```
import re
import string
import torch
import pandas as pd
import numpy as np
from sklearn.preprocessing import LabelEncoder
from torch.utils.data import Dataset, DataLoader
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, f1_score
from google.colab import drive
from transformers import Trainer, TrainingArguments, AutoTokenizer, RobertaModel
import torch.nn as nn
import torch.optim as optim
from tqdm import tqdm
import matplotlib.pyplot as plt
```

```
drive.mount('/content/drive')
data_path = '/content/drive/My Drive/restaurants_reviews_dataset'
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

Data Preparation

Loading the Data

```
df1 = pd.read_csv(data_path + '/Restaurants_Train_v2.csv')
df1.head()
```

	id	Sentence	Aspect Term	polarity	from	to
0	3121	But the staff was so horrible to us.	staff	negative	8	13
1	2777	To be completely fair, the only redeeming fact...	food	positive	57	61
2	1634	The food is uniformly exceptional, with a very...	food	positive	4	8
3	1634	The food is uniformly exceptional, with a very...	kitchen	positive	55	62
4	1634	The food is uniformly exceptional, with a very...	menu	neutral	141	145

```
df2 = pd.read_csv(data_path + '/Laptop_Train_v2.csv')
df2.head()
```

	id	Sentence	Aspect Term	polarity	from	to
0	2339	I charge it at night and skip taking the cord ...	cord	neutral	41	45
1	2339	I charge it at night and skip taking the cord ...	battery life	positive	74	86
2	1316	The tech guy then said the service center does...	service center	negative	27	41
3	1316	The tech guy then said the service center does...	"sales" team	negative	109	121
4	1316	The tech guy then said the service center does...	tech guy	neutral	4	12

```
df = pd.concat([df1, df2])
```

```
df.isna().sum()
```

	0
id	0
Sentence	0
Aspect Term	0
polarity	0
from	0
to	0

```
df.shape
```

```
(6051, 6)
```

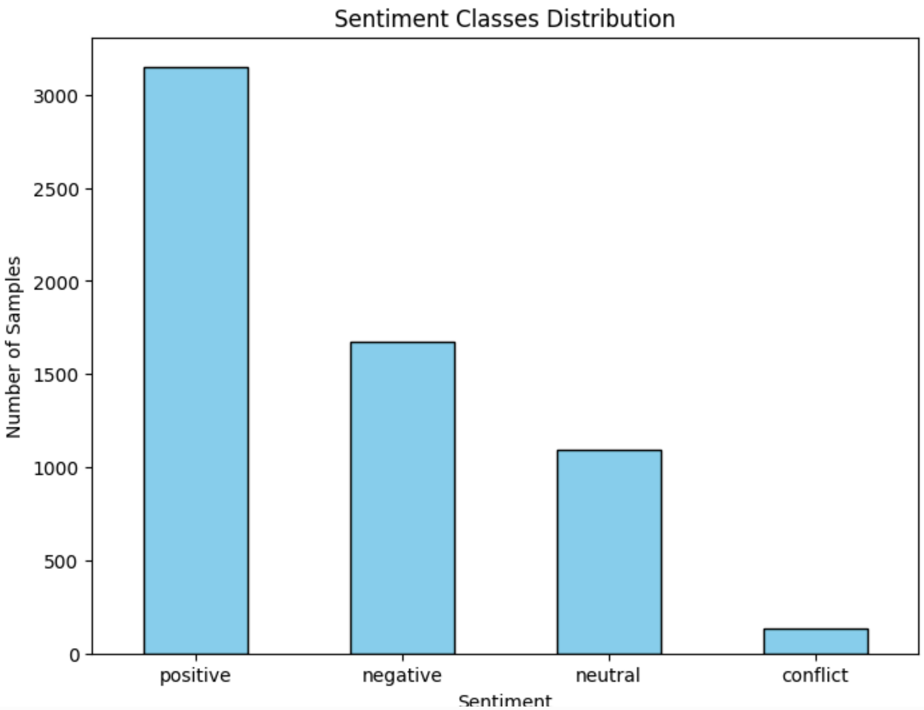
```
class_counts = df["polarity"].value_counts()
class_counts
```

	count
polarity	
positive	3151
negative	1671
neutral	1093
conflict	136

