MELD Dataset Exploratory Data Analysis for Emotion Recognition

Sentiment and emotion analysis for customer service chatbot conversations

1. Import Required Libraries

In [ ]:

```
#!pip install wget
```

In [ ]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import os
import zipfile
from collections import Counter
import warnings
warnings.filterwarnings('ignore')
```

```
In [ ]: # Set style for better visualizations
plt.style.use('seaborn-v0_8-darkgrid')
sns.set_palette("husl")
```

2. Download and Extract MELD Dataset

```
In [ ]: '''
if not os.path.exists('data'):
    os.makedirs('data')
# Download MELD dataset if not already present
meld_url = "http://web.eecs.umich.edu/~mihalcea/downloads/MELD.Raw.tar.gz"
output_path = "data/MELD.Raw.tar.gz"

if not os.path.exists(output_path):
    print("Downloading MELD dataset...")
    wget.download(meld_url, output_path)
    print("\nDownload completed!")
else:
    print("Dataset already downloaded.")

# Extract the dataset
import tarfile
if not os.path.exists('data/MELD.Raw'):
    print("Extracting dataset...")
    with tarfile.open(output_path, 'r:gz') as tar:
        tar.extractall('data/')
```

```
    print("Extraction completed!")
'''
```

Out[ ]:

```
'\nif not os.path.exists(\'data\'):\n    os.makedirs(\'data\')\n# Download ME
LD dataset if not already present\nmeld_url = "http://web.eecs.umich.edu/~mih
alcea/downloads/MELD.Raw.tar.gz"\noutput_path = "data/MELD.Raw.tar.gz"\n\nif
not os.path.exists(output_path):\n    print("Downloading MELD dataset...")\n
wget.download(meld_url, output_path)\n    print("\nDownload completed!")\nels
e:\n    print("Dataset already downloaded.")\n\n# Extract the dataset\nimport
tarfile\nif not os.path.exists(\'data/MELD.Raw\'):\n    print("Extracting dat
aset...")\n    with tarfile.open(output_path, \'r:gz\') as tar:\n        tar.
extractall(\'data/\')\n    print("Extraction completed!")\n'
```

3. Load Dataset Files

In [ ]:

```
# Define paths to the CSV files
# Use raw GitHub URLs for direct file access
train_path = 'https://raw.githubusercontent.com/declare-lab/MELD/master/data/M
dev_path = 'https://raw.githubusercontent.com/declare-lab/MELD/master/data/MEL
test_path = 'https://raw.githubusercontent.com/declare-lab/MELD/master/data/ME

# Load the datasets
print("Loading datasets...")
train_df = pd.read_csv(train_path)
dev_df = pd.read_csv(dev_path)
test_df = pd.read_csv(test_path)
```

```python
print(f"Train set loaded: {train_df.shape}")
print(f"Dev set loaded: {dev_df.shape}")
print(f"Test set loaded: {test_df.shape}")
```

```
Loading datasets...
Train set loaded: (9989, 11)
Dev set loaded: (1109, 11)
Test set loaded: (2610, 11)
```

4. Initial Data Exploration

In [ ]:
```python
# Display basic information about the training dataset
print("=== Training Dataset Info ===")
print(train_df.info())
print("\n=== First 5 rows of training data ===")
print(train_df.head())

# Check column names
print("\n=== Column Names ===")
print(train_df.columns.tolist())
```

```
=== Training Dataset Info ===
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9989 entries, 0 to 9988
Data columns (total 11 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   Sr No.        9989 non-null   int64 
 1   Utterance     9989 non-null   object
 2   Speaker       9989 non-null   object
 3   Emotion       9989 non-null   object
 4   Sentiment     9989 non-null   object
 5   Dialogue_ID   9989 non-null   int64 
 6   Utterance_ID  9989 non-null   int64 
 7   Season        9989 non-null   int64 
 8   Episode       9989 non-null   int64 
 9   StartTime     9989 non-null   object
 10  EndTime       9989 non-null   object
dtypes: int64(5), object(6)
memory usage: 858.6+ KB
None

=== First 5 rows of training data ===
   Sr No.                                          Utterance          Speaker  \
0       1  also I was the point person on my company’s tr...         Chandler   
1       2                   You must’ve had your hands full.  The Interviewer   
2       3                            That I did. That I did.         Chandler   
3       4      So let’s talk a little bit about your duties.  The Interviewer   
4       5                             My duties?  All right.         Chandler   
```

```
    Emotion Sentiment  Dialogue_ID  Utterance_ID  Season  Episode  \
0   neutral   neutral            0             0       8       21
1   neutral   neutral            0             1       8       21
2   neutral   neutral            0             2       8       21
3   neutral   neutral            0             3       8       21
4  surprise  positive            0             4       8       21

      StartTime       EndTime
0  00:16:16,059  00:16:21,731
1  00:16:21,940  00:16:23,442
2  00:16:23,442  00:16:26,389
3  00:16:26,820  00:16:29,572
4  00:16:34,452  00:16:40,917

=== Column Names ===
['Sr No.', 'Utterance', 'Speaker', 'Emotion', 'Sentiment', 'Dialogue_ID', 'Utt
erance_ID', 'Season', 'Episode', 'StartTime', 'EndTime']
```

In [ ]:

```
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 2   Speaker       9989 non-null   object
 3   Emotion       9989 non-null   object
 4   Sentiment     9989 non-null   object
 5   Dialogue_ID   9989 non-null   int64
 6   Utterance_ID  9989 non-null   int64
 7   Season        9989 non-null   int64
 8   Episode       9989 non-null   int64
 9   StartTime     9989 non-null   object
 10  EndTime       9989 non-null   object
dtypes: int64(5), object(6)
memory usage: 858.6+ KB
None

=== First 5 rows of training data ===
   Sr No.                                          Utterance          Speaker
\
0       1  also I was the point person on my company’s tr...         Chandler
1       2                   You must’ve had your hands full.  The Interviewer
2       3                            That I did. That I did.         Chandler
3       4      So let’s talk a little bit about your duties.  The Interviewer
4       5                              My duties?  All right.         Chandler
```

```
    Emotion Sentiment  Dialogue_ID  Utterance_ID  Season  Episode  \
0   neutral   neutral            0             0       8       21
1   neutral   neutral            0             1       8       21
2   neutral   neutral            0             2       8       21
3   neutral   neutral            0             3       8       21
4  surprise  positive            0             4       8       21

      StartTime       EndTime
0  00:16:16,059  00:16:21,731
1  00:16:21,940  00:16:23,442
2  00:16:23,442  00:16:26,389
3  00:16:26,820  00:16:29,572
4  00:16:34,452  00:16:40,917

=== Column Names ===
['Sr No.', 'Utterance', 'Speaker', 'Emotion', 'Sentiment', 'Dialogue_ID', 'Utt
erance_ID', 'Season', 'Episode', 'StartTime', 'EndTime']
```

5. Dataset Statistics

In [ ]:

```
# Combined dataset statistics
total_utterances = len(train_df) + len(dev_df) + len(test_df)
print(f"Total utterances in dataset: {total_utterances}")
print(f"Training set: {len(train_df)} ({len(train_df)/total_utterances*100:.1f
print(f"Development set: {len(dev_df)} ({len(dev_df)/total_utterances*100:.1f}
print(f"Test set: {len(test_df)} ({len(test_df)/total_utterances*100:.1f}%)")
```

```python
# Check for missing values
print("\n=== Missing Values in Training Set ===")
print(train_df.isnull().sum())
```

```
Total utterances in dataset: 13708
Training set: 9989 (72.9%)
Development set: 1109 (8.1%)
Test set: 2610 (19.0%)

=== Missing Values in Training Set ===
Sr No.          0
Utterance       0
Speaker         0
Emotion         0
Sentiment       0
Dialogue_ID     0
Utterance_ID    0
Season          0
Episode         0
StartTime       0
EndTime         0
dtype: int64
```

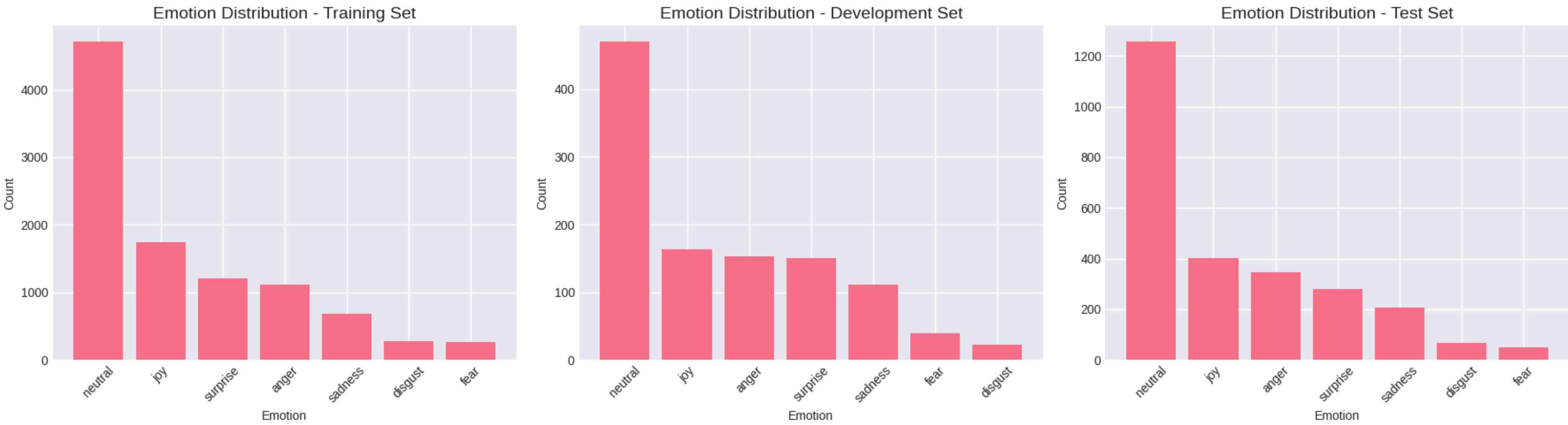
6. Emotion Distribution Analysis

In [ ]:

```python
# Analyze emotion distribution across datasets
def plot_emotion_distribution(train_df, dev_df, test_df):
```

```python
fig, axes = plt.subplots(1, 3, figsize=(18, 5))

# Training set
emotion_counts_train = train_df['Emotion'].value_counts()
axes[0].bar(emotion_counts_train.index, emotion_counts_train.values)
axes[0].set_title('Emotion Distribution - Training Set', fontsize=14)
axes[0].set_xlabel('Emotion')
axes[0].set_ylabel('Count')
axes[0].tick_params(axis='x', rotation=45)

# Dev set
emotion_counts_dev = dev_df['Emotion'].value_counts()
axes[1].bar(emotion_counts_dev.index, emotion_counts_dev.values)
axes[1].set_title('Emotion Distribution - Development Set', fontsize=14)
axes[1].set_xlabel('Emotion')
axes[1].set_ylabel('Count')
axes[1].tick_params(axis='x', rotation=45)

# Test set
emotion_counts_test = test_df['Emotion'].value_counts()
axes[2].bar(emotion_counts_test.index, emotion_counts_test.values)
axes[2].set_title('Emotion Distribution - Test Set', fontsize=14)
axes[2].set_xlabel('Emotion')
axes[2].set_ylabel('Count')
axes[2].tick_params(axis='x', rotation=45)

plt.tight_layout()
plt.show()
```

```
plot_emotion_distribution(train_df, dev_df, test_df)
```



In [ ]:

```
# Overall emotion distribution
all_emotions = pd.concat([train_df['Emotion'], dev_df['Emotion'], test_df['Emo
emotion_dist = all_emotions.value_counts()
print("\n=== Overall Emotion Distribution ===")
print(emotion_dist)
print(f"\nTotal unique emotions: {len(emotion_dist)}")
```

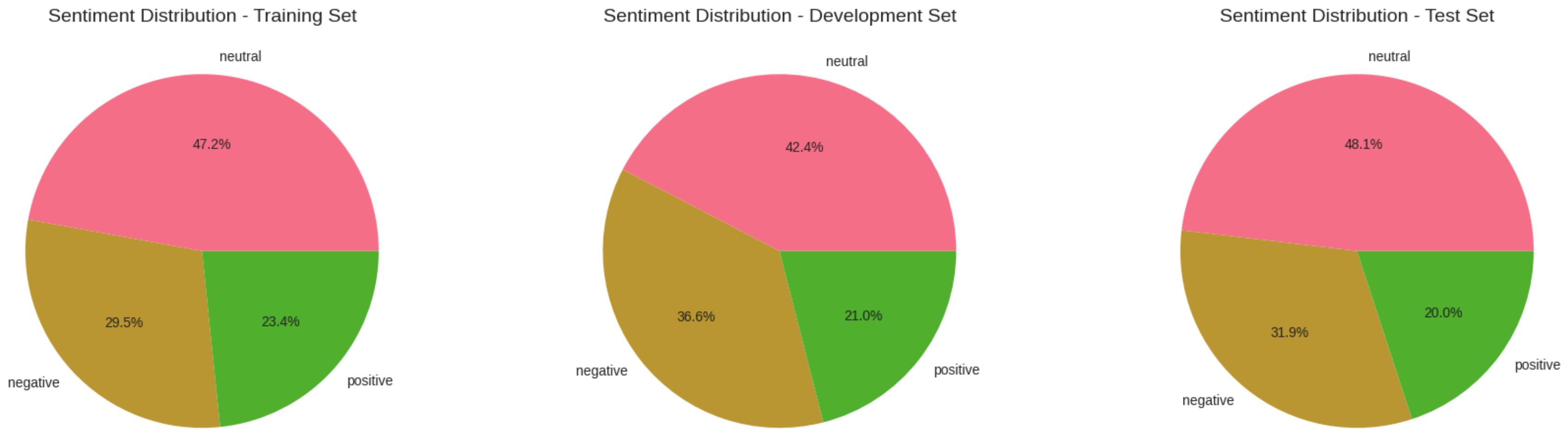
```
=== Overall Emotion Distribution ===
Emotion
neutral     6436
joy         2308
surprise    1636
anger       1607
sadness     1002
disgust      361
fear         358
Name: count, dtype: int64

Total unique emotions: 7
```

7. Sentiment Distribution Analysis

In [ ]:

```
# Analyze sentiment distribution
def plot_sentiment_distribution(train_df, dev_df, test_df):
    fig, axes = plt.subplots(1, 3, figsize=(18, 5))

    datasets = [('Training', train_df), ('Development', dev_df), ('Test', test

    for idx, (name, df) in enumerate(datasets):
        sentiment_counts = df['Sentiment'].value_counts()
        axes[idx].pie(sentiment_counts.values, labels=sentiment_counts.index,
        axes[idx].set_title(f'Sentiment Distribution - {name} Set', fontsize=

    plt.tight_layout()
```

```
    plt.show()

plot_sentiment_distribution(train_df, dev_df, test_df)
```



In [ ]:

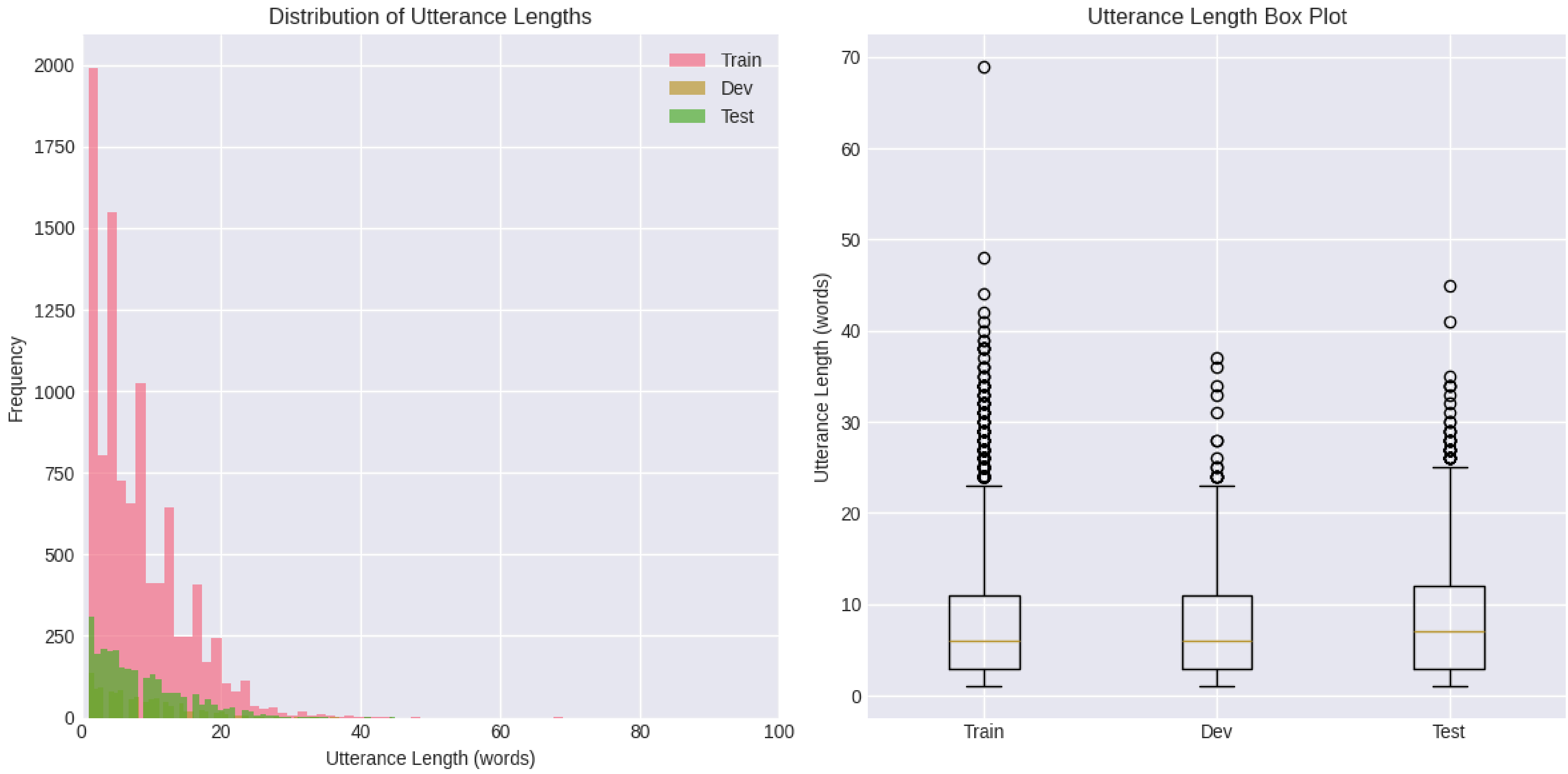
```
# Overall sentiment distribution
all_sentiments = pd.concat([train_df['Sentiment'], dev_df['Sentiment'], test_c
sentiment_dist = all_sentiments.value_counts()
print("\n=== Overall Sentiment Distribution ===")
print(sentiment_dist)
```

```
=== Overall Sentiment Distribution ===
Sentiment
neutral     6436
negative    4184
positive    3088
Name: count, dtype: int64
```

8. Text Length Analysis

In [ ]:
```
# Analyze utterance lengths
train_df['utterance_length'] = train_df['Utterance'].apply(lambda x: len(str(x
dev_df['utterance_length'] = dev_df['Utterance'].apply(lambda x: len(str(x).sp
test_df['utterance_length'] = test_df['Utterance'].apply(lambda x: len(str(x).
```

In [ ]:
```
# Plot utterance length distribution
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.hist(train_df['utterance_length'], bins=50, alpha=0.7, label='Train')
plt.hist(dev_df['utterance_length'], bins=50, alpha=0.7, label='Dev')
plt.hist(test_df['utterance_length'], bins=50, alpha=0.7, label='Test')
plt.xlabel('Utterance Length (words)')
plt.ylabel('Frequency')
plt.title('Distribution of Utterance Lengths')
plt.legend()
plt.xlim(0, 100)

plt.subplot(1, 2, 2)
plt.boxplot([train_df['utterance_length'], dev_df['utterance_length'], test_df
            labels=['Train', 'Dev', 'Test'])
plt.ylabel('Utterance Length (words)')
plt.title('Utterance Length Box Plot')
plt.tight_layout()
plt.show()
```



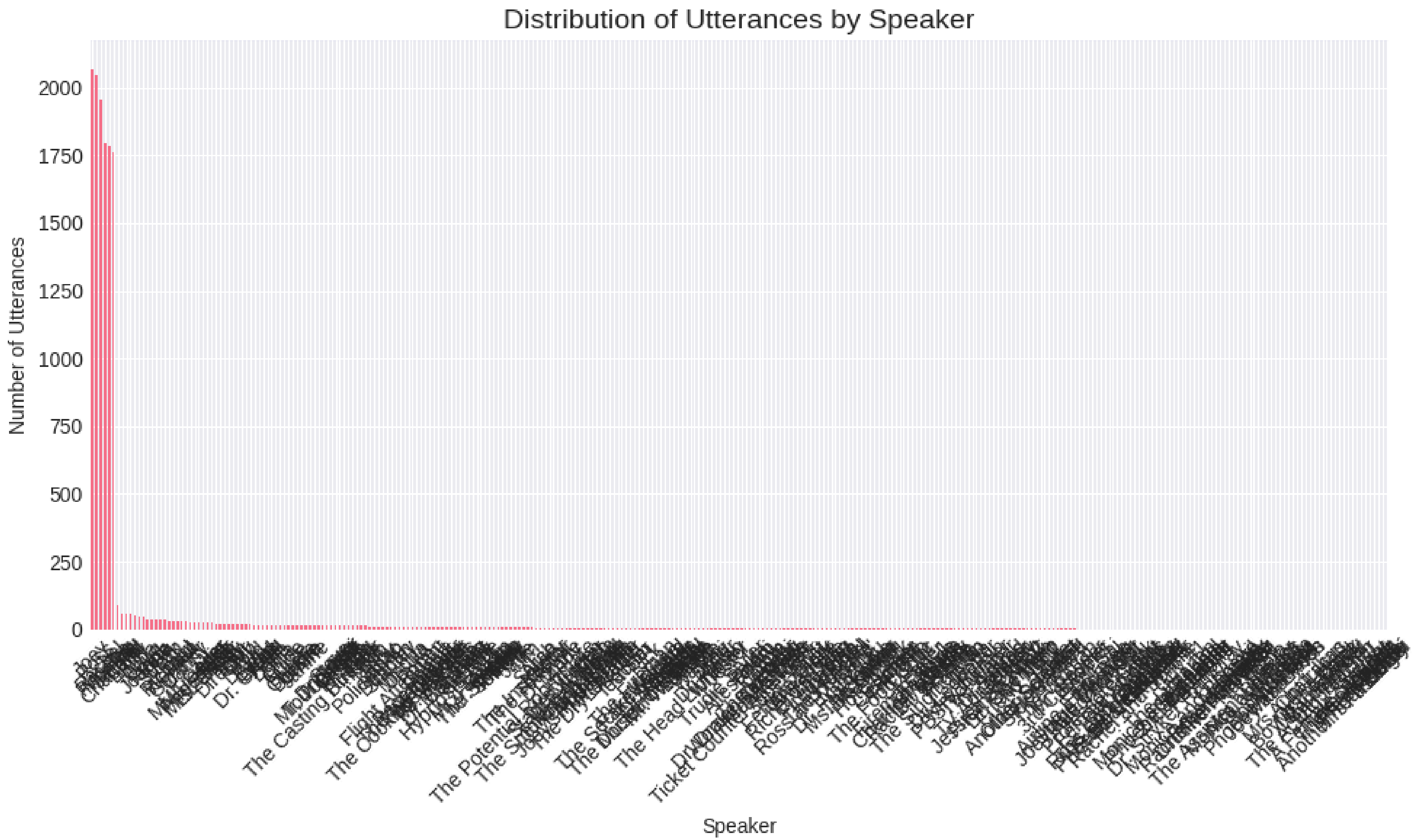

```
In [ ]: # Statistics
print("=== Utterance Length Statistics ===")
print(f"Training set - Mean: {train_df['utterance_length'].mean():.2f}, Mediar
print(f"Dev set - Mean: {dev_df['utterance_length'].mean():.2f}, Median: {dev_
print(f"Test set - Mean: {test_df['utterance_length'].mean():.2f}, Median: {te
```

```
=== Utterance Length Statistics ===
Training set - Mean: 7.95, Median: 6, Max: 69
Dev set - Mean: 7.91, Median: 6, Max: 37
Test set - Mean: 8.21, Median: 7, Max: 45
```

9. Speaker Analysis

In [ ]:

```
# Analyze speaker distribution
all_speakers = pd.concat([train_df['Speaker'], dev_df['Speaker'], test_df['Spe
speaker_counts = all_speakers.value_counts()

plt.figure(figsize=(10, 6))
speaker_counts.plot(kind='bar')
plt.title('Distribution of Utterances by Speaker', fontsize=14)
plt.xlabel('Speaker')
plt.ylabel('Number of Utterances')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

print(f"Total unique speakers: {len(speaker_counts)}")
print("\n=== Speaker Distribution ===")
print(speaker_counts)
```


Distribution of Utterances by Speaker
Number of Utterances
2000
1750
1500
1250
1000
750
500
250
0
Speaker

```
Total unique speakers: 304

=== Speaker Distribution ===
Speaker
Joey        2070
Ross        2048
Rachel      1955
Phoebe      1797
Monica      1782
            ...
Waiter         1
Cookie         1
Passerby       1
Petrie         1
Sergei         1
Name: count, Length: 304, dtype: int64
```

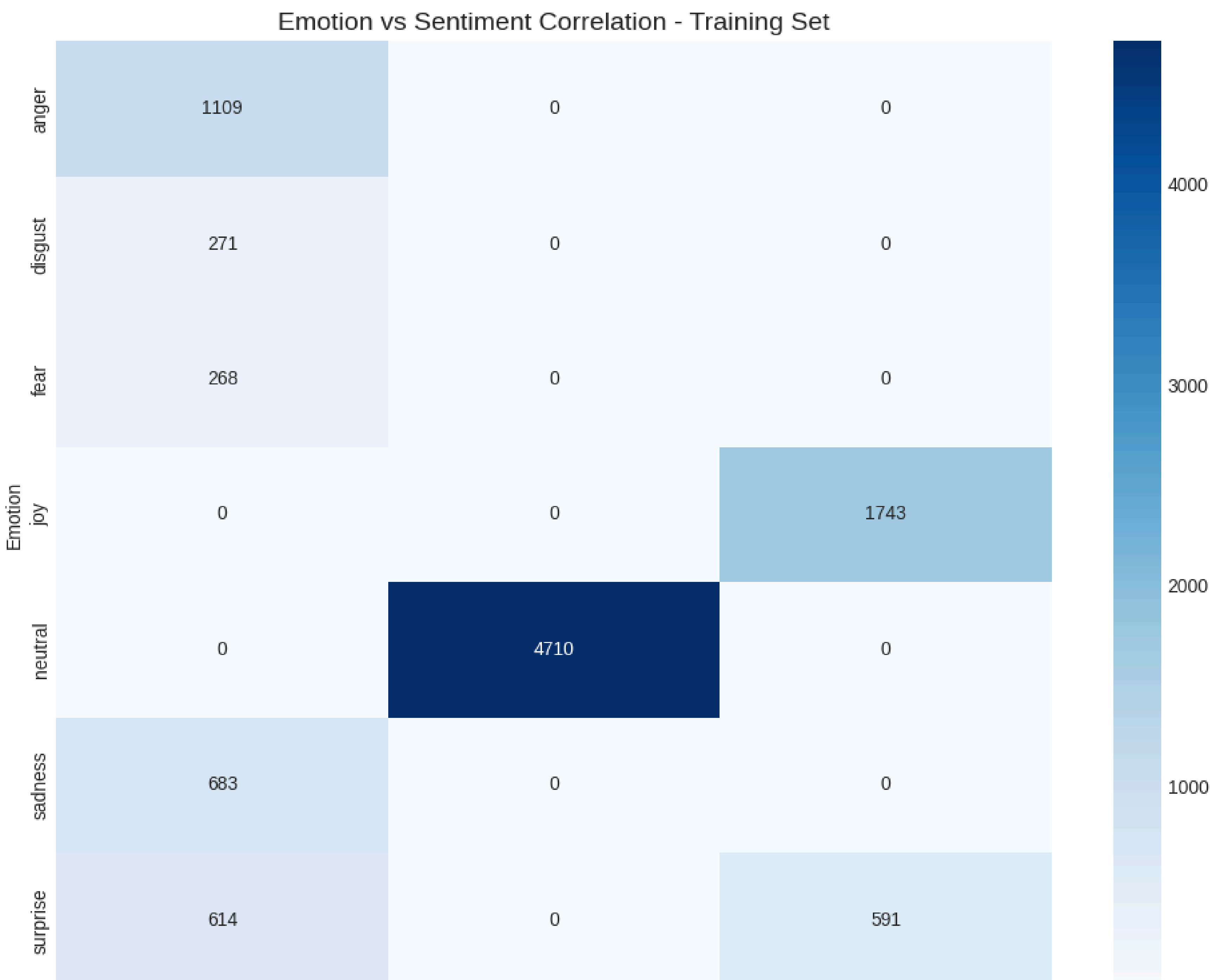
10. Emotion-Sentiment Correlation

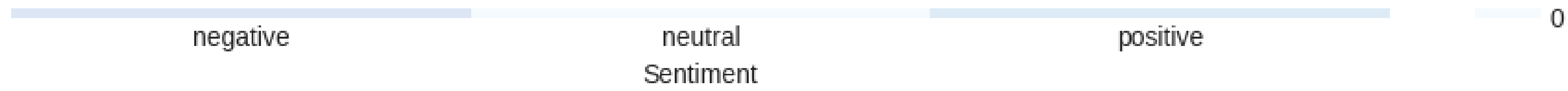
In [ ]:

```
# Analyze correlation between emotion and sentiment
def create_emotion_sentiment_heatmap(df, title):
    emotion_sentiment_crosstab = pd.crosstab(df['Emotion'], df['Sentiment'])

    plt.figure(figsize=(10, 8))
    sns.heatmap(emotion_sentiment_crosstab, annot=True, fmt='d', cmap='Blues')
    plt.title(f'Emotion vs Sentiment Correlation - {title}', fontsize=14)
    plt.xlabel('Sentiment')
```

```python
    plt.ylabel('Emotion')
    plt.tight_layout()
    plt.show()

    return emotion_sentiment_crosstab

print("=== Training Set Emotion-Sentiment Correlation ===")
train_crosstab = create_emotion_sentiment_heatmap(train_df, 'Training Set')
```

