How Data Augmentation using Back-Translation Affects the Text Classification Performance

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Main aim

Description about the project: The primary objective of this project is to assess the impact of augmenting data using the "backtranslation" technique on the performance of text classification tasks. Backtranslation involves converting the original text from one language (in this case, English) into another language (in this case, French), and then translating it back into the original language. This technique proposes that during this transformation, the original text will be regenerated in a different manner, thereby producing augmented text that can be utilized effectively.

The method

Therefore, in this study, I employed the backtranslation technique to address the imbalance in the dataset. Initially, the dataset comprised the following records: (0-159, 1-219, 2-109). After applying backtranslation, the dataset was rebalanced to (0 - 219, 1 - 219, 2 - 218). Subsequently, I separately fine-tuned the BERT model (bert-base-uncased) on both the original and augmented datasets. The performance was evaluated using a separate dataset that had not undergone augmentation.

Hyper-parameters

The hyper-parameter setup used in this evaluation is , epochs = 10, batch size=16, learning rate = 2e-5, optimizer= Adam, and epsilon=1e-8.

Dataset

The Twitter dataset used in this study pertains to abortion stance classification and comprises three classes: 0-against, 1-favor, and 2-none, considering the stance target of "legalization of abortion." This dataset was sourced from "https://paperswithcode.com/dataset/tweeteval".

***Preprocessing ***

I conducted text preprocessing in two stages: 1) prior to data augmentation, and 2) before classification. During the first stage, I employed simple techniques such as removing #, @user mentions, URLs, extra spaces, line breaks, and punctuations. This approach aimed to maintain the augmented data's similarity to the original text. In contrast, for the second stage of preprocessing, I implemented more advanced techniques including stopword removal, stemming, and lemmatization.

Conclusion

The results indicate a reduction in testing accuracy from 62% to 35% with the presence of the augmented dataset. Additionally, the backtranslation technique has resulted in the generation of numerous duplicated records. Duplicate records with consistent labels essentially offer redundant information, as they fail to contribute any novel insights to the model. In fact, incorporating duplicate records may introduce bias, as the model could overly depend on this duplicated data and overestimate the significance of certain patterns, potentially leading to overfitting. However, it's noteworthy that overfitting was not observed in the results.

```
!pip install transformers
!pip install sentencepiece
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/publ
Collecting transformers
  Downloading transformers-4.28.1-py3-none-any.whl (7.0 MB)
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Requirement already satisfied: regex!=2019.12.17 in /usr/local/lib/python3.9/dist-packag
Collecting huggingface-hub<1.0,>=0.11.0
  Downloading huggingface_hub-0.13.4-py3-none-any.whl (200 kB)
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Collecting tokenizers!=0.11.3,<0.14,>=0.11.1
  Downloading tokenizers-0.13.3-cp39-cp39-manylinux_2_17_x86_64.manylinux2014_x86_64.whl
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Requirement already satisfied: typing-extensions>=3.7.4.3 in /usr/local/lib/python3.9/di
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.9/dist-packages (f
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.9/dist-packa
Requirement already satisfied: charset-normalizer~=2.0.0 in /usr/local/lib/python3.9/dis
Requirement already satisfied: urllib3<1.27,>=1.21.1 in /usr/local/lib/python3.9/dist-pa
Installing collected packages: tokenizers, huggingface-hub, transformers
Successfully installed huggingface-hub-0.13.4 tokenizers-0.13.3 transformers-4.28.1
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/publ
Collecting sentencepiece
  Downloading sentencepiece-0.1.98-cp39-cp39-manylinux_2_17_x86_64.manylinux2014_x86_64.
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 1.3/1.3 MB 55.0 MB/s eta 0:00:00
Installing collected packages: sentencepiece
Successfully installed sentencepiece-0.1.98
```

```
import nltk
from nltk.tokenize import word_tokenize
from nltk.stem import SnowballStemmer
from nltk.tokenize import word_tokenize
from nltk.corpus import wordnet
from nltk.stem import WordNetLemmatizer


nltk.download('punkt')
nltk.download('averaged_perceptron_tagger')
nltk.download('wordnet')
nltk.download('omw-1.4')
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     /root/nltk_data...
[nltk_data]   Unzipping taggers/averaged_perceptron_tagger.zip.
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data] Downloading package omw-1.4 to /root/nltk_data...
True
```

```
import torch
import torch.nn as nn
from torch.utils.data import TensorDataset, DataLoader, RandomSampler, SequentialSampler,rar
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report

import transformers
from transformers import BertForSequenceClassification, AdamW, BertConfig,BertTokenizer,get_


import random
import time
import datetime
import gc


import pandas as pd
import json
import csv
import numpy as np

import os
import time
import re


from transformers import MarianMTModel, MarianTokenizer
```

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

```
Mounted at /content/gdrive
```

```
# Setting the base path
base_path =  "/content/gdrive/MyDrive/Lakehead//NLP_Class/Project"
```

```
os.chdir(base_path)
```

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

	Unnamed: 0	text	label	label_text
0	0	we remind ourselves that love means to be will...	1	against
1	1	@user @user and most Islanders have different ...	0	none
2	2	Life is #precious & so are babies, mothers, & ...	1	against
3	3	@user too many people are taking this to serio...	0	none
4	4	Dude i won a #freeshirt from @user ! I never w...	0	none
...	...	...	...	...
482	578	Oh look!!! So not only are antichoice strongly...	2	favor
483	579	@user I don't think I have a right to use some...	2	favor
484	581	People aren't 'pro-life' they're 'pro-birth'. ...	2	favor
485	582	@user i don't follow the news, is there a new ...	0	none
486	583	@user The Gods #Law, the #Truth, is being #sup...	0	none

487 rows × 4 columns

```
# I kept a seperate dataset to evaluate the classification performance before and after data
df_test = pd.read_csv("TweetEval_testdata.csv")
df_test
```

