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HANOI UNIVERSITY OF SCIENCE AND TECHNOLOGY

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Natural Language Processing
Middle Project: Song Classification using BERT

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CONTENTS

- Song genre classification is an interesting and challenging task in the field of natural language processing (NLP).
    - It involves automatically assigning a genre label to a given song based on its audio features or lyrics.
    - Traditionally, experts manually categorized songs, but with the advent of machine learning and data science, we can now automate this process using algorithms
- BERT (Bidirectional Encoder Representations from Transformers) has become a powerful tool for text classification tasks in natural language processing (NLP).

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- Project overview:
  - The goal is to categorize lyrics into specific genres (e.g., disco, hip-hop, rock) based on their content.
  - Applying transfer learning method to leverage knowledge learned from one task to improve performance on another related task.
- BERT overview
  - It captures bidirectional context by considering both left and right context for each token in a sentence.
  - It captures contextual information effectively.
  - Fine-tuning BERT requires less labeled data compared to training from scratch. It provides better performance and faster convergence.

- Dataset Selection
  - The data is composed of four sources. The initial data was forwarded from Sparktech's 2018 Textract Hackathon. This was enhanced with data from other three kaggle datasets: 150K Lyrics Labeled with Spotify Valence, dataset lyrics musics and AZLyrics song lyrics.
  - Dataset link: https://www.kaggle.com/datasets/mateibejan/multilingual-lyrics-for-genre-classification
- Approaches
  - Applying a pre-trained BERT model on the dataset.
  - Adding a classification layer on top of BERT.
  - Training the entire model on labeled data.

- Data Preprocessing
  - Challenges
    - Imbalanced data: the representation of different genres is not balanced
    - Lyric length: BERT has a maximum token limit
  - Solutions
    - Removing all non english song
    - Handling imbalanced class distributions by choosing an equal number of songs per class
    - Chunking song lyrics

- Solution
  - Link: https://www.kaggle.com/code/lehoanglonglong/hust-song-classification-using-bert
  - Source code:

```
import os
import torch
from torch import nn
from torch.utils.data import DataLoader, Dataset
from transformers import BertTokenizer, BertModel, AdamW,
get_linear_schedule_with_warmup
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report
import pandas as pd
```

```
def load_song_data(data_file, bert_model_name, max_length):
  df = pd.read_csv(data_file)
  tokenizer = BertTokenizer.from_pretrained(bert_model_name)
  df['encoding'] = df.apply(lambda x: tokenizer(x['S_Lyric'],
return_tensors='pt', max_length=max_length, padding='max_length',
truncation=True) ,  axis=1)
  encodings = df['encoding'].tolist()
  #texts = df['S_Lyric'].tolist()
  labels = [int(v) for v in df['Genre_Index'].tolist()]
  ids_genres = df[['Genre_Index', 'Genre']].drop_duplicates()
  ids_genres = ids_genres.set_index('Genre_Index')
  return encodings, labels, ids_genres
  #return texts, labels, ids_genres
```

```
class TextClassificationDataset(Dataset):
    def __init__(self, texts, labels, tokenizer, max_length):
        self.texts = texts
        self.labels = labels
        self.tokenizer = tokenizer
        self.max_length = max_length
        pass
    def __len__(self):
        return len(self.texts)
    def __getitem__(self, idx):
        encoding = self.texts[idx]
        label = self.labels[idx]
        return {'input_ids': encoding['input_ids'].flatten(), 'attention_mask':
encoding['attention_mask'].flatten(), 'label': torch.tensor(label)}
```

```python
class BERTClassifier(nn.Module):
    def __init__(self, bert_model_name, num_classes):
        super(BERTClassifier, self).__init__()
        self.bert = BertModel.from_pretrained(bert_model_name)
        self.dropout = nn.Dropout(0.1)
        self.fc = nn.Linear(self.bert.config.hidden_size, num_classes)

    def forward(self, input_ids, attention_mask):
        outputs = self.bert(input_ids=input_ids, attention_mask=attention_mask)
        pooled_output = outputs.pooler_output
        x = self.dropout(pooled_output)
        logits = self.fc(x)
        return logits
```

```python
def train(model, data_loader, optimizer, scheduler, device):
    model.train()
    for batch in data_loader:
        optimizer.zero_grad()
        input_ids = batch['input_ids'].to(device)
        attention_mask = batch['attention_mask'].to(device)
        labels = batch['label'].to(device)
        outputs = model(input_ids=input_ids, attention_mask=attention_mask)
        loss = nn.CrossEntropyLoss()(outputs, labels)
        loss.backward()
        optimizer.step()
        scheduler.step()
```

