emobank-PAD

October 10, 2024

1 Step 1: Import Libraries

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.decomposition import LatentDirichletAllocation
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import Ridge
from sklearn.metrics import mean_squared_error
from sklearn.ensemble import RandomForestRegressor
from sklearn.neural_network import MLPRegressor
import requests
import io
from sklearn.feature_extraction.text import CountVectorizer
```

2 Step 2: Load Dataset

[2]:
```
def get_dataset(url = "https://raw.githubusercontent.com/JULIELab/EmoBank/
↪master/corpus/emobank.csv"):
    response = requests.get(url)
    if response.status_code == 200:
        return pd.read_csv(io.StringIO(response.text))
    else:
        raise Exception(f"Failed to download the dataset. Status code:␣
↪{response.status_code}")
```

[3]:
```
data = get_dataset()
```

[4]:
```
data.head()
```

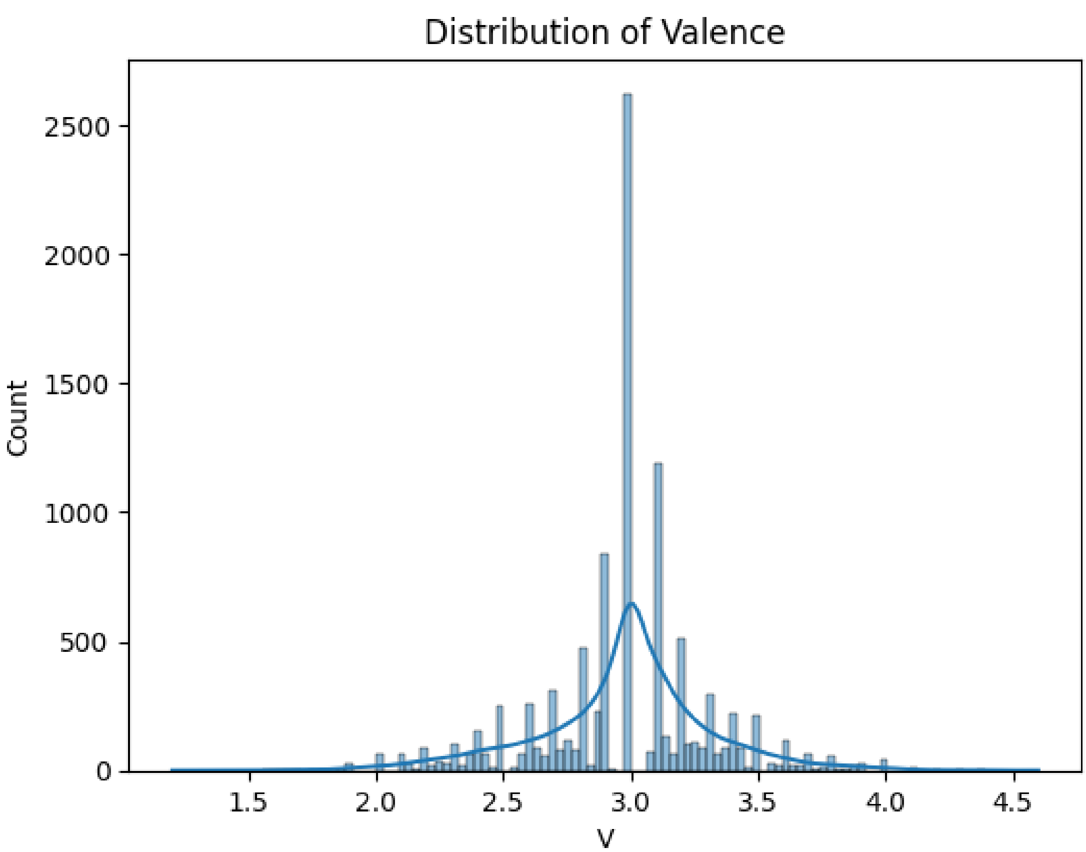
[4]:
```
                     id  split     V     A     D  \
0  110CYL068_1036_1079  train  3.00  3.00  3.20
1  110CYL068_1079_1110   test  2.80  3.10  2.80
2  110CYL068_1127_1130  train  3.00  3.00  3.00
```

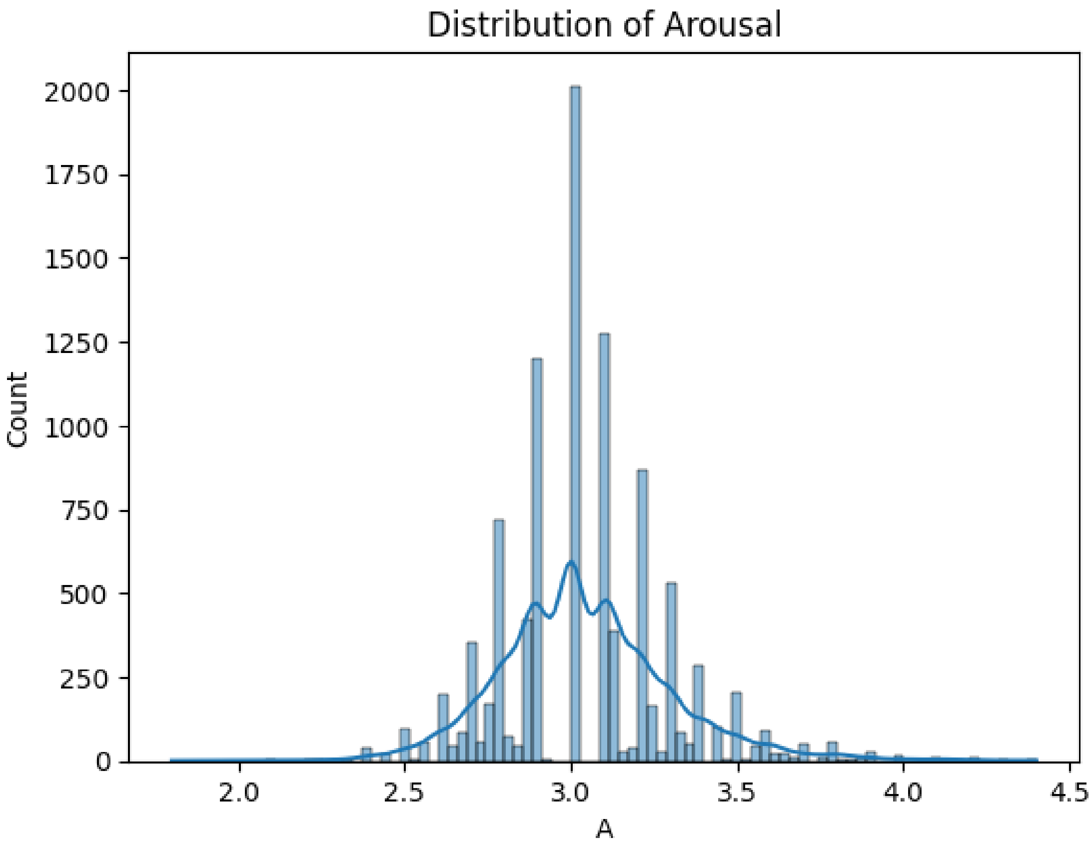
```
3  110CYL068_1137_1188  train  3.44  3.00  3.22
4  110CYL068_1189_1328  train  3.55  3.27  3.46