	Unnamed: 0	text	label	label_text
0	0	Need a ProLife R.E. Agent? - Support a ProLife...	1	against
1	1	Where is the childcare program @user which you...	1	against
2	2	I get several requests with petitions to save ...	1	against
3	3	we must always see others as Christ sees us,we...	1	against
4	4	PRAYERS FOR BABIES Urgent prayer one in Lexing...	1	against
...	...	...	...	...
176	336	Every time you respond to something that frust...	0	none
177	337	Obamcare loses again in the Supreme Court. Rel...	0	none
178	342	BRAVO TO BOTH OF YOU BEAUTIFULLY EXPLAINED HOL...	2	favor
179	344	My body, my life. You fuck it up in a way I'm ...	2	favor
180	345	Thank you @user for treating me with kindness ...	0	none

```
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
device
```

```
device(type='cuda', index=0)
```

Recording class counts

```
df['label'].value_counts()
```

```
1    219
0    159
2    109
Name: label, dtype: int64
```

```
class_counts = df['label'].value_counts().reset_index()
class_counts.columns = ["class", "count"]
class_counts
```

	class	count
0	1	219
1	0	159
2	2	109

```
c1=class_counts.loc[class_counts['class'] == 0, 'count']
c2=class_counts.loc[class_counts['class'] == 1, 'count']
c3=class_counts.loc[class_counts['class'] == 2, 'count']


c1=int(c1)
c2=int(c2)
c3=int(c3)



df_test['label'].value_counts()
```

```
0    63
1    60
2    58
Name: label, dtype: int64
```

Preprocessing

```
# Perform some preprocessing relevant to Twitter text. I do not perform stemming, lemmatizat
# more similar to the original text since we are performing data augmentation

def clean_text(text: str):
    text = text.lower() #change case to lower
    text = text.strip()  # Remove extra spaces
    text = text.replace("#", "")  # Remove hashtags
    text = text.replace("@user", "")  # Remove hashtags
    text = re.sub(r"http\S+", "", text)  # Removed urls
    text = re.sub(r"[^\w\s]", "", text)  # Removed punctuations #Sentence
    return text


df["text"] = df.text.apply(lambda x: clean_text(x))



df
```

	Unnamed: 0	text	label	label_text
0	0	we remind ourselves that love means to be will...	1	against
1	1	and most islanders have different definition...	0	none
2	2	life is precious so are babies mothers fathe...	1	against
3	3	too many people are taking this to seriously ...	0	none
4	4	dude i won a freeshirt from i never win anyt...	0	none
...	...	...	...	...
482	578	oh look so not only are antichoice strongly ag...	2	favor
483	579	i dont think i have a right to use someone el...	2	favor
484	581	people arent prolife theyre probirth when a mo...	2	favor
485	582	i dont follow the news is there a new law tha...	0	none
486	583	the gods law the truth is being supressed the...	0	none

487 rows × 4 columns

Data Augmentation using Backtranslation

Using Backtranslating technique, I convert the selected English text into french and then convert it to English to use as augmented data.

the first model translating English to French

```
# Get the name of the first model
first_model_name = 'Helsinki-NLP/opus-mt-en-fr'

# Get the tokenizer
first_model_tkn = MarianTokenizer.from_pretrained(first_model_name)

# Load the pretrained model based on the name
first_model = MarianMTModel.from_pretrained(first_model_name)
```

```
Downloading (…)olve/main/source.spm: 100%  778k/778k [00:00<00:00, 8.71MB/s]
Downloading (…)olve/main/target.spm: 100%  802k/802k [00:00<00:00, 8.56MB/s]
Downloading (…)olve/main/vocab.json: 100%  1.34M/1.34M [00:00<00:00, 15.4MB/s]
Downloading (…)okenizer_config.json: 100%  42.0/42.0 [00:00<00:00, 1.87kB/s]
```

the second model translating French to English.

```
# Get the name of the second model
second_model_name = 'Helsinki-NLP/opus-mt-fr-en'

# Get the tokenizer
second_model_tkn = MarianTokenizer.from_pretrained(second_model_name)

# Load the pretrained model based on the name
second_model = MarianMTModel.from_pretrained(second_model_name)
```

```
Downloading (…)olve/main/source.spm: 100%  802k/802k [00:00<00:00, 8.77MB/s]
Downloading (…)olve/main/target.spm: 100%  778k/778k [00:00<00:00, 8.15MB/s]
Downloading (…)olve/main/vocab.json: 100%  1.34M/1.34M [00:00<00:00, 12.0MB/s]
Downloading (…)okenizer_config.json: 100%  42.0/42.0 [00:00<00:00, 815B/s]
```

to properly implement the translation feature, we need to add the special token >>{tgt}<< in front of each text that needs to be translated. {tgt} is either fr or en.

```
def format_batch_texts(language_code, batch_texts):

  formated_bach = ">>{}<< {}".format(language_code, batch_texts)

  return formated_bach
```

