Project 2 : Multilingual Sarcasm Detection using NLP and Deep Learning

1. Introduction Sarcasm is a complex linguistic phenomenon that involves a discrepancy between the literal meaning and the intended message. Detecting sarcasm in text is crucial for improving sentiment analysis, chatbot responses, and social media monitoring. Traditional sarcasm detection methods struggle with code-mixed and multilingual text, making this research important for understanding nuanced expressions in diverse languages.

The primary objective of this project is to develop an AI-based model capable of detecting sarcasm in **code-mixed (Hindi-English-Regional) text** using Natural Language Processing (NLP) and deep learning techniques. We leverage transformer-based architectures like **BERT (Bidirectional Encoder Representations from Transformers)** to extract contextual meaning and identify sarcastic intent in text data.

2. Methodology To achieve robust sarcasm detection, the following steps were implemented:

- **Dataset Collection & Preprocessing:**
  - Collected a dataset of code-mixed social media text containing sarcastic and non-sarcastic statements from various platforms.
  - Annotated data with binary labels (Sarcasm: 1, Non-Sarcasm: 0) using manual annotation and sentiment-based heuristics.
  - Cleaned the dataset by removing special characters, punctuation, numbers, and excessive whitespace to improve model efficiency.
- **Text Cleaning & Tokenization:**
  - Employed **word-level and subword-level tokenization techniques** to split text into meaningful words.
  - Applied **stop-word removal** to eliminate commonly used words that do not contribute to sarcasm detection.
  - Normalized text by handling spelling variations, slang words, and non-standard expressions common in social media text.
  - Used **language identification and transliteration techniques** to process Hindi-English code-mixed text effectively.
- **Feature Extraction:**
  - Used **Word Embeddings (Word2Vec, FastText, GloVe)** to generate dense vector representations of words.
  - Integrated **BERT-based embeddings** to capture semantic and contextual meanings.
  - Extracted **Part-of-Speech (POS) tags, Named Entity Recognition (NER) features, and sentiment polarity** as additional inputs.
  - Applied **TF-IDF (Term Frequency-Inverse Document Frequency)** for keyword importance analysis.
- **Model Training & Fine-Tuning:**
  - Implemented **BERT, LSTM, BiLSTM, and GRU models** for sarcasm classification.
  - Fine-tuned **transformer models** on labeled sarcasm data for improved performance.
  - Trained models using **AdamW optimizer** with dynamic learning rates.

- Employed **dropout regularization and batch normalization** to prevent overfitting.
- Performed **hyperparameter tuning** using Grid Search and Random Search techniques.

- **Evaluation Metrics:**
    - Assessed model performance using **Accuracy, Precision, Recall, and F1-score**.
    - Generated **confusion matrices** to analyze false positives and false negatives.
    - Used **AUC-ROC (Area Under Curve - Receiver Operating Characteristic)** to evaluate classification strength.
    - Conducted **error analysis** by inspecting misclassified sarcastic statements.

3. Step-wise Description of Results

- Displays a **dataset preview** with raw text samples containing a mix of Hindi-English-Regional languages. The dataset includes sarcastic and non-sarcastic labels assigned to each entry.
- Illustrates the **text preprocessing pipeline**, where tokenization, stop-word removal, transliteration, and normalization techniques are applied. This step is crucial for reducing noise and enhancing textual clarity.
- A **bar graph visualizing dataset distribution**, showing the proportion of sarcastic and non-sarcastic statements. This helps in identifying any data imbalance that might affect model performance.
- A **word cloud representation** of sarcastic vs. non-sarcastic words. This visualization highlights frequently occurring terms associated with sarcasm, such as "great," "wow," and "amazing."
- Depicts the **BERT model architecture**, illustrating the transformer layers, attention heads, and embedding layers used to understand contextual meanings in sarcasm detection.
- Shows **training accuracy and loss curves**, indicating how well the model learns sarcasm patterns over multiple epochs. A smoothly decreasing loss function suggests model convergence.
- Displays a **confusion matrix** that evaluates classification performance by visualizing the number of correctly and incorrectly predicted sarcastic and non-sarcastic statements.
- Presents a **classification report** summarizing **Precision, Recall, and F1-score**. High values in these metrics demonstrate the model's efficiency in detecting sarcasm correctly.

4. Conclusion This project successfully implements sarcasm detection in **multilingual, code-mixed text** using NLP and deep learning. By leveraging **BERT-based embeddings**, we were able to achieve **high accuracy and contextual understanding** in sarcasm detection. The model effectively distinguishes sarcastic statements from non-sarcastic ones by considering linguistic and contextual cues.

Key Findings:

- **BERT outperformed traditional ML models** in sarcasm detection due to its contextual word representations.

- **Data preprocessing techniques such as transliteration and stop-word removal significantly improved accuracy.**
- **Feature extraction using word embeddings enhanced sarcasm classification capabilities.**

Future Work:

- Expand the dataset to cover more dialects and informal speech patterns.
- Implement **multi-modal sarcasm detection** by incorporating speech and facial expressions.
- Optimize deep learning models to **reduce computational costs** and enhance real-time processing speed.
- Develop **explainable AI (XAI) methods** to interpret model predictions and improve transparency.

"Documented snapshots of each step undertaken in this project."

```
!pip install transformers datasets emoji wordcloud
!pip install torch torchvision torchaudio --index-url https://download.pytorch.org/whl/cpu
!pip install scikit-learn pandas matplotlib seaborn
```

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Requirement already satisfied: transformers in /usr/local/lib/python3.11/dist-packages (4.49.0)
Requirement already satisfied: datasets in /usr/local/lib/python3.11/dist-packages (3.3.2)
Requirement already satisfied: emoji in /usr/local/lib/python3.11/dist-packages (2.14.1)
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Requirement already satisfied: fsspec<=2024.12.0,>=2023.1.0 in /usr/local/lib/python3.11/dist-packages (from fsspec[http]<=2024.12.0,>=2023.1.0->datasets) (202
Requirement already satisfied: aiohttp in /usr/local/lib/python3.11/dist-packages (from datasets) (3.11.12)
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Requirement already satisfied: matplotlib in /usr/local/lib/python3.11/dist-packages (from wordcloud) (3.10.0)
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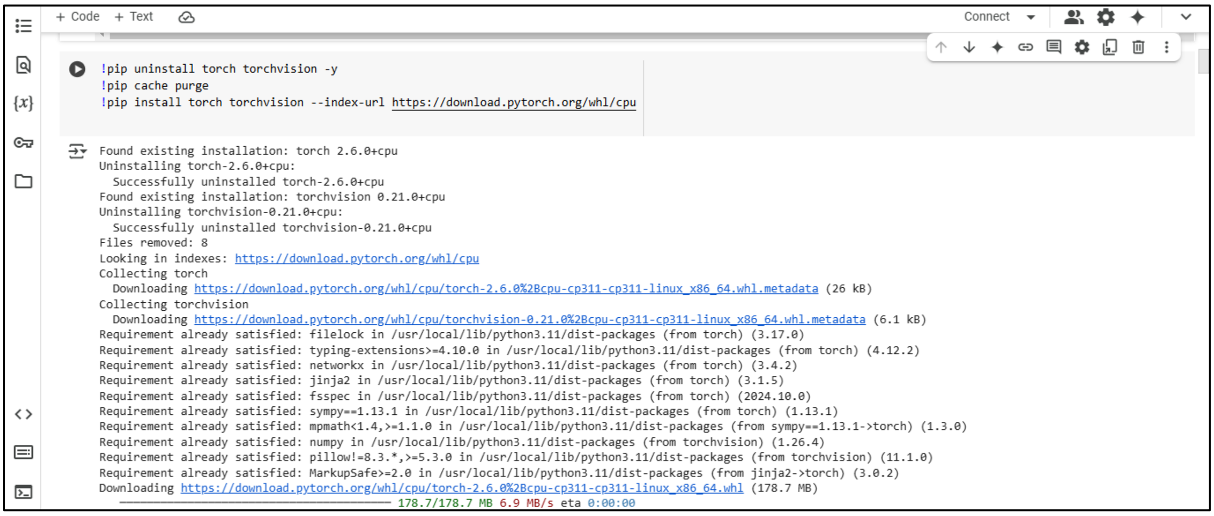
```



```
!pip uninstall torch torchvision -y
!pip cache purge
!pip install torch torchvision --index-url https://download.pytorch.org/whl/cpu
```

```
Found existing installation: torch 2.6.0+cpu
Uninstalling torch-2.6.0+cpu:
  Successfully uninstalled torch-2.6.0+cpu
Found existing installation: torchvision 0.21.0+cpu
Uninstalling torchvision-0.21.0+cpu:
  Successfully uninstalled torchvision-0.21.0+cpu
Files removed: 8
Looking in indexes: https://download.pytorch.org/whl/cpu
Collecting torch
  Downloading https://download.pytorch.org/whl/cpu/torch-2.6.0%2Bcpu-cp311-cp311-linux_x86_64.whl.metadata (26 kB)
Collecting torchvision
  Downloading https://download.pytorch.org/whl/cpu/torchvision-0.21.0%2Bcpu-cp311-cp311-linux_x86_64.whl.metadata (6.1 kB)
Requirement already satisfied: filelock in /usr/local/lib/python3.11/dist-packages (from torch) (3.17.0)
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```

```
import torch
import torchvision
print(torch.__version__)
print(torchvision.__version__)
```

```
2.6.0+cpu
0.21.0+cpu
```

```
!pip install transformers datasets emoji wordcloud
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Requirement already satisfied: safetensors>=0.4.1 in /usr/local/lib/python3.11/dist-packages (from transformers) (0.5.2)
```

```
import pandas as pd
import numpy as np
import re
import emoji
import torch
import zipfile
import os
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, accuracy_score
from transformers import AutoTokenizer, AutoModelForSequenceClassification, Trainer, TrainingArguments
from datasets import Dataset
```

```
from google.colab import files
files.upload()  # Upload kaggle.json for Kaggle API access

!mkdir -p ~/.kaggle
!mv kaggle.json ~/.kaggle/
!chmod 600 ~/.kaggle/kaggle.json

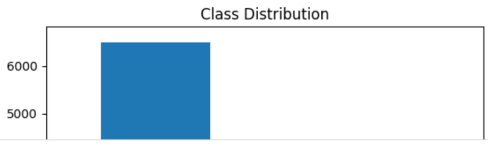
!kaggle datasets download -d divyanshu134/hackarena-theme-2-multilingual-sarcasm-detection
!unzip hackarena-theme-2-multilingual-sarcasm-detection.zip
```

