> 74.90003332222592 Loss -> 0.5005987129747986
16000/36360 - Steps. Acc -> 74.91252186953261 Loss -> 0.5012123916950845
20000/36360 - Steps. Acc -> 75.10497900419917 Loss -> 0.49939285131635797
24000/36360 - Steps. Acc -> 75.28328611898017 Loss -> 0.4964890349150409
28000/36360 - Steps. Acc -> 75.36780459934295 Loss -> 0.4956048784577715
32000/36360 - Steps. Acc -> 75.46244219472565 Loss -> 0.4941313240382392
36000/36360 - Steps. Acc -> 75.55271636484835 Loss -> 0.4932982139910192
The Total Accuracy for Epoch 1: 75.55005500550055
Training Loss Epoch: 0.4933189037998747
Training Accuracy Epoch: 75.55005500550055

9090/? [19:18<00:00, 7.94it/s]

0/36360 - Steps. Acc -> 50.0 Loss -> 0.504364013671875
4000/36360 - Steps. Acc -> 78.6963036963037 Loss -> 0.4418542991270433
8000/36360 - Steps. Acc -> 79.29785107446277 Loss -> 0.43365769777009483
12000/36360 - Steps. Acc -> 79.2485838053982 Loss -> 0.43665888609680553
```

## Validating on Test data

```
28000/36360 - Steps. Acc -> 79.27796029138695 Loss -> 0.438034513488347
```

```
def validate_model(model, testing_loader):
    model.eval()

    n_correct = 0; n_wrong = 0; total = 0;  tr_loss = 0; nb_tr_steps = 0 ; nb_tr_examples
    with torch.no_grad():
        for _, data in enumerate(testing_loader, 0):

            sent_ids = data['sent_ids'].to(device, dtype = torch.long)
            doc_ids = data['doc_ids'].to(device, dtype = torch.long)
            sent_mask = data['sent_mask'].to(device, dtype = torch.long)
            doc_mask = data['doc_mask'].to(device, dtype = torch.long)
            targets = data['targets'].to(device, dtype = torch.float)

            outputs = model(sent_ids, doc_ids, sent_mask, doc_mask)
            loss = loss_function(outputs, targets)
            tr_loss += loss.item()

            n_correct += torch.count_nonzero(targets == (outputs > 0.5)).item()
```

```
            nb_tr_steps += 1
            nb_tr_examples+=targets.size(0)

            if _%print_n_steps==0:
                loss_step = tr_loss/nb_tr_steps
                accu_step = (n_correct*100)/nb_tr_examples
                print(str(_* test_params["batch_size"]) + "/" + str(len(train_df)) + " - S


    epoch_loss = tr_loss/nb_tr_steps
    epoch_accu = (n_correct*100)/nb_tr_examples
    print(f"Validation Loss Epoch: {epoch_loss}")
    print(f"Validation Accuracy Epoch: {epoch_accu}")

    return epoch_accu


acc = validate_model(model, testing_loader)
print("Accuracy on test data = %0.2f%%" % acc)
```

```
     0/36360 - Steps. Acc -> 100.0 Loss -> 0.21701841056346893
     4000/36360 - Steps. Acc -> 72.45254745254745 Loss -> 0.5545358245673178
     8000/36360 - Steps. Acc -> 72.26386806596702 Loss -> 0.5560186264086059
     12000/36360 - Steps. Acc -> 72.3842052649117 Loss -> 0.5529276827584253
     16000/36360 - Steps. Acc -> 72.40689827543115 Loss -> 0.5542377780823112
     20000/36360 - Steps. Acc -> 72.18556288742252 Loss -> 0.5571002556363795
     24000/36360 - Steps. Acc -> 72.01299783369439 Loss -> 0.5587622496356712
     28000/36360 - Steps. Acc -> 72.11112698185974 Loss -> 0.5577171036901495
     32000/36360 - Steps. Acc -> 72.14723159605049 Loss -> 0.5559926967292189
     36000/36360 - Steps. Acc -> 72.1808687923564 Loss -> 0.5554238062607717
     40000/36360 - Steps. Acc -> 72.04279572042796 Loss -> 0.5591030108741764
     44000/36360 - Steps. Acc -> 72.10480865375875 Loss -> 0.5586429715395967
     Validation Loss Epoch: 0.5576838044902116
     Validation Accuracy Epoch: 72.17419993401518
     Accuracy on test data = 72.17%
```