function responsible for the translation of the batch of texts

```
def perform_translation(batch_texts, model, tokenizer, language="fr"):
    # Prepare the text data into appropriate format for the model
    formated_batch_texts = format_batch_texts(language, batch_texts)

    # Generate translation using model
    translated = model.generate(**tokenizer(formated_batch_texts, return_tensors="pt", paddi

    # Convert the generated tokens indices back into text
    translated_texts = tokenizer.decode(translated[0], skip_special_tokens=True)

    return translated_texts



def perform_back_translation(batch_texts, original_language="en", temporary_language="fr"):

  # Translate from Original to Temporary Language
  tmp_translated_batch = perform_translation(batch_texts, first_model, first_model_tkn, temp

  # Translate Back to English
  back_translated_batch = perform_translation(tmp_translated_batch, second_model, second_moc

  return back_translated_batch


# Declare global lists to store results

augmented_data =[]
augmented_data_labels =[]
original_data = []


def appending_data(new_text, label, original):

  augmented_data.append(new_text)
  augmented_data_labels.append(label)
  original_data.append(original)
```

```
# Call API to generate text

class_1=0
class_2=0
class_3=0

# Set the max records upto 219 as class 1 has this highest number of records
max_records=219
i=0

for index, row in df.iterrows():

  original_text = row['text']
  class_label = row['label']

  print(i)
  i+=1

  # calling the function to add a token to the text
  formated_text = format_batch_texts("fr", original_text)
  # print(formated_text)
  # print(formated_exp)
  # print("\n")


  if(class_label==0 and c1+class_1 < max_records):
    augmented_text = perform_back_translation(formated_text)
    appending_data(augmented_text, class_label, original_text)
    class_1+=1

  elif (class_label==1 and c2+class_2 < max_records):
    augmented_text = perform_back_translation(formated_text)
    appending_data(augmented_text, class_label, original_text)
    class_2+=1

  elif (class_label==2 and c3+class_3 < max_records):
    augmented_text = perform_back_translation(formated_text)
    appending_data(augmented_text, class_label, original_text)
    class_3+=1
```

```
0
1
/usr/local/lib/python3.9/dist-packages/transformers/generation/utils.py:1313: UserWar
  warnings.warn(
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```

```
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53
```

```
New_dataset = pd.DataFrame({'original_text': original_data, 'new_text': augmented_data, 'lab
```

```
New_dataset
```

	original_text	new_text	label
0	and most islanders have different definition...	Most islanders have different definitions of r...	0
1	too many people are taking this to seriously ...	Too many people take this seriously.	0
2	dude i won a freeshirt from i never win anyt...	Dude I won a freeshirt from I never won anythi...	0
3	like yall can try and push your views on me an...	As Yall can try and push your views on me anyw...	0
4	just because it is legal doesnt make it god ho...	Just because it's legal doesn't make God the h...	0
...	...	...	...
164	complications come with all types of medical ...	· Complications come with all types of medical...	2
165	what doesnt reduce abortions making it illegal...	What does not reduce abortions makes it illega...	2

```
New_dataset['label'].value_counts()
```

```
2    109
0     60
Name: label, dtype: int64
```

```
New_dataset.to_csv("augmented_data.csv", index=False)
```

```
New_dataset = pd.read_csv("augmented_data.csv")
```

Combine augmented data with original dataset

```
# prepare original dataset and testing set
originaldata = df.drop(['Unnamed: 0', 'label_text'], axis=1)
originaldata

testdata = df_test.drop(['Unnamed: 0', 'label_text'], axis=1)
testdata
```

	text	label
0	Need a ProLife R.E. Agent? - Support a ProLife...	1
1	Where is the childcare program @user which you...	1
2	I get several requests with petitions to save ...	1
3	we must always see others as Christ sees us,we...	1
4	PRAYERS FOR BABIES Urgent prayer one in Lexing...	1
...	...	...
176	Every time you respond to something that frust...	0
177	Obamcare loses again in the Supreme Court. Rel...	0
178	BRAVO TO BOTH OF YOU BEAUTIFULLY EXPLAINED HOL...	2
179	My body, my life. You fuck it up in a way I'm ...	2
180	Thank you @user for treating me with kindness ...	0

181 rows × 2 columns

```
# prepare augmented dataset
augmented = New_dataset.drop(['original_text'], axis=1)
augmented
```

	new_text	label
0	Most islanders have different definitions of r...	0
1	Too many people take this seriously.	0
2	Dude I won a freeshirt from I never won anythi...	0
3	As Yall can try and push your views on me anyw...	0
4	Just because it's legal doesn't make God the h...	0
...	...	...
164	· Complications come with all types of medical...	2
165	What does not reduce abortions makes it illega...	2
166	So look at not only the anti-choice is strongl...	2
167	I don't think I have the right to use someone ...	2
168	• People are not proliferated they are prolife...	2

169 rows × 2 columns

```
frames = [originaldata, augmented.rename(columns={'new_text':'text'})]
final = pd.concat(frames, ignore_index=True)
final
```

	text	label
0	we remind ourselves that love means to be will...	1
1	and most islanders have different definition...	0
2	life is precious so are babies mothers fathe...	1
3	too many people are taking this to seriously ...	0
4	dude i won a freeshirt from i never win anyt...	0
...	...	...
651	· Complications come with all types of medical...	2
652	What does not reduce abortions makes it illega...	2
653	So look at not only the anti-choice is strongl...	2
654	I don't think I have the right to use someone ...	2
655	• People are not proliferated they are prolife...	2

656 rows × 2 columns

```
final['label'].value_counts()
```

```
1    219
0    219
2    218
Name: label, dtype: int64
```

```
final.to_csv("final_dataset.csv", index=False)
```

Preprocessing data for classification

In addition to basic preprocessing, perform further preprocessing, such as stop word removal, stemming, lemmatization.

```
# This is the function to map NTLK position tags - for lemmatizing
def get_wordnet_pos(tag):
    if tag.startswith('J'):
        return wordnet.ADJ
    elif tag.startswith('V'):
        return wordnet.VERB
    elif tag.startswith('N'):
        return wordnet.NOUN
    elif tag.startswith('R'):
        return wordnet.ADV
    else:
        return wordnet.NOUN
```

```
# Use a tokenizer from the NLTK library

def preprocessing_stage2(text: str):

    text = text.lower() #change case to lower
    text = text.strip()  # Remove extra spaces
    text = text.replace("#", "")  # Remove hashtags
    text = text.replace("@user", "")  # Remove hashtags
    text = re.sub(r"http\S+", "", text)  # Removed urls
    text = re.sub(r"[^\w\s]", "", text)  # Removed punctuations #Sentence


    processed_sentence = []
    stemmed_sentence = []
    lemmatized_sentence = []


    # First stopword removal-------------------
    stopwords = ["that", "and", "is", "it", "a", "an", "the", "this",  "to"]

    # Tokenize the sentence
    words = word_tokenize(text)
    for w in words:
        if w not in stopwords:
            processed_sentence.append(w)
    text = " ".join(processed_sentence)


