

```
!pip install datasets transformers scikit-learn pandas joblib
```

```
Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-packages (from datasets) (3.16.1)
Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.10/dist-packages (from datasets) (1.26.4)
Requirement already satisfied: pyarrow>=15.0.0 in /usr/local/lib/python3.10/dist-packages (from datasets) (17.0.0)
Collecting dill<0.3.9,>=0.3.0 (from datasets)
  Downloading dill-0.3.8-py3-none-any.whl.metadata (10 kB)
Requirement already satisfied: requests>=2.32.2 in /usr/local/lib/python3.10/dist-packages (from datasets) (2.32.3)
Requirement already satisfied: tqdm>=4.66.3 in /usr/local/lib/python3.10/dist-packages (from datasets) (4.66.6)
Collecting xxhash (from datasets)
  Downloading xxhash-3.5.0-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (12 kB)
Collecting multiprocess<0.70.17 (from datasets)
  Downloading multiprocess-0.70.16-py310-none-any.whl.metadata (7.2 kB)
Collecting fsspec<=2024.9.0,>=2023.1.0 (from fsspec[http]<=2024.9.0,>=2023.1.0->datasets)
  Downloading fsspec-2024.9.0-py3-none-any.whl.metadata (11 kB)
Requirement already satisfied: aiohttp in /usr/local/lib/python3.10/dist-packages (from datasets) (3.11.9)
Requirement already satisfied: huggingface-hub>=0.23.0 in /usr/local/lib/python3.10/dist-packages (from datasets) (0.26.3)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from datasets) (24.2)
Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.10/dist-packages (from datasets) (6.0.2)
Requirement already satisfied: regex!=2019.12.17 in /usr/local/lib/python3.10/dist-packages (from transformers) (2024.9.11)
Requirement already satisfied: tokenizers<0.21,>=0.20 in /usr/local/lib/python3.10/dist-packages (from transformers) (0.20.1)
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Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.10/dist-packages (from pandas) (2.8.2)
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Requirement already satisfied: frozenlist>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from aiohttp->datasets) (1.5.0)
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Requirement already satisfied: typing-extensions>=3.7.4.3 in /usr/local/lib/python3.10/dist-packages (from huggingface-hub)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.8.2->pandas) (1.17.0)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests>=2.32.2->datasets) (3.4.0)
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Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests>=2.32.2->datasets) (2024.8.30)
Downloading datasets-3.1.0-py3-none-any.whl (480 kB)
 480.6/480.6 kB 33.0 MB/s eta 0:00:00
Downloading dill-0.3.8-py3-none-any.whl (116 kB)
 116.3/116.3 kB 10.2 MB/s eta 0:00:00
Downloading fsspec-2024.9.0-py3-none-any.whl (179 kB)
 179.3/179.3 kB 16.9 MB/s eta 0:00:00
Downloading multiprocess-0.70.16-py310-none-any.whl (134 kB)
 134.8/134.8 kB 12.6 MB/s eta 0:00:00
Downloading xxhash-3.5.0-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (194 kB)
 194.1/194.1 kB 18.4 MB/s eta 0:00:00
Installing collected packages: xxhash, fsspec, dill, multiprocess, datasets
  Attempting uninstall: fsspec
    Found existing installation: fsspec 2024.10.0
    Uninstalling fsspec-2024.10.0:
      Successfully uninstalled fsspec-2024.10.0
ERROR: pip's dependency resolver does not currently take into account all the packages that are installed. This behaviour is the source of the following dependency issues.
gcsfs 2024.10.0 requires fsspec==2024.10.0, but you have fsspec 2024.9.0 which is incompatible.
Successfully installed datasets-3.1.0 dill-0.3.8 fsspec-2024.9.0 multiprocess-0.70.16 xxhash-3.5.0
```