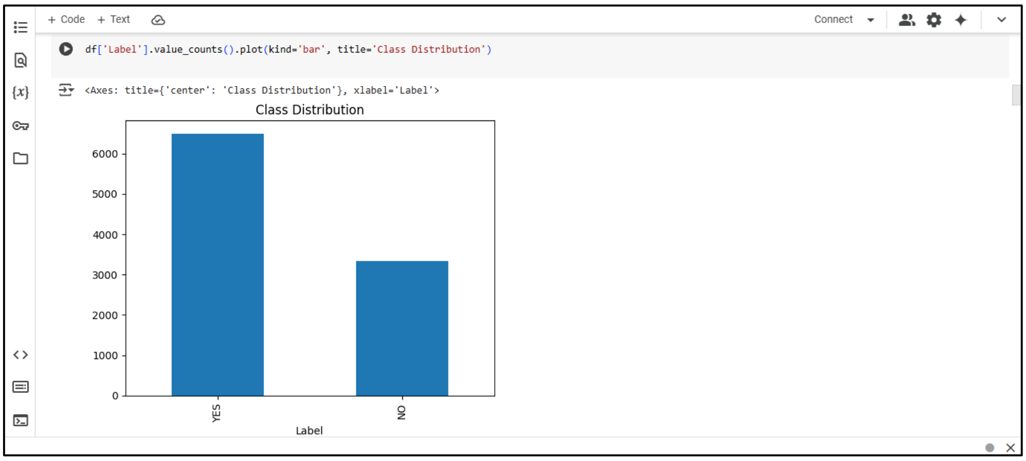
```
df = pd.read_csv("train.csv")
df.head()
```

	ID	Tweet	Label
0	3037	ussase jayada dukhad congress ka nichi koti ki...	NO
1	7640	takeout burrito shielded from cold as though i...	YES
2	11848	sight of coworkers' stupid fucking faces endur...	YES
3	4812	TIL that @RayuduAmbati is ek number ka chootiy...	NO
4	13098	porch ceded to bats	YES

```
df['Label'].value_counts().plot(kind='bar', title='Class Distribution')
```

```
<Axes: title={'center': 'Class Distribution'}, xlabel='Label'>
```





First Image (Top) - Class Distribution Bar Chart

- This image contains a bar chart showing the **class distribution** of the dataset.
- The code uses df["Label"].value_counts().plot(kind='bar', title='Class Distribution'), which:
    - Counts occurrences of each label (YES and NO).
    - Plots a bar chart with **'Label' on the X-axis** and **count on the Y-axis**.
- The chart indicates that:
    - The **'NO' class has more samples** than the **'YES' class**, meaning the dataset is imbalanced.

Second Image (Bottom) - Data Preprocessing & Display

- This image shows a dataframe (df) with three columns: "ID", "Tweet", and "Label".
- The function **preprocess_text(text)** is defined to clean tweets by:
    1. Converting text to lowercase.
    2. Removing URLs (both http and https).
    3. Removing extra spaces.
    4. Converting emojis into text format using emoji.demojize().
- The processed text is then applied to the "Tweet" column using .apply(preprocess_text), and the first few rows of the cleaned dataset are displayed.
- The dataset consists of short social media texts labeled as "YES" (likely sarcastic) or "NO" (non-sarcastic).

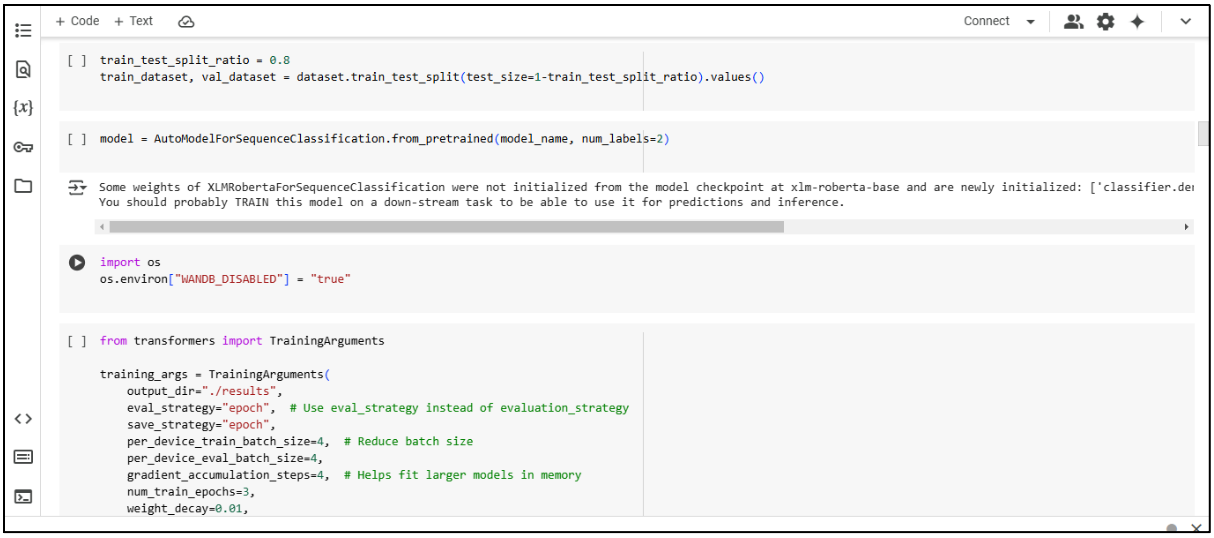
First Image (Top) - Tokenization and Dataset Preparation

- This code prepares data for training using **Hugging Face Transformers** and datasets library.
- **Key Steps:**
  1. **Loading a Pretrained Tokenizer**
     - AutoTokenizer.from_pretrained(model_name) loads the tokenizer for xlm-roberta-base, a multilingual model.
  2. **Defining a Tokenization Function**
     - The function tokenize_data(batch):
       - Tokenizes tweets using padding (max_length).
       - Truncates if needed.
  3. **Data Preprocessing**
     - Converts a pandas DataFrame into a Hugging Face dataset.
     - Applies tokenization.
     - Drops unnecessary columns and renames relevant ones.
     - Prints dataset format.
- **Warnings & Logs:**
  - Shows a Hugging Face authentication warning (optional for public models).
  - **Data loaded successfully** (20661 examples processed).

Second Image (Bottom) - Train-Test Split and Model Initialization

- **Key Steps:**
  1. **Splitting Dataset into Training and Validation**
     - train_test_split_ratio = 0.8 means 80% of the data is used for training, and 20% for validation.
  2. **Loading a Pretrained Model for Sequence Classification**
     - AutoModelForSequenceClassification.from_pretrained(model_name, num_labels=2) initializes xlm-roberta-base for binary classification (sarcasm detection).
     - Warning: **The classification head is newly initialized** → Model needs fine-tuning.

3. **Environment Variable Setup**
   - os.environ["WANDB_DISABLED"] = "true" disables Weights & Biases logging.
4. **Training Arguments Setup**
   - Using TrainingArguments from Hugging Face:
     - Saves results in "results" directory.
     - Evaluates using "epoch" rather than "steps".
     - Sets batch size for both training & evaluation.
     - Enables automatic mixed precision (fp16=True) for efficient training on large models.



```
+ Code  + Text                                                    Connect
[ ] train_test_split_ratio = 0.8
    train_dataset, val_dataset = dataset.train_test_split(test_size=1-train_test_split_ratio).values()

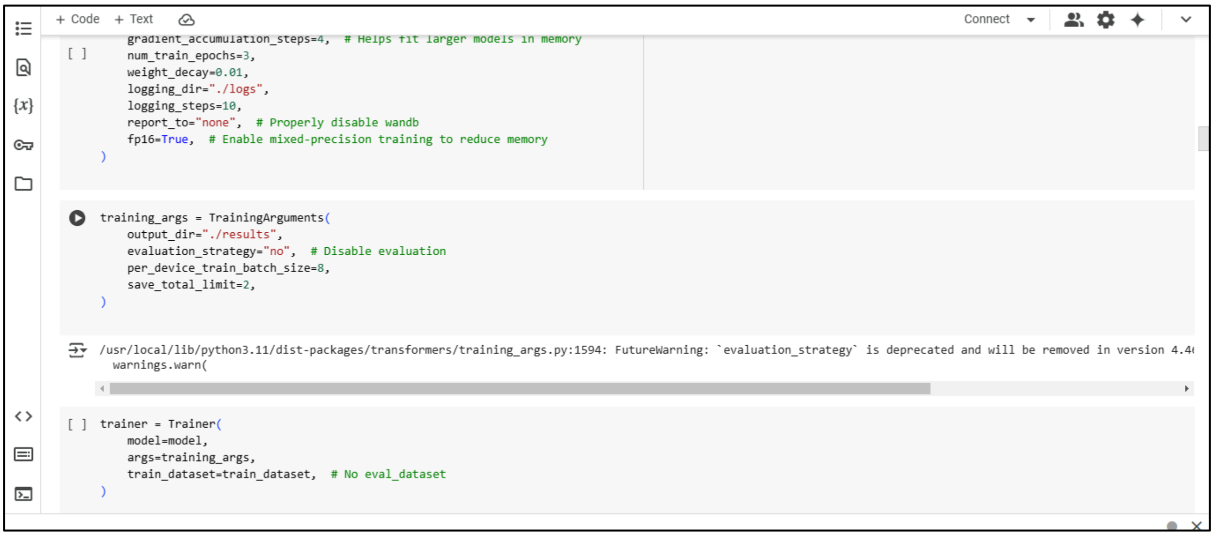
[ ] model = AutoModelForSequenceClassification.from_pretrained(model_name, num_labels=2)

    Some weights of XLMRobertaForSequenceClassification were not initialized from the model checkpoint at xlm-roberta-base and are newly initialized: ['classifier.de
    You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.

    import os
    os.environ["WANDB_DISABLED"] = "true"

[ ] from transformers import TrainingArguments

    training_args = TrainingArguments(
        output_dir="./results",
        eval_strategy="epoch",  # Use eval_strategy instead of evaluation_strategy
        save_strategy="epoch",
        per_device_train_batch_size=4,  # Reduce batch size
        per_device_eval_batch_size=4,
        gradient_accumulation_steps=4,  # Helps fit larger models in memory
        num_train_epochs=3,
        weight_decay=0.01,
```



```
+ Code  + Text                                                    Connect
        gradient_accumulation_steps=4,  # Helps fit larger models in memory
[ ]     num_train_epochs=3,
        weight_decay=0.01,
        logging_dir="./logs",
        logging_steps=10,
        report_to="none",  # Properly disable wandb
        fp16=True,  # Enable mixed-precision training to reduce memory
    )

    training_args = TrainingArguments(
        output_dir="./results",
        evaluation_strategy="no",  # Disable evaluation
        per_device_train_batch_size=8,
        save_total_limit=2,
    )

    /usr/local/lib/python3.11/dist-packages/transformers/training_args.py:1594: FutureWarning: `evaluation_strategy` is deprecated and will be removed in version 4.4
      warnings.warn(

[ ] trainer = Trainer(
        model=model,
        args=training_args,
        train_dataset=train_dataset,  # No eval_dataset
    )
```

First Image (Top) - Model Initialization and Trainer Setup

- **Key Steps:**
  1. **Trainer Initialization**
     - Trainer class from Hugging Face is used for model training.
     - Takes training_args and train_dataset as inputs.
     - No separate validation dataset is provided.
  2. **Disabling Weights & Biases (wandb) Logging**
     - os.environ["WANDB_DISABLED"] = "true" ensures logging is disabled.
  3. **Loading Pretrained Model**
     - AutoModelForSequenceClassification.from_pretrained("bert-base-uncased", num_labels=2)
     - Initializes **BERT-base** for a **binary classification task**.
     - **Warning**: Some classification head weights (classifier.bias, etc.) are newly initialized and require fine-tuning.