    #second stemming--------------------------------
    # Initialize the stemmer
    snow = SnowballStemmer('english')

    # Tokenize the sentence
    words = word_tokenize(text)
    for w in words:
        # Stem the word/token
        stemmed_sentence.append(snow.stem(w))
    stemmed_text = " ".join(stemmed_sentence)


    #thrid lemmatization----------------------------------------
    # Initialize the lemmatizer
    wl = WordNetLemmatizer()

    # Tokenize the sentence
    words = word_tokenize(stemmed_text)
    # Get position tags
    word_pos_tags = nltk.pos_tag(words)
    # Map the position tag and lemmatize the word or token
    for idx, tag in enumerate(word_pos_tags):
        lemmatized_sentence.append(wl.lemmatize(tag[0], get_wordnet_pos(tag[1])))
```

```
    lemmatized_text = " ".join(lemmatized_sentence)

    return lemmatized_text


originaldata["text"] = originaldata.text.apply(lambda x: preprocessing_stage2(x))
final["text"] = final.text.apply(lambda x: preprocessing_stage2(x))
testdata["text"] = testdata.text.apply(lambda x: preprocessing_stage2(x))


originaldata
```

	text	label
0	we remind ourselv love mean be will give until...	1
1	most island have differ definit of time access...	0
2	life precious so be babi mother father pleas s...	1
3	too mani peopl be take serious semst	0
4	dude i win freeshirt from i never win anyth lo...	0
...	...	...
482	oh look so not onli be antichoic strong agains...	2
483	i dont think i have right use someon el bodi w...	2
484	peopl arent prolif theyr probirth when mother ...	2
485	i dont follow news there new law all gay peopl...	0
486	god law truth be supress they thing they be et...	0

487 rows × 2 columns

```
final
```

	text	label
0	we remind ourselv love mean be will give until...	1
1	most island have differ definit of time access...	0
2	life precious so be babi mother father pleas s...	1
3	too mani peopl be take serious semst	0
4	dude i win freeshirt from i never win anyth lo...	0
...	...	...
651	complic come with all type of medic procedur d...	2
652	what doe not reduc abort make illeg what make ...	2
653	so look at not onli antichoic strong against p...	2
654	i dont think i have right use someon el bodi w...	2
655	peopl be not prolifer they be prolifer when mo...	2

656 rows × 2 columns

Perform Classification

Original dataset

```
def to_list(dataset):
  labels = dataset['label'].tolist()
  texts = dataset['text'].tolist()

  print(pd.Series(labels).value_counts())

  return labels, texts



label_list, texts = to_list(originaldata)
```

```
1    219
0    159
2    109
dtype: int64
```

```
# Load the BERT tokenizer
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased', do_lower_case=True)
```

```
Downloading (…)solve/main/vocab.txt:                    232k/232k [00:00<00:00,
100%                                                    3.47MB/s]
Downloading (…)okenizer_config.json:                    28.0/28.0 [00:00<00:00,
100%                                                    565B/s]
```

```
max_len = 0

# For every tweet.
for sent in texts:

    # Tokenize the text and add `[CLS]` and `[SEP]` tokens.
    input_ids = tokenizer.encode(sent, add_special_tokens=True)

    # Update the maximum sentence length.
    max_len = max(max_len, len(input_ids))

print('Max sentence length: ', max_len)
```

```
Max sentence length:  41
```

```
input_ids = []
attention_masks = []

# For every tweet...
for text in texts:
    encoded_dict = tokenizer.encode_plus(
                        text,                      # Sentence to encode.
                        add_special_tokens = True, # Add '[CLS]' and '[SEP]'
                        max_length = max_len,           # Pad & truncate all sentences.
                        truncation = True,
                        pad_to_max_length = True,
                        return_attention_mask = True,   # Construct attn. masks.
                        return_tensors = 'pt',     # Return pytorch tensors.
                   )

    # Add the encoded sentence to the list.
    input_ids.append(encoded_dict['input_ids'])

    # And its attention mask (simply differentiates padding from non-padding).
    attention_masks.append(encoded_dict['attention_mask'])

# Convert the lists into tensors.
input_ids = torch.cat(input_ids, dim=0)
attention_masks = torch.cat(attention_masks, dim=0)
labels = torch.tensor(label_list)

# Print sentence 0, now as a list of IDs.
print('Original: ', texts[0])
print('Token IDs:', input_ids[0])
```

```
/usr/local/lib/python3.9/dist-packages/transformers/tokenization_utils_base.py:2354: Fut
  warnings.warn(
Original:  we remind ourselv love mean be will give until hurt mother teresa
Token IDs: tensor([  101,  2057, 10825, 14635,  2884,  2615,  2293,  2812,  2022,  2097,
         2507,  2127,  3480,  2388, 12409,   102,     0,     0,     0,     0,
            0,     0,     0,     0,     0,     0,     0,     0,     0,     0,
            0,     0,     0,     0,     0,     0,     0,     0,     0,     0,
            0])
```

```
# Combine the training inputs into a TensorDataset.
dataset = TensorDataset(input_ids, attention_masks, labels)

# Create a 80-20 train-validation split.

train_size = int(0.8 * len(dataset))
val_size = len(dataset)  - train_size

# Divide the dataset by randomly selecting samples.
train_dataset, val_dataset = random_split(dataset, [train_size, val_size])

print('{:>5,} training samples'.format(train_size))
print('{:>5,} validation samples'.format(val_size))
```

```
  389 training samples
   98 validation samples
```

```

batch_size = 16


train_dataloader = DataLoader(
            train_dataset,  # The training samples.
            sampler = RandomSampler(train_dataset), # Select batches randomly
            batch_size = batch_size # Trains with this batch size.
        )

