case2-2440013071.ipynb

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Case 2: Text Classification using Large Language Model (using RoBERTa)

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Video link: https://youtu.be/9gAuTkfC50M

Import Google Drive to colab

The data will be accessed from here.

```
[ ] # import drive to colab
    from google.colab import drive
    drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
[ ] # view files
    ! ls
```

```
drive  sample_data
```

```
[ ] # setting project directory
    %cd drive/My Drive/uas-text-mining
```

```
/content/drive/.shortcut-targets-by-id/17_YgSKIOhK4PGF8Wqf_24NDQ3BGKkPZA/uas-text-mining
```

We need to install `transformers` to build the model.

```
[ ] pip install transformers
```

```
Collecting transformers
  Downloading transformers-4.30.2-py3-none-any.whl (7.2 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 7.2/7.2 MB 69.8 MB/s eta 0:00:00
Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-packages (from transformers) (3.12.2)
Collecting huggingface-hub<1.0,>=0.14.1 (from transformers)
  Downloading huggingface_hub-0.16.4-py3-none-any.whl (268 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 268.8/268.8 kB 30.6 MB/s eta 0:00:00
Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.10/dist-packages (from transformers) (1.22.4)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from transformers) (23.1)
Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.10/dist-packages (from transformers) (6.0)
Requirement already satisfied: regex!=2019.12.17 in /usr/local/lib/python3.10/dist-packages (from transformers) (2022.10.31)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages (from transformers) (2.27.1)
Collecting tokenizers!=0.11.3,<0.14,>=0.11.1 (from transformers)
  Downloading tokenizers-0.13.3-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (7.8 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 7.8/7.8 MB 101.5 MB/s eta 0:00:00
Collecting safetensors>=0.3.1 (from transformers)
  Downloading safetensors-0.3.1-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (1.3 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 1.3/1.3 MB 75.2 MB/s eta 0:00:00
Requirement already satisfied: tqdm>=4.27 in /usr/local/lib/python3.10/dist-packages (from transformers) (4.65.0)
Requirement already satisfied: fsspec in /usr/local/lib/python3.10/dist-packages (from huggingface-hub<1.0,>=0.14.1->transformers) (2023.6.0)
Requirement already satisfied: typing-extensions>=3.7.4.3 in /usr/local/lib/python3.10/dist-packages (from huggingface-hub<1.0,>=0.14.1->transformers) (4.6.3)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests->transformers) (1.26.16)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests->transformers) (2023.5.7)
Requirement already satisfied: charset-normalizer~=2.0.0 in /usr/local/lib/python3.10/dist-packages (from requests->transformers) (2.0.12)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests->transformers) (3.4)
Installing collected packages: tokenizers, safetensors, huggingface-hub, transformers
Successfully installed huggingface-hub-0.16.4 safetensors-0.3.1 tokenizers-0.13.3 transformers-4.30.2
```

Load Data

Now, we load the data 'data_1B.csv' and let's see what's in there... (the process done here is the same as we did on the first case)

```
[ ] # import libraries
    import pandas as pd
    import numpy as np
    import matplotlib.pyplot as plt
```

```
[ ] # read data
    df = pd.read_csv('data_1B.csv')

    df.head(5)
```

	Unnamed: 0	text	label
0	0	AV2 Women Maternity Wear/Feedind/Nursing Top &...	Clothing & Accessories
1	1	Houskipper Professional Spray Mop with Best 36...	Household
2	2	Tat-Sat Ceramic Fondue Burner , Black This Fon...	Household
3	3	Prestige Plastic Hand Blender, Orange Save tim...	Household
4	4	Gorilla Renesa+ Energy Saving 5 Star Rated Cei...	Household

we can see here that maybe this Unnamed: 0 field is just the index of our observations, so we can just remove them.

```
# drop out the first field, we will only take text and label field
df1 = df.iloc[:, 1:].copy()

df1.head(5)
```

	text	label
0	AV2 Women Maternity Wear/Feedind/Nursing Top &...	Clothing & Accessories
1	Houskipper Professional Spray Mop with Best 36...	Household

2	Tat-Sat Ceramic Fondue Burner , Black This Fon...	Household
3	Prestige Plastic Hand Blender, Orange Save tim...	Household
4	Gorilla Renesa+ Energy Saving 5 Star Rated Cei...	Household

now, we have a dataframe with 2 variables, which are 'text' and 'label'. The 'text' is the sentences and they are classified into a label in 'label' field. Let's find out more in EDA!

Exploratory Data Analysis

Now, we will gather more information about our dataset in this section. (the process done here is the same as we did on the first case)

```
[ ] # view shape
    df1.shape
```

```
(12606, 2)
```

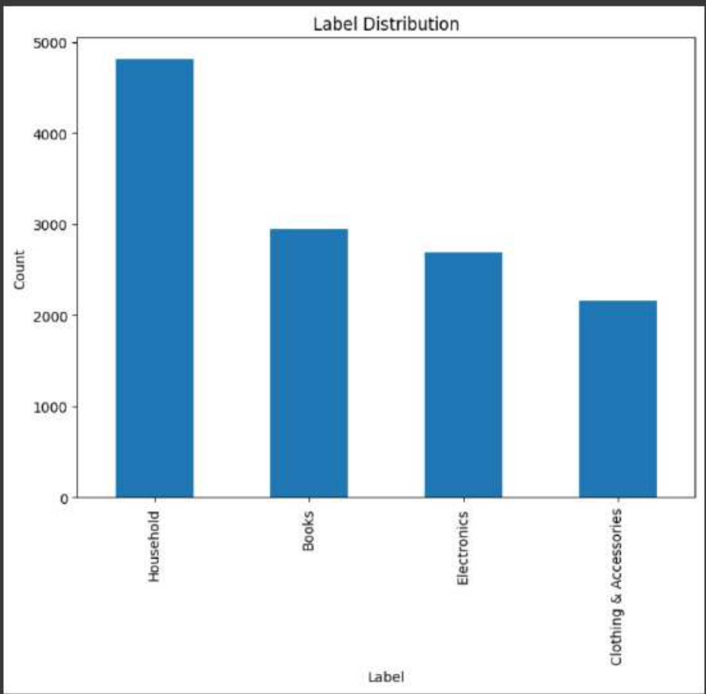
```
[ ] df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12606 entries, 0 to 12605
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   text    12606 non-null  object
 1   label   12606 non-null  object
dtypes: object(2)
memory usage: 197.1+ KB
```