▼ Data Preprocessing

```
import pandas as pd
from sklearn.feature_extraction.text import CountVectorizer
from datasets import load_dataset
import pickle
import joblib

# Load the GoEmotions dataset using Hugging Face Datasets library
dataset = load_dataset("go_emotions")

# Convert datasets to pandas DataFrames
train_df = dataset['train'].to_pandas()
validation_df = dataset['validation'].to_pandas()
test_df = dataset['test'].to_pandas()

# Function to preprocess data by filtering multi-label samples
```

```

def preprocess_data(df):
    # Filter out multi-label samples
    df = df[df['labels'].apply(lambda x: len(x) == 1)].copy()
    # Extract the single label
    df['label'] = df['labels'].apply(lambda x: x[0])
    df = df.reset_index(drop=True)
    return df

# Preprocess train, validation, and test datasets
train_data = preprocess_data(train_df)
validation_data = preprocess_data(validation_df)
test_data = preprocess_data(test_df)

# Vectorization for Baseline Models with Enhanced Preprocessing
vectorizer = CountVectorizer(
    stop_words='english',      # Remove stop words
    ngram_range=(1, 2),       # Include unigrams and bigrams
    max_features=5000          # Limit to top 5000 features
)

# Fit the vectorizer on the training data and transform
X_train_baseline = vectorizer.fit_transform(train_data['text'])
X_validation_baseline = vectorizer.transform(validation_data['text'])
X_test_baseline = vectorizer.transform(test_data['text'])


y_train_baseline = train_data['label'].values
y_validation_baseline = validation_data['label'].values
y_test_baseline = test_data['label'].values

# Save processed data for further use
processed_data = {
    "baseline": {
        "X_train": X_train_baseline,
        "y_train": y_train_baseline,
        "X_validation": X_validation_baseline,
        "y_validation": y_validation_baseline,
        "X_test": X_test_baseline,
        "y_test": y_test_baseline,
    }
}

# Save to a file for later use
with open("processed_data.pkl", "wb") as f:
    pickle.dump(processed_data, f)

# Save the vectorizer separately
joblib.dump(vectorizer, 'vectorizer.joblib')

```

 /usr/local/lib/python3.10/dist-packages/huggingface_hub/utils/_auth.py:94: UserWarning:
 The secret `HF_TOKEN` does not exist in your Colab secrets.
 To authenticate with the Hugging Face Hub, create a token in your settings tab (<https://huggingface.co/settings/tokens>), set
 You will be able to reuse this secret in all of your notebooks.
 Please note that authentication is recommended but still optional to access public models or datasets.

README.md: 100%	9.40k/9.40k [00:00<00:00, 355kB/s]
train-00000-of-00001.parquet: 100%	2.77M/2.77M [00:00<00:00, 31.8MB/s]
validation-00000-of-00001.parquet: 100%	350k/350k [00:00<00:00, 8.39MB/s]
test-00000-of-00001.parquet: 100%	347k/347k [00:00<00:00, 6.80MB/s]
Generating train split: 100%	43410/43410 [00:00<00:00, 183902.52 examples/s]
Generating validation split: 100%	5426/5426 [00:00<00:00, 74570.17 examples/s]
Generating test split: 100%	5427/5427 [00:00<00:00, 70588.80 examples/s]
['vectorizer.joblib']	

✎ Mini BERT Model for Emotion Classification

```

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