```
=== Training Set Emotion-Sentiment Correlation ===
```


Emotion vs Sentiment Correlation - Training Set
Emotion
anger
disgust
fear
joy
neutral
sadness
surprise
1109
0
0
271
0
0
268
0
0
0
0
1743
0
4710
0
683
0
0
614
0
591
4000
3000
2000
1000

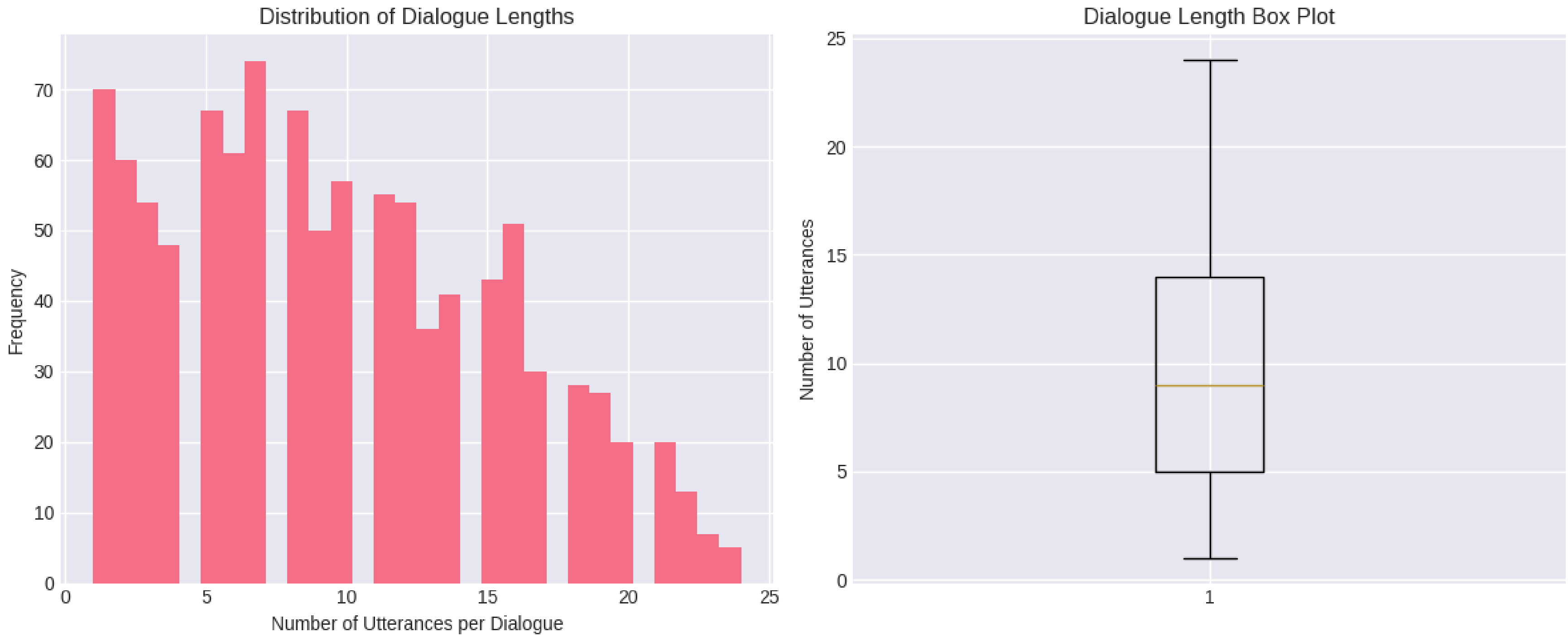


11. Dialogue Context Analysis

In [ ]:

```
# Analyze dialogue structure
dialogue_counts = train_df['Dialogue_ID'].value_counts()
print(f"Total dialogues in training set: {len(dialogue_counts)}")
print(f"Average utterances per dialogue: {dialogue_counts.mean():.2f}")
print(f"Min utterances in a dialogue: {dialogue_counts.min()}")
print(f"Max utterances in a dialogue: {dialogue_counts.max()}")

# Plot dialogue length distribution
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.hist(dialogue_counts.values, bins=30)
plt.xlabel('Number of Utterances per Dialogue')
plt.ylabel('Frequency')
plt.title('Distribution of Dialogue Lengths')

plt.subplot(1, 2, 2)
plt.boxplot(dialogue_counts.values)
plt.ylabel('Number of Utterances')
plt.title('Dialogue Length Box Plot')
plt.tight_layout()
plt.show()
```

```
Total dialogues in training set: 1038
Average utterances per dialogue: 9.62
Min utterances in a dialogue: 1
Max utterances in a dialogue: 24
```



12. Sample Conversations Analysis

In [ ]:

```python
# Display sample conversations with emotions
def display_sample_dialogue(df, dialogue_id, max_utterances=10):
    dialogue = df[df['Dialogue_ID'] == dialogue_id].head(max_utterances)
    print(f"\n=== Sample Dialogue (ID: {dialogue_id}) ===")
    for idx, row in dialogue.iterrows():
```

```
        print(f"{row['Speaker']}: {row['Utterance']}")
        print(f"   Emotion: {row['Emotion']}, Sentiment: {row['Sentiment']}")
        print()

# Display a few sample dialogues
sample_dialogue_ids = train_df['Dialogue_ID'].unique()[:3]
for dialogue_id in sample_dialogue_ids:
    display_sample_dialogue(train_df, dialogue_id)
```

=== Sample Dialogue (ID: 0) ===
Chandler: also I was the point person on my company’s transition from the KL-5 to GR-6 system.
   Emotion: neutral, Sentiment: neutral

The Interviewer: You must’ve had your hands full.
   Emotion: neutral, Sentiment: neutral

Chandler: That I did. That I did.
   Emotion: neutral, Sentiment: neutral

The Interviewer: So let’s talk a little bit about your duties.
   Emotion: neutral, Sentiment: neutral

Chandler: My duties? All right.
   Emotion: surprise, Sentiment: positive

The Interviewer: Now you’ll be heading a whole division, so you’ll have a lot of duties.
   Emotion: neutral, Sentiment: neutral

Chandler: I see.
   Emotion: neutral, Sentiment: neutral

The Interviewer: But there’ll be perhaps 30 people under you so you can dump a certain amount on them.
   Emotion: neutral, Sentiment: neutral

Chandler: Good to know.

```
   Emotion: neutral, Sentiment: neutral

The Interviewer: We can go into detail
   Emotion: neutral, Sentiment: neutral


=== Sample Dialogue (ID: 1) ===
Joey: But then who? The waitress I went out with last month?
   Emotion: surprise, Sentiment: negative

Rachel: You know? Forget it!
   Emotion: sadness, Sentiment: negative

Joey: No-no-no-no, no! Who, who were you talking about?
   Emotion: surprise, Sentiment: negative

Rachel: No, I-I-I-I don't, I actually don't know
   Emotion: fear, Sentiment: negative

Joey: Ok!
   Emotion: neutral, Sentiment: neutral

Joey: All right, well...
   Emotion: neutral, Sentiment: neutral

Rachel: Yeah, sure!
   Emotion: neutral, Sentiment: neutral
```

```
=== Sample Dialogue (ID: 2) ===
Chandler: Hey, Mon.
   Emotion: neutral, Sentiment: neutral

Monica: Hey-hey-hey. You wanna hear something that sucks.
   Emotion: neutral, Sentiment: neutral

Chandler: Do I ever.
   Emotion: joy, Sentiment: positive

Monica: Chris says they’re closing down the bar.
   Emotion: sadness, Sentiment: negative

Chandler: No way!
   Emotion: surprise, Sentiment: negative

Monica: Yeah, apparently they’re turning it into some kinda coffee place.
   Emotion: neutral, Sentiment: neutral

Chandler: Just coffee! Where are we gonna hang out now?
   Emotion: disgust, Sentiment: negative

Monica: Got me.
   Emotion: sadness, Sentiment: negative

Chandler: Can I get a beer.
   Emotion: neutral, Sentiment: neutral

Monica: Hey, did you pick a roommate?
```

```
Emotion: neutral, Sentiment: neutral
```

13. Word Frequency Analysis

In [ ]:
```
from collections import Counter
import re

# Function to clean and tokenize text
def tokenize(text):
    # Convert to lowercase and remove punctuation
    text = str(text).lower()
    text = re.sub(r'[^\w\s]', '', text)
    return text.split()

# Get word frequencies for each emotion
emotion_words = {}
for emotion in train_df['Emotion'].unique():
    emotion_utterances = train_df[train_df['Emotion'] == emotion]['Utterance']
    all_words = []
    for utterance in emotion_utterances:
        all_words.extend(tokenize(utterance))
    emotion_words[emotion] = Counter(all_words).most_common(20)
```

In [ ]:
```
# Display top words for each emotion
print("=== Top 10 Words per Emotion ===")
for emotion, word_counts in emotion_words.items():
```

```
    print(f"\n{emotion}:")
    for word, count in word_counts[:10]:
        print(f"  {word}: {count}")
```

```
=== Top 10 Words per Emotion ===

neutral:
  you: 1373
  i: 1318
  the: 916
  to: 783
  a: 773
  and: 538
  that: 457
  it: 449
  okay: 425
  yeah: 406

surprise:
  you: 387
  what: 254
  oh: 238
  i: 211
  the: 150
  my: 138
  a: 124
  that: 122
  god: 114
  are: 105

fear:
  i: 132
  you: 82
```

```
  to: 57
  a: 45
  no: 44
  dont: 39
  oh: 37
  im: 37
  and: 33
  the: 33

sadness:
  i: 364
  you: 190
  to: 162
  the: 143
  a: 126
  im: 120
  and: 119
  sorry: 97
  it: 95
  me: 92

joy:
  i: 535
  you: 499
  the: 287
  to: 251
  a: 249
  oh: 232
  and: 223
```

```
  it: 216
  so: 164
  hey: 143

disgust:
  you: 96
  i: 78
  the: 74
  a: 69
  to: 51
  and: 44
  that: 44
  oh: 41
  no: 35
  it: 33

anger:
  you: 431
  i: 374
  the: 247
  to: 218
  and: 174
  a: 168
  it: 157
  that: 143
  me: 137
  no: 130
```

14. Emotion Transition Analysis

In [ ]:
```
# Analyze emotion transitions within dialogues
def analyze_emotion_transitions(df):
    transitions = []

    for dialogue_id in df['Dialogue_ID'].unique():
        dialogue = df[df['Dialogue_ID'] == dialogue_id].sort_values('Utterance
        emotions = dialogue['Emotion'].tolist()

        for i in range(len(emotions) - 1):
            transitions.append((emotions[i], emotions[i+1]))

    return Counter(transitions)
```

In [ ]:
```
# Get emotion transitions
transitions = analyze_emotion_transitions(train_df)
top_transitions = transitions.most_common(15)

print("=== Top 15 Emotion Transitions ===")
for (from_emotion, to_emotion), count in top_transitions:
    print(f"{from_emotion} → {to_emotion}: {count}")
```

```
=== Top 15 Emotion Transitions ===
neutral → neutral: 2354
neutral → joy: 631
joy → neutral: 602
joy → joy: 520
neutral → surprise: 500
surprise → neutral: 492
anger → neutral: 358
neutral → anger: 352
anger → anger: 314
neutral → sadness: 212
sadness → neutral: 206
surprise → surprise: 179
surprise → joy: 167
joy → surprise: 165
sadness → sadness: 147
```

In [ ]:

```python
# Create transition matrix
unique_emotions = sorted(train_df['Emotion'].unique())
transition_matrix = pd.DataFrame(0, index=unique_emotions, columns=unique_emot

for (from_emotion, to_emotion), count in transitions.items():
    transition_matrix.loc[from_emotion, to_emotion] = count
```

In [ ]:

```python
# Normalize by row to get probabilities
transition_prob = transition_matrix.div(transition_matrix.sum(axis=1), axis=0)

plt.figure(figsize=(10, 8))
sns.heatmap(transition_prob, annot=True, fmt='.2f', cmap='YlOrRd')
```

```
plt.title('Emotion Transition Probability Matrix')
plt.xlabel('To Emotion')
plt.ylabel('From Emotion')
plt.tight_layout()
plt.show()
```


Emotion Transition Probability Matrix
From Emotion
anger
disgust
fear
joy
neutral
sadness
surprise
0.31 0.02 0.03 0.11 0.36 0.07 0.10
0.14 0.16 0.03 0.07 0.36 0.10 0.14
0.14 0.02 0.12 0.13 0.41 0.07 0.11
0.08 0.02 0.02 0.34 0.39 0.05 0.11
0.08 0.02 0.02 0.15 0.56 0.05 0.12
0.10 0.03 0.03 0.11 0.34 0.24 0.14
0.10 0.03 0.03 0.15 0.45 0.07 0.16
0.5
0.4
0.3
0.2
0.1

15. Summary Statistics and Insights

In [ ]:

```
print("=== MELD Dataset Summary ===")
print(f"Total utterances: {total_utterances}")
print(f"Total unique dialogues: {len(pd.concat([train_df['Dialogue_ID'], dev_d
print(f"Average utterance length: {pd.concat([train_df['utterance_length'], de
print(f"\nEmotion classes: {sorted(train_df['Emotion'].unique())}")
print(f"Sentiment classes: {sorted(train_df['Sentiment'].unique())}")

# Class imbalance analysis
print("\n=== Class Imbalance Analysis ===")
emotion_imbalance = emotion_dist.max() / emotion_dist.min()
sentiment_imbalance = sentiment_dist.max() / sentiment_dist.min()
print(f"Emotion class imbalance ratio: {emotion_imbalance:.2f}")
print(f"Sentiment class imbalance ratio: {sentiment_imbalance:.2f}")
```

```
=== MELD Dataset Summary ===
Total utterances: 13708
Total unique dialogues: 1039
Average utterance length: 8.00 words

Emotion classes: ['anger', 'disgust', 'fear', 'joy', 'neutral', 'sadness', 'su
rprise']
Sentiment classes: ['negative', 'neutral', 'positive']

=== Class Imbalance Analysis ===
Emotion class imbalance ratio: 17.98
Sentiment class imbalance ratio: 2.08
```

In [ ]:

```
# Key insights for model development
print("\n=== Key Insights for Model Development ===")
print("1. The dataset shows significant class imbalance, especially in emotior
print("2. Neutral emotion is dominant, which might affect model performance")
print("3. Average utterance length is relatively short, suitable for transforr
print("4. Strong correlation between certain emotions and sentiments")
print("5. Context from dialogue flow could be important for emotion recognitic
```

```
=== Key Insights for Model Development ===
1. The dataset shows significant class imbalance, especially in emotions
2. Neutral emotion is dominant, which might affect model performance
3. Average utterance length is relatively short, suitable for transformer mode
ls
4. Strong correlation between certain emotions and sentiments
5. Context from dialogue flow could be important for emotion recognition
```

16. Prepare Data for Transformer Models

In [ ]:

```
# Create a function to prepare data for transformer models
def prepare_for_transformers(df):
    """
    Prepare the dataset for transformer-based models
    """
    # Create emotion to index mapping
    emotion_to_idx = {emotion: idx for idx, emotion in enumerate(sorted(df['Em
    sentiment_to_idx = {sentiment: idx for idx, sentiment in enumerate(sorted(

    # Add numerical labels
    df['emotion_label'] = df['Emotion'].map(emotion_to_idx)
    df['sentiment_label'] = df['Sentiment'].map(sentiment_to_idx)

    # Group by dialogue for context modeling
    dialogues = []
    for dialogue_id in df['Dialogue_ID'].unique():
        dialogue = df[df['Dialogue_ID'] == dialogue_id].sort_values('Utterance
        dialogues.append({
            'dialogue_id': dialogue_id,
            'utterances': dialogue['Utterance'].tolist(),
            'speakers': dialogue['Speaker'].tolist(),
            'emotions': dialogue['emotion_label'].tolist(),
            'sentiments': dialogue['sentiment_label'].tolist()
        })
```

```
    return dialogues, emotion_to_idx, sentiment_to_idx
```

In [ ]:

```
# Prepare training data
train_dialogues, emotion_to_idx, sentiment_to_idx = prepare_for_transformers(t
print(f"Prepared {len(train_dialogues)} dialogues for training")
print(f"\nEmotion mapping: {emotion_to_idx}")
print(f"\nSentiment mapping: {sentiment_to_idx}")
```