Here, we can tell that there are 12606 observations in our dataset where there is likely no NULL values.

Now, we will check the count of the text's label and see the distributions.

```
[ ] # check the count of text label
    label_counts = df1['label'].value_counts()

    # plot into bar chart
    plt.figure(figsize=(8, 6))
    label_counts.plot(kind='bar')
    plt.title('Label Distribution')
    plt.xlabel('Label')
    plt.ylabel('Count')
    plt.show()
```




```
[ ] # see the distribution of the text label in numbers
    label_counts
```

```
Household                 4810
Books                     2946
Electronics               2693
Clothing & Accessories    2157
Name: label, dtype: int64
```

We can see here that the class is imbalanced, where most texts classified as 'Household' (around 40%, while the other are around 20%).

Hence, we will use this information later for modeling.

Now, let's see several samples of records..

```
# preview several samples of records
print('Text: \n', df1['text'].iloc[500])
print('Label: \n', df1['label'].iloc[500])
print('\n')
print('Text: \n', df1['text'].iloc[5000])
print('Label: \n', df1['label'].iloc[5000])
```

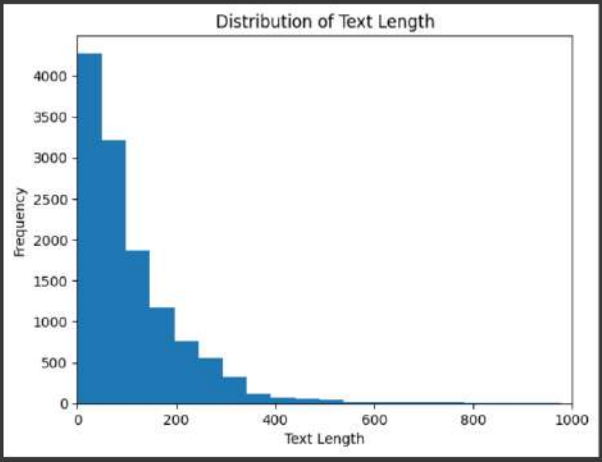
```
Text:
```

```
 Alexvyan Universal World Travel Power Plug, European Adapter, AC Outlet Plugs for All Countries (White) - Pack of 2 Size name:Pack of 2   Stop carrying multiple adapters and make
Label:
 Electronics


Text:
 Cenizas Casual Black Waistcoat Blazers for Men Slim fit Party wear Cenizas provides you with the latest, trendy blazers & waistcoats,to make you feel Good In All Wedding And Part
Label:
 Clothing & Accessories
```

We can see here that we might need some cleaning, such as making the characters into lowercase, remover punctuations, etc. This will be done in the next process, pre-processing process.

Then, we want to know the distribution of our text length in order to set the max_length in the modelling process.

```
# find out the distribution of text length
df1['length'] = df1['text'].apply(lambda x: len(x.split()))

plt.hist(df1['length'], bins=120)
plt.xlabel('Text Length')
plt.ylabel('Frequency')
plt.title('Distribution of Text Length')
plt.xlim(0, 1000)
plt.show()
```



From the plot above, we can tell that our texts are centered to lower text length. Most samples have around under 200 words in it. If we look at the graph thoroughly, we can see there is a bit sample having more than 400 text length, that might considered as outliers (out of the majority of our data).

Hence, later in the modelling, **we will take the max_length of 256** because it's approximate boundary for our data text, where we can have most of the observations below the limit (and only a few that exceed the limit). We have to set the parameter max_length because RoBERTa model has limitation on the maximum length of input sequence they can handle. So, if the input sequence exceed that length, it needs to be truncated or shortened to fit the model's requirement. On the other side, the ones which shorter than max_length will be padded until matching the maximum length.

Setting the appropiate max_length value is important, because we want to balance the trade-off between retaining important information in longer sequences and managing computational resources and model memory.

Pre-Processing Process

In the preprocessing process, we will clean the data by removing URLs, remove punctuation, and convert to lowercase. Then, we will do tokenization and remove the stopwords inside the texts. Lastly, we do lemmatization to get the data into the normal (lemma) form and bring back into string. **In the modelling process, we will be using pre-trained model from RoBERTa (A Robustly Optimized BERT Pretraining Approach).** Although RoBERTA already includes tokenization and vectorization, we did the same pre-processing process to match the pre-processing on the first case.

```
import re
import string
import nltk
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
```

```
nltk.download('stopwords')
nltk.download('wordnet')
nltk.download('punkt')
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
True
```

```
# define pre-processing functions
def preprocess_text(text):
    text = re.sub(r"http\S+|www\S+|https\S+", "", text) # remove URLs
    text = text.translate(str.maketrans("", "", string.punctuation)) # remove punctuation
    text = text.lower() #convert to lowercase

    # tokenization
    tokens = nltk.word_tokenize(text)

    # remove stopwords
    stop_words = set(stopwords.words('english'))
    tokens = [token for token in tokens if token not in stop_words]

    # lemmatization
```

```
    tokens = [lemmatizer.lemmatize(token, pos='v') for token in tokens] # also remove gerund or +ing into verb (base word)

    # join back token into string
    preprocessed_text = " ".join(tokens)

    return preprocessed_text
```

Here, we joined the tokens back into string because the RoBERTa takes the string format and will do the tokenization along with vectorization (inside the pre-trained model).