```

```

# Define the Small-BERT model
class SmallBERT(nn.Module):
    def __init__(self, vocab_size, hidden_size, num_heads, num_layers, max_seq_len, intermediate_size):
        super(SmallBERT, self).__init__()

        # Embedding layers
        self.token_embeddings = nn.Embedding(vocab_size, hidden_size)
        self.position_embeddings = nn.Embedding(max_seq_len, hidden_size)
        self.layer_norm = nn.LayerNorm(hidden_size)
        self.dropout = nn.Dropout(0.1)

        # Transformer layers
        self.transformer_blocks = nn.ModuleList([
            TransformerBlock(hidden_size, num_heads, intermediate_size) for _ in range(num_layers)
        ])

        # Output layer for MLM
        self.mlm_head = nn.Linear(hidden_size, vocab_size)

    def forward(self, input_ids, return_logits=False):
        # Embedding layer
        seq_len = input_ids.size(1)
        positions = torch.arange(seq_len, device=input_ids.device).unsqueeze(0)
        x = self.token_embeddings(input_ids) + self.position_embeddings(positions)
        x = self.layer_norm(x)
        x = self.dropout(x)

        # Pass through transformer blocks
        for block in self.transformer_blocks:
            x = block(x)

        # By default, return hidden states
        if return_logits:
            # If return_logits=True, return MLM logits
            logits = self.mlm_head(x)
            return logits
        else:
            # Return just the hidden states
            return x

class TransformerBlock(nn.Module):
    def __init__(self, hidden_size, num_heads, intermediate_size):
        super(TransformerBlock, self).__init__()

        # Self-attention layer
        self.attention = nn.MultiheadAttention(embed_dim=hidden_size, num_heads=num_heads, dropout=0.1)
        self.norm1 = nn.LayerNorm(hidden_size)
        self.dropout1 = nn.Dropout(0.1)

        # Feed-forward network
        self.ffn = nn.Sequential(
            nn.Linear(hidden_size, intermediate_size),
            nn.GELU(),
            nn.Linear(intermediate_size, hidden_size),
        )
        self.norm2 = nn.LayerNorm(hidden_size)
        self.dropout2 = nn.Dropout(0.1)

    def forward(self, x):
        # Self-attention
        attn_output, _ = self.attention(x, x, x)
        x = self.norm1(x + self.dropout1(attn_output))

        # Feed-forward
        ffn_output = self.ffn(x)
        x = self.norm2(x + self.dropout2(ffn_output))

        return x

# Define testing function
def test_models(small_model, small_config, bert_base_model_name="bert-base-uncased"):
    # Load the pre-trained BERT-base model and its configuration
    bert_base = AutoModel.from_pretrained(bert_base_model_name)
    bert_base_config = AutoConfig.from_pretrained(bert_base_model_name)
    bert_base_config_dict = bert_base_config.to_dict()
    tokenizer = AutoTokenizer.from_pretrained(bert_base_model_name)

```

```

print("\n--- Comparing Architectures ---\n")
print("BERT-base architecture:")
print(bert_base)
print("\nSmall-BERT architecture:")
print(small_model)

print("\n--- Counting Parameters ---\n")
bert_base_params = sum(p.numel() for p in bert_base.parameters() if p.requires_grad)
small_params = sum(p.numel() for p in small_model.parameters() if p.requires_grad)
print(f"BERT-base parameter count: {bert_base_params}")
print(f"Small-BERT parameter count: {small_params}")

print("\n--- Comparing Configurations ---\n")
for key in small_config:
    bert_value = bert_base_config_dict.get(key, "N/A")
    small_value = small_config[key]
    print(f"{key}: BERT-base={bert_value}, Small-BERT={small_value}")

print("\n--- Inspecting Embedding Shapes ---\n")
bert_embedding_shape = bert_base.embeddings.word_embeddings.weight.shape
small_embedding_shape = small_model.token_embeddings.weight.shape
print(f"BERT-base embedding shape: {bert_embedding_shape}")
print(f"Small-BERT embedding shape: {small_embedding_shape}")

print("\n--- Running a Forward Pass ---\n")
input_text = "This is a test sentence."
inputs = tokenizer(input_text, return_tensors="pt", max_length=128, truncation=True, padding="max_length")

# Run through BERT-base: it returns last_hidden_state by default
with torch.no_grad():
    bert_outputs = bert_base(**inputs)
print(f"BERT-base output shape: {bert_outputs.last_hidden_state.shape}")

# Run through Small-BERT: now returns hidden states by default
with torch.no_grad():
    small_outputs = small_model(inputs["input_ids"])
print(f"Small-BERT output shape: {small_outputs.shape}")

# Verify MLM logits
logits = small_model(inputs["input_ids"], return_logits=True)
print(f"Small-BERT MLM logits shape: {logits.shape}")

print("\n--- Validation Complete ---")

# Initialize Small-BERT model
small_model = SmallBERT(
    vocab_size=30522, hidden_size=256, num_heads=4, num_layers=4, max_seq_len=128, intermediate_size=1024
)

# Small-BERT configuration
small_config = {
    "vocab_size": 30522,
    "hidden_size": 256,
    "num_attention_heads": 4,
    "num_hidden_layers": 4,
    "intermediate_size": 1024,
    "max_position_embeddings": 128,
}

# Run the test
test_models(small_model, small_config)