                                                        text
0        Remember what she said in my last letter? "
1                          If I wasn't working here.
2                                                        .."
3  Goodwill helps people get off of public assist…
4  Sherry learned through our Future Works class …
```

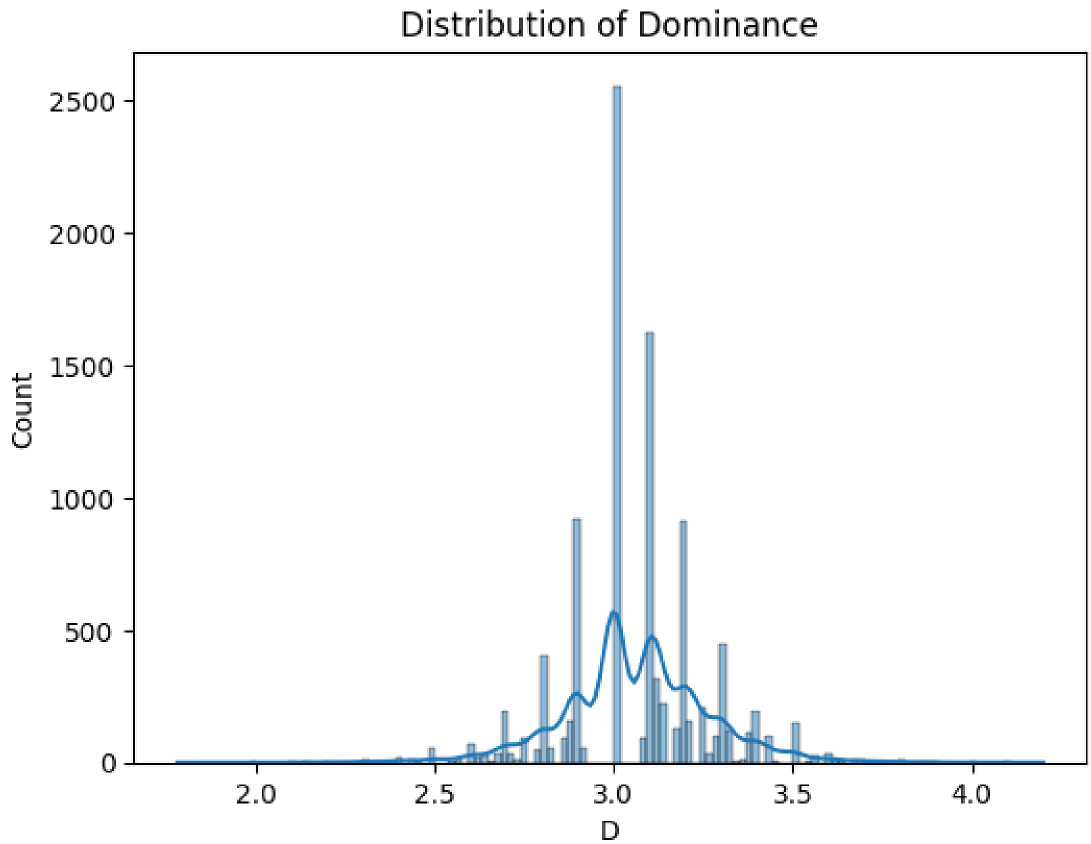
3 Step 3: Exploratory Data Analysis

Visualize the distribution of Valence, Arousal, and Dominance

[5]:
```
sns.histplot(data['V'], kde=True).set_title('Distribution of Valence')
plt.show()

sns.histplot(data['A'], kde=True).set_title('Distribution of Arousal')
plt.show()