Then, we try applying the pre-process function into the text data and see the sample results!

```
[ ] # apply the pre-processing process into the text data
    df1['clean_text'] = df1['text'].apply(preprocess_text)
```

```
[ ] print('Text: \n', df1['text'].iloc[500])
    print('Cleaned Text: \n', df1['clean_text'].iloc[500])
    print('Label: \n', df1['label'].iloc[500])
    print('\n')
    print('Text: \n', df1['text'].iloc[5000])
    print('Cleaned Text: \n', df1['clean_text'].iloc[5000])
    print('Label: \n', df1['label'].iloc[5000])
```

```
Text:
 Alexvyan Universal World Travel Power Plug, European Adapter, AC Outlet Plugs for All Countries (White) - Pack of 2 Size name:Pack of 2   Stop carrying multiple adapters and make
Cleaned Text:
 alexvyan universal world travel power plug european adapter ac outlet plug countries white pack 2 size namepack 2 stop carry multiple adapters make travel convenient smartpro all
Label:
 Electronics


Text:
 Cenizas Casual Black Waistcoat Blazers for Men Slim fit Party wear Cenizas provides you with the latest, trendy blazers & waistcoats,to make you feel Good In All Wedding And Part
Cleaned Text:
 cenizas casual black waistcoat blazers men slim fit party wear cenizas provide latest trendy blazers waistcoatsto make feel good wed party function
Label:
 Clothing & Accessories
```

Here, we can see that the data has successfully cleaned.

Now, we tried to define several configuration needed for the next processes..

```
import torch
from transformers import RobertaTokenizer, RobertaForSequenceClassification
from torch.utils.data import DataLoader, TensorDataset
from torch.optim import AdamW
from tqdm import tqdm
```

```
[ ] class Config:
        def __init__(self):
            super(Config, self).__init__()

            self.SEED = 42 # random seed = 42; for reproducibility
            self.MODEL_PATH = 'roberta-base' # the pretrained model
            self.NUM_CLASSES = 4 # number of classes in our dataset

            self.LABELS = {'Household':0,
              'Books':1,
              'Electronics':2,
              'Clothing & Accessories':3
              }

            # data
            self.TOKENIZER = RobertaTokenizer.from_pretrained(self.MODEL_PATH) # using tokenizer from pretrained model
            self.MAX_LENGTH = 256 # the max length (already explained)
            self.BATCH_SIZE = 16 # number of batch size, where the data will be inputted into batch with this number of data in each batch
            self.TEST_SPLIT = 0.20 # for train-test splitting
            self.VAL_SPLIT = 0.50 # for test-validation splitting

            # model
            self.DEVICE = torch.device('cuda' if torch.cuda.is_available() else 'cpu') # use cuda if available
            self.LR = 2e-5 # learning rate = 2.10^-5 = 0.00002
            self.OPTIMIZER = 'AdamW' # optimizer = AdamW
            self.CRITERION = 'CrossEntropyLoss' # criterion = CrossEntropyLoss
            self.EPOCHS = 3 # number of epoch(s) for training process

    config = Config()
```

```
Downloading (…)olve/main/vocab.json: 100% 899k/899k [00:00<00:00, 4.97MB/s]
Downloading (…)olve/main/merges.txt: 100% 456k/456k [00:00<00:00, 7.17MB/s]
Downloading (…)lve/main/config.json: 100% 481/481 [00:00<00:00, 6.14kB/s]
```

In this model, we will be using the tokenizer from pretrained model. We use the pretrained model roberta-base.

Hence, we will do fine-tuning from the pretrained model where the model will be trained on specific task. Before that, we use 8:1:1 train-test-validation split from the full dataset.

We use AdamW (Adam with Weight Decay) optimizer. This optimizer applies weight decay to the parameters during the parameter update step. This helps prevent overfitting and improves the generalization of the model.

We also use CrossEntropyLoss (Cross-Entropy Loss) as our loss function, where this function is suitable for multiclass problem.

The labels will be formatted into numbers, where 'Household':0, 'Books':1, 'Electronics':2, 'Clothing & Accessories':3.

There are hyperparameter we use for the modelling, like learning rate = 2.10^-5. we also use 3 epochs.

Then, we create Dataset class to create a PyTorch dataset object that can be used for training, validation, or testing process later.

```
[ ] class Dataset(torch.utils.data.Dataset):
        def __init__(self, data): # initializations; takes data arguments
            self.labels = [config.LABELS[label] for label in data['label']]
```

```
        self.texts = data['clean_text'].values
        self.tokenizer = config.TOKENIZER
        self.max_length = config.MAX_LENGTH

    def __len__(self):
        return len(self.labels) # return length of labels

    def __getitem__(self, idx):
        # fetch text and label corresponding to the index
        text = self.texts[idx]
        label = self.labels[idx]

        # encode the text using tokenizer.encode_plus method
        encoding = self.tokenizer.encode_plus(
            text,
            max_length=self.max_length, # maximum of the sequence length
            padding='max_length', # pads the input shorter than the max_length into the max_length
            truncation=True, # perform truncation to text with length longer than max_length
            return_tensors='pt'
        )

        # returned as tensor
        return {
            'input_ids': encoding['input_ids'].squeeze(),
            'attention_mask': encoding['attention_mask'].squeeze(),
            'labels': torch.tensor(label)
        }
```