```
#Saving the model

import os
os.makedirs("models", exist_ok=True)
torch.save(model.state_dict(), "models/minilm_bal_exsum.pth")
!gsutil cp -r models $sum_dir
```

```
     Copying file://models/minilm_bal_exsum.pth...
     / [1 files][ 69.7 MiB/ 69.7 MiB]
     Operation completed over 1 objects/69.7 MiB.
```

```
!pip install -q transformers  rouge-score sentence-transformers
```

```
           |████████████████████████████████| 79 kB 7.4 MB/s
           |████████████████████████████████| 1.2 MB 72.2 MB/s
       Building wheel for sentence-transformers (setup.py) ... done
```

```
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import spacy
from tqdm.notebook import tqdm

#!pip install pyyaml==5.4.1
#import plotly.express as px

import os
import torch
import torch.nn as nn
import torch.nn.functional as F
import numpy as np

from transformers import AutoTokenizer, AutoModel
nlp = spacy.load('en_core_web_sm')

model_path = "/content/drive/MyDrive/PlakshaNLP/Project/models/minilm_bal_exsum.pth"

from torch import cuda
device = 'cuda' if cuda.is_available() else 'cpu'

#Our Trained Model
extractive_model = SentenceBertClass()
extractive_model.load_state_dict(torch.load(model_path, map_location=torch.device(device)
extractive_model.eval();


tokenizer = AutoTokenizer.from_pretrained('sentence-transformers/paraphrase-MiniLM-L3-v2')

# tokenize text as required by BERT based models
def get_tokens(text, tokenizer):
  inputs = tokenizer.batch_encode_plus(
            text,
            add_special_tokens=True,
            max_length=512,
            padding="max_length",
            return_token_type_ids=True,
            truncation=True
        )
  ids = inputs['input_ids']
  mask = inputs['attention_mask']
  return ids, mask


def predict(model,sents, doc):
  sent_id, sent_mask = get_tokens(sents,tokenizer)
  sent_id, sent_mask = torch.tensor(sent_id, dtype=torch.long),torch.tensor(sent_mask, dty

  doc_id, doc_mask = get_tokens([doc],tokenizer)
  doc_id, doc_mask = doc_id * len(sents), doc_mask* len(sents)
  doc_id, doc_mask = torch.tensor(doc_id, dtype=torch.long),torch.tensor(doc_mask, dtype=t
```

```
  preds = model(sent_id, doc_id, sent_mask, doc_mask)
  return preds
```

# Part 3: Summarize Function for our model

```
def summarize(doc, model, min_sentence_length=14, top_k=3, batch_size=3):
  doc = doc.replace("\n","")
  doc_sentences = []
  for·sent·in·nlp(doc).sents:
····if·len(sent)·>·min_sentence_length:·
·····doc_sentences.append(str(sent))
··
··doc_id, doc_mask = get_tokens([doc],tokenizer)
  doc_id, doc_mask = doc_id * batch_size, doc_mask* batch_size
  doc_id, doc_mask = torch.tensor(doc_id, dtype=torch.long),torch.tensor(doc_mask, dtype=t

  scores = []
  # run predictions using some batch size
  for i in tqdm(range(int(len(doc_sentences) / batch_size) + 1)):
    batch_start = i*batch_size
    batch_end = (i+1) * batch_size if (i+1) * batch_size < len(doc) else len(doc)-1
    batch = doc_sentences[batch_start: batch_end]
    if batch:
      preds = predict(model, batch, doc)
      scores = scores + preds.tolist()

  sent_pred_list = [{"sentence": doc_sentences[i], "score": scores[i][0], "index":i} for i
  sorted_sentences = sorted(sent_pred_list, key=lambda k: k['score'], reverse=True)

  sorted_result = sorted_sentences[:top_k]
  sorted_result = sorted(sorted_result, key=lambda k: k['index'])

  summary = [ x["sentence"] for x in sorted_result]
  summary = " ".join(summary)

  return summary, scores, doc_sentences


long_text = '''It is a beautiful afternoon, just after rain. The mist has spread around th

I reach the entrance of the temple where I’m asked to leave my shoes in the cloakroom. By

All of a sudden I see the Man with the Moustache, handling people’s shoes. He looks old an

I walk into the front yard of Dambulla Temple to see the entrance to five caves carved int

I want to learn about him, what is he doing here, where does he come from. I don’t speak h


print(long_text)

     It is a beautiful afternoon, just after rain. The mist has spread around the trees ar

     I reach the entrance of the temple where I’m asked to leave my shoes in the cloakroo
```

