Mounting Google Drive to Access Files

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

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

Install required libraries

```
# Install pyarrow for reading Parquet files
!pip install pyarrow

# Install Hugging Face libraries: transformers, datasets, and evaluate
!pip install -q transformers datasets evaluate
```

```
Requirement already satisfied: pyarrow in /usr/local/lib/python3.11/dist-packages (18.1.0)
```

Imports

```
# Data handling and numerical operations
import pandas as pd
import numpy as np

# PyTorch for deep learning
import torch

# Visualization libraries
import seaborn as sns
import matplotlib.pyplot as plt

# Hugging Face tools for datasets and transformers
from datasets import Dataset
from transformers import BertTokenizerFast, BertForSequenceClassification
from transformers import DataCollatorWithPadding, Trainer, TrainingArguments

# Evaluation tools
import evaluate
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
```

Load alternate AG News Parquet files

```
# Set file paths for training and test Parquet files stored in Google Drive
train_path = "/content/drive/MyDrive/Colab Notebooks/Ass_2/train-00000-of-00001 (2).parquet"
test_path = "/content/drive/MyDrive/Colab Notebooks/Ass_2/test-00000-of-00001 (1).parquet"

# Load the Parquet files into pandas DataFrames
train_df = pd.read_parquet(train_path)
test_df = pd.read_parquet(test_path)

# Print the number of samples in each dataset
print("Train Size:", len(train_df))
print("Test Size:", len(test_df))

# Display the first few rows of the training data
train_df.head()
```

```
Train Size: 120000
Test Size: 7600
```

	text	label
0	Wall St. Bears Claw Back Into the Black (Reute...	2
1	Carlyle Looks Toward Commercial Aerospace (Reu...	2
2	Oil and Economy Cloud Stocks' Outlook (Reuters...	2
3	Iraq Halts Oil Exports from Main Southern Pipe...	2

Class labels

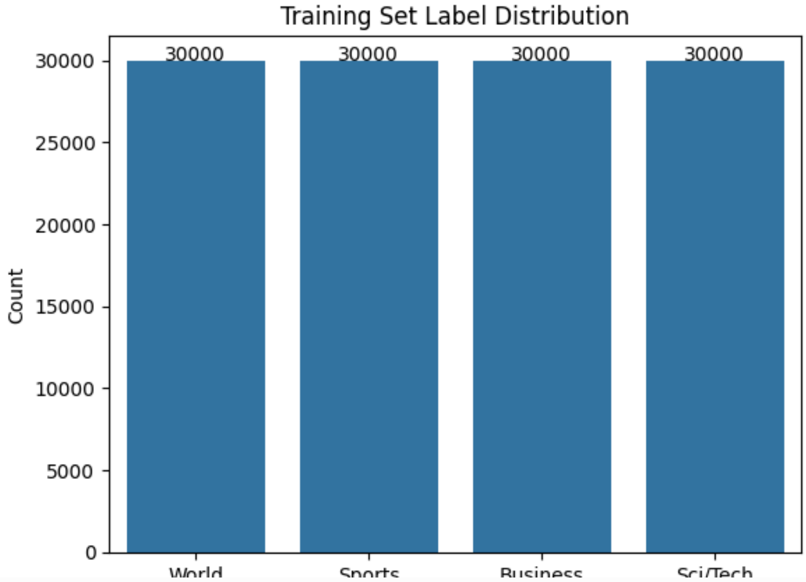
```
# Define the names for each class label
label_names = ['World', 'Sports', 'Business', 'Sci/Tech']
```

EDA: Visualizing the Class Distribution with Counts on Bars

```
# Plot the count of each class in the training data
ax = sns.countplot(x="label", data=train_df)
plt.title("Training Set Label Distribution")
plt.xlabel("Class")
plt.ylabel("Count")
plt.xticks(ticks=[0, 1, 2, 3], labels=label_names)

# Add the exact count value on top of each bar for clarity
for p in ax.patches:
    height = p.get_height()
    ax.text(p.get_x() + p.get_width()/2., height + 5,  # 5 is vertical offset
            f'{int(height)}', ha="center")

plt.show()
```



Tokenizer

```
# Load BERT tokenizer
tokenizer = BertTokenizerFast.from_pretrained("bert-base-uncased")

# Tokenize the text and cut off if too long
def tokenize_function(example):
    return tokenizer(example["text"], truncation=True)
```