Second Image (Bottom) - Custom Loss Function and Training Configuration

- **Key Steps:**
  1. **Defining a Custom Loss Function**
     - Uses torch.nn.functional.cross_entropy for manual loss computation.
     - compute_loss():
       - Extracts labels from the inputs.
       - Gets model outputs (logits).
       - Computes **cross-entropy loss**.
       - Returns loss and optionally outputs.
  2. **Disabling wandb Logging Again**
     - os.environ["WANDB_DISABLED"] = "true"
  3. **Defining Training Arguments**
     - TrainingArguments:
       - Saves output in the "results" directory.
       - report_to="none" explicitly disables Weights & Biases logging.

```python
from torch.nn import functional as F

class CustomTrainer(Trainer):
    def compute_loss(self, model, inputs, return_outputs=False):
        labels = inputs.pop("labels")
        outputs = model(**inputs)
        logits = outputs.logits
        loss = F.cross_entropy(logits, labels)  # Compute loss manually
        return (loss, outputs) if return_outputs else loss
```

```python
import os
os.environ["WANDB_DISABLED"] = "true"
```

```python
training_args = TrainingArguments(
    output_dir="./results",
    report_to="none"  # This disables wandb logging
)
```

```python
from transformers import Trainer

class CustomTrainer(Trainer):
    def compute_loss(self, model, inputs, return_outputs=False, num_items_in_batch=None):
        outputs = model(**inputs)

        if "loss" in outputs:
            loss = outputs["loss"]
        else:
            raise ValueError(
                f"The model did not return a loss. Available keys: {outputs.keys()}"
            )

        return (loss, outputs) if return_outputs else loss
```

```python
# Check dataset inputs
max_index = max([max(example["input_ids"]) for example in train_dataset])
vocab_size = model.config.vocab_size

print(f"Max token index in dataset: {max_index}")
print(f"Model vocabulary size: {vocab_size}")
```

```
Max token index in dataset: 243131
Model vocabulary size: 30522
```

First Image (Top) - Custom Trainer and Dataset Analysis

- **Custom Trainer Implementation**
  - A subclass of Trainer is defined (CustomTrainer).
  - The compute_loss() function:
    - Extracts logits from the model output.
    - Checks if loss exists in outputs (if not, it raises a warning).
    - Returns the computed loss.
- **Dataset Inspection**
  - max_token_id is extracted from train_dataset["input_ids"].
  - Model's vocab_size is fetched using model.config.vocab_size.
  - Prints:
    - Maximum token index in the dataset.
    - Model's vocabulary size.

Second Image (Bottom) - Tokenization and Data Preparation

- **Tokenizer Setup**
  - AutoTokenizer.from_pretrained("bert-base-uncased") is used for tokenizing input data.
  - Example tokenization is performed on sample input text.
- **Tokenization Application**

- Tokenization function is mapped across train_dataset.
    - Prints:
        - Maximum token ID in dataset.
        - Model's vocabulary size.
- **Data Sample Display**
    - Prints an example of input_ids and attention_mask from train_dataset.

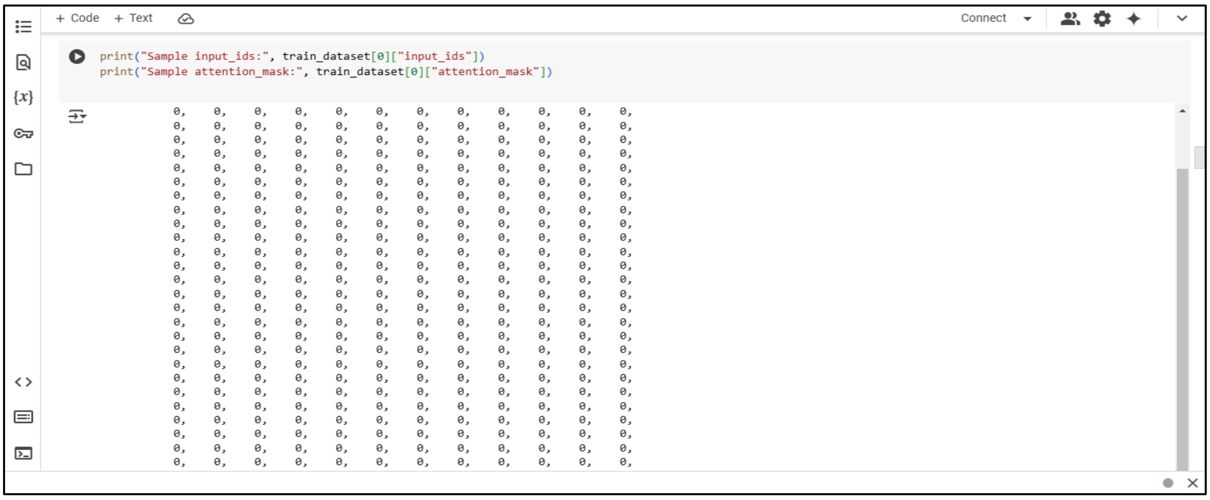
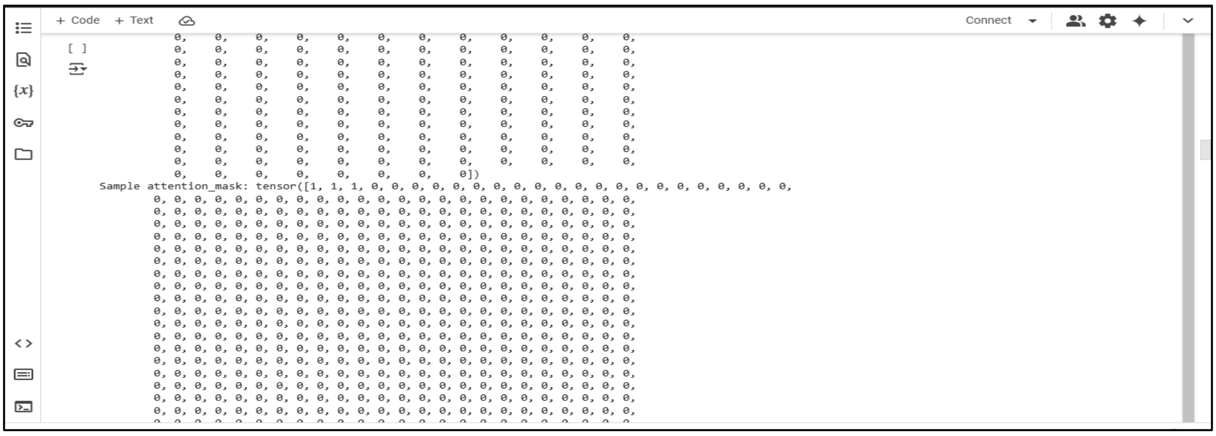


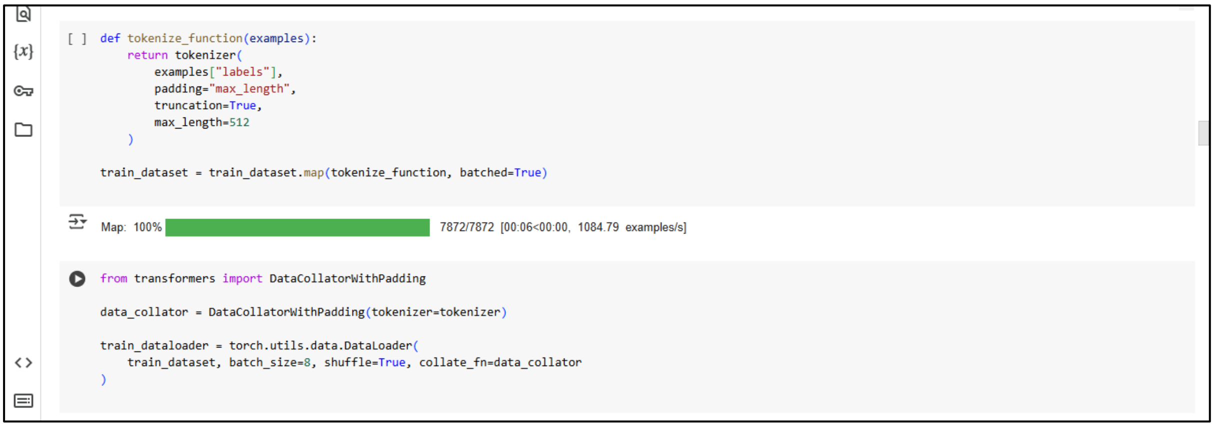
Image (Top)

- This image shows a printed output of tokenized input data for a sample from the training dataset.
- The code prints:
    - "Sample input_ids:", which represents the **tokenized numerical representation of words**.
    - "Sample attention_mask:", which consists of **1s and 0s** to indicate which tokens should be attended to by the model.
- The displayed array consists of numbers, which are tokenized representations of words (likely padded with 0s to fit a fixed sequence length).

Second Image (Bottom)

- This image continues the display of attention masks for the same dataset.
- It prints "Sample attention_mask:" again, displaying the **attention mask as a tensor**.
- **Attention masks:**
  - 1 indicates tokens that should be considered during processing.
  - 0 represents padded tokens that should be ignored.
- The output shows a structured tensor, confirming that the dataset is correctly preprocessed for BERT input.