```
All of a sudden I see the Man with the Moustache, handling people’s shoes. He looks c

I walk into the front yard of Dambulla Temple to see the entrance to five caves carve

I want to learn about him, what is he doing here, where does he come from. I don’t sp
```

```
summary, scores, sentences = summarize(long_text, extractive_model, min_sentence_length=14
```

```
100%                                                4/4 [00:02<00:00, 1.77it/s]
```

```
summary
```

```
'I walk into the front yard of Dambulla Temple to see the entrance to five caves car
ved into the mountain. These caves have been converted into shrine rooms painted wit
h intricate patterns of religious images on the celling, following the contours of t
he rock.  When I took the 20th photo of Buddha and reached in total 100 photos of t
```

## Evaluating the model on Real HBR article using ROUGE

```
!pip install rouge
```

```
Collecting rouge
  Downloading rouge-1.0.1-py3-none-any.whl (13 kB)
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages (from ro
Installing collected packages: rouge
Successfully installed rouge-1.0.1
```

```
from rouge import Rouge
ROUGE = Rouge()
```

```
Article='''
Based on the reaction to our earlier article on the competing demands for both compassion

Take, for example, Justin (not his real name), who runs the customer relations group for a

Justin’s dilemma is typical, and the demands from both his seniors and his juniors are ent

Executives’ most frequent and salient interactions are with stakeholders (shareholders, bo

Speaking of those front lines, consider the world of the frontline employee. When it comes

How can middle managers cope with these competing pressures? Focus on two sets of actions.

Work with executives to increase compassion and change the performance dialogue
It’s our experience that most executives would be willing to demonstrate more compassion a

“Tell” is about fixing the information flow by making top leaders aware of the extent of t
```

```
"Show" recognizes that there is no substitute for firsthand experiences, and we've found t

Before taking either approach, recognize that framing is very important; if not managed we

Empower, connect, and motivate employees
Inasmuch as you need to keep showing compassion toward your staff, you don't need to fix e

Data, however, is only part of the solution. Another way middle managers can aid employees
'''


official_summary= '''
After two years of turmoil, employees need their managers to show compassion.
At the same time, executives expect their managers and their teams to deliver results.
Middle managers are often the ones feeling that tension most acutely.
How can they cope with these competing pressures? Focus on two sets of actions.
First, work to increase the organization's "compassion capacity" — that is, help equip
both senior executives and employees to shoulder more of the burden in delivering compassi
it doesn't fall entirely on you.
Second, work with both executives and employees to lower the perceived pressure of perform
'''


summary, scores, sentences = summarize(Article, extractive_model, min_sentence_length=14,
```

```
100% 11/11 [00:06<00:00, 1.87it/s]
```

```
summary
```

```
'They feel torn between performance demands from above and calls for compassion from
below. Even when senior leaders try to seek out information, most employees put on a
brave face because they're afraid to show weakness or vulnerability. Research shows
that power reduces empathy, which means they identify less with both the frontline e
```

```
ROUGE.get_scores(summary, official_summary)
```

```
[{'rouge-1': {'f': 0.25373133832368017,
   'p': 0.2786885245901639,
   'r': 0.2328767123287671},
  'rouge-2': {'f': 0.0493827112444754,
   'p': 0.06153846153846154,
   'r': 0.041237113402061855},
  'rouge-l': {'f': 0.25373133832368017,
   'p': 0.2786885245901639,
   'r': 0.2328767123287671}}]
```

## Comparing ROUGE score against the Default Summarizer

```
!pip install git+https://github.com/dmmiller612/bert-extractive-summarizer.git
```

```
from summarizer import Summarizer
```

```
default_model = Summarizer()


predicted = default_model(Article, min_length=60, ratio=0.01)


ROUGE.get_scores(predicted, official_summary)
```

```
[{'rouge-1': {'f': 0.3521126710603055,
   'p': 0.36231884057971014,
   'r': 0.3424657534246575},
  'rouge-2': {'f': 0.10810810311994179,
   'p': 0.1136363636363636363,
   'r': 0.10309278350515463},
  'rouge-l': {'f': 0.3239436569757985,
   'p': 0.3333333333333333,
   'r': 0.3150684931506849}}]
```

## Oberservations

The trained model scored F-score of 0.25 (rouge1) vs the default model with F-score of 0.35 (rouge-1).

This maybe improved by using larger pretrained BERT model instead of Sentence BERT.

✓ 0s completed at 5:20 PM