# For validation the order doesn't matter, so we'll just read them sequentially.
validation_dataloader = DataLoader(
            val_dataset, # The validation samples.
            sampler = SequentialSampler(val_dataset), # Pull out batches sequentially.
            batch_size = batch_size # Evaluate with this batch size.
        )


# Load BertForSequenceClassification, the pretrained BERT model with a single
# linear classification layer on top.

model = BertForSequenceClassification.from_pretrained(
    "bert-base-uncased", # Use the 12-layer BERT model, with an uncased vocab.
    num_labels = 3, # The number of output labels--3 for stance classification.
    output_attentions = False, # Whether the model returns attentions weights.
    output_hidden_states = False, # Whether the model returns all hidden-states.
)

model = model.to(device)
```

```
Downloading pytorch_model.bin:  100%  440M/440M [00:01<00:00, 297MB/s]
Some weights of the model checkpoint at bert-base-uncased were not used when initializir
- This IS expected if you are initializing BertForSequenceClassification from the checkp
- This IS NOT expected if you are initializing BertForSequenceClassification from the ch
Some weights of BertForSequenceClassification were not initialized from the model checkp
```

```
optimizer = AdamW(model.parameters(),
                  lr = 2e-5, # args.learning_rate - default is 5e-5, our notebook had 2e-5
                  eps = 1e-8 # args.adam_epsilon  - default is 1e-8.
                )
```

```
/usr/local/lib/python3.9/dist-packages/transformers/optimization.py:391: FutureWarning:
  warnings.warn(
```

```
epochs = 10

# Total number of training steps is [number of batches] x [number of epochs].
total_steps = len(train_dataloader) * epochs

# Create the learning rate scheduler.
scheduler = get_linear_schedule_with_warmup(optimizer,
                                            num_warmup_steps = 0,
                                            num_training_steps = total_steps)
```

```
total_steps
```

```
250
```

```
# Function to calculate the accuracy of our predictions vs labels
def flat_accuracy(preds, labels):
    pred_flat = np.argmax(preds, axis=1).flatten()
    labels_flat = labels.flatten()
    return np.sum(pred_flat == labels_flat) / len(labels_flat)


def format_time(elapsed):
    '''
    Takes a time in seconds and returns a string hh:mm:ss
    '''
    # Round to the nearest second.
    elapsed_rounded = int(round((elapsed)))
    # Format as hh:mm:ss
    return str(datetime.timedelta(seconds=elapsed_rounded))
```

```
seed_val = 42
random.seed(seed_val)
np.random.seed(seed_val)
torch.manual_seed(seed_val)
torch.cuda.manual_seed_all(seed_val)
training_stats = []
t_acc=[]
t_loss=[]
v_acc=[]
v_loss=[]

# Measure the total training time for the whole run.
total_t0 = time.time()

# For each epoch...
for epoch_i in range(0, epochs):

    #               Training
    print("")
    print('======== Epoch {:} / {:} ========'.format(epoch_i + 1, epochs))
    print('Training...')

    # Measure how long the training epoch takes.
    t0 = time.time()
    total_train_loss = 0
    total_train_accuracy = 0
    model.train()

    for step, batch in enumerate(train_dataloader):
        b_input_ids = batch[0].to(device)
        b_input_mask = batch[1].to(device)
        b_labels = batch[2].to(device)
        optimizer.zero_grad()
        output = model(b_input_ids,
                       token_type_ids=None,
                       attention_mask=b_input_mask,
                       labels=b_labels)
        # ------------------------------------------------------------ Added by me
        # Move logits and labels to CPU if we are using GPU
        logits = output.logits
        logits = logits.detach().cpu().numpy()
        label_ids = b_labels.to('cpu').numpy()

        total_train_accuracy += flat_accuracy(logits, label_ids)
        # ------------------------------------------------------------

        loss = output.loss
        total_train_loss += loss.item()
        # Perform a backward pass to calculate the gradients.
        loss.backward()
        torch.nn.utils.clip_grad_norm_(model.parameters(), 1.0)
```

```
    optimizer.step()
    # Update the learning rate.
    scheduler.step()

# Report the final accuracy for this validation run.
avg_train_accuracy = total_train_accuracy / len(train_dataloader)
print("  Train Accuracy: {0:.2f}".format(avg_train_accuracy))
# ------------------------------------------------

# Calculate the average loss over all of the batches.
avg_train_loss = total_train_loss / len(train_dataloader)

# Measure how long this epoch took.
training_time = format_time(time.time() - t0)
print("")
print("  Average training loss: {0:.2f}".format(avg_train_loss))
print("  Training epcoh took: {:}".format(training_time))



#               Validation
# After the completion of each training epoch, measure our performance on
# the validation set.
print("")
print("Running Validation...")
t0 = time.time()

model.eval()
# Tracking variables
total_eval_accuracy = 0
best_eval_accuracy = 0
total_eval_loss = 0
nb_eval_steps = 0


# Evaluate data for one epoch
for batch in validation_dataloader:
    b_input_ids = batch[0].to(device)
    b_input_mask = batch[1].to(device)
    b_labels = batch[2].to(device)

    with torch.no_grad():
        output= model(b_input_ids,
                              token_type_ids=None,
                              attention_mask=b_input_mask,
                              labels=b_labels)
    loss = output.loss
    total_eval_loss += loss.item()
    # Move logits and labels to CPU if we are using GPU
    logits = output.logits
    logits = logits.detach().cpu().numpy()
```

```
        label_ids = b_labels.to('cpu').numpy()

        total_eval_accuracy += flat_accuracy(logits, label_ids)

    # Report the final accuracy for this validation run.
    avg_val_accuracy = total_eval_accuracy / len(validation_dataloader)
    print("  Accuracy: {0:.2f}".format(avg_val_accuracy))
    # Calculate the average loss over all of the batches.
    avg_val_loss = total_eval_loss / len(validation_dataloader)
    # Measure how long the validation run took.
    validation_time = format_time(time.time() - t0)
    if avg_val_accuracy > best_eval_accuracy:
        torch.save(model, 'bert_model1')
        best_eval_accuracy = avg_val_accuracy
    print("  Validation Loss: {0:.2f}".format(avg_val_loss))