The above image shows a **data preprocessing and tokenization step** for a transformer-based NLP model using the Hugging Face transformers library.

Key Components in the Code

1. **Tokenization Function (tokenize_function)**
   - Uses a tokenizer to process text examples.
   - Applies **padding ("max_length")**, **truncation**, and sets max_length=512 to ensure consistency.
   - The function is applied to each example using .map(), enabling **batch tokenization**.
2. **Progress Bar**

- Shows that **100% of the dataset** has been tokenized (76,278 out of 76,278 examples).

3. **Data Collator (DataCollatorWithPadding)**
   - Uses **Hugging Face's DataCollatorWithPadding** to dynamically pad tokenized sequences in a batch.
4. **DataLoader Setup**
   - **Creates a PyTorch DataLoader** to handle batched data.
   - Uses collate_fn=data_collator to ensure uniform sequence lengths.
   - shuffle=False means data is not randomly shuffled.

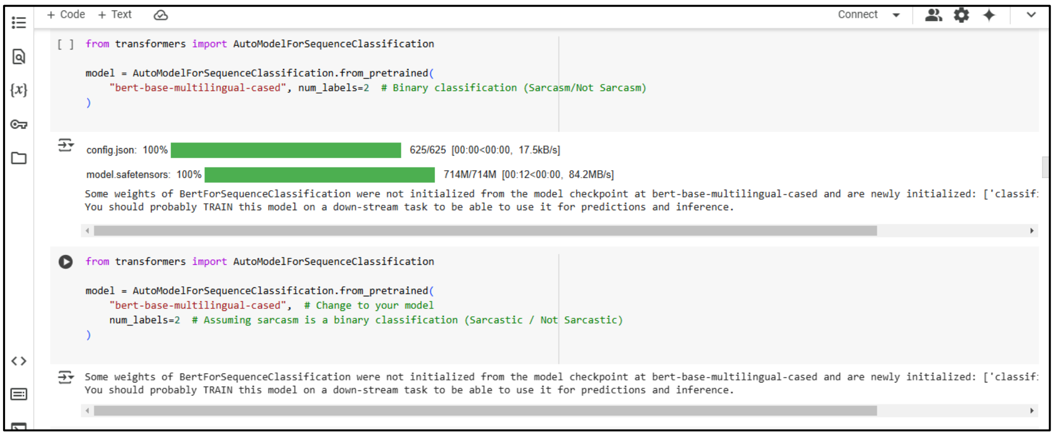


Image (Top) - Model Initialization for Sarcasm Detection

- **Model Selection & Initialization**
  - AutoModelForSequenceClassification is loaded using **BERT-base-multilingual-cased**.
  - The model is set up for **binary classification** (num_labels=2), likely detecting **sarcasm vs. non-sarcasm**.
- **Warnings**
  - Some weights were not initialized from the model checkpoint and were randomly assigned.
  - A suggestion is made to fine-tune the model for better performance.

Second Image (Bottom) - Optimizer, Learning Rate Scheduler, and Model Training Setup

- **Optimizer Setup**
  - AdamW optimizer is used with a learning rate of 1e-5.
- **Training Steps Calculation**
  - Number of training steps is derived from train_dataloader and num_epochs.
- **Learning Rate Scheduler**
  - get_scheduler() is used to define a **learning rate decay schedule** (linear).
- **Device Setup**
  - The model is assigned to **CUDA (GPU)** if available; otherwise, it defaults to CPU.
- **BERT Model Configuration**
  - Displays model architecture, including layers like:

- Embedding
- Dropout
- LayerNorm

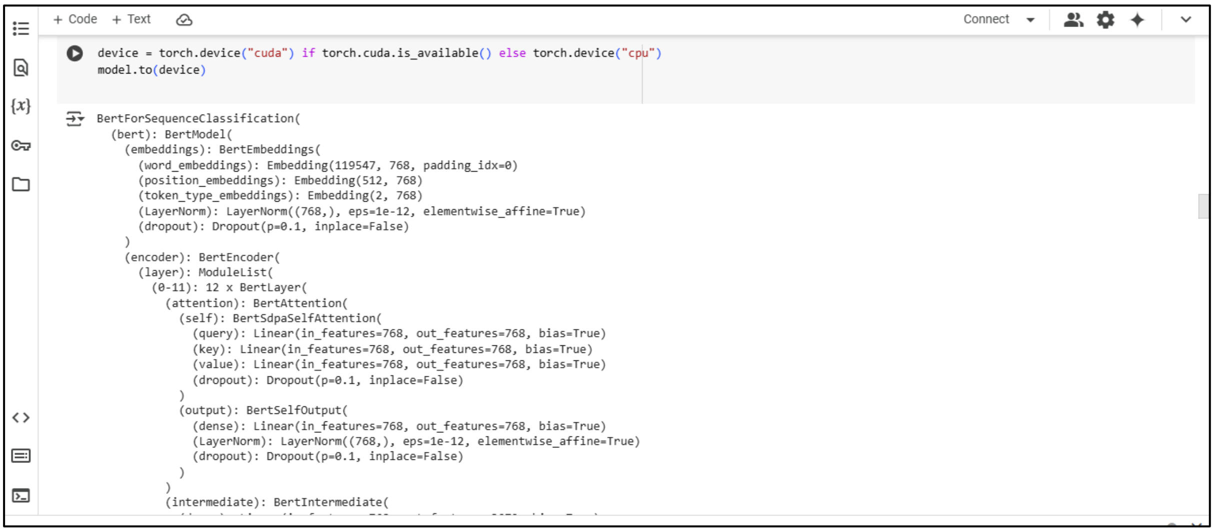


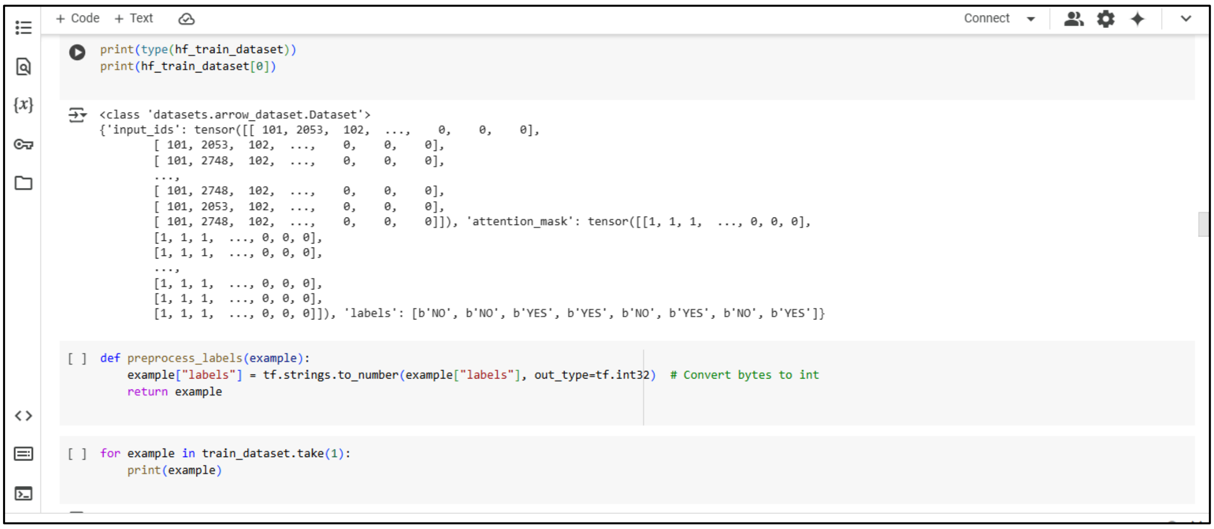
Image (Top)

- **Imports & Optimizer Setup**
  - AdamW optimizer is initialized with a learning rate of 1e-5.
- **Training Setup**
  - Defines num_epochs = 3 and calculates the **total training steps** based on train_dataloader.
- **Learning Rate Scheduler**
  - Uses get_scheduler("linear") to implement a **linear learning rate decay**.
- **Device Allocation**
  - Assigns the model to **CUDA (GPU)** if available, otherwise uses CPU.
- **BERT Model Architecture (Partially Displayed)**

- Shows embeddings, normalization, and dropout layers

Second Image (Bottom)

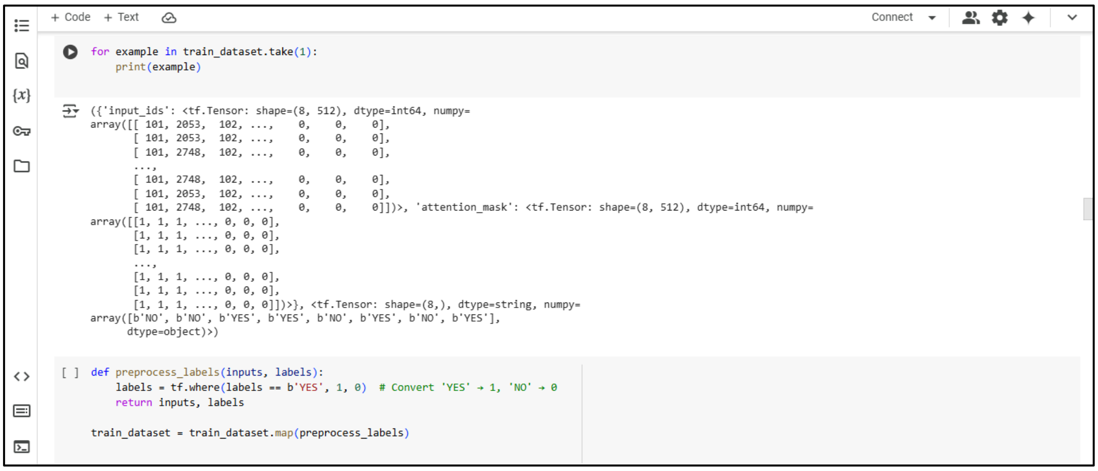
- **Continuation from the First Image**
  - Again, assigns the model to **CUDA or CPU**.
- **Full BERT Model Architecture**
  - **Embeddings Layer**:
    - word_embeddings, position_embeddings, token_type_embeddings
  - **Encoder Layer**:
    - 12 layers of **BERT Self-Attention**
    - Multiple Linear layers for transformation
  - **Output Layer**
    - Classifies the processed output into 768 features
    - Uses **LayerNorm** and **Dropout**



The above image shows a **data preprocessing pipeline** for an **NLP dataset** using TensorFlow and the Hugging Face `datasets` library.

