Lab 2 Homework

113062513 林奕廷

Implementation

Data Preparation

For data preparation, I extract tweet_id, identification, text, and emotion columns for the training dataset and tweet_id, identification, and text for the testing dataset.

Below is the emotion distribution in the training data:

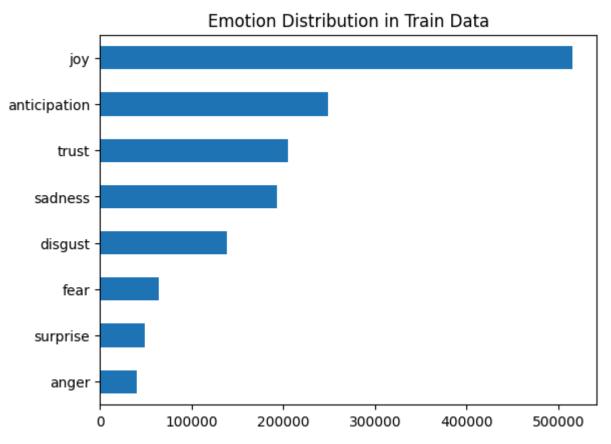


Figure 1. Emotion distribution in train data

Preprocessing

Here I use AutoTokenizer in Hugging Face Transformers to select a tokenizer that matches the pretrained model. Then I use LabelEncoder to transform the "emotion" column into integer labels.

```
tokenizer = AutoTokenizer.from_pretrained("microsoft/deberta-v3-base")
data_collator = DataCollatorWithPadding(tokenizer=tokenizer)
encoder = LabelEncoder().fit(train_df['emotion'])
num_labels = len(encoder.classes_)

# Tokenize the dataset
def tokenize(batch):
    tokenized_text = tokenizer(batch['text'], truncation=True)
    batch.update(tokenized_text)
    batch['label'] = encoder.transform(batch['emotion'])
    return batch
```

Training

I utilize AutoModelForSequenceClassification to apply a pre-trained model on Hugging Face. The class has a classification head on top of the model outputs for classification task training. With this AutoModel, we only need to set up training arguments such as epochs, batch size, fp16, etc.

```
training args = TrainingArguments(
    output_dir='results_deberta_v3',
    num_train_epochs=3,
    per_device_train_batch_size=32, #32
    per_device_eval_batch_size=32, #32
    eval_strategy='steps',
    eval steps=10000, #10000
    save_strategy='steps',
    save_steps=10000, #10000
    logging_steps=1000,
    save_total_limit=5,
    load best model at end=False, #True
   fp16=True,
   torch compile=True,
)
trainer = Trainer(
    model=model,
    args=training_args,
    train_dataset=train_val_dataset['train'],
    eval_dataset=train_val_dataset['test'],
    data_collator=data_collator,
    compute_metrics=compute_metrics,
)
```

Results

I train several pre-trained Transformer models available on Huggingface including BERT, RoBERTa, and DeBERTa v3 with various batch sizes and epoch settings. By utilizing the powerful BERT models and tokenizers, I obtain fairly good results without feature engineering steps, significantly reducing the efforts needed.

However, Transformer-based models require some GPU memory and take time to train. Results also show that the models tend to overfit the training dataset when train epochs > 3.

To further enhance the performance, one can search for feature engineering techniques that suit BERT models.

Submission

Submission and Description		Private Score (i)	Public Score (i)	Selected
\odot	submission_deberta_v3_3epoch.csv Complete · 15d ago · Trained on DeBERTa for 3 e	0.55789	0.57154	
\odot	submission_deberta_v3_3epoch.csv Complete · 16d ago · Trained on DeBERTa for 3 e	0.54764	0.56146	
\odot	submission_roberta_10epoch_last_c Complete · 16d ago · Trained on RoBERTa for 10	0.52541	0.53653	
\odot	submission_roberta_10epoch.csv Complete · 17d ago · Trained on RoBERTa for 10	0.51528	0.53167	
\odot	submission_roberta_3epoch.csv Complete · 17d ago · Trained on RoBERTa for 3 e	0.54816	0.56255	
\odot	submission_roberta_1epoch.csv Complete · 17d ago · Trained on RoBERTa for 1 e	0.52479	0.53888	
\odot	submission.csv Complete · 18d ago · First attempt	0.52075	0.53860	