```
plt.figure(figsize=(8, 6))
class_counts.plot(kind='bar', color='skyblue', edgecolor='black')

plt.xlabel("Sentiment")
plt.ylabel("Number of Samples")
plt.title("Sentiment Classes Distribution")
plt.xticks(rotation=0)

plt.show()
```



Dropping Unimportant Columns & Rows

```
df.drop(['id', 'from', 'to'], axis=1, inplace=True)
```

```
df.head()
```

	Sentence	Aspect Term	polarity
0	But the staff was so horrible to us.	staff	negative
1	To be completely fair, the only redeeming fact...	food	positive
2	The food is uniformly exceptional, with a very...	food	positive
3	The food is uniformly exceptional, with a very...	kitchen	positive
4	The food is uniformly exceptional, with a very...	menu	neutral

```
df.drop(df[df.polarity == 'conflict'].index, inplace = True)
```

```
df = df.rename(columns={"Sentence": "text", "Aspect Term": "aspect", "polarity": "label"})
```

```
df.shape
```

```
(5818, 3)
```

Cleaning Reviews Text

```
def clean_text(text):
  """Clean and preprocess text data
  Parameters:
  -----------
  text : str
  The text to clean

  Returns:
  --------
  str
  Cleaned text
  """

  # Convert to lowercase
  text = text.lower()

  # Handle contractions
  contractions = {
      "isn't": "is not", "aren't": "are not", "wasn't": "was not", "weren't": "were not","haven't": "have not",
      "hasn't": "has not", "hadn't": "had not", "doesn't": "does not", "don't": "do not", "didn't": "did not",
      "won't": "will not", "wouldn't": "would not", "can't": "cannot", "couldn't": "could not", "shouldn't": "should not",
      "mightn't": "might not", "mustn't": "must not", "i'm": "i am", "you're": "you are", "he's": "he is", "she's": "she is",
      "it's": "it is", "we're": "we are", "they're": "they are", "i've": "i have", "you've": "you have", "we've": "we have",
      "they've": "they have", "i'd": "i would", "you'd": "you would", "he'd": "he would", "she'd": "she would", "it'd": "it would",
      "we'd": "we would", "they'd": "they would", "i'll": "i will", "you'll": "you will", "he'll": "he will", "she'll": "she will",
      "it'll": "it will", "we'll": "we will", "they'll": "they will", "didnt": "did not", "dont": "do not", "cant": "cannot", "wont": "will not",
      }

  for contraction, expansion in contractions.items():
    text = text.replace(contraction, expansion)

  # Preserve emotions
  emoticons = {
      ':)': ' HAPPY_FACE ',
      ':(': ' SAD_FACE ',
      ':D': ' LAUGH_FACE ',
      ':/': ' CONFUSED_FACE '
      }
  for emoticon, replacement in emoticons.items():
    text = text.replace(emoticon, replacement)


  # Remove punctuation but preserve sentence structure
  text = re.sub(f'[{re.escape(string.punctuation)}]', ' ', text)

  # Remove extra whitespace
  text = re.sub(r'\s+', ' ', text).strip()

  # Restore emotions
  for placeholder, emoticon in {v: k for k, v in emoticons.items()}.items():
    text = text.replace(placeholder, emoticon)

  return text
```

Encoding Polarity Column

```
sentiment_encoder = LabelEncoder()

df['label'] = sentiment_encoder.fit_transform(df['label'])

label_mapping = dict(zip(sentiment_encoder.classes_, range(len(sentiment_encoder.classes_))))
print(label_mapping)
```

```
{'negative': 0, 'neutral': 1, 'positive': 2}
```

```
df['label'].dtype
```

```
dtype('int64')
```

```
df["label"] = df["label"].apply(
    lambda x: x.iloc[0] if isinstance(x, pd.Series) else (x[0] if isinstance(x, list) else x)
)
```