    # ------------------------------------------------------------
    t_acc.append(avg_train_accuracy)
    t_loss.append(avg_train_loss)
    v_acc.append(avg_val_accuracy)
    v_loss.append(avg_val_loss)
    #-------------------------------------------------------------

    training_stats.append(
        {
            'epoch': epoch_i + 1,
            'Training Loss': avg_train_loss,
            'Training Accur': avg_train_accuracy,
            'Valid. Loss': avg_val_loss,
            'Valid. Accur.': avg_val_accuracy,
            'Training Time': training_time,
            'Validation Time': validation_time
        }
    )
print("")
print("Training complete!")

print("Total training took {:} (h:mm:ss)".format(format_time(time.time()-total_t0)))
```

```
 ======== Epoch 1 / 10 ========
 Training...
   Train Accuracy: 0.44

   Average training loss: 1.06
   Training epcoh took: 0:00:06

 Running Validation...
   Accuracy: 0.59
   Validation Loss: 0.94
```

```
======== Epoch 2 / 10 ========
Training...
  Train Accuracy: 0.64

  Average training loss: 0.91
  Training epcoh took: 0:00:03

Running Validation...
  Accuracy: 0.61
  Validation Loss: 0.88

======== Epoch 3 / 10 ========
Training...
  Train Accuracy: 0.72

  Average training loss: 0.73
  Training epcoh took: 0:00:03

Running Validation...
  Accuracy: 0.48
  Validation Loss: 1.12

======== Epoch 4 / 10 ========
Training...
  Train Accuracy: 0.78

  Average training loss: 0.61
  Training epcoh took: 0:00:03

Running Validation...
  Accuracy: 0.61
  Validation Loss: 0.88

======== Epoch 5 / 10 ========
Training...
  Train Accuracy: 0.86

  Average training loss: 0.44
  Training epcoh took: 0:00:03

Running Validation...
  Accuracy: 0.68
  Validation Loss: 0.81

======== Epoch 6 / 10 ========
Training...
```

```
from sklearn.metrics import classification_report, confusion_matrix
from sklearn import metrics
import matplotlib.pyplot as plt
import numpy as np
```

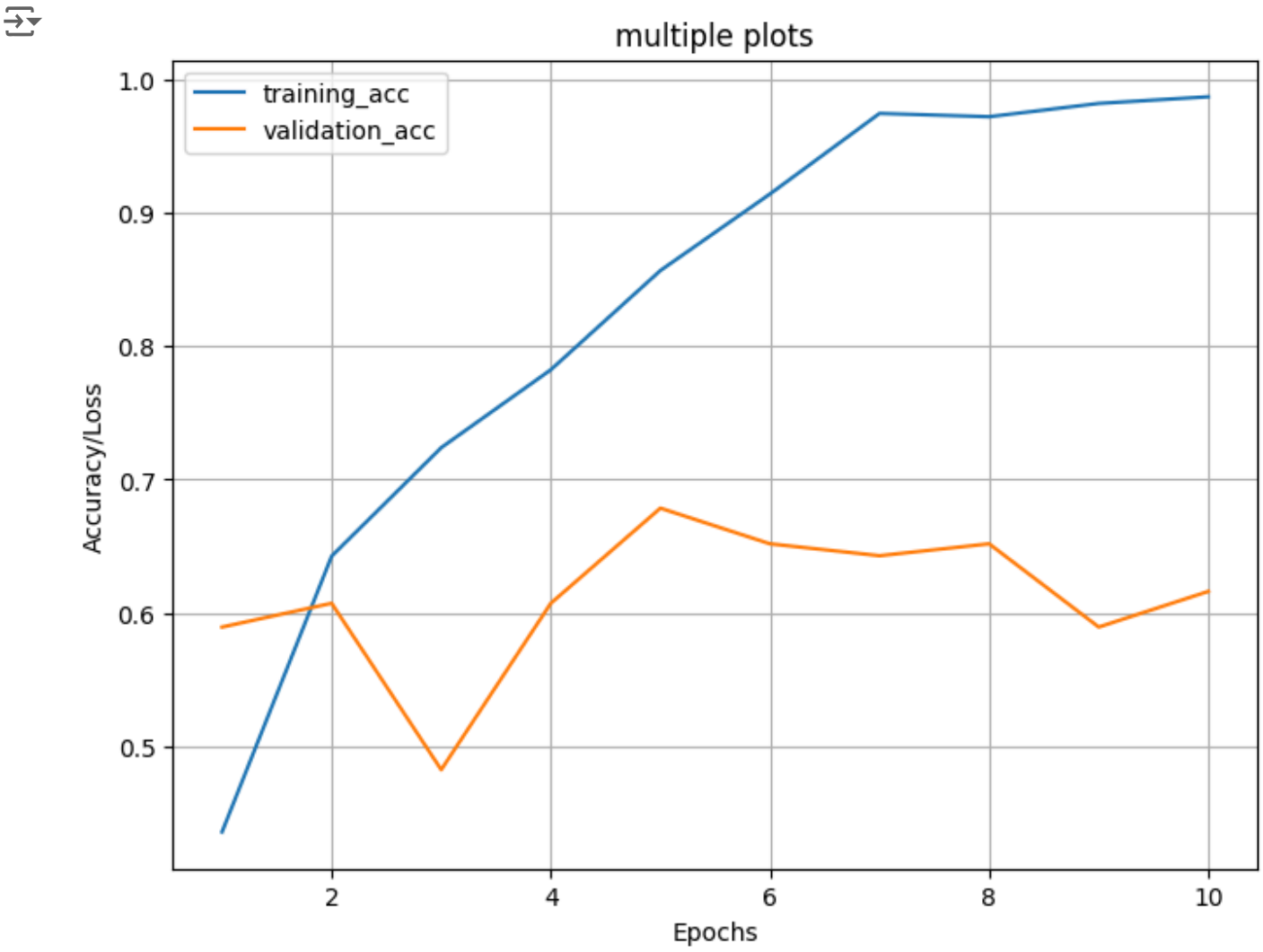
```
x = np.array([1, 2, 3, 4,5,6,7,8,9,10])
y = t_acc
y2 = v_acc

fig, ax = plt.subplots(figsize=(8,6))

plt.plot(x, y, label='training_acc')
plt.plot(x, y2, label='validation_acc')
plt.legend(loc="upper left")
plt.grid()