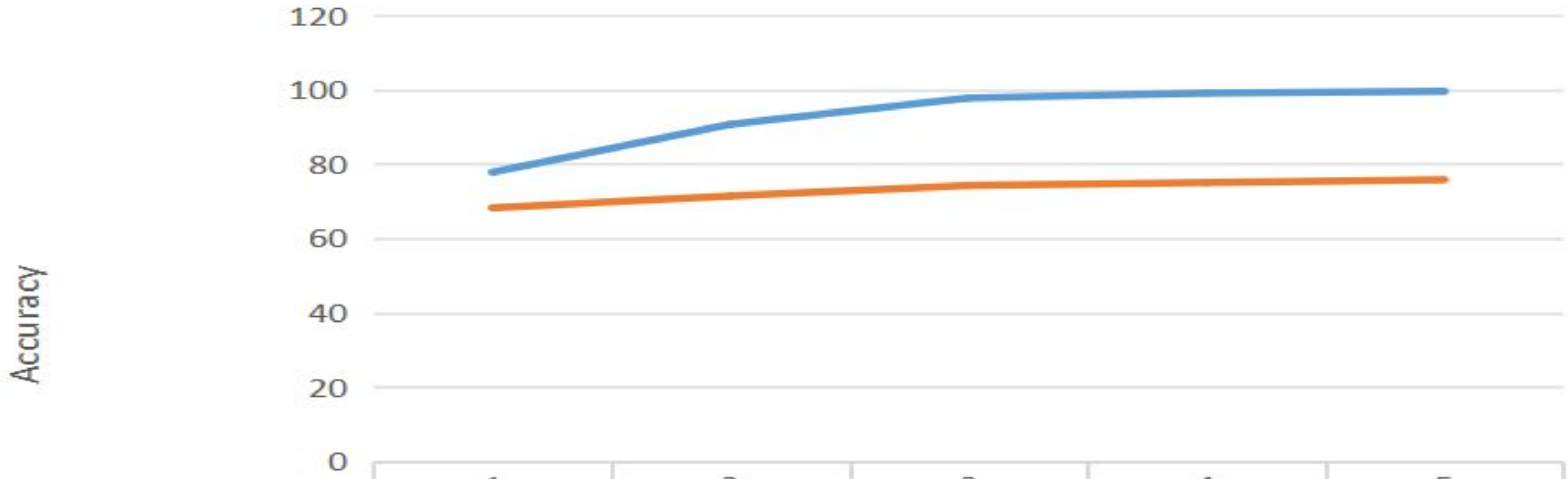
```
def evaluate(model, data_loader, device):
    model.eval()
    predictions = []
    actual_labels = []
    with torch.no_grad():
        for batch in data_loader:
            input_ids = batch['input_ids'].to(device)
            attention_mask = batch['attention_mask'].to(device)
            labels = batch['label'].to(device)
            outputs = model(input_ids=input_ids, attention_mask=attention_mask)
            _, preds = torch.max(outputs, dim=1)
            predictions.extend(preds.cpu().tolist())
            actual_labels.extend(labels.cpu().tolist())
    return accuracy_score(actual_labels, predictions),
classification_report(actual_labels, predictions)
```

```python
# Set up parameters
bert_model_name = 'bert-base-uncased'
max_length = 128
batch_size = 16
num_epochs = 10
learning_rate = 2e-5
data_file = "/kaggle/input/smallsongs2/l_df.csv"
texts, labels, ids_genres = load_song_data(data_file, bert_model_name,
max_length)
train_texts, val_texts, train_labels, val_labels = train_test_split(texts,
labels, test_size=0.2)
```

```
tokenizer = BertTokenizer.from_pretrained(bert_model_name)
train_dataset = TextClassificationDataset(train_texts, train_labels, tokenizer,
max_length)
val_dataset = TextClassificationDataset(val_texts, val_labels, tokenizer, max_length)
train_dataloader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True)
val_dataloader = DataLoader(val_dataset, batch_size=batch_size)
num_classes = ids_genres.shape[0]
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model = BERTClassifier(bert_model_name, num_classes) #.to(device)
model = torch.nn.DataParallel(model).to(device) #.to(device).to(device)
optimizer = AdamW(model.parameters(), lr=learning_rate)
total_steps = len(train_dataloader) * num_epochs
scheduler = get_linear_schedule_with_warmup(optimizer, num_warmup_steps=0,
num_training_steps=total_steps)
```

```
for epoch in range(num_epochs):
  print(f"Epoch {epoch + 1}/{num_epochs}")
  train(model, train_dataloader, optimizer, scheduler, device)
  accuracy, report = evaluate(model, train_dataloader, device)
  print(f"Train Accuracy: {accuracy:.4f}")
  accuracy, report = evaluate(model, val_dataloader, device)
  print(f"Validation Accuracy: {accuracy:.4f}")
  torch.save(model.state_dict(), f"version-{epoch}-acc-{accuracy:.4f}.pth")
  print(report)
```

EVALUATION



	1	2	3	4	5
Training	77.8	90.7	97.8	99.1	99.6
Validation	68.2	71.4	74.2	75	75.8

Epoch

- Text classification is a fundamental task in natural language processing (NLP) that involves automatically determining the class or category to which a piece of text belongs.
- We applied transformer-based model in the project (BERT) in order to capture rich contextual information, making it effective for downstream tasks.
- We could gain a better result with BigBird model but the new model asks for a greater GPU resource which is beyond the current investment.
- According to industry standard, a good accuracy is above 70%.

THANK YOU !