```
print(type(df.loc[0, "label"]))   # Should print: <class 'int'>
```

```
<class 'pandas.core.series.Series'>
```

```
print(df["label"].iloc[0])
print(type(df["label"].iloc[0]))
```

```
0
<class 'numpy.int64'>
```

Fine-Tuning roBERTa

```
train_df, tst_df = train_test_split(df, test_size=0.2, random_state=42)
val_df, test_df = train_test_split(tst_df, test_size=0.3, random_state=42)
```

Tokenizer

```
tokenizer = AutoTokenizer.from_pretrained("roberta-base")
```

```
/usr/local/lib/python3.11/dist-packages/huggingface_hub/utils/_auth.py:94: UserWarning:
The secret `HF_TOKEN` does not exist in your Colab secrets.
To authenticate with the Hugging Face Hub, create a token in your settings tab (https://huggingface.co/settings/tokens), set it as secret in your Google Colab and restart your session.
You will be able to reuse this secret in all of your notebooks.
Please note that authentication is recommended but still optional to access public models or datasets.
  warnings.warn(
```

tokenizer_config.json: 100% 25.0/25.0 [00:00<00:00, 2.43kB/s]

config.json: 100% 481/481 [00:00<00:00, 48.1kB/s]

vocab.json: 100% 899k/899k [00:00<00:00, 3.86MB/s]

merges.txt: 100% 456k/456k [00:00<00:00, 1.06MB/s]

tokenizer.json: 100% 1.36M/1.36M [00:00<00:00, 3.15MB/s]

Dataset Class

```
class AspectSentimentDataset(Dataset):
    def __init__(self, dataframe, tokenizer, max_len=128):
        self.df = dataframe.reset_index(drop=True)
        self.tokenizer = tokenizer
        self.max_len = max_len

    def __len__(self):
        return len(self.df)

    def __getitem__(self, idx):
      if isinstance(idx, (list, np.ndarray, pd.Series)):
            if len(idx) != 1:
                raise ValueError(f"Expected scalar idx, but got batch: {idx}")
            idx = int(idx[0])
      elif isinstance(idx, torch.Tensor):
            idx = idx.item()
      else:
            idx = int(idx)

      # Safe scalar access
      review = str(self.df.at[idx, "text"])
      aspect = str(self.df.at[idx, "aspect"])
      label = int(self.df.at[idx, "label"])

      encoded = self.tokenizer(
          review,
          aspect,
          truncation=True,
          padding="max_length",
          max_length=self.max_len,
          return_tensors="pt"
      )
      item = {
          "input_ids": encoded["input_ids"].squeeze(0),
          "attention_mask": encoded["attention_mask"][0].squeeze(0),
          "label": torch.tensor(label, dtype=torch.long)
          }
      return item
```

```
train_dataset = AspectSentimentDataset(train_df, tokenizer)
val_dataset = AspectSentimentDataset(val_df, tokenizer)
test_dataset = AspectSentimentDataset(test_df, tokenizer)

# DataLoaders
train_loader = DataLoader(train_dataset, batch_size=16, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=16, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=16)
```

Saving Functions

```
def save_checkpoint(model, optimizer, epoch, loss, filename='checkpoint.pth'):
    checkpoint = {
```

```
        'model_state_dict': model.state_dict(),
        'optimizer_state_dict': optimizer.state_dict(),
        'epoch': epoch,
        'loss': loss
    }
    torch.save(checkpoint, filename)
```

```
def load_checkpoint(model, optimizer, filename='checkpoint.pth'):
    checkpoint = torch.load(filename)
    model.load_state_dict(checkpoint['model_state_dict'])
    optimizer.load_state_dict(checkpoint['optimizer_state_dict'])
    epoch = checkpoint['epoch']
    loss = checkpoint['loss']
    return model, optimizer, epoch, loss
```

Trial 1

Model Architecture