Then, we start doing the splitting process. The ratio is 8:1:1 for train-test-validation set. The dataset will be splitted by paying attention to the 'label' classes, so there wont be imbalanced split.

```
[ ] # train-test-val split
    # split the dataset into train, test, and validation set. we are using 8:1:1 train-test-val ratio.
    from sklearn.model_selection import train_test_split

    np.random.seed(config.SEED)
    # Splitting into train and remaining data (validation + test)
    df_train, df_remaining = train_test_split(df1, test_size=config.TEST_SPLIT, stratify=df1['label'], random_state=42)

    # Splitting the remaining data into validation and test
    df_val, df_test = train_test_split(df_remaining, test_size=config.VAL_SPLIT, stratify=df_remaining['label'], random_state=42)

    print(len(df_train), len(df_val), len(df_test))

    10084 1261 1261
```

Then, we perform the pytorch object creation using the Dataset class, and sent it to dataloader.

```
[ ] train_data = Dataset(df_train)
    val_data = Dataset(df_val)

    train_dataloader = DataLoader(train_data, batch_size=config.BATCH_SIZE)
    val_dataloader = DataLoader(val_data, batch_size=config.BATCH_SIZE)

    b = next(iter(train_dataloader))
    for k, v in b.items():
        print(f'{k} shape: {v.shape}')

    input_ids shape: torch.Size([16, 256])
    attention_mask shape: torch.Size([16, 256])
    labels shape: torch.Size([16])
```

Building Model

Now, we will start the modelling process by defining the Model from pre-trained model.

```
from torch import nn
from transformers import RobertaModel

class RoBERTaClassifier(nn.Module):
    def __init__(self, dropout=0.3):
        # initialize the model
        super(RoBERTaClassifier, self).__init__()

        self.roberta = RobertaModel.from_pretrained(config.MODEL_PATH) # loads pretrained model
        self.dropout = nn.Dropout(dropout) # do dropout regularization with dropout = 0.3 (prevent overfitting)
        self.linear = nn.Linear(768, config.NUM_CLASSES) # maps the output to the number of classes
        self.relu = nn.ReLU() # do ReLU activation function (self.relu) to introduce non-linearity.

    def forward(self, input_ids, attention_mask):
        outputs = self.roberta(input_ids=input_ids, attention_mask=attention_mask)
        o2 = outputs[1]
        dropout_output = self.dropout(o2)
        linear_output = self.linear(dropout_output)
        final_output = self.relu(linear_output)

        return final_output
```

```
[ ] # specify the device using cuda
    device = config.DEVICE
    device

    device(type='cuda')
```

Then, we define the training and validation process here below:

```
[ ] def train(model, train_dataloader, val_dataloader, learning_rate, epochs):
        torch.manual_seed(config.SEED) # set seed
        use_cuda = torch.cuda.is_available() # make sure cude is available to use
        device = torch.device("cuda" if use_cuda else "cpu")

        # define loss function and optimizer (along with specified learning rate)
        criterion = nn.CrossEntropyLoss()
        optimizer = AdamW(model.parameters(), lr=learning_rate)
```

```python
    # move the model and the loss function to the appropriate device
    model.to(device)
    criterion.to(device)

    # initialize the best validation loss to a very high value
    best_val_loss = float('inf')

    # start the training loop for the specified number of epochs
    for epoch_num in range(epochs):
        # initialize variables to keep track of total accuracy and loss during training
        total_acc_train = 0
        total_loss_train = 0

        # set the model to train mode
        model.train()
        for batch in tqdm(train_dataloader):
            # unpack the batch contents and push them to the device (cuda or cpu).
            input_ids = batch['input_ids'].to(device)
            attention_mask = batch['attention_mask'].to(device)
            labels = batch['labels'].to(device)

            # zero-ing the gradients
            optimizer.zero_grad()
            # forward pass
            outputs = model(input_ids, attention_mask)