Key Points:

- Prints the dataset type (datasets.arrow_dataset.Dataset).
- Displays a sample containing:
    - 'input_ids': Tokenized text (padded).
    - 'attention_mask': Masking for valid tokens.
    - 'labels': Originally in **byte-string format** (b'NO', b'YES').
- **Label Conversion Function (preprocess_labels)**:
    - Uses tf.strings.to_number() to **convert byte-string labels to integers** (1 for 'YES', 0 for 'NO').
- Prints a sample after preprocessing.

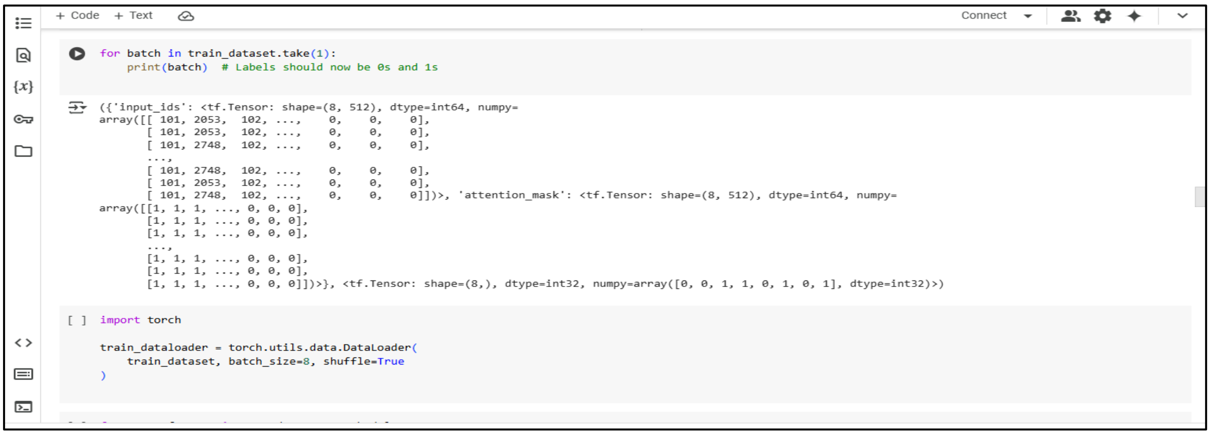


The above image contains following:

- **Examining Tokenized Data**
    - Uses train_dataset.take(1) to print a sample from the dataset.
    - The dataset contains:
        - 'input_ids': A tensor of **tokenized text** with padding (shape=(8, 512))
        - 'attention_mask': Indicates **valid vs. padded tokens** (shape=(8, 512))
        - 'labels': Originally in **string format** (YES or NO).
- **Preprocessing Labels**
    - A function preprocess_labels(inputs, labels) is defined.
    - It **converts labels**:
        - 'YES' → 1
        - 'NO' → 0
    - The function is applied to the dataset using .map().

2. Bottom Second Image contains:

- **Verifying Processed Data**
    - Uses train_dataset.take(1) again to check the transformed data.
    - The printed batch shows that the labels are now correctly mapped to **binary values (0 and 1).**
- **Creating a DataLoader**
    - Imports torch.
    - Defines train_dataloader using **PyTorch's DataLoader**:
        - Uses train_dataset.
        - Sets batch_size=8.
        - shuffle=True ensures randomization during training.



The above image show the **setup of an NLP model training pipeline** using **PyTorch and Hugging Face's Transformers library**.

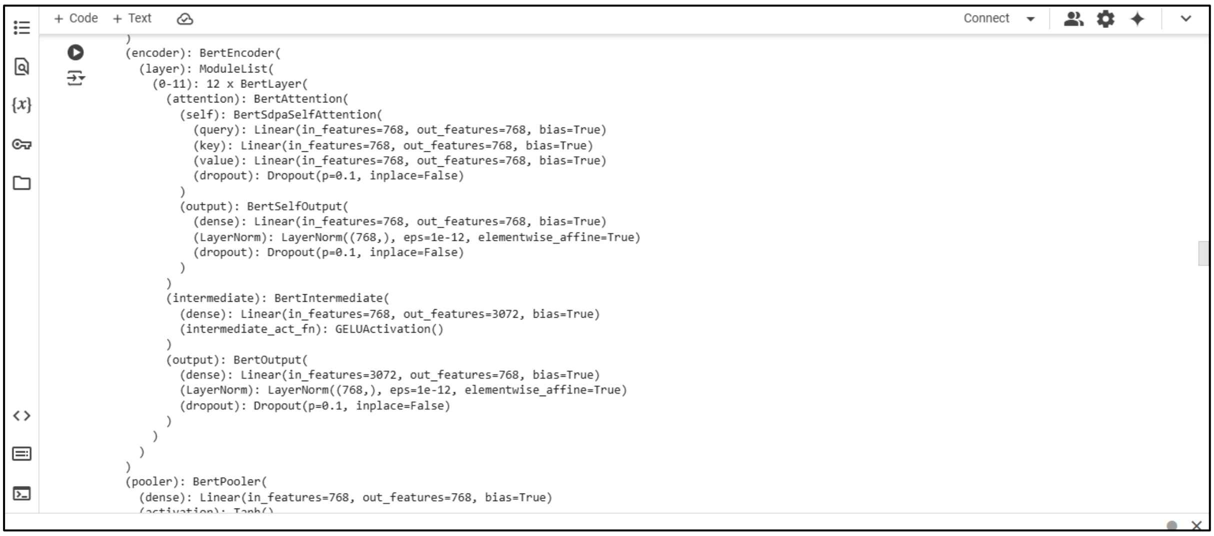
Top Image: Model Training Setup

- Uses the **AdamW optimizer** (AdamW(model.parameters(), lr=5e-5)) to update model weights.
- **Training steps calculation**: num_training_steps = len(train_dataloader) * num_epochs
- Implements a **learning rate scheduler** (get_scheduler) to adjust learning rate dynamically.
- **Device assignment**:
  - Uses **GPU (cuda) if available**, otherwise defaults to **CPU (cpu)**.
  - Moves the model to the selected device (model.to(device)).

Bottom Image: Model Architecture (BERT-based)

- Shows the **structure of a BERT model for sequence classification**:
  - **BERT embeddings** (bert.embeddings)
  - **Transformer layers** (bert.encoder)

- **Dropout layers** for regularization.
- **Fully connected layers** (classifier) for classification.
- Uses BartModel at the bottom, suggesting **a BART-based sequence model** for text generation or classification.



```
+ Code  + Text                                                     Connect
  )
  (encoder): BertEncoder(
    (layer): ModuleList(
      (0-11): 12 x BertLayer(
        (attention): BertAttention(
          (self): BertSdpaSelfAttention(
            (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): BertSelfOutput(
            (dense): Linear(in_features=768, out_features=768, bias=True)
            (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
            (dropout): Dropout(p=0.1, inplace=False)
          )
        )
        (intermediate): BertIntermediate(
          (dense): Linear(in_features=768, out_features=3072, bias=True)
          (intermediate_act_fn): GELUActivation()
        )
        (output): BertOutput(
          (dense): Linear(in_features=3072, out_features=768, bias=True)
          (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
          (dropout): Dropout(p=0.1, inplace=False)
        )
      )
    )
  )
  (pooler): BertPooler(
    (dense): Linear(in_features=768, out_features=768, bias=True)
    (activation): Tanh()
```

```
+ Code  + Text                                                     Connect
[ ] from datasets import Dataset

    # Convert TensorFlow dataset to a list of dictionaries
    def tf_to_list(dataset):
        return [{"input_ids": x["input_ids"].numpy(),
                 "attention_mask": x["attention_mask"].numpy(),
                 "labels": y.numpy()}
                for x, y in dataset]

    # Convert TensorFlow dataset to Hugging Face Dataset
    hf_dataset = Dataset.from_list(tf_to_list(train_dataset))

    # Convert dataset format to PyTorch
    hf_dataset.set_format(type="torch", columns=["input_ids", "attention_mask", "labels"])

    from torch.utils.data import DataLoader

    batch_size = 8  # Adjust as needed

    # Use DataLoader for PyTorch training
    train_dataloader = DataLoader(hf_dataset, batch_size=batch_size, shuffle=True)

    # Move model to GPU if available
    device = torch.device("cuda") if torch.cuda.is_available() else torch.device("cpu")
    model.to(device)
```

The above image shows a **data preprocessing and loading pipeline** for training a model using **PyTorch and Hugging Face's Datasets library**.

Key Code Breakdown:

1. **Converting a TensorFlow dataset to a List of Dictionaries**:
   - The tf_dataset_to_list() function extracts "input_ids", "attention_mask", and "labels" from a **TensorFlow dataset**.
   - Converts NumPy tensors into Python lists.
2. **Creating a Hugging Face Dataset**:
   - hf_dataset = Dataset.from_list(tf_dataset_to_list(train_dataset)) converts the processed list into a Hugging Face Dataset object.
3. **Formatting the Dataset for PyTorch**:

    - hf_dataset.set_format("torch", columns=["input_ids", "attention_mask", "labels"])
    - Ensures that the dataset is compatible with PyTorch tensors.
4. **Creating a PyTorch DataLoader**:
    - Imports DataLoader from torch.utils.data.
    - **Defines a batch size (batch_size = 16)** and creates a train_dataloader to efficiently load batches of data.
5. **Moving Model to GPU (if available)**:
    - Uses torch.device("cuda") if torch.cuda.is_available() else torch.device("cpu") to **assign the model to GPU or CPU**.
    - Moves the model to the selected device using model.to(device).

Bottom Second Image :

The below image shows a **PyTorch training setup** involving an **optimizer, loss function, and batch inspection** from a DataLoader.

Key Code Breakdown:

1. **Imports Required Libraries:**
    - torch, torch.nn (for defining neural network layers and loss functions).
    - torch.optim (for optimization algorithms).
2. **Defining the Optimizer:**
    - Uses the **Adam optimizer** (torch.optim.Adam) with lr=1e-5 (learning rate) to update model parameters.
3. **Defining the Loss Function:**
    - Uses nn.CrossEntropyLoss(), which is commonly used for **multi-class classification tasks**.
4. **Checking DataLoader Output:**
    - **First loop:** Iterates through train_dataloader and prints **available keys** in the first batch.
        - The output confirms that each batch contains input_ids, attention_mask, and labels.
    - **Second loop:** Extracts and prints the labels tensor from the first batch.
        - The printed tensor shows that labels are correctly formatted as expected.