# for index in range(len(x)):
#   ax.text(x[index], y[index], y[index], size=12)

plt.xlabel("Epochs")
plt.ylabel("Accuracy/Loss")
plt.title('multiple plots')
plt.show()
```



Testing the performance

```
testlabels, testtexts = to_list(testdata)
```

```
0    63
1    60
2    58
dtype: int64
```

```
test_input_ids = []
test_attention_masks = []
for tweet in testtexts:
    encoded_dict = tokenizer.encode_plus(
                        tweet,
                        add_special_tokens = True,
                        max_length = max_len,
                        pad_to_max_length = True,
                        return_attention_mask = True,
                        return_tensors = 'pt',
                   )
    test_input_ids.append(encoded_dict['input_ids'])
    test_attention_masks.append(encoded_dict['attention_mask'])

test_input_ids = torch.cat(test_input_ids, dim=0)
test_attention_masks = torch.cat(test_attention_masks, dim=0)
```

```
Truncation was not explicitly activated but `max_length` is provided a specific value, p
/usr/local/lib/python3.9/dist-packages/transformers/tokenization_utils_base.py:2354: Fut
  warnings.warn(
```

```
test_dataset = TensorDataset(test_input_ids, test_attention_masks)
test_dataloader = DataLoader(
            test_dataset, # The validation samples.
            sampler = SequentialSampler(test_dataset), # Pull out batches sequentially.
            batch_size = batch_size # Evaluate with this batch size.
        )
```

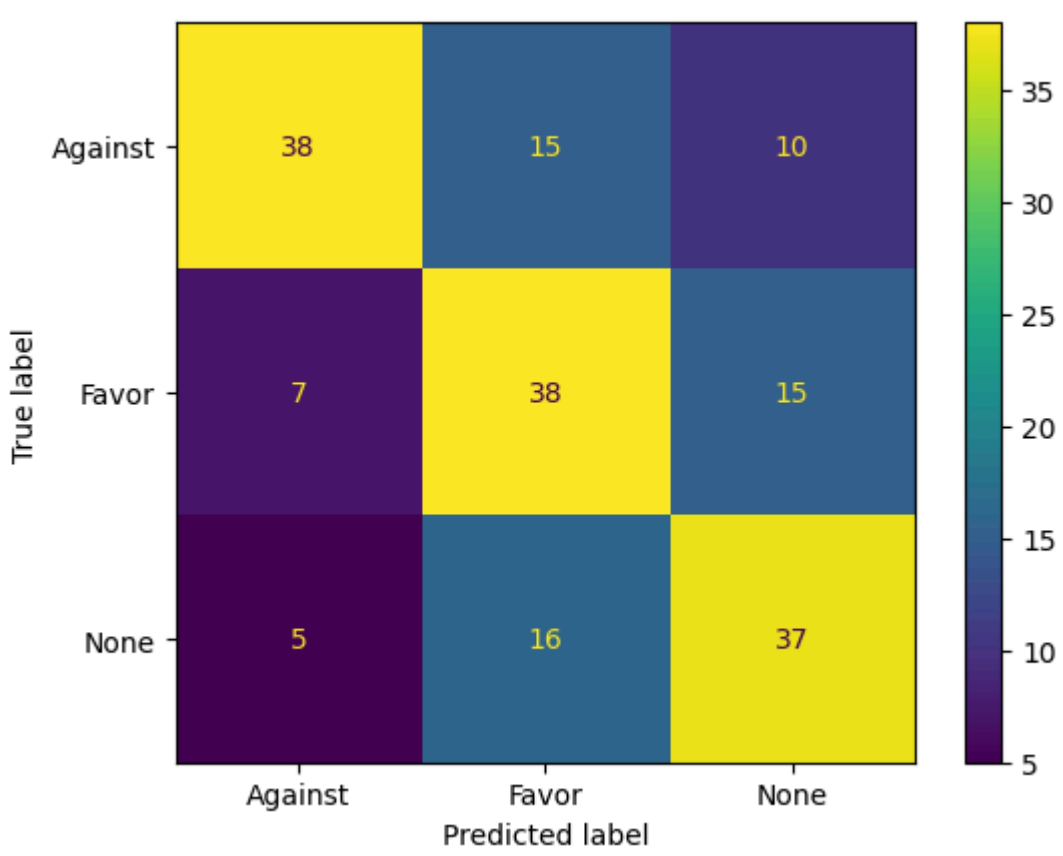
```
predictions = []
my_predictions=[]
for batch in test_dataloader:
        b_input_ids = batch[0].to(device)
        b_input_mask = batch[1].to(device)
        # b_labels = batch[2].to(device)
        with torch.no_grad():
            output= model(b_input_ids,
                                token_type_ids=None,
                                attention_mask=b_input_mask)
            logits = output.logits
            logits = logits.detach().cpu().numpy()
            pred_flat = np.argmax(logits, axis=1).flatten()

            predictions.extend(list(pred_flat))


target_names = ['Against', 'Favor', 'None']

confusion_matrix = metrics.confusion_matrix(testlabels, predictions)
cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = confusion_matrix, display_lab
cm_display.plot()
plt.show()


print(classification_report(testlabels, predictions,target_names=target_names))
```



	precision	recall	f1-score	support
Against	0.76	0.60	0.67	63
Favor	0.55	0.63	0.59	60
None	0.60	0.64	0.62	58
accuracy			0.62	181
macro avg	0.64	0.62	0.63	181
weighted avg	0.64	0.62	0.63	181

Classification after augmentation