sns.histplot(data['D'], kde=True).set_title('Distribution of Dominance')
plt.show()
```




Distribution of Arousal
2000
1750
1500
1250
1000
750
500
250
0
Count
2.0
2.5
3.0
3.5
4.0
4.5
A

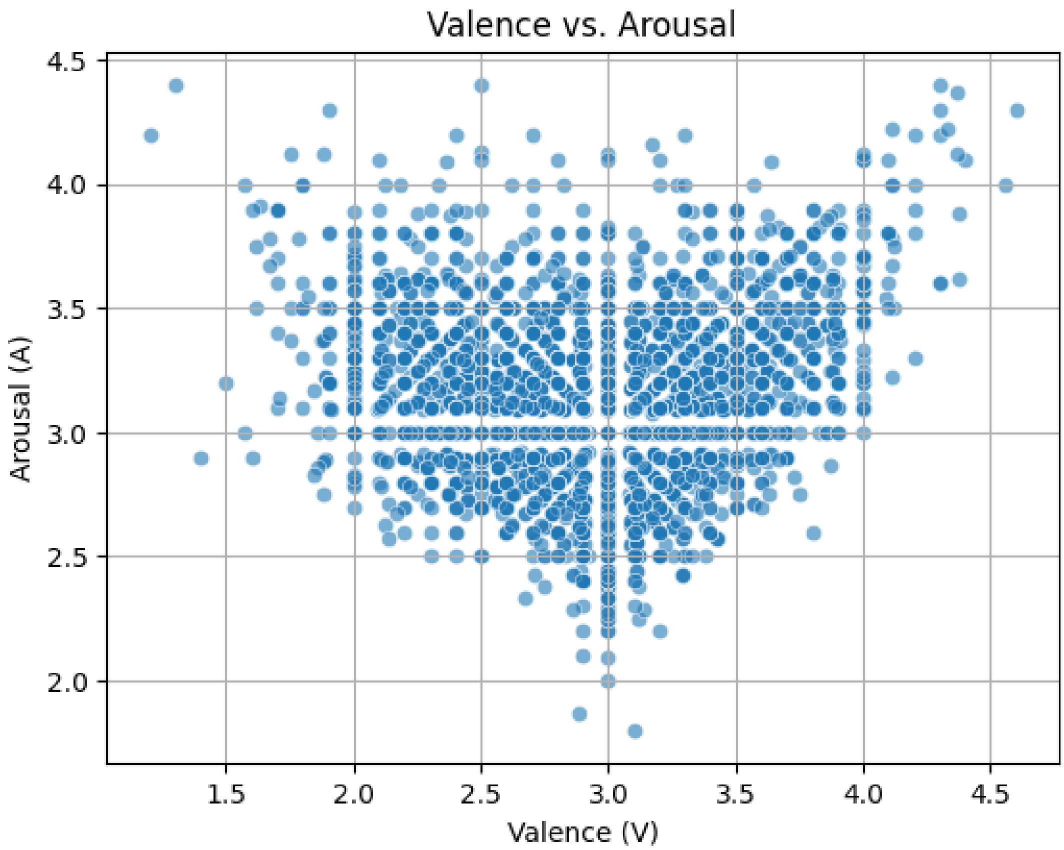


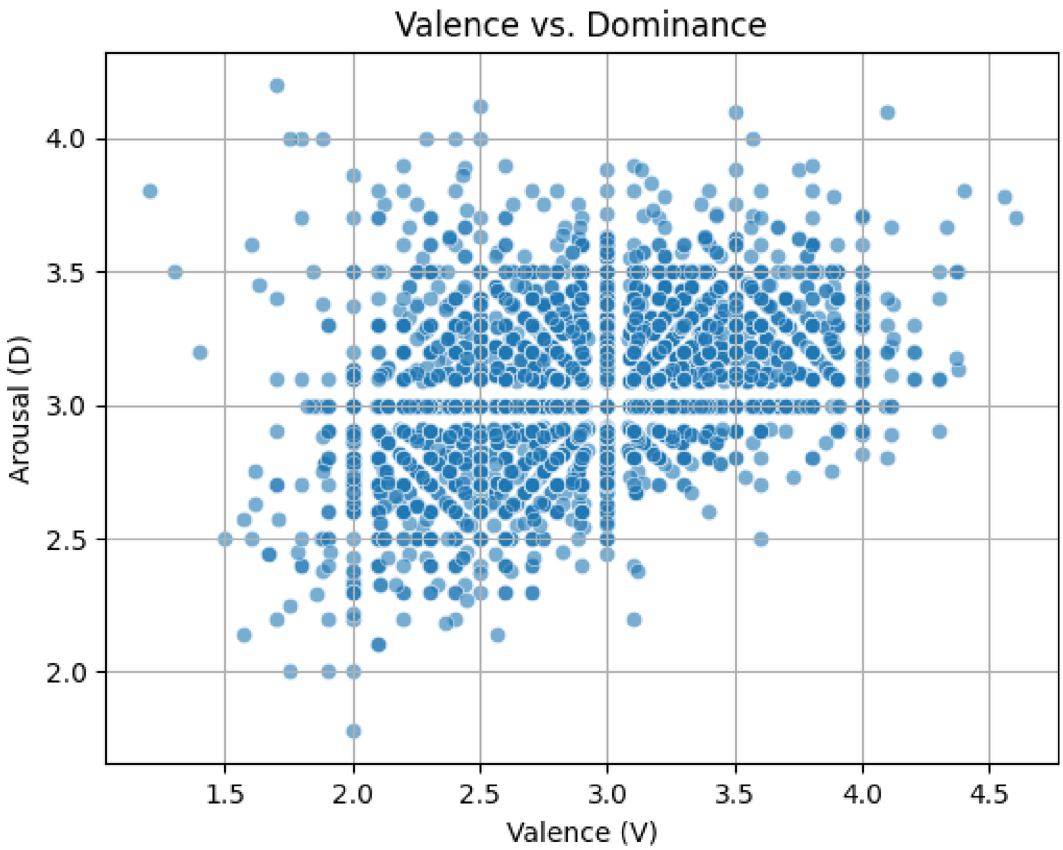
4 Step 4: Preprocessing

Split into training and testing sets

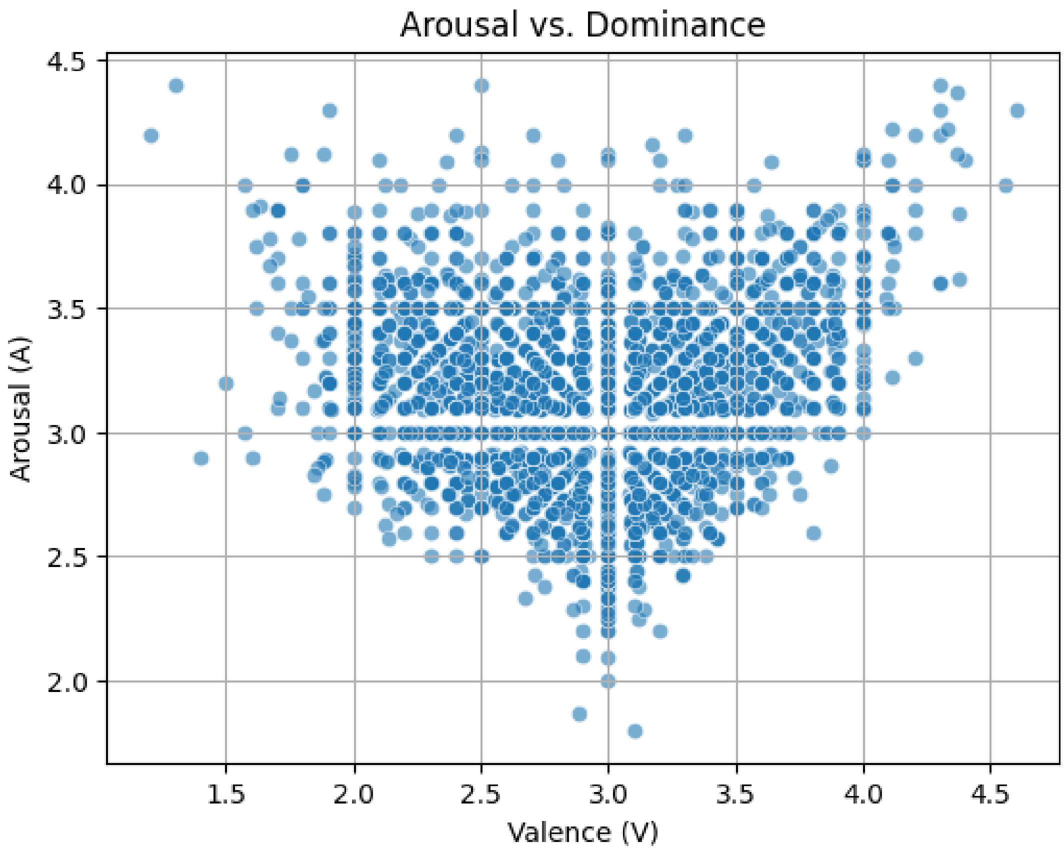
[6]:
```
# Drop rows with NaN in V or A
data = data.dropna(subset=['V', 'A', 'D'])