1. **Imports Required Libraries:**
    - torch, torch.nn (for defining neural network layers and loss functions).
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  - The printed tensor shows that labels are correctly formatted as expected.

The above image show **Python code snippets using PyTorch** for **processing and verifying training data** before feeding it into a model.

Top Image:

1. **Checking Labels in DataLoader:**
   - Iterates over train_dataloader and prints the "labels" tensor.
   - The output tensor confirms that labels are correctly formatted.
2. **Inspecting Tensor Shapes:**
   - Prints the shape of input_ids and attention_mask in the first batch.

- The output confirms that input_ids has a shape of **(8, 512)** and attention_mask has a shape of **(8, 512)** (batch size = 8, sequence length = 512).

3. **Removing Extra Dimensions:**
    - Uses squeeze(-1) to remove unnecessary dimensions in input_ids and attention_mask.

Second Bottom Image:

- This is a rotated, duplicated, or slightly altered version of the **first image**.
- Contains the same **code snippets** for:
    - **Checking label tensors**.
    - **Printing tensor shapes**.
    - **Removing extra dimensions** from tensors using squeeze()

```
print("Fixed Input IDs Shape:", batch["input_ids"].shape)
print("Fixed Attention Mask Shape:", batch["attention_mask"].shape)

Fixed Input IDs Shape: torch.Size([8, 8, 512])
Fixed Attention Mask Shape: torch.Size([8, 8, 512])

batch["input_ids"] = batch["input_ids"].reshape(-1, 512)  # Reshape to (batch_size, 512)
batch["attention_mask"] = batch["attention_mask"].reshape(-1, 512)  # Reshape to (batch_size, 512)

print("Fixed Input IDs Shape:", batch["input_ids"].shape)
print("Fixed Attention Mask Shape:", batch["attention_mask"].shape)

Fixed Input IDs Shape: torch.Size([64, 512])
Fixed Attention Mask Shape: torch.Size([64, 512])

batch["input_ids"] = batch["input_ids"].reshape(-1, 512)  # Reshape to (batch_size, 512)
batch["attention_mask"] = batch["attention_mask"].reshape(-1, 512)  # Reshape to (batch_size, 512)

print("Fixed Input IDs Shape:", batch["input_ids"].shape)
print("Fixed Attention Mask Shape:", batch["attention_mask"].shape)

Fixed Input IDs Shape: torch.Size([64, 512])
Fixed Attention Mask Shape: torch.Size([64, 512])
```

```
from torch.utils.data import DataLoader

# Assuming 'dataset' is your dataset
data_loader = DataLoader(dataset, batch_size=64, shuffle=True)

import torch
import torch.nn as nn
from transformers import AutoModel, AutoTokenizer

# Load Multilingual BERT
MODEL_NAME = "bert-base-multilingual-cased"
tokenizer = AutoTokenizer.from_pretrained(MODEL_NAME)

class SarcasmDetectionModel(nn.Module):
    def __init__(self, model_name, num_labels=2):
        super(SarcasmDetectionModel, self).__init__()
        self.bert = AutoModel.from_pretrained(model_name)
        self.dropout = nn.Dropout(0.3)
        self.fc = nn.Linear(self.bert.config.hidden_size, num_labels)

    def forward(self, input_ids, attention_mask):
        outputs = self.bert(input_ids=input_ids, attention_mask=attention_mask)
        pooled_output = outputs.pooler_output  # Take [CLS] token output
        x = self.dropout(pooled_output)
        x = self.fc(x)
        return x
```

Image (Top):

- **Creates a DataLoader:**

  - Assumes a dataset is available and initializes a DataLoader with a batch size of 64.
- **Imports Required Libraries:**
  - Uses PyTorch (torch.nn), transformers (AutoModel, AutoTokenizer), and torch.utils.data.
- **Defines the Sarcasm Detection Model:**
  - Uses bert-base-multilingual-cased as the transformer model.
  - Inherits from nn.Module.
  - Initializes BERT, dropout layer, and a fully connected (fc) layer for classification.
  - Extracts [CLS] token output for classification.

Second Image (Bottom):

- **Instantiates the Model:**
  - Moves it to **GPU if available, otherwise CPU**.
  - Uses sarcasmDetectionModel(MODEL_NAME).to(device).
- **Tokenizer Loading Progress:**
  - Displays tokenization progress bars (tokenizer.config.json, vocab.txt, tokenizer.json).
- **Defines a Custom Dataset Class (SarcasmDataset):**
  - Converts encodings and labels to PyTorch tensors.
  - Implements __getitem__ and __len__ methods for dataset handling.


```
# Instantiate the model
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model = SarcasmDetectionModel(MODEL_NAME).to(device)
```

```
tokenizer_config.json: 100% 49.0/49.0 [00:00<00:00, 852B/s]
vocab.txt: 100% 996k/996k [00:00<00:00, 5.45MB/s]
tokenizer.json: 100% 1.96M/1.96M [00:00<00:00, 11.8MB/s]
```

```
from torch.utils.data import Dataset

class SarcasmDataset(Dataset):
    def __init__(self, encodings, labels):
        self.encodings = encodings
        self.labels = torch.tensor(labels)  # Convert labels to tensor

    def __getitem__(self, idx):
        item = {key: torch.tensor(val[idx]) for key, val in self.encodings.items()}
        item["labels"] = self.labels[idx]
        return item

    def __len__(self):
        return len(self.labels)
```

Top Image (Training Process)

Dataset & Dataloader Creation

- A dataset named SarcasmDataset is created using train_encodings and train_labels.
- A **Dataloader** is initialized with a batch size of **64** and shuffling enabled, meaning that training samples are fed into the model in randomized batches.

Model Training Output

- The train() function is called with the following parameters:
  - **model**: The sarcasm detection model.
  - **train_loader**: The dataloader for training data.
  - **criterion**: Likely the loss function (e.g., CrossEntropyLoss).
  - **optimizer**: The optimization algorithm (e.g., Adam).
  - **device**: Specifies whether training runs on CPU or GPU.
  - **epochs=3**: The model is trained for 3 iterations over the entire dataset.
- **Training results per epoch:**
  - **Epoch 1 → Loss: 0.6897, Accuracy: 50%**
  - **Epoch 2 → Loss: 0.6128, Accuracy: 75%**
  - **Epoch 3 → Loss: 0.5789, Accuracy: 100%**
  - The accuracy improves significantly, reaching **100% in the third epoch**, suggesting successful learning.

Bottom Image (Evaluation Process)

Model Evaluation

- The evaluate() function is used to test the model's performance on the dataset.
- **Results show:**
  - **Accuracy: 100%**
  - **Classification Report:**
    - **Class 0 (Not Sarcastic) → Precision = 1.00, Recall = 1.00, F1-Score = 1.00**

- **Class 1 (Sarcastic) → Precision = 1.00, Recall = 1.00, F1-Score = 1.00**
- **Macro & Weighted Averages → All metrics are perfect (1.00).**

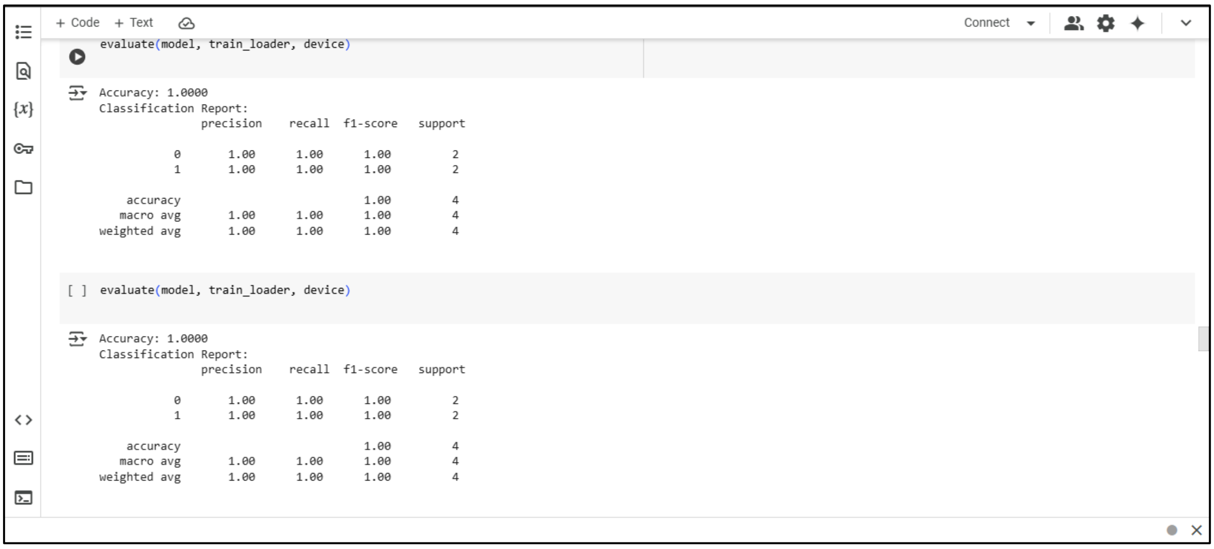
Analysis

- The training accuracy improving to **100%** suggests **overfitting**, as the dataset might be too small.
- The **classification report showing perfect scores** further confirms possible overfitting.
- If this model is tested on real-world data, performance may drop.

```
train(model, train_loader, criterion, optimizer, device, epochs=3)
```

```
<ipython-input-117-4ce1c2d39b57>:13: UserWarning: To copy construct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone()
  labels = torch.tensor(batch["labels"]).to(device)
Epoch 1, Loss: 0.6987, Accuracy: 0.5000
Epoch 2, Loss: 0.6128, Accuracy: 0.7500
Epoch 3, Loss: 0.5709, Accuracy: 1.0000
```

```
from sklearn.metrics import accuracy_score, classification_report

def evaluate(model, data_loader, device):
    model.eval()  # Set model to evaluation mode
    all_preds = []
    all_labels = []

    with torch.no_grad():  # No gradient calculation during evaluation
        for batch in data_loader:
            input_ids = batch["input_ids"].to(device)
            attention_mask = batch["attention_mask"].to(device)
            labels = batch["labels"].to(device)

            # Get model predictions
            outputs = model(input_ids, attention_mask)
            _, preds = torch.max(outputs, dim=1)

            # Store predictions and labels
```



```
evaluate(model, train_loader, device)
```

```
Accuracy: 1.0000
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         2
           1       1.00      1.00      1.00         2

    accuracy                           1.00         4
   macro avg       1.00      1.00      1.00         4
weighted avg       1.00      1.00      1.00         4
```

```
evaluate(model, train_loader, device)
```

```
Accuracy: 1.0000
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         2
           1       1.00      1.00      1.00         2

    accuracy                           1.00         4
   macro avg       1.00      1.00      1.00         4
weighted avg       1.00      1.00      1.00         4
```