```



config.json: 100%	570/570 [00:00<00:00, 39.1kB/s]
model.safetensors: 100%	440M/440M [00:02<00:00, 220MB/s]
tokenizer_config.json: 100%	48.0/48.0 [00:00<00:00, 3.26kB/s]
vocab.txt: 100%	232k/232k [00:00<00:00, 554kB/s]
tokenizer.json: 100%	466k/466k [00:00<00:00, 2.01MB/s]

--- Comparing Architectures ---

BERT-base architecture:

```
BertModel(
  (embeddings): BertEmbeddings(
    (word_embeddings): Embedding(30522, 768, padding_idx=0)
    (position_embeddings): Embedding(512, 768)
    (token_type_embeddings): Embedding(2, 768)
    (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
    (dropout): Dropout(p=0.1, inplace=False)
  )
  (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()
  )
)
```

Small-BERT architecture:

```
SmallBert(
  (token_embeddings): Embedding(30522, 256)
  (position_embeddings): Embedding(128, 256)
  (layer_norm): LayerNorm((256,), eps=1e-05, elementwise_affine=True)
  (dropout): Dropout(p=0.1, inplace=False)
  (transformer_blocks): ModuleList(
    (0-3): 4 x TransformerBlock(
      (attention): MultiheadAttention(
        (out_proj): NonDynamicallyQuantizableLinear(in_features=256, out_features=256, bias=True)
      )
      (norm1): LayerNorm((256,), eps=1e-05, elementwise_affine=True)
      (dropout1): Dropout(p=0.1, inplace=False)
      (ffn): Sequential(
        (0): Linear(in_features=256, out_features=1024, bias=True)
        (1): GELU(approximate='none')
        (2): Linear(in_features=1024, out_features=256, bias=True)
      )
      (norm2): LayerNorm((256,), eps=1e-05, elementwise_affine=True)
      (dropout2): Dropout(p=0.1, inplace=False)
    )
  )
  (mlm_head): Linear(in_features=256, out_features=30522, bias=True)
)
```

--- Counting Parameters ---

BERT-base parameter count: 109482240
Small-BERT parameter count: 18850106

--- Comparing Configurations ---

vocab_size: BERT-base=30522, Small-BERT=30522
hidden_size: BERT-base=768, Small-BERT=256
num_attention_heads: BERT-base=12, Small-BERT=4
num_hidden_layers: BERT-base=12, Small-BERT=4
intermediate_size: BERT-base=3072, Small-BERT=1024
max_position_embeddings: BERT-base=512, Small-BERT=128

--- Inspecting Embedding Shapes ---

BERT-base embedding shape: torch.Size([30522, 768])
Small-BERT embedding shape: torch.Size([30522, 256])

--- Running a Forward Pass ---

BERT-base output shape: torch.Size([1, 128, 768])
Small-BERT output shape: torch.Size([1, 128, 256])
Small-BERT MLM logits shape: torch.Size([1, 128, 30522])