# Define a function to remove outliers using IQR
# def remove_outliers(df, column):
#     Q1 = df[column].quantile(0.25)
#     Q3 = df[column].quantile(0.75)
#     IQR = Q3 - Q1
#     lower_bound = Q1 - 1.5 * IQR
#     upper_bound = Q3 + 1.5 * IQR
#     return df[(df[column] >= lower_bound) & (df[column] <= upper_bound)]

# Apply the function to Valence (V), Arousal (A), and Dominance (D)
# data = remove_outliers(data, 'V')
# data = remove_outliers(data, 'A')
```

```
# data = remove_outliers(data, 'D')

# Replace NaN with a placeholder (e.g., an empty string)
data['text'] = data['text'].fillna('')

# Scatter plot for Valence (V) and Arousal (A)
sns.scatterplot(x='V', y='A', data=data, alpha=0.6)

# Customize the plot
plt.xlabel("Valence (V)")
plt.ylabel("Arousal (A)")
plt.title("Valence vs. Arousal")

# Add grid lines
plt.grid(True)

# Show the plot
plt.show()

# Scatter plot for Valence (V) and Dominance (D)
sns.scatterplot(x='V', y='D', data=data, alpha=0.6)

# Customize the plot
plt.xlabel("Valence (V)")
plt.ylabel("Arousal (D)")
plt.title("Valence vs. Dominance")

# Add grid lines
plt.grid(True)

# Show the plot
plt.show()

# Scatter plot for Arousal (A) and Dominance (D)
sns.scatterplot(x='V', y='A', data=data, alpha=0.6)

# Customize the plot
plt.xlabel("Valence (V)")
plt.ylabel("Arousal (A)")
plt.title("Arousal vs. Dominance")

# Add grid lines
plt.grid(True)

# Show the plot
plt.show()
```

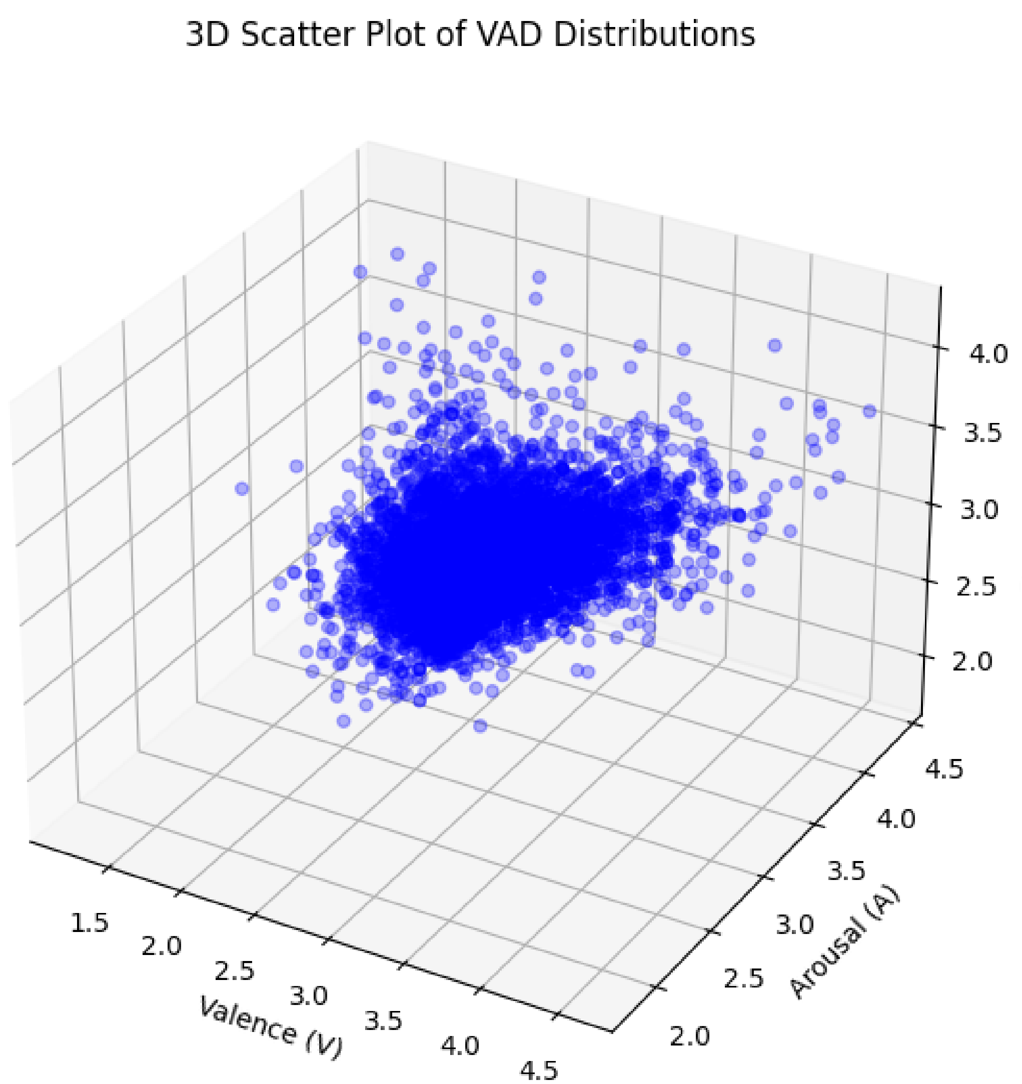

Valence vs. Arousal
Arousal (A)
Valence (V)
4.5
4.0
3.5
3.0
2.5
2.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5



Valence vs. Dominance
Arousal (D)
Valence (V)
4.0
3.5
3.0
2.5
2.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5



[7]:
```
# Create a figure for 3D plot
fig = plt.figure(figsize=(10, 7))
ax = fig.add_subplot(111, projection='3d')