```
class AspectSentimentClassifier(nn.Module):
    def __init__(self, model_name='roberta-base', num_labels=3):
        super().__init__()
        self.roberta = RobertaModel.from_pretrained(model_name)
        self.dropout = nn.Dropout(0.2)

        hidden_size = self.roberta.config.hidden_size

        self.classifier = nn.Sequential(
            nn.Linear(hidden_size, 512),
            nn.ReLU(),
            nn.LayerNorm(512),
            nn.Linear(512, 128),
            nn.GELU(),
            nn.Linear(128, num_labels)
        )

    def forward(self, input_ids, attention_mask):
        outputs = self.roberta(
            input_ids=input_ids,
            attention_mask=attention_mask
        )
        cls_embedding = outputs.last_hidden_state[:, 0, :]
        cls_embedding = self.dropout(cls_embedding)
        logits = self.classifier(cls_embedding)
        return logits
```

Training

```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print("Using device:", device)

model1 = AspectSentimentClassifier()
model1.to(device)
```

```
criterion = nn.CrossEntropyLoss()
optimizer = optim.AdamW(model1.parameters(), lr=2e-5)

epochs = 5

def compute_accuracy(preds, labels):
    preds = torch.argmax(preds, dim=1)
    return (preds == labels).float().mean().item()
```

```
Using device: cuda
Some weights of RobertaModel were not initialized from the model checkpoint at roberta-base and are newly initialized: ['pooler.dense.bias', 'pooler.dense.weight']
You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.
```

```
# Training
best_val_acc = 0.0
best_val_loss = float('inf')

for epoch in range(epochs):
    model1.train()
    total_train_loss = 0
    total_train_acc = 0

    loop = tqdm(train_loader, desc=f"Epoch {epoch+1}/{epochs}")

    for batch in loop:
        input_ids = batch["input_ids"].to(device)
        attention_mask = batch["attention_mask"].to(device)
        labels = batch["label"].to(device)

        optimizer.zero_grad()
        outputs = model1(input_ids=input_ids, attention_mask=attention_mask)
        loss = criterion(outputs, labels)
        acc = compute_accuracy(outputs, labels)

        loss.backward()
        optimizer.step()

        total_train_loss += loss.item()
        total_train_acc += acc

        loop.set_postfix(loss=loss.item(), acc=acc)

    avg_train_loss = total_train_loss / len(train_loader)
    avg_train_acc = total_train_acc / len(train_loader)
    print(f"\nTrain Loss: {avg_train_loss:.4f} | Train Acc: {avg_train_acc:.4f}")

    # Validation
    model1.eval()
    total_val_loss = 0
    total_val_acc = 0

    with torch.no_grad():
        for batch in val_loader:
            input_ids = batch["input_ids"].to(device)
            attention_mask = batch["attention_mask"].to(device)
            labels = batch["label"].to(device)
```

```
            outputs = model1(input_ids=input_ids, attention_mask=attention_mask)
            loss = criterion(outputs, labels)
            acc = compute_accuracy(outputs, labels)

            total_val_loss += loss.item()
            total_val_acc += acc

    avg_val_loss = total_val_loss / len(val_loader)
    avg_val_acc = total_val_acc / len(val_loader)
    print(f"Val Loss: {avg_val_loss:.4f} | Val Acc: {avg_val_acc:.4f}\n")

    # Save model only if val accuracy is better AND val loss doesn't increase significantly
    if avg_val_acc > best_val_acc and avg_val_loss <= best_val_loss + 0.01:
        best_val_acc = avg_val_acc
        best_val_loss = avg_val_loss
        save_checkpoint(model1, optimizer, epoch, avg_val_loss, 'best_model1.pth')
        print(f"✅ New best model saved with acc: {best_val_acc:.4f}, loss: {best_val_loss:.4f}\n")
```

```
Epoch 1/5: 100%|██████████| 291/291 [01:43<00:00,  2.80it/s, acc=0.786, loss=0.631]

Train Loss: 0.6746 | Train Acc: 0.7190
Val Loss: 0.5214 | Val Acc: 0.7801

✅ New best model saved with acc: 0.7801, loss: 0.5214

Epoch 2/5: 100%|██████████| 291/291 [01:42<00:00,  2.83it/s, acc=0.929, loss=0.121]

Train Loss: 0.4262 | Train Acc: 0.8359
Val Loss: 0.5837 | Val Acc: 0.8057

Epoch 3/5: 100%|██████████| 291/291 [01:42<00:00,  2.84it/s, acc=0.929, loss=0.293]