```
Prepared 1038 dialogues for training

Emotion mapping: {'anger': 0, 'disgust': 1, 'fear': 2, 'joy': 3, 'neutral': 4,
'sadness': 5, 'surprise': 6}

Sentiment mapping: {'negative': 0, 'neutral': 1, 'positive': 2}
```

In [ ]:

```
# Save mappings for later use
import json
if not os.path.exists('data'):
    os.makedirs('data')

mappings = {
    'emotion_to_idx': emotion_to_idx,
    'sentiment_to_idx': sentiment_to_idx,
    'idx_to_emotion': {v: k for k, v in emotion_to_idx.items()},
    'idx_to_sentiment': {v: k for k, v in sentiment_to_idx.items()}
}

with open('data/label_mappings.json', 'w') as f:
```

```
    json.dump(mappings, f, indent=2)
print("\nLabel mappings saved to 'data/label_mappings.json'")
```

```
Label mappings saved to 'data/label_mappings.json'
```

Conclusion

This EDA reveals several important insights for building emotion recognition models:

1. **Class Imbalance**: The dataset shows significant imbalance, particularly with "neutral" emotion being dominant. Consider using weighted loss functions or resampling techniques.

2. **Multi-modal Nature**: While we focused on text, MELD includes audio and visual features that could enhance model performance.

3. **Context Importance**: Emotions often depend on dialogue context, making this dataset ideal for context-aware transformer models.

4. **Short Utterances**: Most utterances are relatively short (median ~10 words), which is suitable for transformer architectures.

5. **Speaker Patterns**: Different speakers show distinct emotion patterns, which could be leveraged in multi-speaker models.

Next steps:

- Implement transformer-based models (BERT, RoBERTa, etc.) for emotion classification
- Experiment with context-aware architectures that consider dialogue history
- Apply techniques to handle class imbalance
- Consider multi-task learning for joint emotion and sentiment prediction

Model Implementation

Implementation of LSTM, BERT, RoBERTa with context-aware models using TensorFlow

1. Import Required Libraries and Setup

In [ ]:

```
import pandas as pd
import numpy as np
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers, Model
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping, ReduceL
import tensorflow_hub as hub
import tensorflow_text as text
from transformers import TFAutoModel, AutoTokenizer, TFBertModel, TFRobertaMod
from sklearn.metrics import classification_report, confusion_matrix, f1_score
```

```python
from sklearn.utils.class_weight import compute_class_weight
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt
import seaborn as sns
from tqdm import tqdm
import json
import pickle
import warnings
warnings.filterwarnings('ignore')
```

In [ ]:
```python
# Set random seeds
def set_seed(seed=42):
    np.random.seed(seed)
    tf.random.set_seed(seed)

set_seed(42)
```

In [ ]:
```python
# Check GPU availability
print("Num GPUs Available: ", len(tf.config.list_physical_devices('GPU')))
if len(tf.config.list_physical_devices('GPU')) > 0:
    print("GPU is available")
    # Enable mixed precision for better performance
    from tensorflow.keras.mixed_precision import set_global_policy
    set_global_policy('mixed_float16')
```

```
Num GPUs Available:  1
GPU is available
```

2. Data Preprocessing and Dataset Classes

In [ ]:
```
import numpy as np
import tensorflow as tf
from transformers import AutoTokenizer

class MELDDataGeneratorBERT(tf.keras.utils.Sequence):
    """Fixed data generator for MELD dataset with proper tokenization"""
    def __init__(self, dialogues, tokenizer, batch_size=32, max_length=128,
                 context_window=3, shuffle=True):
        self.dialogues = dialogues
        self.tokenizer = tokenizer
        self.batch_size = batch_size
        self.max_length = max_length
        self.context_window = context_window
        self.shuffle = shuffle

        # IMPORTANT: Set tokenizer max length
        self.tokenizer.model_max_length = max_length

        # Prepare data
        self.utterances = []
        self.contexts = []
        self.emotions = []
        self.sentiments = []
        self._prepare_data()
```

```
        self.indices = np.arange(len(self.utterances))
        if self.shuffle:
            np.random.shuffle(self.indices)

    def _prepare_data(self):
        """Flatten dialogues into utterances with context"""
        for dialogue in self.dialogues:
            utterances = dialogue['utterances']
            emotions = dialogue['emotions']
            sentiments = dialogue['sentiments']
            speakers = dialogue['speakers']

            for i in range(len(utterances)):
                # Current utterance - ensure it's a string
                self.utterances.append(str(utterances[i]))
                # Ensure emotions and sentiments are integers
                self.emotions.append(int(emotions[i]))
                self.sentiments.append(int(sentiments[i]))

                # Context (previous utterances)
                context = []
                for j in range(max(0, i - self.context_window), i):
                    context.append(f"{speakers[j]}: {utterances[j]}")
                self.contexts.append(" [SEP] ".join(context) if context else '

    def __len__(self):
        return int(np.ceil(len(self.utterances) / self.batch_size))
```

```
    def __getitem__(self, idx):
        # Get batch indices
        start_idx = idx * self.batch_size
        end_idx = min((idx + 1) * self.batch_size, len(self.utterances))
        batch_indices = self.indices[start_idx:end_idx]

        batch_texts = []
        batch_emotions = []
        batch_sentiments = []

        for i in batch_indices:
            # Combine context and utterance
            if self.contexts[i]:
                text = f"{self.contexts[i]} [SEP] {self.utterances[i]}"
            else:
                text = self.utterances[i]

            batch_texts.append(text)
            batch_emotions.append(self.emotions[i])
            batch_sentiments.append(self.sentiments[i])

        # Tokenize batch with explicit parameters
        encoded = self.tokenizer(
            batch_texts,
            padding='max_length',
            truncation=True,
            max_length=self.max_length,
            return_tensors='np',
            return_attention_mask=True,
```

```python
            return_token_type_ids=False  # BERT might return this, we don't ne
        )

        # Ensure we have the right shape
        input_ids = encoded['input_ids']
        attention_mask = encoded['attention_mask']

        # Pad manually if needed (shouldn't be necessary but just in case)
        if input_ids.shape[1] < self.max_length:
            pad_length = self.max_length - input_ids.shape[1]
            input_ids = np.pad(input_ids, ((0, 0), (0, pad_length)),
                                 constant_values=self.tokenizer.pad_token_id)
            attention_mask = np.pad(attention_mask, ((0, 0), (0, pad_length)),
                                      constant_values=0)
        elif input_ids.shape[1] > self.max_length:
            input_ids = input_ids[:, :self.max_length]
            attention_mask = attention_mask[:, :self.max_length]

        # Convert to proper numpy arrays with correct dtypes
        input_ids = np.array(input_ids, dtype=np.int32)
        attention_mask = np.array(attention_mask, dtype=np.int32)

        # Return dictionaries with numpy arrays
        return {
            'input_ids': input_ids,
            'attention_mask': attention_mask
        }, {
            'emotion': np.array(batch_emotions, dtype=np.int32),
            'sentiment': np.array(batch_sentiments, dtype=np.int32)
```

```python
        }

    def on_epoch_end(self):
        """Shuffle indices after each epoch"""
        if self.shuffle:
            np.random.shuffle(self.indices)
```

In [ ]:
```python
class MELDDataGenerator(tf.keras.utils.Sequence):
    """Fixed data generator with proper max_length padding"""

    def __init__(self, dialogues, tokenizer, batch_size=32, max_length=128,
                 context_window=3, shuffle=True):
        self.dialogues = dialogues
        self.tokenizer = tokenizer
        self.batch_size = batch_size
        self.max_length = max_length
        self.context_window = context_window
        self.shuffle = shuffle

        # Prepare data
        self.utterances = []
        self.contexts = []
        self.emotions = []
        self.sentiments = []
        self._prepare_data()

        self.indices = np.arange(len(self.utterances))
        if self.shuffle:
            np.random.shuffle(self.indices)
```

```
    def _prepare_data(self):
        """Flatten dialogues into utterances with context"""
        for dialogue in self.dialogues:
            utterances = dialogue['utterances']
            emotions = dialogue['emotions']
            sentiments = dialogue['sentiments']
            speakers = dialogue['speakers']

            for i in range(len(utterances)):
                # Current utterance
                self.utterances.append(utterances[i])
                self.emotions.append(emotions[i])
                self.sentiments.append(sentiments[i])

                # Context (previous utterances)
                context = []
                for j in range(max(0, i - self.context_window), i):
                    context.append(f"{speakers[j]}: {utterances[j]}")
                self.contexts.append(" [SEP] ".join(context) if context else '

    def __len__(self):
        return int(np.ceil(len(self.utterances) / self.batch_size))

    def __getitem__(self, idx):
        batch_indices = self.indices[idx * self.batch_size:(idx + 1) * self.ba

        batch_texts = []
        batch_emotions = []
```

```python
        batch_sentiments = []

        for i in batch_indices:
            # Combine context and utterance
            if self.contexts[i]:
                text = f"{self.contexts[i]} [SEP] {self.utterances[i]}"
            else:
                text = self.utterances[i]

            batch_texts.append(text)
            batch_emotions.append(self.emotions[i])
            batch_sentiments.append(self.sentiments[i])

        # Tokenize batch with FIXED padding to max_length
        encoded = self.tokenizer(
            batch_texts,
            padding='max_length',  # Changed from padding=True
            truncation=True,
            max_length=self.max_length,
            return_tensors='tf'
        )

        return {
            'input_ids': encoded['input_ids'],
            'attention_mask': encoded['attention_mask']
        }, {
            'emotion': tf.convert_to_tensor(batch_emotions),
            'sentiment': tf.convert_to_tensor(batch_sentiments)
        }
```

```python
    def on_epoch_end(self):
        if self.shuffle:
            np.random.shuffle(self.indices)
```

In [ ]:

```python
# Test function to verify the generator works correctly
def test_data_generator(dialogues, tokenizer, batch_size=16, max_length=128):
    """Test the data generator to ensure it works correctly"""

    print("Testing data generator...")

    # Create generator
    generator = MELDDataGenerator(
        dialogues,
        tokenizer,
        batch_size=batch_size,
        max_length=max_length,
        shuffle=False
    )

    print(f"Total batches: {len(generator)}")
    print(f"Total samples: {len(generator.utterances)}")

    # Test first batch
    batch_x, batch_y = generator[0]

    print(f"\nFirst batch shapes:")
    print(f"  input_ids: {batch_x['input_ids'].shape}")
    print(f"  attention_mask: {batch_x['attention_mask'].shape}")
```

```python
    print(f"  emotions: {batch_y['emotion'].shape}")
    print(f"  sentiments: {batch_y['sentiment'].shape}")

    # Verify shapes
    actual_batch_size = batch_x['input_ids'].shape[0]
    assert actual_batch_size <= batch_size, f"Batch size too large! Expected <
    assert batch_x['input_ids'].shape[1] == max_length, f"Max length mismatch
    assert batch_x['attention_mask'].shape == batch_x['input_ids'].shape, "Att
    assert batch_y['emotion'].shape[0] == actual_batch_size, "Emotion batch si
    assert batch_y['sentiment'].shape[0] == actual_batch_size, "Sentiment batc

    print("\n✓ Data generator test passed!")

    # Print sample data
    print("\nSample from first batch:")
    print(f"  Text (decoded): {tokenizer.decode(batch_x['input_ids'][0], skip_
    print(f"  Emotion label: {batch_y['emotion'][0]}")
    print(f"  Sentiment label: {batch_y['sentiment'][0]}")

    return generator
```

In [ ]:
```python
def create_tf_dataset(dialogues, tokenizer, batch_size=32, max_length=128,
                      context_window=3, shuffle=True):
    """Create TensorFlow dataset from dialogues"""
    utterances = []
    contexts = []
    emotions = []
    sentiments = []
```

```
    # Prepare data
    for dialogue in dialogues:
        utts = dialogue['utterances']
        emos = dialogue['emotions']
        sents = dialogue['sentiments']
        speakers = dialogue['speakers']

        for i in range(len(utts)):
            utterances.append(utts[i])
            emotions.append(emos[i])
            sentiments.append(sents[i])

            # Context
            context = []
            for j in range(max(0, i - context_window), i):
                context.append(f"{speakers[j]}: {utts[j]}")
            contexts.append(" [SEP] ".join(context) if context else "")

    # Create dataset from tensors
    dataset = tf.data.Dataset.from_tensor_slices((utterances, contexts, emotio

    if shuffle:
        dataset = dataset.shuffle(buffer_size=1000)

    # Map function to combine context and utterance and tokenize
    def map_fn(utterance, context, emotion, sentiment):
        text = tf.cond(tf.equal(tf.strings.length(context), 0),
                       lambda: utterance,
                       lambda: tf.strings.join([context, "[SEP]", utterance],
```

```
        # Tokenize
        encoded = tokenizer(
            text,
            padding='max_length',
            truncation=True,
            max_length=max_length,
            return_tensors='tf'
        )

        return {
            'input_ids': tf.squeeze(encoded['input_ids'], axis=0),
            'attention_mask': tf.squeeze(encoded['attention_mask'], axis=0)
        }, {
            'emotion': tf.cast(emotion, tf.int32),
            'sentiment': tf.cast(sentiment, tf.int32)
        }

    dataset = dataset.map(map_fn, num_parallel_calls=tf.data.AUTOTUNE)

    # Batch the dataset
    dataset = dataset.batch(batch_size)

    # Set the shapes of the batched tensors
    dataset = dataset.map(
        lambda x, y: (
            {'input_ids': tf.ensure_shape(x['input_ids'], (None, max_length)),
             'attention_mask': tf.ensure_shape(x['attention_mask'], (None, ma
            {'emotion': tf.ensure_shape(y['emotion'], (None,)),
```

```python
            'sentiment': tf.ensure_shape(y['sentiment'], (None,))}
        ),
        num_parallel_calls=tf.data.AUTOTUNE
    )


    dataset = dataset.prefetch(tf.data.AUTOTUNE)

    return dataset
```

In [ ]:
```python
def create_tf_dataset_2(dialogues, tokenizer, batch_size=32, max_length=128,
                        context_window=3, shuffle=True):
    """Create TensorFlow dataset from dialogues"""
    utterances = []
    contexts = []
    emotions = []
    sentiments = []

    # Prepare data
    for dialogue in dialogues:
        utts = dialogue['utterances']
        emos = dialogue['emotions']
        sents = dialogue['sentiments']
        speakers = dialogue['speakers']

        for i in range(len(utts)):
            utterances.append(utts[i])
            emotions.append(emos[i])
            sentiments.append(sents[i])
```

```python
        # Context
        context = []
        for j in range(max(0, i - context_window), i):
            context.append(f"{speakers[j]}: {utts[j]}")
        contexts.append(" [SEP] ".join(context) if context else "")

# Create dataset
def generator():
    indices = np.arange(len(utterances))
    if shuffle:
        np.random.shuffle(indices)

    for i in indices:
        text = f"{contexts[i]} [SEP] {utterances[i]}" if contexts[i] else
        yield text, emotions[i], sentiments[i]

# Define output signature
output_signature = (
    tf.TensorSpec(shape=(), dtype=tf.string),
    tf.TensorSpec(shape=(), dtype=tf.int32),
    tf.TensorSpec(shape=(), dtype=tf.int32)
)

dataset = tf.data.Dataset.from_generator(
    generator,
    output_signature=output_signature
)
```

```python
    # Tokenize and batch
    def tokenize_batch(texts, emotions, sentiments):
        # This will be called with batched data
        encoded = tokenizer(
            texts.numpy().tolist(),
            padding=True,
            truncation=True,
            max_length=max_length,
            return_tensors='tf'
        )

        return {
            'input_ids': encoded['input_ids'],
            'attention_mask': encoded['attention_mask'],
            'emotion_labels': emotions,
            'sentiment_labels': sentiments
        }

    dataset = dataset.batch(batch_size)
    dataset = dataset.map(
        lambda x, y, z: tf.py_function(
            tokenize_batch,
            [x, y, z],
            {
                'input_ids': tf.int32,
                'attention_mask': tf.int32,
                'emotion_labels': tf.int32,
                'sentiment_labels': tf.int32
            }
```