ax.scatter(data['V'], data['A'], data['D'], color='blue', label='Actual VAD',␣
 ↪alpha=0.3)

ax.set_xlabel('Valence (V)')
ax.set_ylabel('Arousal (A)')
ax.set_zlabel('Dominance (D)')
ax.set_title('3D Scatter Plot of VAD Distributions')

# Show the plot
plt.show()
```

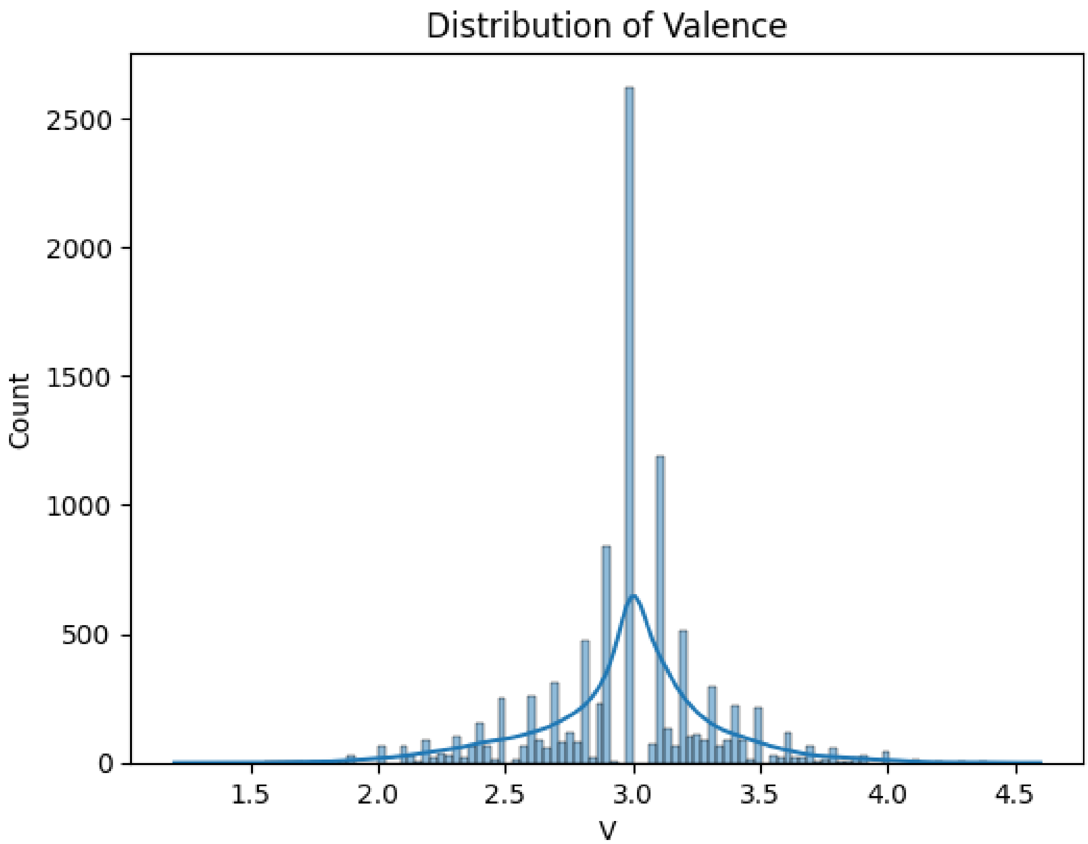


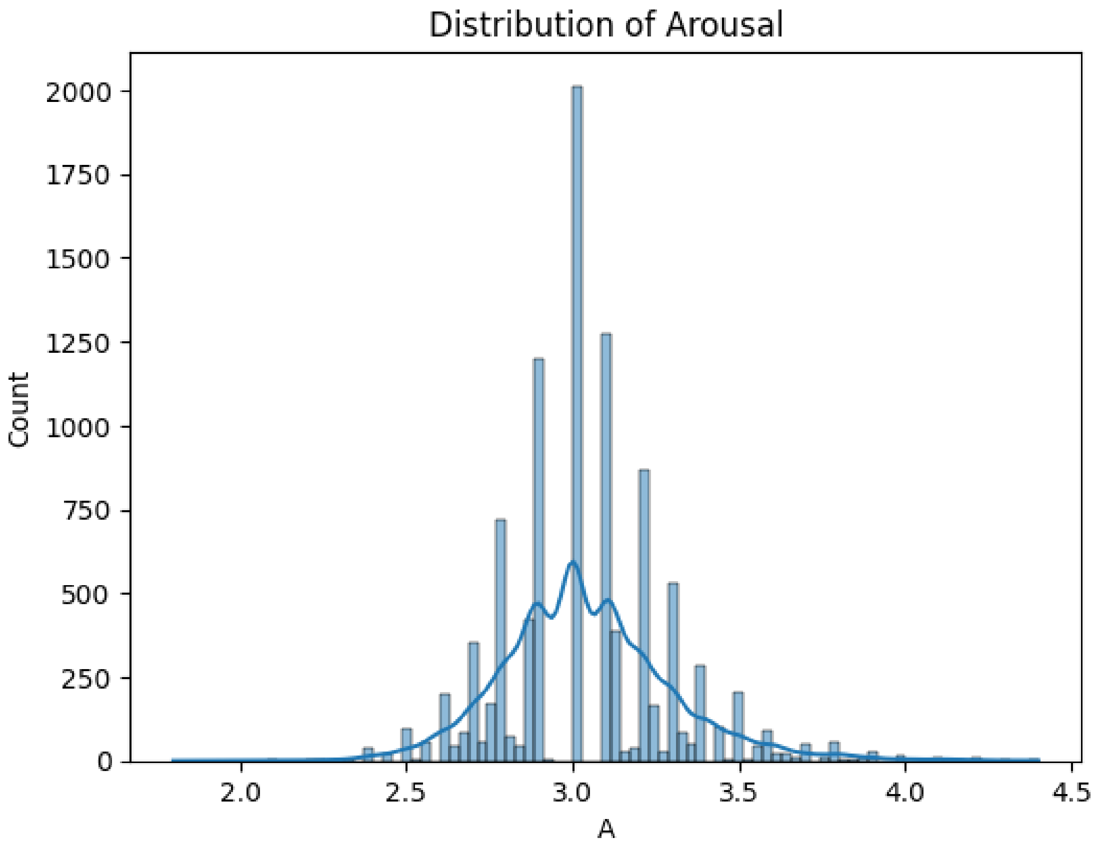
[8]:
```
# Continue with train-test split and TF-IDF processing
train_data, test_data = train_test_split(data, test_size=0.2, random_state=42)