--- Validation Complete ---

```
import torch
import torch.nn as nn
from torch.utils.data import Dataset, DataLoader
from transformers import AutoTokenizer, AdamW
from tqdm import tqdm

class SmallBERTForSequenceClassification(nn.Module):
    def __init__(self, small_bert, num_classes):
        super(SmallBERTForSequenceClassification, self).__init__()
        self.small_bert = small_bert
        self.classifier = nn.Linear(256, num_classes)

    def forward(self, input_ids, attention_mask=None):
        hidden_states = self.small_bert(input_ids, return_logits=False)
        cls_embedding = hidden_states[:, 0, :]
        logits = self.classifier(cls_embedding)
        return logits

class GoEmotionsDataset(Dataset):
    def __init__(self, texts, labels, tokenizer, max_length=128):
        self.texts = texts.tolist()
        self.labels = labels.tolist()
        self.tokenizer = tokenizer
        self.max_length = max_length

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

    def __getitem__(self, idx):
        text = self.texts[idx]
        label = self.labels[idx]
        encoding = self.tokenizer(
            text,
            truncation=True,
            padding='max_length',
            max_length=self.max_length,
            return_tensors='pt'
        )
        input_ids = encoding['input_ids'].squeeze(0)
        attention_mask = encoding['attention_mask'].squeeze(0)
        return input_ids, attention_mask, label

num_classes = len(train_data['label'].unique())

tokenizer = AutoTokenizer.from_pretrained("bert-base-uncased")
train_dataset = GoEmotionsDataset(train_data['text'], train_data['label'], tokenizer)
val_dataset = GoEmotionsDataset(validation_data['text'], validation_data['label'], tokenizer)
test_dataset = GoEmotionsDataset(test_data['text'], test_data['label'], tokenizer)

train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=32, shuffle=False)
```

```

test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False)

# Initialize Small-BERT
small_bert = SmallBERT(
    vocab_size=30522,
    hidden_size=256,
    num_heads=4,
    num_layers=4,
    max_seq_len=128,
    intermediate_size=1024
)

model = SmallBERTForSequenceClassification(small_bert, num_classes)
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model.to(device)

optimizer = AdamW(model.parameters(), lr=2e-5)
criterion = nn.CrossEntropyLoss()

epochs = 3
for epoch in range(epochs):
    model.train()
    total_loss = 0
    for batch in tqdm(train_loader, desc=f"Training Epoch {epoch+1}/{epochs}"):
        input_ids, attention_mask, labels = batch
        input_ids = input_ids.to(device)
        attention_mask = attention_mask.to(device)
        labels = labels.to(device)

        optimizer.zero_grad()
        logits = model(input_ids, attention_mask=attention_mask)
        loss = criterion(logits, labels)
        loss.backward()
        optimizer.step()

        total_loss += loss.item()
    avg_train_loss = total_loss / len(train_loader)

    model.eval()
    correct = 0
    total = 0
    with torch.no_grad():
        for batch in val_loader:
            input_ids, attention_mask, labels = batch
            input_ids = input_ids.to(device)
            attention_mask = attention_mask.to(device)
            labels = labels.to(device)

            logits = model(input_ids, attention_mask=attention_mask)
            preds = torch.argmax(logits, dim=1)
            correct += (preds == labels).sum().item()
            total += labels.size(0)
    val_acc = correct / total

    print(f"Epoch: {epoch+1}, Train Loss: {avg_train_loss:.4f}, Val Acc: {val_acc:.4f}")

# Save the trained model
torch.save(model.state_dict(), "small_bert_model.pth")
print("Model saved to 'small_bert_model.pth'")

# Test
model.eval()
correct = 0
total = 0
with torch.no_grad():
    for batch in test_loader:
        input_ids, attention_mask, labels = batch
        input_ids = input_ids.to(device)
        attention_mask = attention_mask.to(device)
        labels = labels.to(device)

        logits = model(input_ids, attention_mask=attention_mask)
        preds = torch.argmax(logits, dim=1)
        correct += (preds == labels).sum().item()
        total += labels.size(0)

```

```
test_acc = correct / total
print(f"Test Accuracy: {test_acc:.4f}")
```

```
➦ Training Epoch 1/3: 100%|██████████| 1135/1135 [00:48<00:00, 23.32it/s]
Epoch: 1, Train Loss: 2.6208, Val Acc: 0.3500
Training Epoch 2/3: 100%|██████████| 1135/1135 [00:47<00:00, 24.09it/s]
Epoch: 2, Train Loss: 2.6078, Val Acc: 0.3500
Training Epoch 3/3: 100%|██████████| 1135/1135 [00:47<00:00, 23.98it/s]
Epoch: 3, Train Loss: 2.6072, Val Acc: 0.3500
Model saved to 'small_bert_model.pth'
Test Accuracy: 0.3499
```