```
        ),
        num_parallel_calls=tf.data.AUTOTUNE
    )

    if shuffle:
        dataset = dataset.shuffle(buffer_size=1000)

    dataset = dataset.prefetch(tf.data.AUTOTUNE)

    return dataset
```

3. Model Architectures

3.1 LSTM-based Model

In [ ]:
```
class LSTMEmotionModel(tf.keras.Model):
    """LSTM model for emotion and sentiment classification"""
    def __init__(self, vocab_size, embedding_dim=300, lstm_units=256,
                 num_emotions=7, num_sentiments=3, dropout_rate=0.3):
        super(LSTMEmotionModel, self).__init__()

        # Embedding layer
        self.embedding = layers.Embedding(vocab_size, embedding_dim)

        # LSTM layers
        self.lstm1 = layers.Bidirectional(
            layers.LSTM(lstm_units, return_sequences=True, dropout=dropout_rat
```

```python
        )
        self.lstm2 = layers.Bidirectional(
            layers.LSTM(lstm_units, dropout=dropout_rate)
        )

        # Dropout
        self.dropout = layers.Dropout(dropout_rate)

        # Task-specific heads
        self.emotion_dense = layers.Dense(128, activation='relu')
        self.emotion_output = layers.Dense(num_emotions, name='emotion')

        self.sentiment_dense = layers.Dense(128, activation='relu')
        self.sentiment_output = layers.Dense(num_sentiments, name='sentiment')

    def call(self, inputs, training=False):
        # Embedding
        x = self.embedding(inputs['input_ids'])

        # LSTM encoding
        x = self.lstm1(x, training=training)
        x = self.lstm2(x, training=training)

        # Dropout
        x = self.dropout(x, training=training)

        # Task-specific predictions
        emotion_features = self.emotion_dense(x)
        emotion_logits = self.emotion_output(emotion_features)
```

```
        sentiment_features = self.sentiment_dense(x)
        sentiment_logits = self.sentiment_output(sentiment_features)

        return {
            'emotion': emotion_logits,
            'sentiment': sentiment_logits
        }
```

3.2 BERT-based Multi-Task Model

In [ ]:

```
# Disable mixed precision for inference to avoid dtype issues
tf.keras.mixed_precision.set_global_policy('float32')

class BERTMultiTaskModel(tf.keras.Model):
    """BERT model for multi-task emotion and sentiment classification"""
    def __init__(self, model_name='bert-base-uncased', num_emotions=7,
                 num_sentiments=3, dropout_rate=0.3):
        super(BERTMultiTaskModel, self).__init__()

        # BERT encoder
        self.bert = TFAutoModel.from_pretrained(model_name)
        hidden_size = self.bert.config.hidden_size

        # Freeze BERT layers initially (optional)
        self.bert.trainable = True

        # Dropout
```

```
        self.dropout = tf.keras.layers.Dropout(dropout_rate)

        # Emotion classification head
        self.emotion_dense1 = tf.keras.layers.Dense(hidden_size, activation='r
        self.emotion_dropout = tf.keras.layers.Dropout(dropout_rate)
        self.emotion_dense2 = tf.keras.layers.Dense(hidden_size // 2, activati
        self.emotion_output = tf.keras.layers.Dense(num_emotions, name='emotio

        # Sentiment classification head
        self.sentiment_dense1 = tf.keras.layers.Dense(hidden_size, activation=
        self.sentiment_dropout = tf.keras.layers.Dropout(dropout_rate)
        self.sentiment_dense2 = tf.keras.layers.Dense(hidden_size // 2, activa
        self.sentiment_output = tf.keras.layers.Dense(num_sentiments, name='se

    def call(self, inputs, training=False):
        # Ensure input_ids are int32
        input_ids = tf.cast(inputs['input_ids'], tf.int32)
        attention_mask = tf.cast(inputs['attention_mask'], tf.int32)

        # BERT encoding
        bert_outputs = self.bert(
            input_ids=input_ids,
            attention_mask=attention_mask,
            training=training
        )

        # Use pooled output (CLS token)
        pooled_output = bert_outputs.pooler_output
        pooled_output = self.dropout(pooled_output, training=training)
```

```python
        # Emotion prediction
        emotion_x = self.emotion_dense1(pooled_output)
        emotion_x = self.emotion_dropout(emotion_x, training=training)
        emotion_x = self.emotion_dense2(emotion_x)
        emotion_logits = self.emotion_output(emotion_x)

        # Sentiment prediction
        sentiment_x = self.sentiment_dense1(pooled_output)
        sentiment_x = self.sentiment_dropout(sentiment_x, training=training)
        sentiment_x = self.sentiment_dense2(sentiment_x)
        sentiment_logits = self.sentiment_output(sentiment_x)

        return {
            'emotion': emotion_logits,
            'sentiment': sentiment_logits
        }
```

3.3 Context-Aware DialogueRNN Model

In [ ]:

```python
class DialogueRNN(tf.keras.Model):
    """DialogueRNN for context-aware emotion recognition"""
    def __init__(self, base_model_name='bert-base-uncased', hidden_dim=128,
                 num_emotions=7, num_sentiments=3, dropout_rate=0.3):
        super(DialogueRNN, self).__init__()

        # Base encoder (BERT or RoBERTa)
        self.encoder = TFAutoModel.from_pretrained(base_model_name)
```

```python
        encoder_hidden_size = self.encoder.config.hidden_size

        # Global GRU for context
        self.global_gru = layers.Bidirectional(
            layers.GRU(hidden_dim, return_sequences=True)
        )

        # Emotion GRU
        self.emotion_gru = layers.GRU(hidden_dim, return_sequences=False)

        # Attention mechanism
        self.attention = layers.MultiHeadAttention(
            num_heads=8, key_dim=hidden_dim
        )

        # Fusion layer
        self.fusion = layers.Dense(hidden_dim, activation='relu')

        # Dropout
        self.dropout = layers.Dropout(dropout_rate)

        # Classification heads
        self.emotion_output = layers.Dense(num_emotions, name='emotion')
        self.sentiment_output = layers.Dense(num_sentiments, name='sentiment')

    def call(self, inputs, training=False):
        # Ensure proper dtypes
        input_ids = tf.cast(inputs['input_ids'], tf.int32)
        attention_mask = tf.cast(inputs['attention_mask'], tf.int32)
```

```
        # Encode utterance
        encoded = self.encoder(
            input_ids=input_ids,
            attention_mask=attention_mask,
            training=training
        )

        # Get CLS token representation
        utterance_features = encoded.pooler_output

        # Add sequence dimension for GRU
        utterance_features = tf.expand_dims(utterance_features, axis=1)

        # Global context (simplified for single utterance inference)
        global_context = self.global_gru(utterance_features, training=trainin

        # Apply attention
        attended_features = self.attention(
            utterance_features, global_context,
            training=training
        )

        # Emotion modeling
        emotion_features = self.emotion_gru(attended_features, training=train
        emotion_features = self.dropout(emotion_features, training=training)

        # Fusion
        final_features = self.fusion(emotion_features)
```

```
        # Predictions
        emotion_logits = self.emotion_output(final_features)
        sentiment_logits = self.sentiment_output(final_features)

        return {
            'emotion': emotion_logits,
            'sentiment': sentiment_logits
        }
```

3.4 COSMIC-style Model with Attention

In [ ]:
```
class COSMICModel(tf.keras.Model):
    """COSMIC-style model with commonsense reasoning"""
    def __init__(self, model_name='roberta-base', num_emotions=7,
                 num_sentiments=3, dropout_rate=0.3):
        super(COSMICModel, self).__init__()

        # Main encoder
        self.encoder = TFAutoModel.from_pretrained(model_name)
        hidden_size = self.encoder.config.hidden_size

        # Commonsense encoder (can be same or different model)
        self.commonsense_encoder = TFAutoModel.from_pretrained('bert-base-unca

        # Cross-attention for fusion
        self.cross_attention = layers.MultiHeadAttention(
            num_heads=8, key_dim=hidden_size // 8
```

```python
        )

        # Fusion layers
        self.fusion_dense1 = layers.Dense(hidden_size, activation='relu')
        self.fusion_dropout = layers.Dropout(dropout_rate)
        self.fusion_dense2 = layers.Dense(hidden_size // 2, activation='relu')

        # Self-attention
        self.self_attention = layers.MultiHeadAttention(
            num_heads=8, key_dim=hidden_size // 16
        )

        # Classification heads
        self.emotion_output = layers.Dense(num_emotions, name='emotion')
        self.sentiment_output = layers.Dense(num_sentiments, name='sentiment')

        self.dropout = layers.Dropout(dropout_rate)

    def call(self, inputs, commonsense_inputs=None, training=False):
        input_ids = tf.cast(inputs['input_ids'], tf.int32)
        attention_mask = tf.cast(inputs['attention_mask'], tf.int32)
        # Encode utterance
        utterance_outputs = self.encoder(
            input_ids=input_ids,
            attention_mask=attention_mask,
            training=training
        )
        utterance_features = utterance_outputs.pooler_output
```

```
        if commonsense_inputs is not None:
            # Encode commonsense
            commonsense_outputs = self.commonsense_encoder(
                commonsense_inputs['input_ids'],
                attention_mask=commonsense_inputs['attention_mask'],
                training=training
            )
            commonsense_features = commonsense_outputs.pooler_output

            # Cross-attention fusion
            utterance_features = tf.expand_dims(utterance_features, axis=1)
            commonsense_features = tf.expand_dims(commonsense_features, axis=

            fused_features = self.cross_attention(
                utterance_features,
                commonsense_features,
                training=training
            )
            fused_features = tf.squeeze(fused_features, axis=1)

            # Further fusion
            fused_features = self.fusion_dense1(fused_features)
            fused_features = self.fusion_dropout(fused_features, training=tra
            final_features = self.fusion_dense2(fused_features)
        else:
            final_features = utterance_features

        final_features = self.dropout(final_features, training=training)
```

```
        # Predictions
        emotion_logits = self.emotion_output(final_features)
        sentiment_logits = self.sentiment_output(final_features)

        return {
            'emotion': emotion_logits,
            'sentiment': sentiment_logits
        }
```

4. Loss Functions and Metrics

In [ ]:
```
class MultiTaskLoss(tf.keras.losses.Loss):
    """Multi-task loss with task weighting"""
    def __init__(self, emotion_weight=1.0, sentiment_weight=0.5,
                 emotion_class_weights=None, sentiment_class_weights=None):
        super(MultiTaskLoss, self).__init__()
        self.emotion_weight = emotion_weight
        self.sentiment_weight = sentiment_weight
        self.emotion_class_weights = emotion_class_weights
        self.sentiment_class_weights = sentiment_class_weights

    def call(self, y_true, y_pred):
        # Separate emotion and sentiment losses
        emotion_loss = tf.keras.losses.sparse_categorical_crossentropy(
            y_true['emotion'], y_pred['emotion'], from_logits=True
        )
        sentiment_loss = tf.keras.losses.sparse_categorical_crossentropy(
```

```
            y_true['sentiment'], y_pred['sentiment'], from_logits=True
        )

        # Apply class weights if provided
        if self.emotion_class_weights is not None:
            emotion_weights = tf.gather(self.emotion_class_weights, y_true['en
            emotion_loss = emotion_loss * emotion_weights

        if self.sentiment_class_weights is not None:
            sentiment_weights = tf.gather(self.sentiment_class_weights, y_true
            sentiment_loss = sentiment_loss * sentiment_weights

        # Compute weighted sum
        total_loss = (self.emotion_weight * tf.reduce_mean(emotion_loss) +
                      self.sentiment_weight * tf.reduce_mean(sentiment_loss))

        return total_loss
```

In [ ]:

```
class FocalLoss(tf.keras.losses.Loss):
    """Focal Loss for handling class imbalance"""
    def __init__(self, gamma=2.0, alpha=None):
        super(FocalLoss, self).__init__()
        self.gamma = gamma
        self.alpha = alpha

    def call(self, y_true, y_pred):
        # Convert to one-hot
        y_true_one_hot = tf.one_hot(tf.cast(y_true, tf.int32),
                                    depth=tf.shape(y_pred)[-1])
```

```python
        # Compute softmax
        y_pred_softmax = tf.nn.softmax(y_pred)

        # Compute cross entropy
        ce = -y_true_one_hot * tf.math.log(y_pred_softmax + 1e-7)

        # Compute focal term
        focal_term = tf.pow(1.0 - y_pred_softmax, self.gamma)

        # Compute focal loss
        focal_loss = focal_term * ce

        # Apply alpha if provided
        if self.alpha is not None:
            alpha_t = tf.gather(self.alpha, tf.cast(y_true, tf.int32))
            focal_loss = alpha_t * focal_loss

        return tf.reduce_mean(tf.reduce_sum(focal_loss, axis=-1))
```

In [ ]:

```python
# Custom metrics
class MacroF1Score(tf.keras.metrics.Metric):
    """Macro F1 Score metric"""
    def __init__(self, num_classes, name='macro_f1', **kwargs):
        super(MacroF1Score, self).__init__(name=name, **kwargs)
        self.num_classes = num_classes
        self.precision = tf.keras.metrics.Precision()
        self.recall = tf.keras.metrics.Recall()
```

```
    def update_state(self, y_true, y_pred, sample_weight=None):
        y_pred = tf.argmax(y_pred, axis=-1)
        self.precision.update_state(y_true, y_pred, sample_weight)
        self.recall.update_state(y_true, y_pred, sample_weight)

    def result(self):
        precision = self.precision.result()
        recall = self.recall.result()
        f1 = 2 * (precision * recall) / (precision + recall + 1e-7)
        return f1

    def reset_state(self):
        self.precision.reset_state()
        self.recall.reset_state()
```

5. Training Functions

In [ ]:
```
def create_model(model_type, num_emotions, num_sentiments, tokenizer=None):
    """Factory function to create models based on type"""

    if model_type == 'lstm':
        if tokenizer is None:
            raise ValueError("LSTM model requires a tokenizer to get vocab_si
        return LSTMEmotionModel(
            vocab_size=tokenizer.vocab_size,
            num_emotions=num_emotions,
            num_sentiments=num_sentiments
```

```python
        )

    elif model_type == 'bert':
        return BERTMultiTaskModel(
            model_name='bert-base-uncased',
            num_emotions=num_emotions,
            num_sentiments=num_sentiments
        )

    elif model_type == 'roberta':
        return BERTMultiTaskModel(
            model_name='roberta-base',
            num_emotions=num_emotions,
            num_sentiments=num_sentiments
        )

    elif model_type == 'dialoguernn':
        return DialogueRNN(
            base_model_name='bert-base-uncased',
            num_emotions=num_emotions,
            num_sentiments=num_sentiments
        )

    elif model_type == 'cosmic':
        return COSMICModel(
            model_name='roberta-base',
            num_emotions=num_emotions,
            num_sentiments=num_sentiments
        )
```

```python
    else:
        raise ValueError(f"Unknown model type: {model_type}")
```

In [ ]:
```python
def create_callbacks(model_name, patience=5):
    """Create training callbacks"""
    callbacks = [
        ModelCheckpoint(
            f'best_{model_name}_model.weights.h5',
            monitor='val_loss',
            save_best_only=True,
            save_weights_only=True,
            verbose=1
        ),
        EarlyStopping(
            monitor='val_loss',
            patience=patience,
            restore_best_weights=True,
            verbose=1
        ),
        ReduceLROnPlateau(
            monitor='val_loss',
            factor=0.5,
            patience=patience//2,
            min_lr=1e-7,
            verbose=1
        ),
        tf.keras.callbacks.TensorBoard(
            log_dir=f'./logs/{model_name}',
```