# --- Preprocessing options: CountVectorizer, TF-IDF, Word2Vec ---

# Option 1: Using CountVectorizer for LDA (original approach)

# count_vectorizer = CountVectorizer(max_features=5000, stop_words='english')
# data_counts = count_vectorizer.fit_transform(data['text'])
# X_train_counts = count_vectorizer.transform(train_data['text'])
# X_test_counts = count_vectorizer.transform(test_data['text'])
# # Applying LDA
# lda = LatentDirichletAllocation(n_components=20, random_state=42)
```

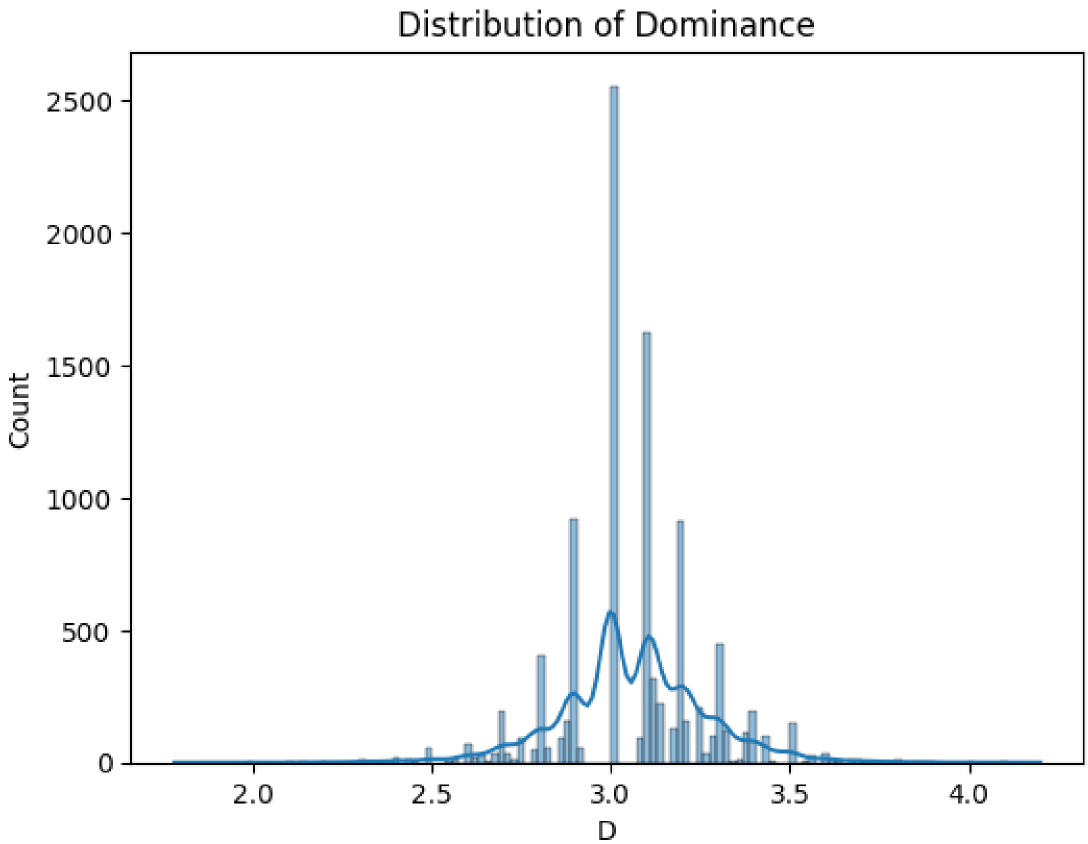
```
# lda.fit_transform(data_counts)
# X_train = lda.transform(X_train_counts)
# X_test = lda.transform(X_test_counts)