✓ Confusion Matrix for Mini Bert

```
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

# Collect predictions and true labels from the test set
print("Predicting on the test set.")
y_test = []
y_pred = []

model.eval()
with torch.no_grad():
    for batch in test_loader:
        input_ids, attention_mask, labels = batch
        input_ids = input_ids.to(device)
        attention_mask = attention_mask.to(device)
        labels = labels.to(device)

        logits = model(input_ids, attention_mask=attention_mask)
        predictions = torch.argmax(logits, dim=1)

        y_test.extend(labels.cpu().numpy())
        y_pred.extend(predictions.cpu().numpy())

# Compute the confusion matrix
print("Computing the confusion matrix.")
conf_matrix = confusion_matrix(y_test, y_pred)

# Get sorted unique labels
labels = sorted(set(y_test))

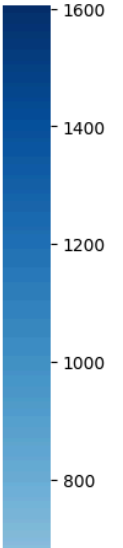
# Print the confusion matrix
print("Confusion Matrix:")
print(conf_matrix)

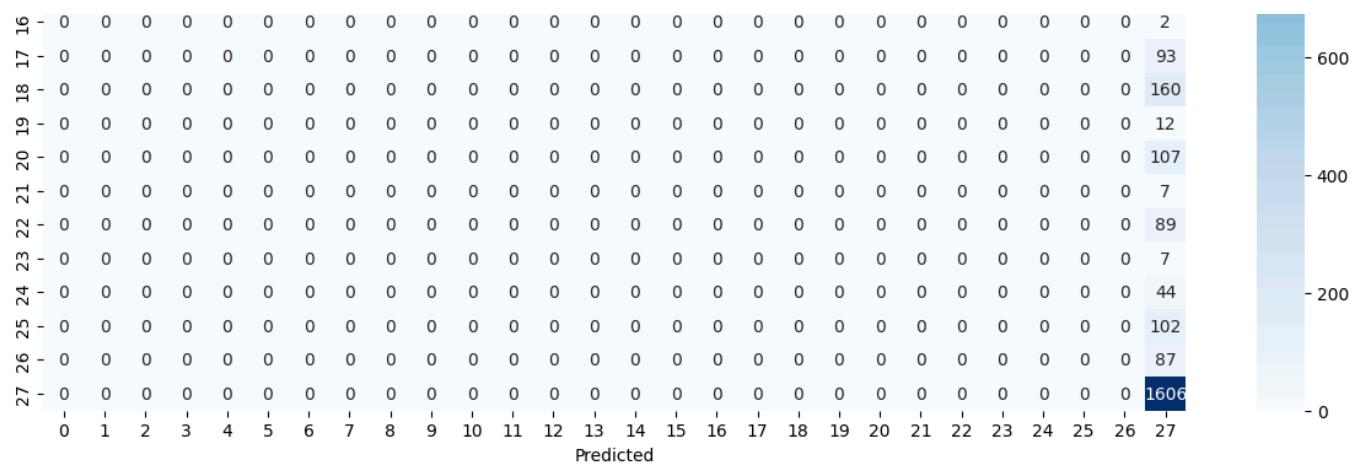
# Plot the confusion matrix as a heatmap
plt.figure(figsize=(15, 10))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=labels, yticklabels=labels)
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("True")
plt.show()
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Confusion Matrix





✓ Precision & Recall & F1 score

✓ Overall

```
from sklearn.metrics import precision_score, recall_score, f1_score

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        input_ids = input_ids.to(device)
        attention_mask = attention_mask.to(device)
        labels = labels.to(device)

        logits = model(input_ids, attention_mask=attention_mask)
        predictions = torch.argmax(logits, dim=1)

        y_test.extend(labels.cpu().numpy())
        y_pred.extend(predictions.cpu().numpy())

# Compute weighted metrics with zero_division=0
precision = precision_score(y_test, y_pred, average='weighted', zero_division=0)
recall = recall_score(y_test, y_pred, average='weighted', zero_division=0)
f1 = f1_score(y_test, y_pred, average='weighted', zero_division=0)

print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1 Score: {f1:.4f}")
```

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🔄 Predicting on the test set.
Precision: 0.1224
Recall: 0.3499
F1 Score: 0.1814
```

✓ By Class

```
from sklearn.metrics import precision_score, recall_score, f1_score

# Collect predictions and true labels from the test set
print("Predicting on the test set.")
y_test = []
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```

```

model.eval()
with torch.no_grad():
    for batch in test_loader:
        input_ids, attention_mask, labels = batch
        input_ids = input_ids.to(device)
        attention_mask = attention_mask.to(device)
        labels = labels.to(device)

        logits = model(input_ids, attention_mask=attention_mask)
        predictions = torch.argmax(logits, dim=1)

        y_test.extend(labels.cpu().numpy())
        y_pred.extend(predictions.cpu().numpy())

