# NLP - EXP - 7 (Applications of BERT Model)

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#### Dataset

```
### sentiment_train.csv ###

sentence,label
Ok brokeback mountain is such a horrible movie.,0
Brokeback Mountain was so awesome.,1
friday hung out with kelsie and we went and saw The Da Vinci Code SUCKED!!!!!,0
I am going to start reading the Harry Potter series again because that is one awesome story.,1
"Is it just me, or does Harry Potter suck?...",0
The Da Vinci Code sucked big time.,0
I am going to start reading the Harry Potter series again because that is one awesome story.,1
"For those who are Harry Potter ignorant, the true villains of this movie are awful creatures called dementors.",0
"Harry Potter dragged Draco Malfoy 's trousers down past his hips and sucked him into his throat with vigor, making whimpering noises ar "So as felicia's mom is cleaning the table, felicia grabs my keys and we dash out like freakin mission impossible.",1
I love The Da Vinci Code...,1
```

### ▼ Fine Tuning Bert Model Code

```
!pip install transformers
     Requirement already satisfied: transformers in /usr/local/lib/python3.10/dist-packages (4.33.2)
     Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-packages (from transformers) (3.12.2)
     Requirement already satisfied: huggingface-hub<1.0,>=0.15.1 in /usr/local/lib/python3.10/dist-packages (from transformers) (0.17.1)
     Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.10/dist-packages (from transformers) (1.23.5)
     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) (6.0.1)
     Requirement already satisfied: regex!=2019.12.17 in /usr/local/lib/python3.10/dist-packages (from transformers) (2023.6.3)
     Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages (from transformers) (2.31.0)
     Requirement already satisfied: tokenizers!=0.11.3,<0.14,>=0.11.1 in /usr/local/lib/python3.10/dist-packages (from transformers) (0.
     Requirement already satisfied: safetensors>=0.3.1 in /usr/local/lib/python3.10/dist-packages (from transformers) (0.3.3)
     Requirement already satisfied: tqdm>=4.27 in /usr/local/lib/python3.10/dist-packages (from transformers) (4.66.1)
     Requirement already satisfied: fsspec in /usr/local/lib/python3.10/dist-packages (from huggingface-hub<1.0,>=0.15.1->transformers)
     Requirement already satisfied: typing-extensions>=3.7.4.3 in /usr/local/lib/python3.10/dist-packages (from huggingface-hub<1.0,>=0.
     Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests->transformers) (3
     Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests->transformers) (3.4)
     Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests->transformers) (2.0.4)
     Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests->transformers) (2023.7.
import torch
```

▼ Dataset cleaning and diving: train - validation set

from torch.utils.data import DataLoader, TensorDataset

from sklearn.model\_selection import train\_test\_split from sklearn.metrics import classification\_report

import pandas as pd

import re

```
# Load the dataset
data = pd.read_csv('sentiment_train.csv')

# Clean and preprocess the sentences (remove special characters, lowercasing, etc.)
def clean_text(text):
    text = re.sub(r'[^A-Za-z0-9]+', ' ', text)
    return text.lower().strip()

data['sentence'] = data['sentence'].apply(clean_text)

# Split the dataset into train and validation sets
train_data, val_data = train_test_split(data, test_size=0.2, random_state=42)
```

from transformers import BertTokenizer, BertForSequenceClassification, AdamW, get linear schedule with warmup

#### Download 'bert-base-uncased' Tokenizer

```
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
def tokenize_data(data, max_length):
    input_ids = []
    attention_masks = []
    for sentence in data['sentence']:
        encoded = tokenizer.encode_plus(
            sentence,
            add special tokens=True,
            max_length=max_length,
            padding='max_length',
            truncation=True,
            return_tensors='pt',
            return_attention_mask=True
        input_ids.append(encoded['input_ids'])
        attention_masks.append(encoded['attention_mask'])
    input_ids = torch.cat(input_ids, dim=0)
    attention_masks = torch.cat(attention_masks, dim=0)
    labels = torch.tensor(data['label'].tolist())
    return TensorDataset(input_ids, attention_masks, labels)
max_length = 128  # Adjust this value as needed
train_dataset = tokenize_data(train_data, max_length)
val_dataset = tokenize_data(val_data, max_length)
```