Convert to HF Dataset and tokenize

```
# Change pandas data to Hugging Face Dataset
train_dataset = Dataset.from_pandas(train_df)
test_dataset = Dataset.from_pandas(test_df)

# Apply tokenizer to the data in batches
train_dataset = train_dataset.map(tokenize_function, batched=True)
test_dataset = test_dataset.map(tokenize_function, batched=True)
```

```
Map: 100%    120000/120000 [00:08<00:00, 10983.85 examples/s]
```

Load BERT model

```
# Load pre-trained BERT with a classification head for 4 classes
model = BertForSequenceClassification.from_pretrained("bert-base-uncased", num_labels=4)
```

```
Some weights of BertForSequenceClassification were not initialized from the model checkpoint at bert-base-uncased and are new
You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.
```

Define accuracy metric

```
# Load accuracy metric from evaluate library
accuracy = evaluate.load("accuracy")

# Define a function to compute accuracy from model predictions
def compute_metrics(eval_pred):
    logits, labels = eval_pred
    predictions = np.argmax(logits, axis=-1)  # Get predicted class
    return accuracy.compute(predictions=predictions, references=labels)
```

Training arguments

```
# Set training parameters:
# - Save and evaluate model after each epoch
# - Batch size of 16 for training and evaluation
# - Learning rate 2e-5
# - Train for 3 epochs
# - Apply weight decay for regularization
# - Load best model at the end
# - Disable external logging (like WandB)
training_args = TrainingArguments(
    output_dir="./results",
    eval_strategy="epoch",
    save_strategy="epoch",
    logging_dir="./logs",
    per_device_train_batch_size=16,
    per_device_eval_batch_size=16,
    learning_rate=2e-5,
    num_train_epochs=3,
    weight_decay=0.01,
    load_best_model_at_end=True,
    report_to=[]
)
```

```
# Create a Trainer object to handle training and evaluation
# It uses the model, training arguments, datasets, padding, and metrics defined earlier
trainer = Trainer(
    model=model,
    args=training_args,
    train_dataset=train_dataset,
    eval_dataset=test_dataset,
    data_collator=DataCollatorWithPadding(tokenizer),
    compute_metrics=compute_metrics
```

```
)
```

Train the model

```
# Start training the model using the Trainer
trainer.train()
```

[22500/22500 27:50, Epoch 3/3]

Epoch	Training Loss	Validation Loss	Accuracy
1	0.194600	0.176466	0.943553
2	0.126200	0.192912	0.948553
3	0.078600	0.238891	0.946053

Evaluate on test set

```
# Evaluate the trained model on the test dataset
metrics = trainer.evaluate(test_dataset)

# Print the accuracy score on the test data
print("Test Accuracy:", metrics["eval_accuracy"])
```

Predict on test set

```
# Get model predictions on the test dataset
predictions = trainer.predict(test_dataset)
logits = predictions.predictions

# Convert logits to predicted class labels
predicted_labels = np.argmax(logits, axis=-1)

# Add predicted labels and class names to the test DataFrame
test_df["predicted_label"] = predicted_labels
test_df["predicted_class"] = test_df["predicted_label"].map(lambda x: label_names[x])
test_df["true_class"] = test_df["label"].map(lambda x: label_names[x])

# Display 10 random samples with their text, true class, and predicted class
test_df[["text", "true_class", "predicted_class"]].sample(10)
```

	text	true_class	predicted_class
7094	Fan v Fan: Manchester City-Tottenham Hotspur T...	Sports	Sports
1017	Paris Tourists Search for Key to 'Da Vinci Cod...	World	Sci/Tech
2850	Net firms: Don't tax VoIP The Spanish-American...	Sci/Tech	Sci/Tech
1452	Dependent species risk extinction The global e...	Sci/Tech	Sci/Tech
457	EDS Is Charter Member of Siebel BPO Alliance (...	Sci/Tech	Sci/Tech
6256	Campbell 9 Pct. Profit #39;Hmmm Hmmm Good #39...	Business	Business
6281	Forgoing stiff upper lip, Charles jousts with ...	World	World
4999	Profit Plunges at International Game Tech Inte...	Business	Business
2941	Salvaging Genesis Despite a seemingly calamito...	Sci/Tech	Sci/Tech

Confusion matrix

```
# Compute the confusion matrix comparing true and predicted labels
cm = confusion_matrix(test_df["label"], test_df["predicted_label"])
```

```
# Create a plot for the confusion matrix with class labels
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=label_names)

# Display the confusion matrix with a blue color map
disp.plot(cmap="Blues")
plt.title("Confusion Matrix - AG News Alternate Test Set")
plt.show()
```