```
            histogram_freq=1
        )
    ]
    return callbacks
```

In [ ]:

```
def train_model_simple(model, train_data, val_data, epochs=10, callbacks=None)
    """Train the model"""
    history = model.fit(
        train_data,
        validation_data=val_data,
        epochs=epochs,
        callbacks=callbacks,
        verbose=1
    )
    return history

def train_model(model_type, train_gen, val_gen, config, callbacks):
    """Train a specific model type"""

    # Create model
    tokenizer = train_gen.tokenizer
    num_emotions = len(json.load(open('data/label_mappings.json'))['emotion_to
    num_sentiments = len(json.load(open('data/label_mappings.json'))['sentimen

    model = create_model(
        model_type=model_type,
        num_emotions=num_emotions,
        num_sentiments=num_sentiments,
        tokenizer=tokenizer
```

```
    )

    # Build model
    dummy_input = next(iter(train_gen))[0]
    _ = model(dummy_input)

    # Compile model
    optimizer = tf.keras.optimizers.Adam(learning_rate=config['learning_rate']

    model.compile(
        optimizer=optimizer,
        loss={
            'emotion': tf.keras.losses.SparseCategoricalCrossentropy(from_log
            'sentiment': tf.keras.losses.SparseCategoricalCrossentropy(from_lo
        },
        metrics={
            'emotion': ['accuracy'],
            'sentiment': ['accuracy']
        },
        loss_weights={
            'emotion': config['emotion_weight'],
            'sentiment': config['sentiment_weight']
        }
    )

    # Train
    history = model.fit(
        train_gen,
        validation_data=val_gen,
```

```
        epochs=config['num_epochs'],
        callbacks=callbacks,
        verbose=1
    )

    return model, history
```

In [ ]:

```
import numpy as np
import tensorflow as tf
from sklearn.metrics import classification_report, confusion_matrix
from tqdm import tqdm

def evaluate_model(model, test_data, mappings):
    """Evaluate model and generate classification reports"""
    emotion_preds = []
    sentiment_preds = []
    emotion_labels = []
    sentiment_labels = []

    for batch in tqdm(test_data, desc='Evaluating'):
        inputs, labels = batch
        predictions = model(inputs, training=False)

        # Handle predictions (these are tensors)
        if isinstance(predictions['emotion'], tf.Tensor):
            emotion_preds.extend(tf.argmax(predictions['emotion'], axis=-1).nu
            sentiment_preds.extend(tf.argmax(predictions['sentiment'], axis=-1
        else:
            emotion_preds.extend(np.argmax(predictions['emotion'], axis=-1))
```

```python
            sentiment_preds.extend(np.argmax(predictions['sentiment'], axis=-1

        # Handle labels (these might be numpy arrays or tensors)
        if isinstance(labels['emotion'], tf.Tensor):
            emotion_labels.extend(labels['emotion'].numpy())
            sentiment_labels.extend(labels['sentiment'].numpy())
        else:
            emotion_labels.extend(labels['emotion'])
            sentiment_labels.extend(labels['sentiment'])

    # Convert to numpy arrays
    emotion_preds = np.array(emotion_preds)
    sentiment_preds = np.array(sentiment_preds)
    emotion_labels = np.array(emotion_labels)
    sentiment_labels = np.array(sentiment_labels)

    # Generate reports
    emotion_report = classification_report(
        emotion_labels, emotion_preds,
        target_names=list(mappings['idx_to_emotion'].values()),
        output_dict=True
    )

    sentiment_report = classification_report(
        sentiment_labels, sentiment_preds,
        target_names=list(mappings['idx_to_sentiment'].values()),
        output_dict=True
    )
```

```
    return {
        'emotion_report': emotion_report,
        'sentiment_report': sentiment_report,
        'emotion_preds': emotion_preds,
        'sentiment_preds': sentiment_preds,
        'emotion_labels': emotion_labels,
        'sentiment_labels': sentiment_labels
    }
```

6. Training Pipeline

6.1 Train Pipeline - Baseline model

In [ ]:

```
def main(model_type='bert'):
    # Configuration
    config = {
        'model_type': model_type,  # 'bert', 'roberta', 'lstm', 'dialoguernn',
        'model_name': 'bert-base-uncased',
        'batch_size': 16,
        'learning_rate': 2e-5,
        'num_epochs': 10,
        'max_length': 128,
        'context_window': 3,
        'emotion_weight': 1.0,
        'sentiment_weight': 0.5
    }
```

```python
# Load data
print("Loading data...")

train_df = pd.read_csv(train_path)
dev_df = pd.read_csv(dev_path)
test_df = pd.read_csv(test_path)

# Load label mappings
with open('data/label_mappings.json', 'r') as f:
    mappings = json.load(f)

# Prepare dialogues
train_dialogues, _, _ = prepare_for_transformers(train_df)
dev_dialogues, _, _ = prepare_for_transformers(dev_df)
test_dialogues, _, _ = prepare_for_transformers(test_df)

# Initialize tokenizer
tokenizer = AutoTokenizer.from_pretrained(config['model_name'])

# Set tokenizer properties
tokenizer.model_max_length = config['max_length']
if tokenizer.pad_token is None:
    tokenizer.pad_token = tokenizer.eos_token
    tokenizer.pad_token_id = tokenizer.eos_token_id

# Ensure padding is set correctly
tokenizer.padding_side = 'right'
```

```python
    # Create data generators
    print("Creating data generators...")
    train_gen = MELDDataGenerator(
        train_dialogues, tokenizer,
        batch_size=config['batch_size'],
        max_length=config['max_length'],
        context_window=config['context_window'],
        shuffle=True
    )

    val_gen = MELDDataGenerator(
        dev_dialogues, tokenizer,
        batch_size=config['batch_size'],
        max_length=config['max_length'],
        context_window=config['context_window'],
        shuffle=False
    )

    test_gen = MELDDataGenerator(
        test_dialogues, tokenizer,
        batch_size=config['batch_size'],
        max_length=config['max_length'],
        context_window=config['context_window'],
        shuffle=False
    )

    test_data_generator(train_dialogues[:5], tokenizer,
                       batch_size=config['batch_size'],
                       max_length=config['max_length'])
```

```
# Compute class weights
print("Computing class weights...")
emotion_labels = train_df['emotion_label'].values
sentiment_labels = train_df['sentiment_label'].values

emotion_weights = compute_class_weight(
    'balanced',
    classes=np.unique(emotion_labels),
    y=emotion_labels
)
sentiment_weights = compute_class_weight(
    'balanced',
    classes=np.unique(sentiment_labels),
    y=sentiment_labels
)

emotion_weights = tf.constant(emotion_weights, dtype=tf.float32)
sentiment_weights = tf.constant(sentiment_weights, dtype=tf.float32)

# Initialize model
print(f"Initializing {config['model_type']} model...")
if config['model_type'] == 'bert':
    model = BERTMultiTaskModel(
        model_name=config['model_name'],
        num_emotions=len(mappings['emotion_to_idx']),
        num_sentiments=len(mappings['sentiment_to_idx'])
    )
elif config['model_type'] == 'roberta':
```

```python
        model = BERTMultiTaskModel(
            model_name='roberta-base',
            num_emotions=len(mappings['emotion_to_idx']),
            num_sentiments=len(mappings['sentiment_to_idx'])
        )
    elif config['model_type'] == 'lstm':
        # For LSTM, we need vocab size
        vocab_size = tokenizer.vocab_size
        model = LSTMEmotionModel(
            vocab_size=vocab_size,
            num_emotions=len(mappings['emotion_to_idx']),
            num_sentiments=len(mappings['sentiment_to_idx'])
        )
    elif config['model_type'] == 'cosmic':
        model = COSMICModel(
            model_name=config['model_name'],
            num_emotions=len(mappings['emotion_to_idx']),
            num_sentiments=len(mappings['sentiment_to_idx'])
        )

    # Build model
    dummy_input = next(iter(train_gen))[0]
    _ = model(dummy_input)

    # Compile model
    loss = MultiTaskLoss(
        emotion_weight=config['emotion_weight'],
        sentiment_weight=config['sentiment_weight'],
        emotion_class_weights=emotion_weights,
```

```
        sentiment_class_weights=sentiment_weights
    )

    optimizer = tf.keras.optimizers.Adam(learning_rate=config['learning_rate']

    model.compile(
        optimizer=optimizer,
        loss={
            'emotion': tf.keras.losses.SparseCategoricalCrossentropy(from_log
            'sentiment': tf.keras.losses.SparseCategoricalCrossentropy(from_lo
        },
        metrics={
            'emotion': ['accuracy', MacroF1Score(len(mappings['emotion_to_idx
            'sentiment': ['accuracy', MacroF1Score(len(mappings['sentiment_to_
        },
        loss_weights={
            'emotion': config['emotion_weight'],
            'sentiment': config['sentiment_weight']
        }
    )

    # Print model summary
    model.summary()

    # Create callbacks
    callbacks = create_callbacks(config['model_type'])

    # Train model
    print("Starting training...")
```

```python
    history = train_model_simple(
        model,
        train_gen,
        val_gen,
        epochs=config['num_epochs'],
        callbacks=callbacks
    )

    # Evaluate on test set
    print("\nEvaluating on test set...")
    results = evaluate_model(model, test_gen, mappings)

    print("\n=== Emotion Classification Report ===")
    print(classification_report(
        results['emotion_labels'],
        results['emotion_preds'],
        target_names=list(mappings['idx_to_emotion'].values())
    ))

    print("\n=== Sentiment Classification Report ===")
    print(classification_report(
        results['sentiment_labels'],
        results['sentiment_preds'],
        target_names=list(mappings['idx_to_sentiment'].values())
    ))

    # Plot results
    plot_training_history(history)
    plot_confusion_matrices(results, mappings)
```

```python
    return model, history, results

def plot_training_history(history):
    """Plot training history"""
    fig, axes = plt.subplots(2, 2, figsize=(15, 10))

    # Emotion metrics
    axes[0, 0].plot(history.history['emotion_loss'], label='Train')
    axes[0, 0].plot(history.history['val_emotion_loss'], label='Val')
    axes[0, 0].set_title('Emotion Loss')
    axes[0, 0].set_xlabel('Epoch')
    axes[0, 0].legend()

    axes[0, 1].plot(history.history['emotion_accuracy'], label='Train')
    axes[0, 1].plot(history.history['val_emotion_accuracy'], label='Val')
    axes[0, 1].set_title('Emotion Accuracy')
    axes[0, 1].set_xlabel('Epoch')
    axes[0, 1].legend()

    # Sentiment metrics
    axes[1, 0].plot(history.history['sentiment_loss'], label='Train')
    axes[1, 0].plot(history.history['val_sentiment_loss'], label='Val')
    axes[1, 0].set_title('Sentiment Loss')
    axes[1, 0].set_xlabel('Epoch')
    axes[1, 0].legend()

    axes[1, 1].plot(history.history['sentiment_accuracy'], label='Train')
    axes[1, 1].plot(history.history['val_sentiment_accuracy'], label='Val')
```

```python
    axes[1, 1].set_title('Sentiment Accuracy')
    axes[1, 1].set_xlabel('Epoch')
    axes[1, 1].legend()

    plt.tight_layout()
    plt.savefig('training_history_tf.png')
    plt.show()

def plot_confusion_matrices(results, mappings):
    """Plot confusion matrices"""
    fig, axes = plt.subplots(1, 2, figsize=(15, 6))

    # Emotion confusion matrix
    emotion_cm = confusion_matrix(
        results['emotion_labels'],
        results['emotion_preds']
    )
    sns.heatmap(
        emotion_cm, annot=True, fmt='d',
        xticklabels=list(mappings['idx_to_emotion'].values()),
        yticklabels=list(mappings['idx_to_emotion'].values()),
        ax=axes[0]
    )
    axes[0].set_title('Emotion Confusion Matrix')
    axes[0].set_xlabel('Predicted')
    axes[0].set_ylabel('True')

    # Sentiment confusion matrix
    sentiment_cm = confusion_matrix(
```

```python
        results['sentiment_labels'],
        results['sentiment_preds']
    )
    sns.heatmap(
        sentiment_cm, annot=True, fmt='d',
        xticklabels=list(mappings['idx_to_sentiment'].values()),
        yticklabels=list(mappings['idx_to_sentiment'].values()),
        ax=axes[1]
    )
    axes[1].set_title('Sentiment Confusion Matrix')
    axes[1].set_xlabel('Predicted')
    axes[1].set_ylabel('True')

    plt.tight_layout()
    plt.savefig('confusion_matrices_tf.png')
    plt.show()
```

In [ ]:

```python
train_path = 'https://raw.githubusercontent.com/declare-lab/MELD/master/data/M
dev_path = 'https://raw.githubusercontent.com/declare-lab/MELD/master/data/MEL
test_path = 'https://raw.githubusercontent.com/declare-lab/MELD/master/data/ME
if __name__ == "__main__":
    model_types = ['bert', 'roberta', 'lstm', 'dialoguernn', 'cosmic']
    for model_type in model_types:
    model, history, results = main(model_type='bert')
```

```
Loading data...
Creating data generators...
Testing MELDDataGenerator...
Total batches: 4
Total samples: 58

Batch 0:
  input_ids: (16, 128), dtype: int32
  attention_mask: (16, 128), dtype: int32
  emotion: (16,), dtype: int32
  sentiment: (16,), dtype: int32

Batch 1:
  input_ids: (16, 128), dtype: int32
  attention_mask: (16, 128), dtype: int32
  emotion: (16,), dtype: int32
  sentiment: (16,), dtype: int32

Batch 2:
  input_ids: (16, 128), dtype: int32
  attention_mask: (16, 128), dtype: int32
  emotion: (16,), dtype: int32
  sentiment: (16,), dtype: int32

✓ Data generator test passed!
Computing class weights...
Initializing bert model...
```

```
Some weights of the PyTorch model were not used when initializing the TF 2.0 m
odel TFBertModel: ['cls.seq_relationship.bias', 'cls.predictions.transform.Lay
erNorm.weight', 'cls.predictions.transform.dense.bias', 'cls.predictions.trans
form.dense.weight', 'cls.predictions.transform.LayerNorm.bias', 'cls.predictio
ns.bias', 'cls.seq_relationship.weight']
- This IS expected if you are initializing TFBertModel from a PyTorch model tr
ained on another task or with another architecture (e.g. initializing a TFBert
ForSequenceClassification model from a BertForPreTraining model).
- This IS NOT expected if you are initializing TFBertModel from a PyTorch mode
l that you expect to be exactly identical (e.g. initializing a TFBertForSequen
ceClassification model from a BertForSequenceClassification model).
All the weights of TFBertModel were initialized from the PyTorch model.
If your task is similar to the task the model of the checkpoint was trained o
n, you can already use TFBertModel for predictions without further training.
```

Model: "bert_multi_task_model_6"

Layer (type)	Output Shape	Param
dropout_18 (Dropout)	?	
dense_24 (Dense)	(16, 768)	590,5
dropout_19 (Dropout)	?	
dense_25 (Dense)	(16, 384)	295,2
emotion (Dense)	(16, 7)	2,6
dense_26 (Dense)	(16, 768)	590,5
dropout_20 (Dropout)	?	
dense_27 (Dense)	(16, 384)	295,2
sentiment (Dense)	(16, 3)	1,1

Total params: 1,775,626 (6.77 MB)

Trainable params: 1,775,626 (6.77 MB)

Non-trainable params: 0 (0.00 B)