```
label_list, texts = to_list(final)
```

```
1    219
0    219
2    218
dtype: int64
```

```
max_len = 0

for sent in texts:

    input_ids = tokenizer.encode(sent, add_special_tokens=True)

    max_len = max(max_len, len(input_ids))

print('Max sentence length: ', max_len)
```

```
Max sentence length:  41
```

```
input_ids = []
attention_masks = []

for text in texts:
    encoded_dict = tokenizer.encode_plus(
                        text,
                        add_special_tokens = True,
                        max_length = max_len,
                        truncation = True,
                        pad_to_max_length = True,
                        return_attention_mask = True,
                        return_tensors = 'pt',
                   )


    input_ids.append(encoded_dict['input_ids'])

    attention_masks.append(encoded_dict['attention_mask'])


input_ids = torch.cat(input_ids, dim=0)
attention_masks = torch.cat(attention_masks, dim=0)
labels = torch.tensor(label_list)


print('Original: ', texts[0])
print('Token IDs:', input_ids[0])
```

```
/usr/local/lib/python3.9/dist-packages/transformers/tokenization_utils_base.py:2354: Fut
  warnings.warn(
Original:  we remind ourselv love mean be will give until hurt mother teresa
Token IDs: tensor([  101,  2057, 10825, 14635,  2884,  2615,  2293,  2812,  2022,  2097,
         2507,  2127,  3480,  2388, 12409,   102,     0,     0,     0,     0,
            0,     0,     0,     0,     0,     0,     0,     0,     0,     0,
            0,     0,     0,     0,     0,     0,     0,     0,     0,     0,
            0])
```

```
dataset = TensorDataset(input_ids, attention_masks, labels)

train_size = int(0.8 * len(dataset))
#val_size = int(0.2 * len(dataset))
val_size = len(dataset)  - train_size


train_dataset, val_dataset = random_split(dataset, [train_size, val_size])

print('{:>5,} training samples'.format(train_size))
print('{:>5,} validation samples'.format(val_size))
```

```
  524 training samples
  132 validation samples
```

```
train_dataloader = DataLoader(
            train_dataset,
            sampler = RandomSampler(train_dataset),
            batch_size = batch_size
        )

validation_dataloader = DataLoader(
            val_dataset,
            sampler = SequentialSampler(val_dataset),
            batch_size = batch_size


model = BertForSequenceClassification.from_pretrained(
    "bert-base-uncased",
    num_labels = 3,
    output_attentions = False,
    output_hidden_states = False,
)


model = model.to(device)
```

```
Some weights of the model checkpoint at bert-base-uncased were not used when initializir
- This IS expected if you are initializing BertForSequenceClassification from the checkp
- This IS NOT expected if you are initializing BertForSequenceClassification from the ch
Some weights of BertForSequenceClassification were not initialized from the model checkp
You should probably TRAIN this model on a down-stream task to be able to use it for prec
```

```
total_steps = len(train_dataloader) * epochs

scheduler = get_linear_schedule_with_warmup(optimizer,
                                            num_warmup_steps = 0, # Default value in run_glu
                                            num_training_steps = total_steps)
```

```
total_steps
```

```
330
```

```
# Function to calculate the accuracy of our predictions vs labels
def flat_accuracy(preds, labels):
    pred_flat = np.argmax(preds, axis=1).flatten()
    labels_flat = labels.flatten()
    return np.sum(pred_flat == labels_flat) / len(labels_flat)


def format_time(elapsed):
    '''
    Takes a time in seconds and returns a string hh:mm:ss
    '''
    # Round to the nearest second.
    elapsed_rounded = int(round((elapsed)))
    # Format as hh:mm:ss
    return str(datetime.timedelta(seconds=elapsed_rounded))
```

```
seed_val = 42
random.seed(seed_val)
np.random.seed(seed_val)
torch.manual_seed(seed_val)
torch.cuda.manual_seed_all(seed_val)
training_stats = []
t_acc=[]
t_loss=[]
v_acc=[]
v_loss=[]


total_t0 = time.time()

# For each epoch...
for epoch_i in range(0, epochs):


    #               Training

    print("")
    print('======== Epoch {:} / {:} ========'.format(epoch_i + 1, epochs))
    print('Training...')


    t0 = time.time()
    total_train_loss = 0
    total_train_accuracy = 0
    model.train()

    for step, batch in enumerate(train_dataloader):

        b_input_ids = batch[0].to(device)
        b_input_mask = batch[1].to(device)
        b_labels = batch[2].to(device)
        optimizer.zero_grad()
        output = model(b_input_ids,
                             token_type_ids=None,
                             attention_mask=b_input_mask,
                             labels=b_labels)

        logits = output.logits
        logits = logits.detach().cpu().numpy()
        label_ids = b_labels.to('cpu').numpy()


        total_train_accuracy += flat_accuracy(logits, label_ids)
        # ---------------------------------------------------------

        loss = output.loss
        total_train_loss += loss.item()
```

```
    loss.backward()

    torch.nn.utils.clip_grad_norm_(model.parameters(), 1.0)

    optimizer.step()

    scheduler.step()


avg_train_accuracy = total_train_accuracy / len(train_dataloader)
print("  Train Accuracy: {0:.2f}".format(avg_train_accuracy))

avg_train_loss = total_train_loss / len(train_dataloader)


training_time = format_time(time.time() - t0)
print("")
print("  Average training loss: {0:.2f}".format(avg_train_loss))
print("  Training epcoh took: {:}".format(training_time))


print("")
print("Running Validation...")
t0 = time.time()

model.eval()
# Tracking variables
total_eval_accuracy = 0
best_eval_accuracy = 0
```