# Option 2: Using TF-IDF (new approach)

tfidf_vectorizer = TfidfVectorizer(max_features=5000, stop_words='english')
data_tfidf = tfidf_vectorizer.fit_transform(data['text'])
X_train = tfidf_vectorizer.transform(train_data['text'])
X_test = tfidf_vectorizer.transform(test_data['text'])

# Option 3: Using Word2Vec (new approach)

# from gensim.models import Word2Vec
# def preprocess_word2vec(corpus):
#     return [sentence.split() for sentence in corpus]

# # Train Word2Vec on the training corpus
# word2vec_model = Word2Vec(sentences=preprocess_word2vec(train_data['text']),␣
↪vector_size=100, window=5, min_count=2, workers=4)

# def get_word2vec_embedding(text):
#     words = text.split()
#     vectors = [word2vec_model.wv[word] for word in words if word in␣
↪word2vec_model.wv]
#     if len(vectors) > 0:
#         return np.mean(vectors, axis=0)
#     else:
#         return np.zeros(word2vec_model.vector_size)

# # Transform the training and testing datasets into Word2Vec embeddings
# X_train = np.array([get_word2vec_embedding(text) for text in␣
↪train_data['text']])
# X_test = np.array([get_word2vec_embedding(text) for text in␣
↪test_data['text']])

# Choose targets for Valence, Arousal, and Dominance
v_train, v_test = train_data['V'], test_data['V']
a_train, a_test = train_data['A'], test_data['A']
d_train, d_test = train_data['D'], test_data['D']
```

[9]:
```
sns.histplot(data['V'], kde=True).set_title('Distribution of Valence')
plt.show()

sns.histplot(data['A'], kde=True).set_title('Distribution of Arousal')
plt.show()
```

```
sns.histplot(data['D'], kde=True).set_title('Distribution of Dominance')
plt.show()
```




Distribution of Arousal
Count
A
2000
1750
1500
1250
1000
750
500
250
0
2.0
2.5
3.0
3.5
4.0
4.5



5 Step 5: Build Models

6 5.1 Ridge

[10]:
```
model_v = Ridge(alpha=1.0)
model_v.fit(X_train, v_train)

model_a = Ridge(alpha=1.0)
model_a.fit(X_train, a_train)

model_d = Ridge(alpha=1.0)
model_d.fit(X_train, d_train)

ridge_model = (model_v, model_a, model_d)
```

6.1 5.2 Random Forest

[11]:
```
model_v = RandomForestRegressor(n_estimators=100, random_state=42)
model_v.fit(X_train, v_train)

model_a = RandomForestRegressor(n_estimators=100, random_state=42)
model_a.fit(X_train, a_train)

model_d = RandomForestRegressor(n_estimators=100, random_state=42)
model_d.fit(X_train, d_train)

rf_model = (model_v, model_a, model_d)
```

6.2 5.3 Neural Network Regression

[12]:
```
model_v = MLPRegressor(hidden_layer_sizes=(50, 30), activation='relu',␣
 ↪solver='adam', random_state=42, max_iter=500)
model_v.fit(X_train, v_train)

model_a = MLPRegressor(hidden_layer_sizes=(50, 30), activation='relu',␣
 ↪solver='adam', random_state=42, max_iter=500)
model_a.fit(X_train, a_train)

model_d = MLPRegressor(hidden_layer_sizes=(50, 30), activation='relu',␣
 ↪solver='adam', random_state=42, max_iter=500)
model_d.fit(X_train, d_train)

mlp_model = (model_v, model_a, model_d)
```

[13]:
```
models = [ridge_model, rf_model, mlp_model]
# models = [ridge_model]
```

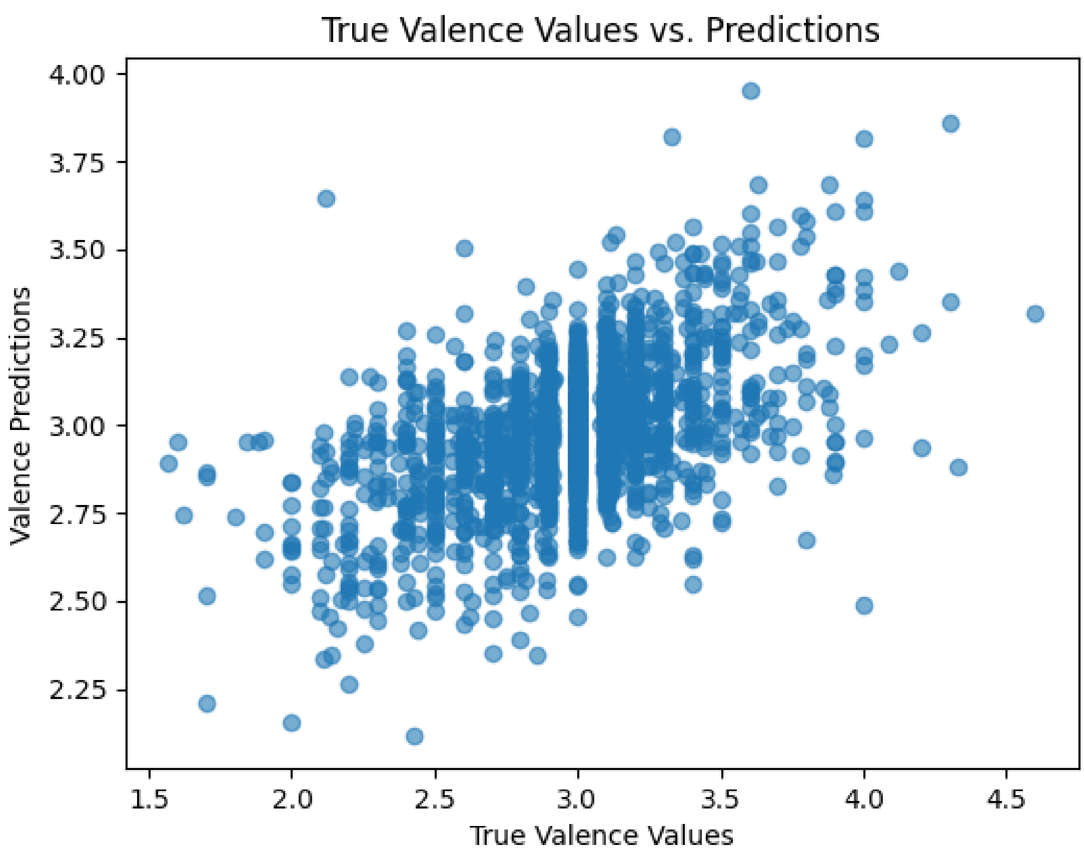
7 Step 6: Evaluate the Models

[14]:
```
from mpl_toolkits.mplot3d import Axes3D