            # compute loss
            loss = criterion(outputs, labels)
            # backward pass and optimization step
            loss.backward()
            optimizer.step()

            # update the total loss and current accuracy for the current batch
            total_loss_train += loss.item()
            total_acc_train += (outputs.argmax(dim=1) == labels).sum().item()

        # initialize variables to keep track of total accuracy and loss during validation
        total_acc_val = 0
        total_loss_val = 0

        # Set the model to evaluation mode
        model.eval()
        # disable gradient calculation for validation
        with torch.no_grad():
            # iterate over validation data
            for batch in val_dataloader:
                # unpack the batch contents and push them to the device (cuda or cpu)
                input_ids = batch['input_ids'].to(device)
                attention_mask = batch['attention_mask'].to(device)
                labels = batch['labels'].to(device)

                # forward pass
                outputs = model(input_ids, attention_mask)

                # compute loss between outputs labels
                loss = criterion(outputs, labels)

                # update the total loss and accuracy for the current batch
                total_loss_val += loss.item()
                total_acc_val += (outputs.argmax(dim=1) == labels).sum().item()

        # compute the average training and validation loss and accuracy
        train_loss_avg = total_loss_train / len(train_dataloader.dataset)
        train_acc_avg = total_acc_train / len(train_dataloader.dataset)
        val_loss_avg = total_loss_val / len(val_dataloader.dataset)
        val_acc_avg = total_acc_val / len(val_dataloader.dataset)

        # print the average losses and accuracies for the epoch
        print(f'Epochs: {epoch_num + 1} | Train Loss: {train_loss_avg:.6f} | Train Accuracy: {train_acc_avg:.6f} '
              f'| Val Loss: {val_loss_avg:.6f} | Val Accuracy: {val_acc_avg:.6f}')

        # save the model if the current validation loss is better than the previous best
        if val_loss_avg < best_val_loss:
            best_val_loss = val_loss_avg
            torch.save(model.state_dict(), 'best_model.pt')
            print(f"Saved model with val loss: {best_val_loss:.3f} as best_model.pt")
```

```python
[ ] # initialize the model
    model = RoBERTaClassifier()
    model.to(device);
```

```
Downloading model.safetensors: 100% 499M/499M [00:03<00:00, 274MB/s]
Some weights of the model checkpoint at roberta-base were not used when initializing RobertaModel: ['lm_head.dense.bias', 'lm_head.layer_norm.bias', 'lm_head.bias', 'lm_head.dense
- This IS expected if you are initializing RobertaModel from the checkpoint of a model trained on another task or with another architecture (e.g. initializing a BertForSequenceCla
- This IS NOT expected if you are initializing RobertaModel from the checkpoint of a model that you expect to be exactly identical (initializing a BertForSequenceClassification mo
Some weights of RobertaModel were not initialized from the model checkpoint at roberta-base and are newly initialized: ['roberta.pooler.dense.weight', 'roberta.pooler.dense.bias']
You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.
```

```python
[ ] # do the training and validation process
    train(model, train_dataloader, val_dataloader, config.LR, config.EPOCHS)
```

```
100%|██████████| 631/631 [07:31<00:00,  1.40it/s]
Epochs: 1 | Train Loss: 0.020918 | Train Accuracy: 0.896767 | Val Loss: 0.011790 | Val Accuracy: 0.955591
Saved model with val loss: 0.012 as best_model.pt
100%|██████████| 631/631 [07:27<00:00,  1.41it/s]
Epochs: 2 | Train Loss: 0.010230 | Train Accuracy: 0.956962 | Val Loss: 0.010719 | Val Accuracy: 0.959556
Saved model with val loss: 0.011 as best_model.pt
100%|██████████| 631/631 [07:27<00:00,  1.41it/s]
Epochs: 3 | Train Loss: 0.007589 | Train Accuracy: 0.968862 | Val Loss: 0.009960 | Val Accuracy: 0.965107
Saved model with val loss: 0.010 as best_model.pt
```

