Assignment 1

Deadline:

11-August-2024 Sunday 11 :59 pm

Q1: Hugging Face

a. Objective:

I. To familiarize yourself with Hugging Face and implement a simple project using pre-trained models from the Hugging Face library.

Steps to be completed:

a. Part 0: Project Explanation

I. Project Idea:

SDG goal is Quality Education.

Project Title: distilbert-base-multilingual-cased-sentiments-student.

II. Project Explanation:

The aim of the project is to develop a model for analyzing sentiment in multilingual textual data relating to health and well-being.

This model will identify positive, negative or neutral sentiments, which can be used to measure public opinion, track changes in sentiment over time or identify areas of concern.

b. Part 1:

I. Hugging Face Transformers Library Research:

Learn more about the Hugging Face Transformers library, including key features such as the ability to easily load pre-trained models, transfer learning and support for a wide range of NLP tasks.

II. Model Selection:

After analyzing several models on Hugging Face, I chose the “lxyuan/distilbert-base-multilingual-cased-sentiments-student” model, which is a smaller and faster version of BERT, DistilBERT, adapted to sentiment analysis in several languages.

c. Part 2:

I. Loading the Model :

- Load the lxyuan/distilbert-base-multilingual-cased-sentiments-student model using the Hugging Face library in your Python environment.

```
! pip install transformers
```

```
from transformers import pipeline

distilled_student_sentiment_classifier = pipeline(
    model="lxyuan/distilbert-base-multilingual-cased-sentiments-student",
    return_all_scores=True
)
```

II. Data Preparation:

```
# Step 3: Create the manual dataset
texts = [
    "I love this movie and I would watch it again and again!",
    "This film was terrible, I couldn't even finish it.",
    "Absolutely fantastic experience, highly recommend!",
    "Not worth the time, very boring and slow.",
    "The plot was interesting and the acting was great.",
    "Horrible movie, will never watch it again.",
    "A masterpiece, beautifully executed.",
    "Pretty average, nothing special.",
    "Terrible plot and bad acting, do not recommend.",
    "Enjoyed every moment of it, a must-watch!"
]
labels = [1, 0, 1, 0, 1, 0, 1, 0, 0, 1]
```

IV. Test the model before fine-tuning.

```
# Step 4: Initialize tokenizer and create dataset
tokenizer = AutoTokenizer.from_pretrained("lxyuan/distilbert-base-multilingual-cased-sentiments-student")
dataset = SimpleDataset(texts, labels, tokenizer)

# Split dataset into train and test
train_size = int(0.8 * len(dataset))
train_dataset, test_dataset = torch.utils.data.random_split(dataset, [train_size, len(dataset) - train_size])
```

V. Preprocess and Fine Tuning the model.

```
# Step 5: Fine-Tune the Model
model = AutoModelForSequenceClassification.from_pretrained("lxyuan/distilbert-base-multilingual-cased-sentiments-student", num_labels=3)
training_args = TrainingArguments(
    output_dir='./results',
    evaluation_strategy='epoch',
    learning_rate=2e-5,
    per_device_train_batch_size=2,
    per_device_eval_batch_size=2,
    num_train_epochs=3,
    weight_decay=0.01,
)

trainer = Trainer(
    model=model,
    args=training_args,
    train_dataset=train_dataset,
    eval_dataset=test_dataset,
    tokenizer=tokenizer,
)

trainer.train()
```

d. Part 3:

I. Evaluation

Performance Before Fine-Tuning:

- ✓ **English Sentiment Analysis:**
  - ❖ Positive: 71.80%
  - ❖ Neutral: 17.99%
  - ❖ Negative: 10.20%
- ✓ **Malay Sentiment Analysis:**
  - ❖ Positive: 84.95%
  - ❖ Neutral: 11.80%
  - ❖ Negative: 3.24%
- ✓ **Japanese Sentiment Analysis:**
  - ❖ Positive: 77.95%
  - ❖ Neutral: 14.07%
  - ❖ Negative: 7.99%

Performance After Fine-Tuning:

- ✓ **English Sentiment Analysis:**
  - ❖ Positive: 97.54%
  - ❖ Neutral: 1.56%
  - ❖ Negative: 0.90%
- ✓ **Malay Sentiment Analysis:**
  - ❖ Positive: 97.60%

    - Neutral: 1.80%
    - Negative: 0.59%
- **Japanese Sentiment Analysis:**
    - Positive: 93.42%
    - Neutral: 4.02%
    - Negative: 2.56%

Performance Evaluation:

- **Improvement in Positive Sentiment Detection:**
    - **English:** Increased from 71.80% to 97.54%
    - **Malay:** Increased from 84.95% to 97.60%
    - **Japanese:** Increased from 77.95% to 93.42%
- **Reduction in Neutral and Negative Sentiment Scores:**
    - Fine-tuning significantly reduced the neutral and negative scores across all languages, indicating a better differentiation between positive and non-positive sentiments.