# Calculate per-class precision, recall, and F1 scores
print("Calculating per-class precision, recall, and F1 scores.")
precision_per_class = precision_score(y_test, y_pred, average=None, zero_division=0)
recall_per_class = recall_score(y_test, y_pred, average=None, zero_division=0)
f1_per_class = f1_score(y_test, y_pred, average=None, zero_division=0)

# Get unique class labels
class_labels = sorted(set(y_test))

# Print per-class metrics
print("Per-Class Metrics (Mini BERT):")
for label, p, r, f in zip(class_labels, precision_per_class, recall_per_class, f1_per_class):
    print(f"Class {label}: Precision={p:.4f}, Recall={r:.4f}, F1 Score={f:.4f}")

```



```

Predicting on the test set.
Calculating per-class precision, recall, and F1 scores.
Per-Class Metrics (Mini BERT):
Class 0: Precision=0.0000, Recall=0.0000, F1 Score=0.0000
Class 1: Precision=0.0000, Recall=0.0000, F1 Score=0.0000
Class 2: Precision=0.0000, Recall=0.0000, F1 Score=0.0000
Class 3: Precision=0.0000, Recall=0.0000, F1 Score=0.0000
Class 4: Precision=0.0000, Recall=0.0000, F1 Score=0.0000
Class 5: Precision=0.0000, Recall=0.0000, F1 Score=0.0000
Class 6: Precision=0.0000, Recall=0.0000, F1 Score=0.0000
Class 7: Precision=0.0000, Recall=0.0000, F1 Score=0.0000
Class 8: Precision=0.0000, Recall=0.0000, F1 Score=0.0000
Class 9: Precision=0.0000, Recall=0.0000, F1 Score=0.0000
Class 10: Precision=0.0000, Recall=0.0000, F1 Score=0.0000
Class 11: Precision=0.0000, Recall=0.0000, F1 Score=0.0000
Class 12: Precision=0.0000, Recall=0.0000, F1 Score=0.0000
Class 13: Precision=0.0000, Recall=0.0000, F1 Score=0.0000
Class 14: Precision=0.0000, Recall=0.0000, F1 Score=0.0000
Class 15: Precision=0.0000, Recall=0.0000, F1 Score=0.0000
Class 16: Precision=0.0000, Recall=0.0000, F1 Score=0.0000
Class 17: Precision=0.0000, Recall=0.0000, F1 Score=0.0000
Class 18: Precision=0.0000, Recall=0.0000, F1 Score=0.0000
Class 19: Precision=0.0000, Recall=0.0000, F1 Score=0.0000
Class 20: Precision=0.0000, Recall=0.0000, F1 Score=0.0000
Class 21: Precision=0.0000, Recall=0.0000, F1 Score=0.0000
Class 22: Precision=0.0000, Recall=0.0000, F1 Score=0.0000
Class 23: Precision=0.0000, Recall=0.0000, F1 Score=0.0000
Class 24: Precision=0.0000, Recall=0.0000, F1 Score=0.0000
Class 25: Precision=0.0000, Recall=0.0000, F1 Score=0.0000
Class 26: Precision=0.0000, Recall=0.0000, F1 Score=0.0000
Class 27: Precision=0.3499, Recall=1.0000, F1 Score=0.5184

```

```

import matplotlib.pyplot as plt
import numpy as np

# Generate a bar plot for precision, recall, and F1 scores per class
x = np.arange(len(class_labels)) # Class indices

# Set the width of the bars
bar_width = 0.2

# Create the bar plots
plt.figure(figsize=(15, 8))
plt.bar(x - bar_width, precision_per_class, bar_width, label='Precision', alpha=0.8, color='blue')
plt.bar(x, recall_per_class, bar_width, label='Recall', alpha=0.8, color='orange')
plt.bar(x + bar_width, f1_per_class, bar_width, label='F1 Score', alpha=0.8, color='green')

# Add labels, title, and legend
plt.xlabel('Class Labels', fontsize=12)
plt.ylabel('Scores', fontsize=12)

```

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plt.title('Per-Class Precision, Recall, and F1 Scores (Mini BERT)', fontsize=16)
plt.xticks(x, class_labels, rotation=90) # Rotate class labels for better readability
plt.legend()

# Adjust layout and show the plot
plt.tight_layout()
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```