From this result, we get that the train and validation loss is considered already small on epoch 1 (meaning it's a great result!). Both training and validation loss also keeps lowering over 3 epochs, resulting in getting higher train and validation accuracy over epochs. We are getting 96.88% train accuracy and 96.51% validation accuracy which is very great result!

Next, we will do the hyperparameter tuning to check other hyperparameters that might be resulting better results than our current model result. But, please keep in mind that comparing training and validation loss alone is not sufficient to evaluate the model's performance – where we will see at the evaluation.

Hyperparameter Tuning

Build model for tuning

For tuning process, we will be using `optuna` as our hyperparameter optimization framework. The hyperparameter we will tune are:

- dropout: 0.3 or 0.5
- learning rate: 1e-6 until 1e-2
- optimizer: Adam, AdamW, RMSProp

to save time and computation resources, we will only do 3 trials for this tuning process and each of them will be tuned for 1 epoch (I've tried using 3 epochs for each trial, but got OutOfMemory Error).

```
[ ] pip install optuna
```

```
Collecting optuna
  Downloading optuna-3.2.0-py3-none-any.whl (390 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 390.6/390.6 kB 12.7 MB/s eta 0:00:00
Collecting alembic>=1.5.0 (from optuna)
  Downloading alembic-1.11.1-py3-none-any.whl (224 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 224.5/224.5 kB 23.2 MB/s eta 0:00:00
Collecting cmaes>=0.9.1 (from optuna)
  Downloading cmaes-0.9.1-py3-none-any.whl (21 kB)
Collecting colorlog (from optuna)
  Downloading colorlog-6.7.0-py2.py3-none-any.whl (11 kB)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from optuna) (1.22.4)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from optuna) (23.1)
Requirement already satisfied: sqlalchemy>=1.3.0 in /usr/local/lib/python3.10/dist-packages (from optuna) (2.0.16)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from optuna) (4.65.0)
Requirement already satisfied: PyYAML in /usr/local/lib/python3.10/dist-packages (from optuna) (6.0)
Collecting Mako (from alembic>=1.5.0->optuna)
  Downloading Mako-1.2.4-py3-none-any.whl (78 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 78.7/78.7 kB 10.0 MB/s eta 0:00:00
Requirement already satisfied: typing-extensions>=4 in /usr/local/lib/python3.10/dist-packages (from alembic>=1.5.0->optuna) (4.6.3)
Requirement already satisfied: greenlet!=0.4.17 in /usr/local/lib/python3.10/dist-packages (from sqlalchemy>=1.3.0->optuna) (2.0.2)
Requirement already satisfied: MarkupSafe>=0.9.2 in /usr/local/lib/python3.10/dist-packages (from Mako->alembic>=1.5.0->optuna) (2.1.3)
Installing collected packages: Mako, colorlog, cmaes, alembic, optuna
Successfully installed Mako-1.2.4 alembic-1.11.1 cmaes-0.9.1 colorlog-6.7.0 optuna-3.2.0
```

```
[ ] import optuna
    from torch.optim import Adam, RMSprop
```

```
[ ] # re-define the model because we have 2 dropout options ([0.3, 0.5])
    class RoBERTaClassifier_tune(nn.Module):
        def __init__(self, dropout):
            super(RoBERTaClassifier_tune, self).__init__()

            self.roberta = RobertaModel.from_pretrained(config.MODEL_PATH)
            self.dropout = nn.Dropout(dropout)
            self.linear = nn.Linear(768, config.NUM_CLASSES)
            self.relu = nn.ReLU()

        def forward(self, input_ids, attention_mask):
            outputs = self.roberta(input_ids=input_ids, attention_mask=attention_mask)
            o2 = outputs[1]
            dropout_output = self.dropout(o2)
            linear_output = self.linear(dropout_output)
            final_output = self.relu(linear_output)

            return final_output
```

```
[ ] # define objective function for Optuna optimization
    def objective(trial):
        # random seeding
        torch.manual_seed(config.SEED)

        # check gpu availability
        use_cuda = torch.cuda.is_available()
        device = torch.device("cuda" if use_cuda else "cpu")

        # sampling the dropout rate, learning rate, and optimizer name using Optuna suggestions
        dropout = trial.suggest_categorical('dropout', [0.3, 0.5])
        learning_rate = trial.suggest_loguniform('learning_rate', 1e-6, 1e-2)
        optimizer_name = trial.suggest_categorical('optimizer', ['adam', 'adamW', 'rmsprop'])

        # create a new instance
        model = RoBERTaClassifier_tune(dropout=dropout)

        # define loss function
        criterion = nn.CrossEntropyLoss()

        # select optimizer based on sampled optimizer name
        if optimizer_name == 'adam':
            optimizer = Adam(model.parameters(), lr=learning_rate)
        elif optimizer_name == 'adamW':
            optimizer = AdamW(model.parameters(), lr=learning_rate)
        elif optimizer_name == 'rmsprop':
            optimizer = RMSprop(model.parameters(), lr=learning_rate)

        # move model and loss function to the appropriate device
        model.to(device)
        criterion.to(device)

        # initialize best validation loss to a very high value
        best_val_loss = float('inf')

        # start the training loop for a fixed number of epochs (1 in this case)
        for epoch_num in range(1):
            # initialize variables to keep track of total accuracy and loss during training
            total_acc_train = 0
            total_loss_train = 0

            # set the model to train mode
            model.train()

            # iterate over the training data
            for batch in tqdm(train_dataloader):
                # move the input IDs, attention mask, and labels to the device
```

```python
            input_ids = batch['input_ids'].to(device)
            attention_mask = batch['attention_mask'].to(device)
            labels = batch['labels'].to(device)

            # zero-ing the gradients
            optimizer.zero_grad()

            # forward pass
            outputs = model(input_ids, attention_mask)

            # compute loss between outputs and labels
            loss = criterion(outputs, labels)

            # backward pass and optimization step
            loss.backward()
            optimizer.step()

            # update the total loss and accuracy for the current batch
            total_loss_train += loss.item()
            total_acc_train += (outputs.argmax(dim=1) == labels).sum().item()

        # initialize variables to keep track of total accuracy and loss during validation
        total_acc_val = 0
        total_loss_val = 0

        # set the model to evaluation mode
        model.eval()

        # disable gradient calculation for validation
        with torch.no_grad():
            # iterate over the validation data
            for batch in val_dataloader:
                # move the input IDs, attention mask, and labels to the device
                input_ids = batch['input_ids'].to(device)
                attention_mask = batch['attention_mask'].to(device)
                labels = batch['labels'].to(device)

                # forward pass
                outputs = model(input_ids, attention_mask)

                # compute loss between outputs and labels
                loss = criterion(outputs, labels)

                # update total loss and accuracy for the current batch
                total_loss_val += loss.item()
                total_acc_val += (outputs.argmax(dim=1) == labels).sum().item()

        # compute the average training and validation loss and accuracy
        train_loss_avg = total_loss_train / len(train_dataloader.dataset)
        train_acc_avg = total_acc_train / len(train_dataloader.dataset)
        val_loss_avg = total_loss_val / len(val_dataloader.dataset)
        val_acc_avg = total_acc_val / len(val_dataloader.dataset)

        # print the average losses and accuracies for the epoch
        print(f'Epochs: {epoch_num + 1} | Train Loss: {train_loss_avg:.6f} | Train Accuracy: {train_acc_avg:.6f} '
              f'| Val Loss: {val_loss_avg:.6f} | Val Accuracy: {val_acc_avg:.6f}')

    return val_acc_avg  # Return the validation accuracy as the objective value
```