```
Starting training...
Epoch 1/10
625/625 ━━━━━━━━━━━━━━━━━━━━ 0s 167ms/step - emotion_accuracy: 0.4327 - emotio
n_loss: 1.6219 - emotion_macro_f1: 0.9091 - loss: 2.1660 - sentiment_accuracy:
0.4307 - sentiment_loss: 1.0881 - sentiment_macro_f1: 0.7610
Epoch 1: val_loss improved from inf to 2.12456, saving model to best_bert_mode
l.weights.h5
625/625 ━━━━━━━━━━━━━━━━━━━━ 162s 196ms/step - emotion_accuracy: 0.4327 - emot
ion_loss: 1.6218 - emotion_macro_f1: 0.9091 - loss: 2.1659 - sentiment_accurac
y: 0.4307 - sentiment_loss: 1.0881 - sentiment_macro_f1: 0.7610 - val_emotion_
accuracy: 0.4265 - val_emotion_loss: 1.6159 - val_emotion_macro_f1: 0.9259 - v
al_loss: 2.1246 - val_sentiment_accuracy: 0.4454 - val_sentiment_loss: 1.0332
- val_sentiment_macro_f1: 0.7722 - learning_rate: 2.0000e-05
Epoch 2/10
625/625 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step - emotion_accuracy: 0.4626 - emotio
n_loss: 1.5432 - emotion_macro_f1: 0.9387 - loss: 2.0725 - sentiment_accuracy:
0.4655 - sentiment_loss: 1.0589 - sentiment_macro_f1: 0.7829
Epoch 2: val_loss improved from 2.12456 to 2.08970, saving model to best_bert_
model.weights.h5
625/625 ━━━━━━━━━━━━━━━━━━━━ 83s 133ms/step - emotion_accuracy: 0.4627 - emoti
on_loss: 1.5432 - emotion_macro_f1: 0.9388 - loss: 2.0725 - sentiment_accurac
y: 0.4656 - sentiment_loss: 1.0588 - sentiment_macro_f1: 0.7830 - val_emotion_
accuracy: 0.4265 - val_emotion_loss: 1.5937 - val_emotion_macro_f1: 0.9259 - v
al_loss: 2.0897 - val_sentiment_accuracy: 0.5059 - val_sentiment_loss: 1.0109
- val_sentiment_macro_f1: 0.7554 - learning_rate: 2.0000e-05
Epoch 3/10
625/625 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step - emotion_accuracy: 0.4763 - emotio
n_loss: 1.5095 - emotion_macro_f1: 0.9413 - loss: 2.0233 - sentiment_accuracy:
0.4975 - sentiment_loss: 1.0277 - sentiment_macro_f1: 0.7973
```

```
Epoch 3: val_loss improved from 2.08970 to 2.04334, saving model to best_bert_
model.weights.h5
625/625 ━━━━━━━━━━━━━━━━━━━━ 83s 132ms/step - emotion_accuracy: 0.4763 - emoti
on_loss: 1.5095 - emotion_macro_f1: 0.9413 - loss: 2.0233 - sentiment_accurac
y: 0.4975 - sentiment_loss: 1.0277 - sentiment_macro_f1: 0.7973 - val_emotion_
accuracy: 0.4292 - val_emotion_loss: 1.5539 - val_emotion_macro_f1: 0.9259 - v
al_loss: 2.0433 - val_sentiment_accuracy: 0.5383 - val_sentiment_loss: 0.9909
- val_sentiment_macro_f1: 0.7100 - learning_rate: 2.0000e-05
Epoch 4/10
625/625 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step - emotion_accuracy: 0.4773 - emotio
n_loss: 1.5049 - emotion_macro_f1: 0.9400 - loss: 2.0153 - sentiment_accuracy:
0.4960 - sentiment_loss: 1.0203 - sentiment_macro_f1: 0.7902
Epoch 4: val_loss improved from 2.04334 to 2.03082, saving model to best_bert_
model.weights.h5
625/625 ━━━━━━━━━━━━━━━━━━━━ 82s 132ms/step - emotion_accuracy: 0.4773 - emoti
on_loss: 1.5049 - emotion_macro_f1: 0.9400 - loss: 2.0153 - sentiment_accurac
y: 0.4960 - sentiment_loss: 1.0203 - sentiment_macro_f1: 0.7902 - val_emotion_
accuracy: 0.4256 - val_emotion_loss: 1.5482 - val_emotion_macro_f1: 0.9259 - v
al_loss: 2.0308 - val_sentiment_accuracy: 0.5374 - val_sentiment_loss: 0.9762
- val_sentiment_macro_f1: 0.7420 - learning_rate: 2.0000e-05
Epoch 5/10
625/625 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step - emotion_accuracy: 0.4814 - emotio
n_loss: 1.4860 - emotion_macro_f1: 0.9378 - loss: 1.9934 - sentiment_accuracy:
0.5050 - sentiment_loss: 1.0157 - sentiment_macro_f1: 0.7901
Epoch 5: val_loss improved from 2.03082 to 2.01919, saving model to best_bert_
model.weights.h5
625/625 ━━━━━━━━━━━━━━━━━━━━ 82s 132ms/step - emotion_accuracy: 0.4814 - emoti
on_loss: 1.4860 - emotion_macro_f1: 0.9378 - loss: 1.9934 - sentiment_accurac
y: 0.5050 - sentiment_loss: 1.0157 - sentiment_macro_f1: 0.7901 - val_emotion_
```

```
accuracy: 0.4509 - val_emotion_loss: 1.5358 - val_emotion_macro_f1: 0.9264 - v
al_loss: 2.0192 - val_sentiment_accuracy: 0.5482 - val_sentiment_loss: 0.9761
- val_sentiment_macro_f1: 0.6935 - learning_rate: 2.0000e-05
Epoch 6/10
625/625 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step - emotion_accuracy: 0.4905 - emotio
n_loss: 1.4731 - emotion_macro_f1: 0.9437 - loss: 1.9729 - sentiment_accuracy:
0.5137 - sentiment_loss: 1.0001 - sentiment_macro_f1: 0.7912
Epoch 6: val_loss improved from 2.01919 to 1.99994, saving model to best_bert_
model.weights.h5
625/625 ━━━━━━━━━━━━━━━━━━━━ 86s 137ms/step - emotion_accuracy: 0.4905 - emoti
on_loss: 1.4732 - emotion_macro_f1: 0.9437 - loss: 1.9730 - sentiment_accurac
y: 0.5137 - sentiment_loss: 1.0001 - sentiment_macro_f1: 0.7912 - val_emotion_
accuracy: 0.4509 - val_emotion_loss: 1.5210 - val_emotion_macro_f1: 0.9241 - v
al_loss: 1.9999 - val_sentiment_accuracy: 0.5500 - val_sentiment_loss: 0.9640
- val_sentiment_macro_f1: 0.7046 - learning_rate: 2.0000e-05
Epoch 7/10
625/625 ━━━━━━━━━━━━━━━━━━━━ 0s 129ms/step - emotion_accuracy: 0.4714 - emotio
n_loss: 1.4912 - emotion_macro_f1: 0.9352 - loss: 1.9906 - sentiment_accuracy:
0.5198 - sentiment_loss: 0.9991 - sentiment_macro_f1: 0.7828
Epoch 7: val_loss improved from 1.99994 to 1.99046, saving model to best_bert_
model.weights.h5
625/625 ━━━━━━━━━━━━━━━━━━━━ 146s 143ms/step - emotion_accuracy: 0.4714 - emot
ion_loss: 1.4912 - emotion_macro_f1: 0.9352 - loss: 1.9905 - sentiment_accurac
y: 0.5198 - sentiment_loss: 0.9991 - sentiment_macro_f1: 0.7828 - val_emotion_
accuracy: 0.4554 - val_emotion_loss: 1.5139 - val_emotion_macro_f1: 0.9197 - v
al_loss: 1.9905 - val_sentiment_accuracy: 0.5555 - val_sentiment_loss: 0.9613
- val_sentiment_macro_f1: 0.7548 - learning_rate: 2.0000e-05
Epoch 8/10
625/625 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step - emotion_accuracy: 0.4802 - emotio
```

```
n_loss: 1.4718 - emotion_macro_f1: 0.9360 - loss: 1.9682 - sentiment_accuracy:
0.5260 - sentiment_loss: 0.9928 - sentiment_macro_f1: 0.7863
Epoch 8: val_loss improved from 1.99046 to 1.98900, saving model to best_bert_
model.weights.h5
625/625 ━━━━━━━━━━━━━━━━━━━━ 85s 135ms/step - emotion_accuracy: 0.4802 - emoti
on_loss: 1.4718 - emotion_macro_f1: 0.9360 - loss: 1.9682 - sentiment_accurac
y: 0.5260 - sentiment_loss: 0.9928 - sentiment_macro_f1: 0.7863 - val_emotion_
accuracy: 0.4482 - val_emotion_loss: 1.5170 - val_emotion_macro_f1: 0.9223 - v
al_loss: 1.9890 - val_sentiment_accuracy: 0.5645 - val_sentiment_loss: 0.9523
- val_sentiment_macro_f1: 0.7481 - learning_rate: 2.0000e-05
Epoch 9/10
625/625 ━━━━━━━━━━━━━━━━━━━━ 0s 125ms/step - emotion_accuracy: 0.4787 - emotio
n_loss: 1.4671 - emotion_macro_f1: 0.9355 - loss: 1.9618 - sentiment_accuracy:
0.5294 - sentiment_loss: 0.9893 - sentiment_macro_f1: 0.7909
Epoch 9: val_loss improved from 1.98900 to 1.96995, saving model to best_bert_
model.weights.h5
625/625 ━━━━━━━━━━━━━━━━━━━━ 86s 138ms/step - emotion_accuracy: 0.4788 - emoti
on_loss: 1.4671 - emotion_macro_f1: 0.9355 - loss: 1.9618 - sentiment_accurac
y: 0.5294 - sentiment_loss: 0.9893 - sentiment_macro_f1: 0.7909 - val_emotion_
accuracy: 0.4599 - val_emotion_loss: 1.5011 - val_emotion_macro_f1: 0.9185 - v
al_loss: 1.9699 - val_sentiment_accuracy: 0.5636 - val_sentiment_loss: 0.9440
- val_sentiment_macro_f1: 0.7251 - learning_rate: 2.0000e-05
Epoch 10/10
625/625 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step - emotion_accuracy: 0.4836 - emotio
n_loss: 1.4673 - emotion_macro_f1: 0.9349 - loss: 1.9600 - sentiment_accuracy:
0.5289 - sentiment_loss: 0.9864 - sentiment_macro_f1: 0.7893
Epoch 10: val_loss improved from 1.96995 to 1.95427, saving model to best_bert
_model.weights.h5
625/625 ━━━━━━━━━━━━━━━━━━━━ 83s 132ms/step - emotion_accuracy: 0.4836 - emoti
```

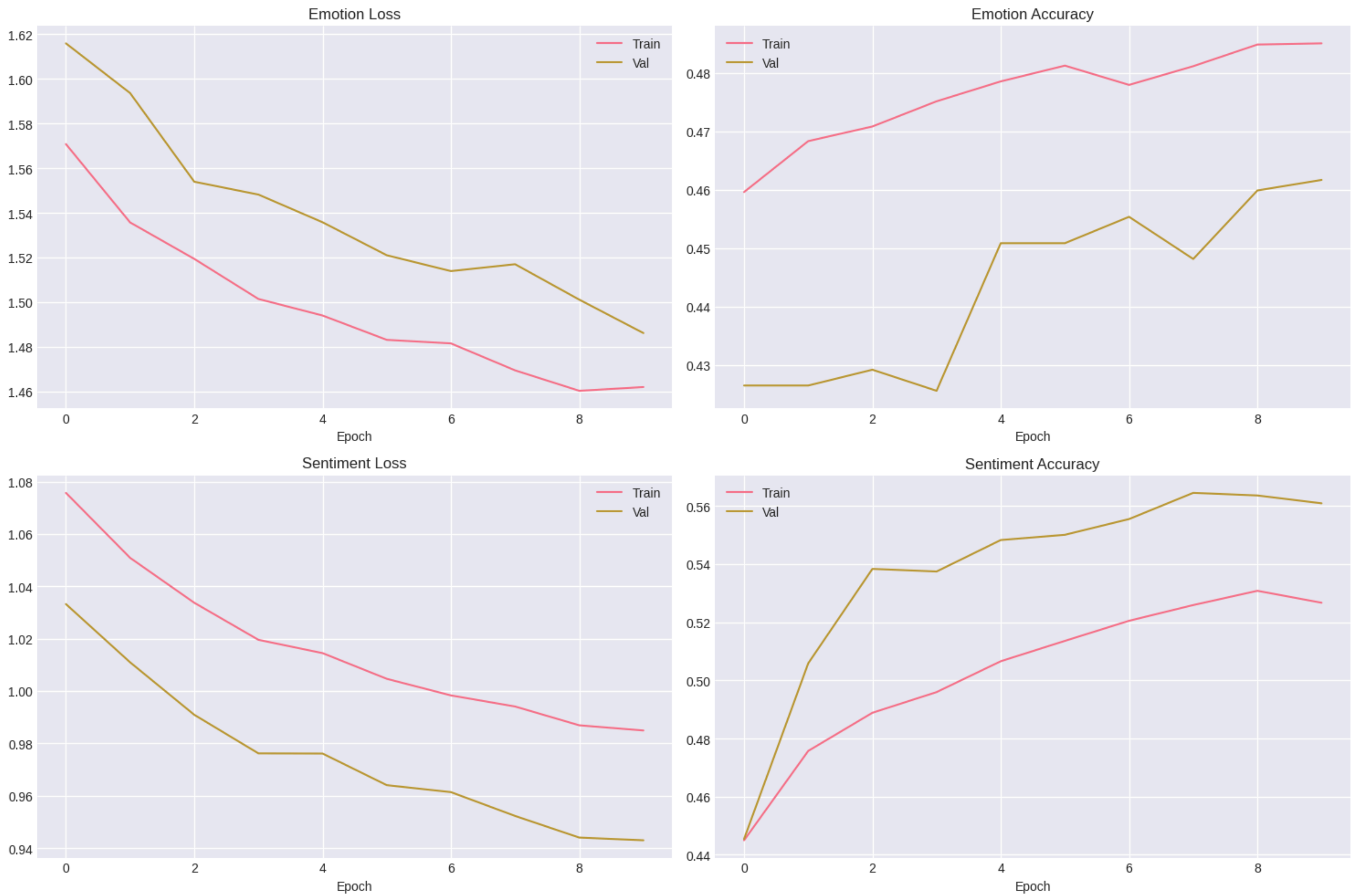
```
on_loss: 1.4673 - emotion_macro_f1: 0.9349 - loss: 1.9600 - sentiment_accurac
y: 0.5289 - sentiment_loss: 0.9864 - sentiment_macro_f1: 0.7893 - val_emotion_
accuracy: 0.4617 - val_emotion_loss: 1.4861 - val_emotion_macro_f1: 0.9062 - v
al_loss: 1.9543 - val_sentiment_accuracy: 0.5609 - val_sentiment_loss: 0.9429
- val_sentiment_macro_f1: 0.7223 - learning_rate: 2.0000e-05
Restoring model weights from the end of the best epoch: 10.