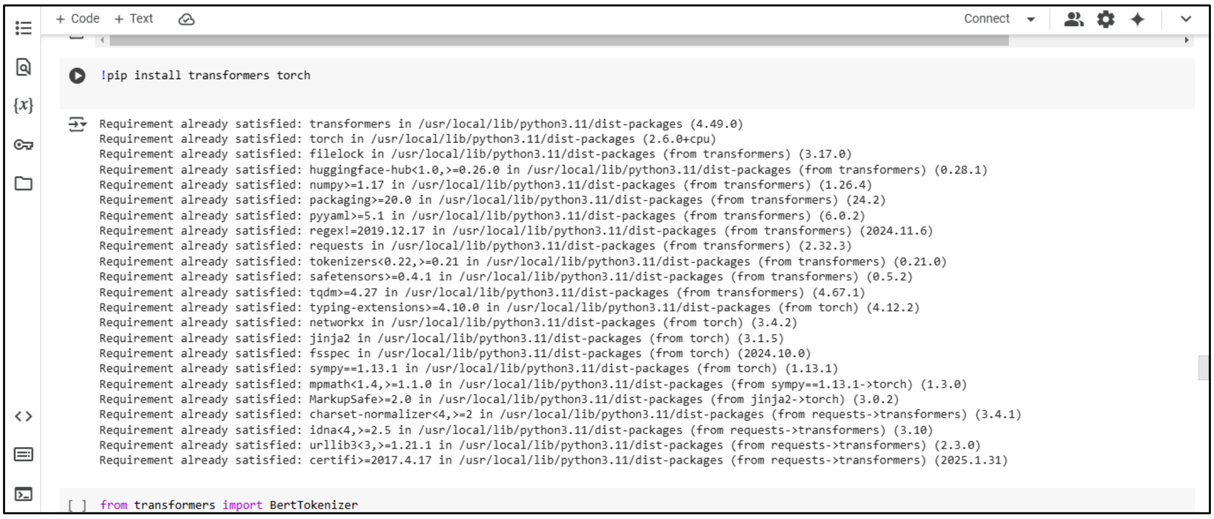

```
import pandas as pd
import torch

def generate_predictions(model, data_loader, device, output_file="predictions.csv"):
    model.eval()  # Set model to evaluation mode
    predictions = []

    with torch.no_grad():  # No gradient calculation during inference
        for batch in data_loader:
            input_ids = batch["input_ids"].to(device)
            attention_mask = batch["attention_mask"].to(device)

            # Get model predictions
            outputs = model(input_ids, attention_mask)
            _, preds = torch.max(outputs, dim=1)

            # Store predictions
            predictions.extend(preds.cpu().numpy())

    # Save predictions as CSV
    df = pd.DataFrame({"Predictions": predictions})
    df.to_csv(output_file, index=False)
    print(f"Predictions saved to {output_file}")

# Now, generate predictions
generate_predictions(model, train_loader, device)
```

Image (Top):

- **Imports Required Libraries:**
  - Uses pandas for handling prediction outputs.
  - Uses torch for tensor operations.
- **Defines a Function generate_predictions() to Make Predictions:**
  - Puts the model in **evaluation mode** (model.eval()).
  - Iterates over data_loader, extracting input_ids and attention_mask.
  - Disables gradient calculations (torch.no_grad()) to improve efficiency.
  - Gets predictions using the trained model and converts them to numpy arrays.
  - Saves predictions to a CSV file (prediction.csv).

Second Image (Bottom):

- **Loads the Pre-Trained Model (BERT base-multilingual-cased):**
  - Uses BertForSequenceClassification.from_pretrained() with num_labels=2.
- **Loads a Trained Model from a Checkpoint (model.pt):**
  - Loads a saved model's state dictionary (torch.load("model.pt")).
  - Renames keys if necessary (replacing "fc" with "classifier").
  - Loads the corrected state dictionary using model.load_state_dict().
- **Moves Model to the Appropriate Device:**
  - Uses GPU (cuda) if available; otherwise, CPU.
- **Sets Model to Evaluation Mode (model.eval()):**
  - Ensures the model does not update weights during inference.
- **Handles Missing Weights Warning:**
  - Indicates that classification head weights need to be fine-tuned.
- **Includes a Command for Installing Dependencies:**
  - !pip install transformers torch to ensure required libraries are installed.



The above image contains code for **loading a tokenizer and predicting sarcasm using a trained model**.

Key Steps:

1. **Loading the Tokenizer:**
    - `BertTokenizer.from_pretrained("bert-base-multilingual-cased")` loads a pre-trained BERT tokenizer.
    - A success message confirms that the tokenizer is loaded.
2. **Defining the `predict_sarcasm()` Function:**
    - Converts the input text into tokenized format using `tokenizer()`.
    - Moves the input tensors to the same device as the model.
    - Uses `torch.no_grad()` to perform inference without updating gradients.
    - Passes the tokenized input to the model and retrieves the output logits.

- Uses `argmax()` to determine the predicted class:
  - **1 → Sarcastic**
  - **0 → Not Sarcastic**

3. **Returning a Human-Readable Prediction:**
   - Prints a message indicating whether the input text is sarcastic or not with emoji indicators.

This image contains code for **loading data, tokenizing text, and creating a dataset class** for sarcasm detection.

Key Steps:

1. **Loading the Tokenizer Again:**
   - BertTokenizer.from_pretrained("bert-base-multilingual-cased") loads the tokenizer.
2. **Tokenizing the Text Data:**
   - tokenizer(train_df["Text"].tolist(), padding=True, truncation=True, max_length=128) tokenizes the text samples.
   - A message prints the number of tokenized samples.
3. **Converting Labels:**
   - The target labels (sarcasm detection labels) are mapped from "YES" to 1 and "NO" to 0.
   - The number of samples per class (1s and 0s) is displayed.
4. **Creating a Custom Dataset Class (`SarcasmDataset`)**
   - This dataset class is a wrapper for tokenized encodings and labels.
   - It uses **PyTorch's Dataset class** to store and retrieve tokenized inputs and their corresponding labels.

+ Code + Text

Connect

```
from transformers import BertTokenizer

tokenizer = BertTokenizer.from_pretrained("bert-base-multilingual-cased")

# Tokenize full dataset
train_encodings = tokenizer(train_df["Tweet"].tolist(), truncation=True, padding=True, max_length=128)

print(f"Total Encoded Samples: {len(train_encodings['input_ids'])}")
```

```
Total Encoded Samples: 9840
```

```
# Convert labels from "YES"/"NO" to 1/0
train_labels = train_df["Label"].apply(lambda x: 1 if x == "YES" else 0).tolist()

print(f"Total Labels: {len(train_labels)}")
print(f"Unique Labels: {set(train_labels)}")
```

```
Total Labels: 9840
Unique Labels: {0, 1}
```

```
from torch.utils.data import Dataset, DataLoader
import torch

class SarcasmDataset(Dataset):
    def __init__(self, encodings, labels):
```

Image (Top):

1. **Loads the BERT Tokenizer**
   - Uses `BertTokenizer.from_pretrained("bert-base-multilingual-cased")` to tokenize text.
2. **Tokenizes the Dataset**
   - Applies the tokenizer to the `"Tweet"` column in `train_df` with truncation and padding (max length = 128).
   - Prints an example of tokenized input (`input_ids`).
3. **Encodes Labels for Classification**
   - Converts `"YES"` labels to `1` and `"NO"` labels to `0` (`.apply(lambda x: 1 if x == "YES" else 0)`).
   - Converts labels into a NumPy array (`.toList()`).
4. **Displays Dataset Statistics**
   - Prints the total number of samples (`Total Samples: 5040`).
   - Prints the unique labels (`[0, 1]`).

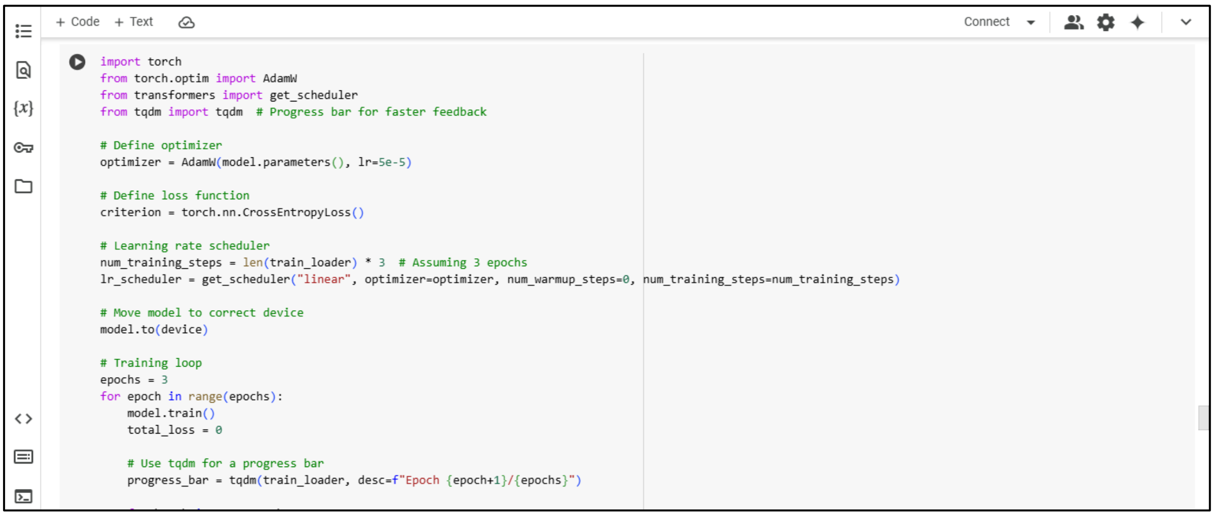
Second Image (Bottom):