Model Tuning

```python
[ ] # do the hyperparamter tuning for 3 trials
    study = optuna.create_study(direction='maximize')
    study.optimize(objective, n_trials=3)

    # get the best trial & best parameters out of the study
    best_trial = study.best_trial
    best_params = best_trial.params
```

```
[I 2023-07-08 15:00:42,318] A new study created in memory with name: no-name-445e6dbf-995a-40a5-90c4-33a80dfbee75
<ipython-input-32-334d4885a252>:7: FutureWarning: suggest_loguniform has been deprecated in v3.0.0. This feature will be removed in v6.0.0. See https://github.com/optuna/optuna/re
  learning_rate = trial.suggest_loguniform('learning_rate', 1e-6, 1e-2)
Some weights of the model checkpoint at roberta-base were not used when initializing RobertaModel: ['lm_head.dense.bias', 'lm_head.layer_norm.bias', 'lm_head.bias', 'lm_head.dense
- This IS expected if you are initializing RobertaModel from the checkpoint of a model trained on another task or with another architecture (e.g. initializing a BertForSequenceCla
- This IS NOT expected if you are initializing RobertaModel from the checkpoint of a model that you expect to be exactly identical (initializing a BertForSequenceClassification mo
Some weights of RobertaModel were not initialized from the model checkpoint at roberta-base and are newly initialized: ['roberta.pooler.dense.weight', 'roberta.pooler.dense.bias']
You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.
100%|██████████| 631/631 [06:55<00:00,  1.52it/s]
[I 2023-07-08 15:07:56,604] Trial 0 finished with value: 0.38144329896907214 and parameters: {'dropout': 0.3, 'learning_rate': 0.003883956343264145, 'optimizer': 'rmsprop'}. Best
Epochs: 1 | Train Loss: 0.087925 | Train Accuracy: 0.381396 | Val Loss: 0.086850 | Val Accuracy: 0.381443
Some weights of the model checkpoint at roberta-base were not used when initializing RobertaModel: ['lm_head.dense.bias', 'lm_head.layer_norm.bias', 'lm_head.bias', 'lm_head.dense
- This IS expected if you are initializing RobertaModel from the checkpoint of a model trained on another task or with another architecture (e.g. initializing a BertForSequenceCla
- This IS NOT expected if you are initializing RobertaModel from the checkpoint of a model that you expect to be exactly identical (initializing a BertForSequenceClassification mo
Some weights of RobertaModel were not initialized from the model checkpoint at roberta-base and are newly initialized: ['roberta.pooler.dense.weight', 'roberta.pooler.dense.bias']
You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.
100%|██████████| 631/631 [07:08<00:00,  1.47it/s]
[I 2023-07-08 15:15:23,848] Trial 1 finished with value: 0.38144329896907214 and parameters: {'dropout': 0.5, 'learning_rate': 0.00018780091755504156, 'optimizer': 'adamW'}. Best
Epochs: 1 | Train Loss: 0.086717 | Train Accuracy: 0.381198 | Val Loss: 0.086850 | Val Accuracy: 0.381443
Some weights of the model checkpoint at roberta-base were not used when initializing RobertaModel: ['lm_head.dense.bias', 'lm_head.layer_norm.bias', 'lm_head.bias', 'lm_head.dense
- This IS expected if you are initializing RobertaModel from the checkpoint of a model trained on another task or with another architecture (e.g. initializing a BertForSequenceCla
- This IS NOT expected if you are initializing RobertaModel from the checkpoint of a model that you expect to be exactly identical (initializing a BertForSequenceClassification mo
Some weights of RobertaModel were not initialized from the model checkpoint at roberta-base and are newly initialized: ['roberta.pooler.dense.weight', 'roberta.pooler.dense.bias']
You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.
100%|██████████| 631/631 [07:08<00:00,  1.47it/s]
[I 2023-07-08 15:22:50,918] Trial 2 finished with value: 0.38144329896907214 and parameters: {'dropout': 0.5, 'learning_rate': 4.989479747449161e-05, 'optimizer': 'rmsprop'}. Best
Epochs: 1 | Train Loss: 0.084995 | Train Accuracy: 0.381694 | Val Loss: 0.086850 | Val Accuracy: 0.381443
```

Now, let's see the best hyperparameters from the tuning process, and compare the results from tuning and our base model results.

```python
[ ] print('Best Trial:')
    print('\tValidation accuracy: ', best_trial.value)
    print('\tParams: ')
    for key, value in best_params.items():
        print("\t    {}: {}".format(key, value))
```

```
Best Trial:
        Validation accuracy:  0.38144329896907214
        Params:
            dropout: 0.3
            learning_rate: 0.003883956343264145
            optimizer: rmsprop
```

Summary of Tuning Process:

Our Base Model:

> dropout=0.3
>
> LR = 2e-5
>
> optimizer = AdamW

Epoch 1 Result:

Epochs: 1 | Train Loss: 0.020918 | Train Accuracy: 0.896767 | Val Loss: 0.011790 | Val Accuracy: 0.955591

Best Trial:

> dropout=0.3
>
> LR = 0.0038839563432664145
>
> optimizer = rmsprop

Epoch 1 Result:

Epochs: 1 | Train Loss: 0.087925 | Train Accuracy: 0.381396 | Val Loss: 0.086850 | Val Accuracy: 0.381443

The best trial uses different optimizer and learning rate from our base model, and resulting a very bad train & validation loss and accuracy. This means our base model is already has the best optimizer. The learning rate here is way bigger than the learning rate we used in our base model.

Although the loss values are quite close between the tuned and base model, the accuracy here showed a very different result.

We also can see that validation loss is lower than the loss in training on both model, meaning both model generalize well to unseen data. A lower validation loss indicates that the model performs well on the validation set, which consists of data that the model hasn't seen during training. This means that both models are not overfitting to the training data. Comparing training and validation loss alone is not sufficient to evaluate the model's performance.

The result of our base model is way better, and the loss is also decreasing on the next epoch.

In conclusion, we will use the base model for as our final model.