Train Loss: 0.3090 | Train Acc: 0.8937
Val Loss: 0.4394 | Val Acc: 0.8283

✅ New best model saved with acc: 0.8283, loss: 0.4394

Epoch 4/5: 100%|██████████| 291/291 [01:42<00:00,  2.84it/s, acc=0.929, loss=0.35]

Train Loss: 0.2157 | Train Acc: 0.9315
Val Loss: 0.4315 | Val Acc: 0.8561

✅ New best model saved with acc: 0.8561, loss: 0.4315

Epoch 5/5: 100%|██████████| 291/291 [01:42<00:00,  2.83it/s, acc=1, loss=0.0975]

Train Loss: 0.1528 | Train Acc: 0.9500
Val Loss: 0.5004 | Val Acc: 0.8479
```

Model Evaluation on Test Data

```
def test_model(model, dataloader, loss_fn):
    model.eval()
    total_loss = 0
    total_correct = 0
    total_samples = 0

    with torch.no_grad():
        for batch in dataloader:
            input_ids = batch['input_ids']
            attention_mask = batch['attention_mask']
```

```
            labels = batch['label']

            # Move to GPU if available
            device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
            input_ids = input_ids.to(device)
            attention_mask = attention_mask.to(device)
            labels = labels.to(device)
            model = model.to(device)

            # Forward pass
            outputs = model(input_ids=input_ids, attention_mask=attention_mask)
            loss = loss_fn(outputs, labels)

            # Compute predictions and metrics
            total_loss += loss.item() * input_ids.size(0)
            preds = torch.argmax(outputs, dim=1)
            total_correct += (preds == labels).sum().item()
            total_samples += input_ids.size(0)

    avg_loss = total_loss / total_samples
    accuracy = total_correct / total_samples
    print(f"Test Loss: {avg_loss:.4f} | Test Accuracy: {accuracy:.4f}")
    return avg_loss, accuracy
```

```
model1, optimizer, loaded_epoch, loaded_loss = load_checkpoint(model1, optimizer, 'best_model1.pth')

test_loss, test_acc = test_model(model1, test_loader, criterion)
```

```
Test Loss: 0.5373 | Test Accuracy: 0.8486
```

```
save_checkpoint(model1, optimizer, epoch, avg_val_loss, data_path + '/roBERTa_model_v1.pth')
```

Trial 2

Model Architenture

Reducing the density of the classifir and adding droupout for bettter generalization

```
class AspectSentimentClassifier2(nn.Module):
    def __init__(self, model_name='roberta-base', num_labels=3):
        super().__init__()
        self.roberta = RobertaModel.from_pretrained(model_name)
        self.dropout = nn.Dropout(0.2)

        hidden_size = self.roberta.config.hidden_size

        self.classifier = nn.Sequential(
            nn.Linear(hidden_size, 256),
            nn.ReLU(),
            nn.Dropout(0.3),
            nn.Linear(256, num_labels)
        )
```

```
    def forward(self, input_ids, attention_mask):
        outputs = self.roberta(
            input_ids=input_ids,
            attention_mask=attention_mask
        )
        cls_embedding = outputs.last_hidden_state[:, 0, :]
        cls_embedding = self.dropout(cls_embedding)
        logits = self.classifier(cls_embedding)
        return logits
```

Training

```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print("Using device:", device)

model2 = AspectSentimentClassifier2()
model2.to(device)

criterion = nn.CrossEntropyLoss()
optimizer = optim.AdamW(model2.parameters(), lr=2e-5)

epochs = 5

def compute_accuracy(preds, labels):
    preds = torch.argmax(preds, dim=1)
    return (preds == labels).float().mean().item()
```

```
Using device: cuda
Some weights of RobertaModel were not initialized from the model checkpoint at roberta-base and are newly initialized: ['pooler.dense.bias', 'pooler.dense.weight']
You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.
```