#### ▼ Download 'bert-base-uncased' Model

```
model = BertForSequenceClassification.from_pretrained('bert-base-uncased', num_labels=2)
```

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

```
batch_size = 32  # Adjust this value as needed
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=batch_size)
num epochs = 5  # Adjust this value as needed
```

### ▼ Training Loop

```
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model.to(device)
optimizer = AdamW(model.parameters(), 1r=2e-5)
scheduler = get_linear_schedule_with_warmup(optimizer, num_warmup_steps=0, num_training_steps=len(train_loader) * num_epochs)
for epoch in range(num epochs):
    model.train()
    total_loss = 0
    # Train Loop
    for batch in train_loader:
        input_ids, attention_mask, labels = batch
        input_ids, attention_mask, labels = input_ids.to(device), attention_mask.to(device), labels.to(device)
        optimizer.zero_grad()
        outputs = model(input_ids, attention_mask=attention_mask, labels=labels)
        loss = outputs.loss
        total_loss += loss.item()
        loss.backward()
        torch.nn.utils.clip_grad_norm_(model.parameters(), 1.0)
        optimizer.step()
        scheduler.step()
```

```
average_loss = total_loss / len(train_loader)
print(f'Epoch {epoch + 1}/{num_epochs}, Train Loss: {average_loss:.4f}')
# Validation
model.eval()
val_loss = 0
predictions, true_labels = [], []
for batch in val_loader:
   input_ids, attention_mask, labels = batch
    input_ids, attention_mask, labels = input_ids.to(device), attention_mask.to(device), labels.to(device)
    with torch.no_grad():
        outputs = model(input_ids, attention_mask=attention_mask, labels=labels)
        loss = outputs.loss # Get the loss value from the outputs
   val loss += loss.item()
   logits = outputs.logits
   predictions.extend(torch.argmax(logits, dim=1).tolist())
   true_labels.extend(labels.tolist())
average_val_loss = val_loss / len(val_loader)
print(f'Epoch {epoch + 1}/{num_epochs}, Validation Loss: {average_val_loss:.4f}')
print(classification_report(true_labels, predictions))
Epoch 1/4, Train Loss: 0.0135
Epoch 1/4, Validation Loss: 0.0306
               precision
                          recall f1-score support
           a
                    1.00
                             0.99
                                       0.99
                                                   192
           1
                    1.00
                             1.00
                                       1.00
                                                   642
     accuracy
                                        1.00
                                                  1134
                    1.00
                              1.00
                                        1.00
                                                  1134
   macro avg
                                                  1134
                    1.00
                              1.00
                                        1.00
weighted avg
 Epoch 2/4, Train Loss: 0.0014
Epoch 2/4, Validation Loss: 0.0325
               precision
                          recall f1-score
                                               support
           0
                    1.00
                             0.99
                                        0.99
                                                   492
           1
                             1.00
                                       1.00
                                                   642
     accuracy
                                        1.00
                                                  1134
                             1.00
                                        1.00
                                                  1134
                    1.00
   macro avg
weighted avg
                   1.00
                             1.00
                                        1.00
                                                  1134
Epoch 3/4, Train Loss: 0.0001
Epoch 3/4, Validation Loss: 0.0336
               precision
                          recall f1-score
           0
                    1.00
                             0.99
                                        0.99
                                                   492
                    1.00
                             1.00
                                       1.00
                                                   642
                                                  1134
                                        1.00
     accuracy
                             1.00
                    1.00
                                       1.00
                                                  1134
   macro avg
                                       1.00
                                                  1134
weighted avg
                   1.00
                             1.00
Epoch 4/4, Train Loss: 0.0010
 Epoch 4/4, Validation Loss: 0.0312
               precision recall f1-score
            0
                    0.99
                             0.99
                                        0.99
                                                   492
                   1.00
                             1.00
                                       1.00
                                                   642
           1
     accuracy
                                        0.99
                                                  1134
                             0.99
                    0.99
                                        0.99
                                                  1134
   macro avg
                   0.99
weighted avg
                             0.99
                                        0.99
                                                  1134
```