Evaluation

Now, we will evaluate our model using the test set.

```
[ ] # call the final model for testing process
    best_model = RoBERTaClassifier()  # Create an instance of the model
    best_model.load_state_dict(torch.load('best_model.pt'))  # Load the final model
    best_model.to(device)  # Move the model to the appropriate device (CPU or GPU)
```

```
Some weights of the model checkpoint at roberta-base were not used when initializing RobertaModel: ['lm_head.dense.bias', 'lm_head.layer_norm.bias', 'lm_head.bias', 'lm_head.dense
- This IS expected if you are initializing RobertaModel from the checkpoint of a model trained on another task or with another architecture (e.g. initializing a BertForSequenceCla
- This IS NOT expected if you are initializing RobertaModel from the checkpoint of a model that you expect to be exactly identical (initializing a BertForSequenceClassification mo
Some weights of RobertaModel were not initialized from the model checkpoint at roberta-base and are newly initialized: ['roberta.pooler.dense.weight', 'roberta.pooler.dense.bias']
You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.
RoBERTaClassifier(
  (roberta): RobertaModel(
    (embeddings): RobertaEmbeddings(
      (word_embeddings): Embedding(50265, 768, padding_idx=1)
      (position_embeddings): Embedding(514, 768, padding_idx=1)
      (token_type_embeddings): Embedding(1, 768)
      (LayerNorm): LayerNorm((768,), eps=1e-05, elementwise_affine=True)
      (dropout): Dropout(p=0.1, inplace=False)
    )
    (encoder): RobertaEncoder(
      (layer): ModuleList(
        (0-11): 12 x RobertaLayer(
          (attention): RobertaAttention(
            (self): RobertaSelfAttention(
              (query): Linear(in_features=768, out_features=768, bias=True)
              (key): Linear(in_features=768, out_features=768, bias=True)
              (value): Linear(in_features=768, out_features=768, bias=True)
              (dropout): Dropout(p=0.1, inplace=False)
            )
            (output): RobertaSelfOutput(
              (dense): Linear(in_features=768, out_features=768, bias=True)
              (LayerNorm): LayerNorm((768,), eps=1e-05, elementwise_affine=True)
              (dropout): Dropout(p=0.1, inplace=False)
            )
          )
          (intermediate): RobertaIntermediate(
            (dense): Linear(in_features=768, out_features=3072, bias=True)
            (intermediate_act_fn): GELUActivation()
          )
          (output): RobertaOutput(
            (dense): Linear(in_features=3072, out_features=768, bias=True)
            (LayerNorm): LayerNorm((768,), eps=1e-05, elementwise_affine=True)
            (dropout): Dropout(p=0.1, inplace=False)
          )
        )
      )
    )
    (pooler): RobertaPooler(
      (dense): Linear(in_features=768, out_features=768, bias=True)
      (activation): Tanh()
    )
  )
  (dropout): Dropout(p=0.3, inplace=False)
  (linear): Linear(in_features=768, out_features=4, bias=True)
  (relu): ReLU()
)
```

```
[ ] test_data = Dataset(df_test)
    test_dataloader = DataLoader(test_data, batch_size=config.BATCH_SIZE, shuffle=False)
```

```
[ ] len(test_data) # just to make sure the data length is correct
```

```
1261
```

For this evaluation, we will use classification report and confusion matrix.

```
[ ] # import metrics
    from sklearn.metrics import classification_report, confusion_matrix
```

```
[ ] # define the evaluation process
    def evaluate(model, test_dataloader):
        # set the model into evaluation mode
        model.eval()

        # initialize empty lists for predictions and labels
        predictions = []
        labels = []

        # disable gradient calculation for evaluation
        with torch.no_grad():
            # Iterate over the test data
            for batch in test_dataloader:
                # Move the input IDs and attention mask to the device
                input_ids = batch['input_ids'].to(device)
                attention_mask = batch['attention_mask'].to(device)
                batch_labels = batch['labels']

                # forward pass
                outputs = model(input_ids, attention_mask)

                # compute predictions and append to the list
                batch_predictions = outputs.argmax(dim=1).cpu().numpy()
                predictions.extend(batch_predictions)

                # append the true labels to the list
                labels.extend(batch_labels)

        # convert the predictions and labels to NumPy arrays
        predictions = np.array(predictions)
        labels = np.array(labels)

        # compute evaluation metrics
        accuracy = (predictions == labels).mean()
        class_report = classification_report(labels, predictions)
        cm = confusion_matrix(labels, predictions)

        # print evaluation metrics
        print(f"Accuracy: {accuracy:.6f}")
        print("Classification Report:")
        print(class_report)
        print("Confusion Matrix:")
        print(cm)

        return accuracy, class_report, cm
```

```
[ ] # run the evaluation
    accuracy, class_report, cm = evaluate(best_model, test_dataloader)
```

```
Accuracy: 0.963521
Classification Report:
              precision    recall  f1-score   support

           0       0.96      0.97      0.97       481
           1       0.97      0.95      0.96       295
           2       0.96      0.95      0.95       269
           3       0.97      0.98      0.97       216

    accuracy                           0.96      1261
   macro avg       0.96      0.96      0.96      1261
weighted avg       0.96      0.96      0.96      1261

Confusion Matrix:
[[467   4   8   2]
 [ 10 281   3   1]
 [  6   4 256   3]
 [  3   1   1 211]]
```

Summary

In this summary, we will gather insights from the model evaluation.

We recall the results from the report from the first case, where we use machine learning to classify the classes (using Support Vector Machine Classifier along with TF-IDF Vectorizer):

```
print_evaluation_result(svm_tfidf_predictions)
```

```
Accuracy:  0.9623314829500397
Precision: 0.9623314829500397
Recall: 0.9623314829500397
F1-score for class 0: 0.9563729683490162
F1-score for class 1: 0.9695550351288057
F1-score for class 2: 0.960377358490566
F1-score for class 3: 0.9637939826619072
Micro F1-score: 0.9637939826619072
Confusion Matrix:
 [[559   4   4  22]
 [  5 414   1  12]
 [  8   2 509  20]
 [  8   2   7 945]]
```

Comparing to the first solving, we can tell that **this case can be handled very well only by using simple Machine Learning** -- here, we have a very similar results among the metrics.

Now, by comparing this results to the training result, **we can see that the test accuracy is already close to the validation accuracy, meaning there is no overfitting.**

We also can tell that the **f1-score for each labels from the LLM Model Evaluation has higher score than the ones from ML model.** This higher f1-score means there are less missclassified class on each labels on the LLM Model than on the ML Model. Our LLM Model still resulting a slightly better classification on the test data.

*note: the portion of test case on ML model is larger (20% out of full dataset) rather than on the LLM (only 10% out of full dataset).

```
[ ]
```