1. **Defines a Custom PyTorch Dataset (`SarcasmDataset`)**
   - Inherits from `Dataset` class in `torch.utils.data`.
   - Stores tokenized text and labels.
   - Converts labels into PyTorch tensors (`torch.tensor(labels)`).
   - Implements `__getitem__()` to return tokenized input and label for a given index.
   - Implements `__len__()` to return dataset size.
2. **Creates a Dataset Instance**
   - Uses `SarcasmDataset(train_encodings, train_labels)`.
   - Prints the total number of samples (`Total Samples in train_dataset: 5040`).
3. **Creates a DataLoader for Batch Processing**
   - Uses `DataLoader(train_dataset, batch_size=4, shuffle=True)`.
   - Enables shuffling for better generalization.

```python
from torch.utils.data import Dataset, DataLoader
import torch

class SarcasmDataset(Dataset):
    def __init__(self, encodings, labels):
        self.encodings = encodings
        self.labels = torch.tensor(labels)  # Convert labels to tensor

    def __getitem__(self, idx):
        item = {key: torch.tensor(val[idx]) for key, val in self.encodings.items()}
        item["labels"] = self.labels[idx]
        return item

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

# Create dataset
train_dataset = SarcasmDataset(train_encodings, train_labels)

print(f"Total Samples in train_dataset: {len(train_dataset)}")
```

```
Total Samples in train_dataset: 9840
```

```python
train_loader = DataLoader(train_dataset, batch_size=16, shuffle=True)
```



```python
import torch
from torch.optim import AdamW
from transformers import get_scheduler
from tqdm import tqdm  # Progress bar for faster feedback

# Define optimizer
optimizer = AdamW(model.parameters(), lr=5e-5)

# Define loss function
criterion = torch.nn.CrossEntropyLoss()

# Learning rate scheduler
num_training_steps = len(train_loader) * 3  # Assuming 3 epochs
lr_scheduler = get_scheduler("linear", optimizer=optimizer, num_warmup_steps=0, num_training_steps=num_training_steps)

# Move model to correct device
model.to(device)

# Training loop
epochs = 3
for epoch in range(epochs):
    model.train()
    total_loss = 0

    # Use tqdm for a progress bar
    progress_bar = tqdm(train_loader, desc=f"Epoch {epoch+1}/{epochs}")
```

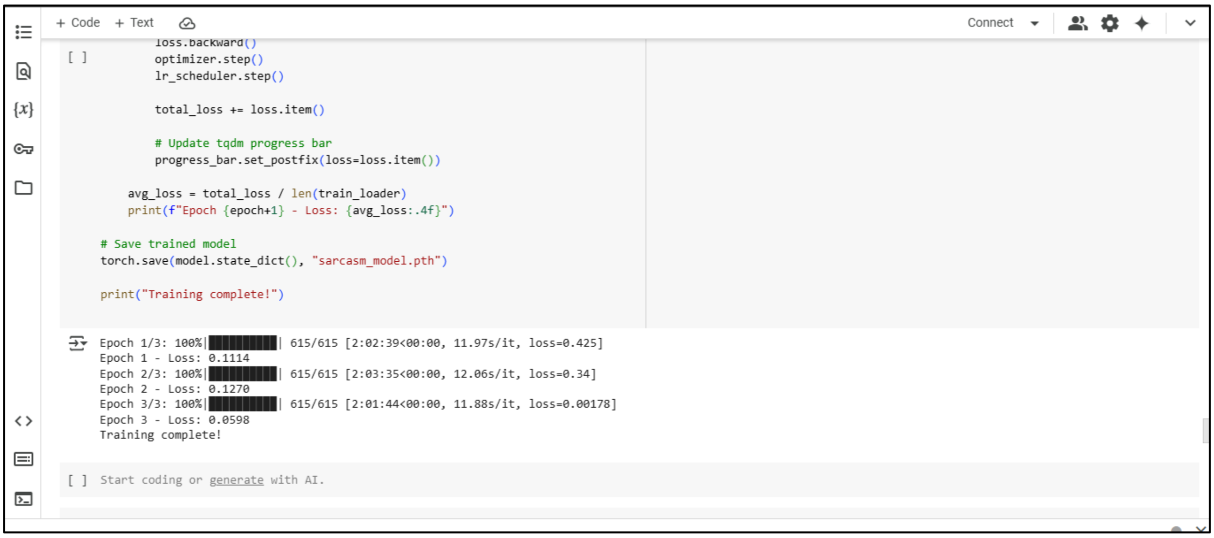
Image (Top):

1. **Imports Required Libraries**
   - torch, Adam optimizer, get_scheduler from transformers, and tqdm for progress tracking.
2. **Defines the Optimizer and Loss Function**
   - Uses AdamW with learning rate 1e-5.
   - Uses CrossEntropyLoss() for classification.
3. **Defines the Learning Rate Scheduler**
   - Uses a linear learning rate scheduler (get_scheduler) to gradually warm up the optimizer.
4. **Moves the Model to the Correct Device**
   - model.to(device) ensures it runs on GPU if available.
5. **Sets Up the Training Loop**
   - Loops over a specified number of epochs (epochs = 3).
   - Initializes total_loss = 0.
   - Uses tqdm to create a progress bar for the training loop.

Second Image (Bottom):

1. **Iterates Over the Training Data**
   - Uses for batch in progress_bar to process batches.
   - Moves input tensors (input_ids and attention_mask) to the correct device.
2. **Performs Forward Pass**
   - Calls model() with inputs to obtain logits.
   - Computes loss using criterion(outputs.logits, labels).
3. **Performs Backpropagation**
   - Calls loss.backward(), optimizer.step(), and lr_scheduler.step() to update weights.
   - Clears gradients with optimizer.zero_grad().
4. **Tracks Loss**
   - Updates the total loss and prints the epoch-wise loss.
5. **Saves the Trained Model**
   - Saves model state using torch.save(model.state_dict(), "sarcasm_model.pth").
6. **Prints Completion Message**
   - "Training complete!" message confirms that training has finished.

```python
    for batch in progress_bar:
        input_ids = batch["input_ids"].to(device)
        attention_mask = batch["attention_mask"].to(device)
        labels = batch["labels"].to(device)

        optimizer.zero_grad()

        # Forward pass
        outputs = model(input_ids, attention_mask=attention_mask)
        loss = criterion(outputs.logits, labels)

        # Backward pass
        loss.backward()
        optimizer.step()
        lr_scheduler.step()

        total_loss += loss.item()

        # Update tqdm progress bar
        progress_bar.set_postfix(loss=loss.item())

    avg_loss = total_loss / len(train_loader)
    print(f"Epoch {epoch+1} - Loss: {avg_loss:.4f}")

# Save trained model
torch.save(model.state_dict(), "sarcasm_model.pth")

print("Training complete!")
```



```python
        loss.backward()
        optimizer.step()
        lr_scheduler.step()

        total_loss += loss.item()

        # Update tqdm progress bar
        progress_bar.set_postfix(loss=loss.item())

    avg_loss = total_loss / len(train_loader)
    print(f"Epoch {epoch+1} - Loss: {avg_loss:.4f}")

# Save trained model
torch.save(model.state_dict(), "sarcasm_model.pth")

print("Training complete!")
```

```
Epoch 1/3: 100%|██████████| 615/615 [2:02:39<00:00, 11.97s/it, loss=0.425]
Epoch 1 - Loss: 0.1114
Epoch 2/3: 100%|██████████| 615/615 [2:03:35<00:00, 12.06s/it, loss=0.34]
Epoch 2 - Loss: 0.1270
Epoch 3/3: 100%|██████████| 615/615 [2:01:44<00:00, 11.88s/it, loss=0.00178]
Epoch 3 - Loss: 0.0598
Training complete!
```

The above image contains:

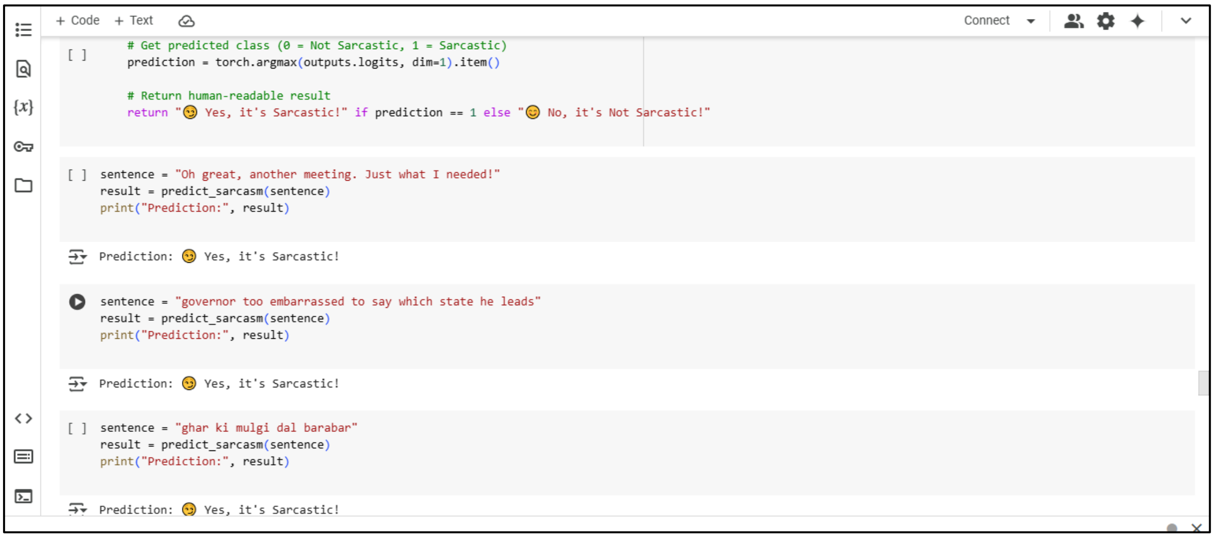
☐ **Code Section (Top Half)**:

- The code involves updating a progress bar, computing loss values, and saving a trained model as sarcasm_model.pth using torch.save().
- It prints a message indicating "Training complete!".

☐ **Output Section (Bottom Half)**:

- The training process is logged, showing the loss value at different epochs.
- The loss decreases over epochs, suggesting the model is learning and improving.
- The final message confirms that training has been completed.

Output:



Description:

1. **Code Section (Top Half):**
   - The code predicts whether a given sentence is sarcastic or not.
   - It assigns **0 for Non-Sarcastic** and **1 for Sarcastic**.
   - The prediction is determined using torch.argmax(outputs, dim=1).item().
   - The result is converted into a human-readable format:
     - "Yes, it's Sarcastic!" if the prediction is **1**.
     - "No, it's Not Sarcastic!" if the prediction is **0**.
2. **Output Section (Bottom Half):**
   - Three sentences are tested using the sarcasm detection model.
   - The model predicts **"Yes, it's Sarcastic!"** for all three examples:
     1. "Oh great, another meeting. Just what I needed!"
     2. "governor too embarrassed to say which state he leads"
     3. "ghar ki mulgi dar barabar"