```
# Training
best_val_acc = 0.0
best_val_loss = float('inf')
for epoch in range(epochs):
    model2.train()
    total_train_loss = 0
    total_train_acc = 0

    loop = tqdm(train_loader, desc=f"Epoch {epoch+1}/{epochs}")

    for batch in loop:
        input_ids = batch["input_ids"].to(device)
        attention_mask = batch["attention_mask"].to(device)
        labels = batch["label"].to(device)

        optimizer.zero_grad()
        outputs = model2(input_ids=input_ids, attention_mask=attention_mask)
        loss = criterion(outputs, labels)
        acc = compute_accuracy(outputs, labels)

        loss.backward()
        optimizer.step()

        total_train_loss += loss.item()
```

```
        total_train_acc += acc

        loop.set_postfix(loss=loss.item(), acc=acc)

    avg_train_loss = total_train_loss / len(train_loader)
    avg_train_acc = total_train_acc / len(train_loader)
    print(f"\nTrain Loss: {avg_train_loss:.4f} | Train Acc: {avg_train_acc:.4f}")

    # Validation
    model2.eval()
    total_val_loss = 0
    total_val_acc = 0

    with torch.no_grad():
        for batch in val_loader:
            input_ids = batch["input_ids"].to(device)
            attention_mask = batch["attention_mask"].to(device)
            labels = batch["label"].to(device)

            outputs = model2(input_ids=input_ids, attention_mask=attention_mask)
            loss = criterion(outputs, labels)
            acc = compute_accuracy(outputs, labels)

            total_val_loss += loss.item()
            total_val_acc += acc

    avg_val_loss = total_val_loss / len(val_loader)
    avg_val_acc = total_val_acc / len(val_loader)
    print(f"Val Loss: {avg_val_loss:.4f} | Val Acc: {avg_val_acc:.4f}\n")

    # Save model only if val accuracy is better AND val loss doesn't increase significantly
    if avg_val_acc > best_val_acc and avg_val_loss <= best_val_loss + 0.01:
        best_val_acc = avg_val_acc
        best_val_loss = avg_val_loss
        save_checkpoint(model2, optimizer, epoch, avg_val_loss, 'best_model2.pth')
        print(f"✅ New best model saved with acc: {best_val_acc:.4f}, loss: {best_val_loss:.4f}\n")
```

```
Epoch 1/5: 100%|██████████| 291/291 [01:43<00:00,  2.80it/s, acc=0.571, loss=0.88]

Train Loss: 0.7322 | Train Acc: 0.6955
Val Loss: 0.5156 | Val Acc: 0.7901

✅ New best model saved with acc: 0.7901, loss: 0.5156

Epoch 2/5: 100%|██████████| 291/291 [01:43<00:00,  2.82it/s, acc=0.643, loss=0.974]

Train Loss: 0.4487 | Train Acc: 0.8330
Val Loss: 0.4822 | Val Acc: 0.7990

✅ New best model saved with acc: 0.7990, loss: 0.4822

Epoch 3/5: 100%|██████████| 291/291 [01:44<00:00,  2.78it/s, acc=0.929, loss=0.215]

Train Loss: 0.3261 | Train Acc: 0.8814
Val Loss: 0.4234 | Val Acc: 0.8332

✅ New best model saved with acc: 0.8332, loss: 0.4234

Epoch 4/5: 100%|██████████| 291/291 [01:45<00:00,  2.76it/s, acc=0.857, loss=0.39]

Train Loss: 0.2290 | Train Acc: 0.9237
```

```
Val Loss: 0.5331 | Val Acc: 0.8223

Epoch 5/5: 100%|██████████| 291/291 [01:43<00:00,  2.80it/s, acc=0.929, loss=0.26]

Train Loss: 0.1619 | Train Acc: 0.9456
Val Loss: 0.5656 | Val Acc: 0.8454
```

Model Evalutaion on Test Data

```
model2, optimizer, loaded_epoch, loaded_loss = load_checkpoint(model2, optimizer, 'best_model2.pth')

test_loss, test_acc = test_model(model2, test_loader, criterion)
```

```
Test Loss: 0.5103 | Test Accuracy: 0.8171
```

```
save_checkpoint(model2, optimizer, epoch, avg_val_loss, data_path + '/roBERTa_model_v2.pth')
```