### Save the Model and Tokenizer

```
# Save the fine-tuned model and tokenizer
model.save_pretrained('/content/fine_tuned_model')
tokenizer.save_pretrained('/content/fine_tuned_model')

    ('/content/fine_tuned_model/tokenizer_config.json',
    '/content/fine_tuned_model/special_tokens_map.json',
    '/content/fine_tuned_model/vocab.txt',
    '/content/fine_tuned_model/added_tokens.json')
```

# Inference (Testing)

```
import torch
from transformers import BertTokenizer, BertForSequenceClassification
# Load the fine-tuned model and tokenizer
model_path = '/content/fine_tuned_model' # Update with your model path
model = BertForSequenceClassification.from_pretrained(model_path)
tokenizer = BertTokenizer.from_pretrained(model_path)
# Define a function for inference
def predict sentiment(sentence):
    # Tokenize the input sentence
    inputs = tokenizer(sentence, return_tensors="pt", padding=True, truncation=True, max_length=128)
    # Perform inference
    with torch.no_grad():
        outputs = model(**inputs)
    # Get the predicted label (0 or 1)
    logits = outputs.logits
    predicted_label = torch.argmax(logits, dim=1).item()
    # Map the label to its meaning
    sentiment = "Positive" if predicted_label == 1 else "Negative"
    return sentiment
     Sentiment: Negative
```

### ▼ Positive Test

```
# Example usage:
test_sentence = "I really enjoyed that movie" # Positive
# test_sentence = "It was a bad movie" # Negative
result = predict_sentiment(test_sentence)
print(f"Sentence: {test_sentence}")
print(f"Sentiment: {result}")

Sentence: I really enjoyed that movie
Sentiment: Positive
```

## ▼ Negative Test

```
# Example usage:
# test_sentence = "I really enjoyed that movie" # Positive
test_sentence = "It was a bad movie" # Negative
result = predict_sentiment(test_sentence)
print(f"Sentence: {test_sentence}")
print(f"Sentiment: {result}")

Sentence: It was a bad movie
Sentiment: Negative
```

## Uploading Model on Hugging Face Server

```
!huggingface-cli login
model.push_to_hub("atharvapawar/Bert-Sentiment-Classification-pos-or-neg", check_pr=True)
tokenizer.push_to_hub("atharvapawar/Bert-Sentiment-Classification-pos-or-neg",check_pr=True)
```

```
To login, `huggingface_hub` requires a token generated from <a href="https://huggingface.green">https://huggingface.green</a>
To login, `huggingface_hub` requires a token generated from <a href="https://huggingface.green">https://huggingface.green</a>
Token:
Add token as git credential? (Y/n) y
Token is valid (permission: write).
Cannot authenticate through git-credential as no helper is defined on your machine.
You might have to re-authenticate when pushing to the Hugging Face Hub.
Run the following command in your terminal in case you want to set the 'store' creder git config --global credential.helper store
```

## Api Testing

```
import requests
API URL = "https://api-inference.huggingface.co/models/atharvapawar/Bert-Sentiment-Classification-pos-or-neg"
def query(payload):
   response = requests.post(API_URL, headers=headers, json=payload)
   return response.json()
def inferenceMain(sentence):
 output = query({ "inputs": sentence, })
 for sample in output:
   highest_score_label = max(sample, key=lambda x: x['score'])
   # print(f'Highest Score Label: {highest_score_label["label"]}, Score: {highest_score_label["score"]}')
   if highest_score_label["label"] == "LABEL_1":
     output = f'\n\n Sentiment: Positive \n Sentence : {sentence} \n Score : {round(highest_score_label["score"] * 100, 2)}'
   else:
     output = f'\n\n Sentiment: Negative \n Sentence : {sentence} \n Score : {round(highest_score_label["score"] * 100, 2)}'
   return output
sentenceList = [ "It was a bad movie", "I really enjoyed that movie" ]
for item in sentenceList:
 print(inferenceMain(item))
     Sentiment: Negative
     Sentence : It was a bad movie
     Score: 99.99
     Sentiment: Positive
     Sentence : I really enjoyed that movie
     Score : 100.0
```

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