Evaluating on test set...
Evaluating: 100%|██████████| 164/164 [00:40<00:00,  4.06it/s]
```

=== Emotion Classification Report ===

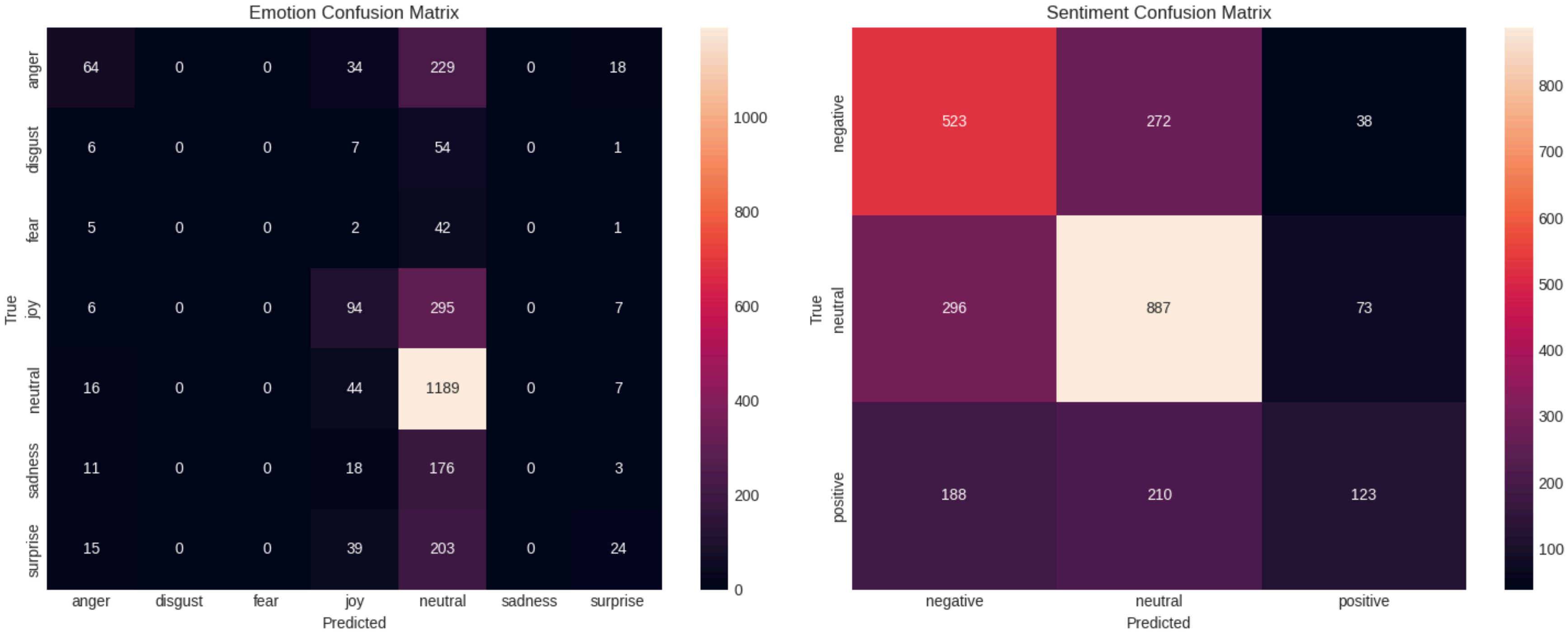
	precision	recall	f1-score	support
anger	0.52	0.19	0.27	345
disgust	0.00	0.00	0.00	68
fear	0.00	0.00	0.00	50
joy	0.39	0.23	0.29	402
neutral	0.54	0.95	0.69	1256
sadness	0.00	0.00	0.00	208
surprise	0.39	0.09	0.14	281
accuracy			0.53	2610
macro avg	0.26	0.21	0.20	2610
weighted avg	0.43	0.53	0.43	2610

=== Sentiment Classification Report ===

	precision	recall	f1-score	support
negative	0.52	0.63	0.57	833
neutral	0.65	0.71	0.68	1256
positive	0.53	0.24	0.33	521
accuracy			0.59	2610
macro avg	0.56	0.52	0.52	2610
weighted avg	0.58	0.59	0.57	2610



Emotion Loss
Emotion Accuracy
Sentiment Loss
Sentiment Accuracy
Train
Val
Epoch



7. Inference and Deployment

In [ ]:
```python
class EmotionSentimentPredictor:
    """Inference class for emotion and sentiment prediction"""
    def __init__(self, model_path, model_type='bert', tokenizer_name='bert-bas
        self.model_type = model_type
        self.tokenizer = AutoTokenizer.from_pretrained(tokenizer_name)

        # Load label mappings
        with open('data/label_mappings.json', 'r') as f:
            self.mappings = json.load(f)
```

```
        # Initialize and load model
        if model_type == 'bert':
            self.model = BERTMultiTaskModel(
                model_name=tokenizer_name,
                num_emotions=len(self.mappings['emotion_to_idx']),
                num_sentiments=len(self.mappings['sentiment_to_idx'])
            )

        # Build model with proper dtype
        dummy_input = {
            'input_ids': tf.zeros((1, 128), dtype=tf.int32),
            'attention_mask': tf.ones((1, 128), dtype=tf.int32)
        }
        _ = self.model(dummy_input)

        # Load weights
        self.model.load_weights(model_path)

    @tf.function
    def predict_batch(self, input_ids, attention_mask):
        """Optimized prediction for batches"""
        # Ensure proper dtypes
        input_ids = tf.cast(input_ids, tf.int32)
        attention_mask = tf.cast(attention_mask, tf.int32)

        inputs = {
            'input_ids': input_ids,
            'attention_mask': attention_mask
```

```
        }

        predictions = self.model(inputs, training=False)

        emotion_probs = tf.nn.softmax(predictions['emotion'])
        sentiment_probs = tf.nn.softmax(predictions['sentiment'])

        emotion_preds = tf.argmax(emotion_probs, axis=-1)
        sentiment_preds = tf.argmax(sentiment_probs, axis=-1)

        return {
            'emotion_preds': emotion_preds,
            'sentiment_preds': sentiment_preds,
            'emotion_probs': emotion_probs,
            'sentiment_probs': sentiment_probs
        }

    def predict(self, text, context=None):
        """Predict emotion and sentiment for single text"""
        # Prepare text
        if context:
            full_text = f"{context} [SEP] {text}"
        else:
            full_text = text

        # Tokenize
        encoded = self.tokenizer(
            full_text,
            padding='max_length',
```

```
            truncation=True,
            max_length=128,
            return_tensors='tf'
        )

        # Predict
        predictions = self.predict_batch(
            encoded['input_ids'],
            encoded['attention_mask']
        )

        emotion_idx = predictions['emotion_preds'][0].numpy()
        sentiment_idx = predictions['sentiment_preds'][0].numpy()

        return {
            'emotion': self.mappings['idx_to_emotion'][str(emotion_idx)],
            'sentiment': self.mappings['idx_to_sentiment'][str(sentiment_idx)]
            'emotion_probabilities': predictions['emotion_probs'][0].numpy().t
            'sentiment_probabilities': predictions['sentiment_probs'][0].numpy
        }

    def predict_dialogue(self, utterances, speakers=None):
        """Predict for entire dialogue"""
        predictions = []
        context = ""

        for i, utterance in enumerate(utterances):
            # Add speaker if available
            if speakers:
```

```python
                utterance_with_speaker = f"{speakers[i]}: {utterance}"
            else:
                utterance_with_speaker = utterance

            # Predict
            pred = self.predict(utterance, context)
            predictions.append(pred)

            # Update context
            if context:
                context = f"{context} [SEP] {utterance_with_speaker}"
            else:
                context = utterance_with_speaker

            # Limit context length
            if len(context.split()) > 100:
                context = ' '.join(context.split()[-100:])

        return predictions
```

In [ ]:

```python
# Fixed TensorFlow Serving export function
def export_for_serving(model, export_path):
    """Export model for TensorFlow Serving with proper dtype handling"""

    # Create a serving function with explicit dtype conversions
    @tf.function
    def serving_fn(examples):
        # Parse the examples (assuming they come as strings)
        input_ids = examples['input_ids']
```

```
        attention_mask = examples['attention_mask']

        # Ensure proper dtypes
        input_ids = tf.cast(input_ids, tf.int32)
        attention_mask = tf.cast(attention_mask, tf.int32)

        inputs = {
            'input_ids': input_ids,
            'attention_mask': attention_mask
        }

        predictions = model(inputs, training=False)

        emotion_probs = tf.nn.softmax(predictions['emotion'])
        sentiment_probs = tf.nn.softmax(predictions['sentiment'])

        return {
            'emotion_logits': predictions['emotion'],
            'sentiment_logits': predictions['sentiment'],
            'emotion_probs': emotion_probs,
            'sentiment_probs': sentiment_probs,
            'emotion_predictions': tf.argmax(emotion_probs, axis=-1),
            'sentiment_predictions': tf.argmax(sentiment_probs, axis=-1)
        }

    # Get concrete function with proper signatures
    concrete_serving_fn = serving_fn.get_concrete_function(
        examples={
            'input_ids': tf.TensorSpec(shape=[None, None], dtype=tf.int32, nar
```

```
            'attention_mask': tf.TensorSpec(shape=[None, None], dtype=tf.int32
        }
    )

    # Save the model
    tf.saved_model.save(
        model,
        export_path,
        signatures={'serving_default': concrete_serving_fn}
    )
    print(f"Model exported to {export_path}")
```

In [ ]:

```
def export_keras_model(model, export_path):
    """Export model using Keras SavedModel format with proper file extension"
    # Define the inference function
    @tf.function
    def inference(input_ids, attention_mask):
        # Ensure proper dtypes
        input_ids = tf.cast(input_ids, tf.int32)
        attention_mask = tf.cast(attention_mask, tf.int32)

        inputs = {
            'input_ids': input_ids,
            'attention_mask': attention_mask
        }

        return model(inputs, training=False)

    # Ensure directory exists
```

```python
    os.makedirs(os.path.dirname(export_path) if os.path.dirname(export_path) e

    # Add proper extension if not present
    if not export_path.endswith('.keras') and not export_path.endswith('.h5'):
        export_path = export_path.rstrip('/') + '.keras'

    # Save using Keras native format
    model.save(export_path, overwrite=True)
    print(f"Keras model saved to {export_path}")
```

In [ ]:

```python
# ============= Export Functions =============

def export_all_models():
    """Export all trained models for serving"""

    model_types = ['bert', 'roberta', 'lstm', 'dialoguernn', 'cosmic']

    for model_type in model_types:
        model_path = f'best_{model_type}_model.weights.h5'
        export_path = f'./saved_models/{model_type}/'

        try:
            print(f"\nExporting {model_type} model...")

            # Load model
            predictor = UnifiedEmotionSentimentPredictor(
                model_path=model_path,
                model_type=model_type
            )
```

```python
            # Export
            predictor.model.save(export_path, save_traces=False)
            print(f"Exported to {export_path}")

        except Exception as e:
            print(f"Error exporting {model_type}: {e}")
```

In [ ]:

```python
def load_and_test_saved_model(saved_model_path):
    """Load and test the exported SavedModel"""
    # Load the SavedModel
    loaded_model = tf.saved_model.load(saved_model_path)

    # Get the serving function
    serving_fn = loaded_model.signatures['serving_default']

    # Test with dummy input
    test_input = {
        'input_ids': tf.constant([[101, 2054, 2003, 2115, 2171, 102, 0, 0]], d
        'attention_mask': tf.constant([[1, 1, 1, 1, 1, 1, 0, 0]], dtype=tf.int
    }

    # Make prediction
    output = serving_fn(**test_input)

    print("SavedModel test successful!")
    print(f"Output keys: {list(output.keys())}")
    return output
```

In [ ]:
```
def create_tflite_model(saved_model_path, tflite_path):
    """Convert SavedModel to TFLite for mobile/edge deployment"""
    # Load the converter
    converter = tf.lite.TFLiteConverter.from_saved_model(saved_model_path)

    # Optimize for size (optional)
    converter.optimizations = [tf.lite.Optimize.DEFAULT]

    # Convert
    tflite_model = converter.convert()

    # Save
    with open(tflite_path, 'wb') as f:
        f.write(tflite_model)

    print(f"TFLite model saved to {tflite_path}")
```

In [ ]:
```
# usage
if __name__ == "__main__":
  try:
      # Initialize predictor
      predictor = EmotionSentimentPredictor(
          model_path='best_bert_model.weights.h5', #best_bert_model.weights.h5
          model_type='bert'
      )

      # Single prediction
      result = predictor.predict(
```

```
        text="I can't believe you did that!",
        context="We were supposed to meet at 5pm."
    )
    print(f"Emotion: {result['emotion']}, Sentiment: {result['sentiment']}")

    # Dialogue prediction
    dialogue = [
        "How are you doing today?",
        "Not great, I lost my job.",
        "Oh no, I'm so sorry!",
        "Thanks, I'll be okay."
    ]

    dialogue_predictions = predictor.predict_dialogue(dialogue)
    for i, (utt, pred) in enumerate(zip(dialogue, dialogue_predictions)):
        print(f"Utterance: {utt}")
        print(f"  -> Emotion: {pred['emotion']}, Sentiment: {pred['sentiment

    # Single prediction
    result = predictor.predict(
        text="I'm so frustrated with this service!",
        context="I've been waiting for 2 hours"
     )

    print(f"Emotion: {result['emotion']}, Sentiment: {result['sentiment']}")

    #export_for_serving(model, './saved_model/1/')
    # Export for serving - use the predictor's model
    print("\nExporting model for TensorFlow Serving...")
```

```python
        export_for_serving(predictor.model, './saved_model/1/')

        # Alternative: Export as Keras SavedModel
        print("\nExporting as Keras SavedModel...")
        export_keras_model(predictor.model, './keras_saved_model/')
    except Exception as e:
        print(f"Error: {e}")
        print("\nTroubleshooting tips:")
        print("1. Ensure mixed precision is disabled for inference")
        print("2. Check that input tensors have correct dtypes (int32 for input_
        print("3. Verify model weights are loaded correctly")
        print("4. Consider using export_keras_model() if export_for_serving() fa
```

```
Some weights of the PyTorch model were not used when initializing the TF 2.0 m
odel TFBertModel: ['cls.seq_relationship.bias', 'cls.predictions.transform.Lay
erNorm.weight', 'cls.predictions.transform.dense.bias', 'cls.predictions.trans
form.dense.weight', 'cls.predictions.transform.LayerNorm.bias', 'cls.predictio
ns.bias', 'cls.seq_relationship.weight']
- This IS expected if you are initializing TFBertModel from a PyTorch model tr
ained on another task or with another architecture (e.g. initializing a TFBert
ForSequenceClassification model from a BertForPreTraining model).
- This IS NOT expected if you are initializing TFBertModel from a PyTorch mode
l that you expect to be exactly identical (e.g. initializing a TFBertForSequen
ceClassification model from a BertForSequenceClassification model).
All the weights of TFBertModel were initialized from the PyTorch model.
If your task is similar to the task the model of the checkpoint was trained o
n, you can already use TFBertModel for predictions without further training.
```

```
Emotion: neutral, Sentiment: negative
Utterance: How are you doing today?
  -> Emotion: neutral, Sentiment: neutral
Utterance: Not great, I lost my job.
  -> Emotion: neutral, Sentiment: neutral
Utterance: Oh no, I'm so sorry!
  -> Emotion: neutral, Sentiment: neutral
Utterance: Thanks, I'll be okay.
  -> Emotion: neutral, Sentiment: neutral
Emotion: surprise, Sentiment: negative

Exporting model for TensorFlow Serving...
Model exported to ./saved_model/1/

Exporting as Keras SavedModel...
Keras model saved to ./keras_saved_model.keras
```

Summary

This TensorFlow implementation provides:

1. **Data Processing**: Custom data generators with batching and augmentation
2. **Model Architectures**:
    - LSTM with bidirectional layers
    - BERT/RoBERTa with TensorFlow integration
    - DialogueRNN with attention mechanisms

    - COSMIC-style model with cross-attention
3. **Advanced Features**:
    - Focal loss for extreme imbalance
    - Text augmentation for minority classes
    - Multimodal fusion architecture
    - Mixed precision training support
4. **Training Pipeline**:
    - Callbacks for checkpointing and early stopping
    - TensorBoard integration
    - Learning rate scheduling
5. **Production Features**:
    - Optimized inference with @tf.function
    - TensorFlow Serving export
    - Batch prediction support

The implementation is modular and can be easily extended with new architectures or features.