for model in models:
    print(f"For model:", model)
    (model_v, model_a, model_d) = model

    v_pred = model_v.predict(X_test)

    # Calculate Mean Squared Error (MSE)
    mse = mean_squared_error(v_test, v_pred)
    print("Mean Squared Error:", mse)
```

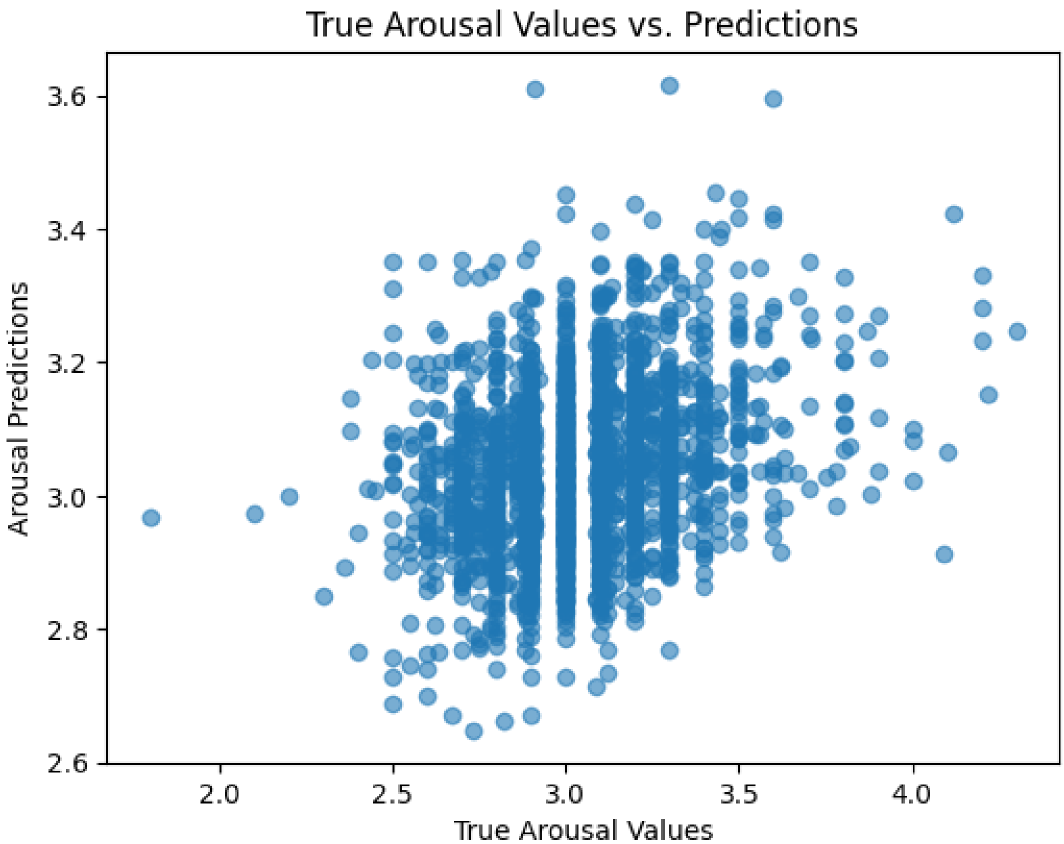
```python
    # Visualize predictions vs. true values
    plt.scatter(v_test, v_pred, alpha=0.6)
    plt.xlabel("True Valence Values")
    plt.ylabel("Valence Predictions")
    plt.title("True Valence Values vs. Predictions")
    plt.show()

    a_pred = model_a.predict(X_test)

    # Calculate Mean Squared Error (MSE)
    mse = mean_squared_error(a_test, a_pred)
    print("Mean Squared Error:", mse)

    # Visualize predictions vs. true values
    plt.scatter(a_test, a_pred, alpha=0.6)
    plt.xlabel("True Arousal Values")
    plt.ylabel("Arousal Predictions")
    plt.title("True Arousal Values vs. Predictions")
    plt.show()

    d_pred = model_d.predict(X_test)

    # Calculate Mean Squared Error (MSE)
    mse = mean_squared_error(d_test, d_pred)
    print("Mean Squared Error:", mse)

    # Visualize predictions vs. true values
    plt.scatter(d_test, d_pred, alpha=0.6)
    plt.xlabel("True Dominance Values")
    plt.ylabel("Dominance Predictions")
    plt.title("True Dominance Values vs. Predictions")
    plt.show()

    # Create a figure for 3D plot
    fig = plt.figure(figsize=(10, 7))
    ax = fig.add_subplot(111, projection='3d')

    # Scatter true VAD values (from the test set)
    ax.scatter(v_test, a_test, d_test, color='blue', label='Actual VAD',␣
↪alpha=0.125)

    # Scatter predicted VAD values
    ax.scatter(v_pred, a_pred, d_pred, color='red', label='Predicted VAD',␣
↪alpha=0.325)

    # Set labels
    ax.set_xlabel('Valence (V)')
```

```
    ax.set_ylabel('Arousal (A)')
    ax.set_zlabel('Dominance (D)')
    ax.set_title('3D Scatter Plot of Predicted vs. Actual VAD')

    # Add a legend
    ax.legend()

    # Show the plot
    plt.show()
```

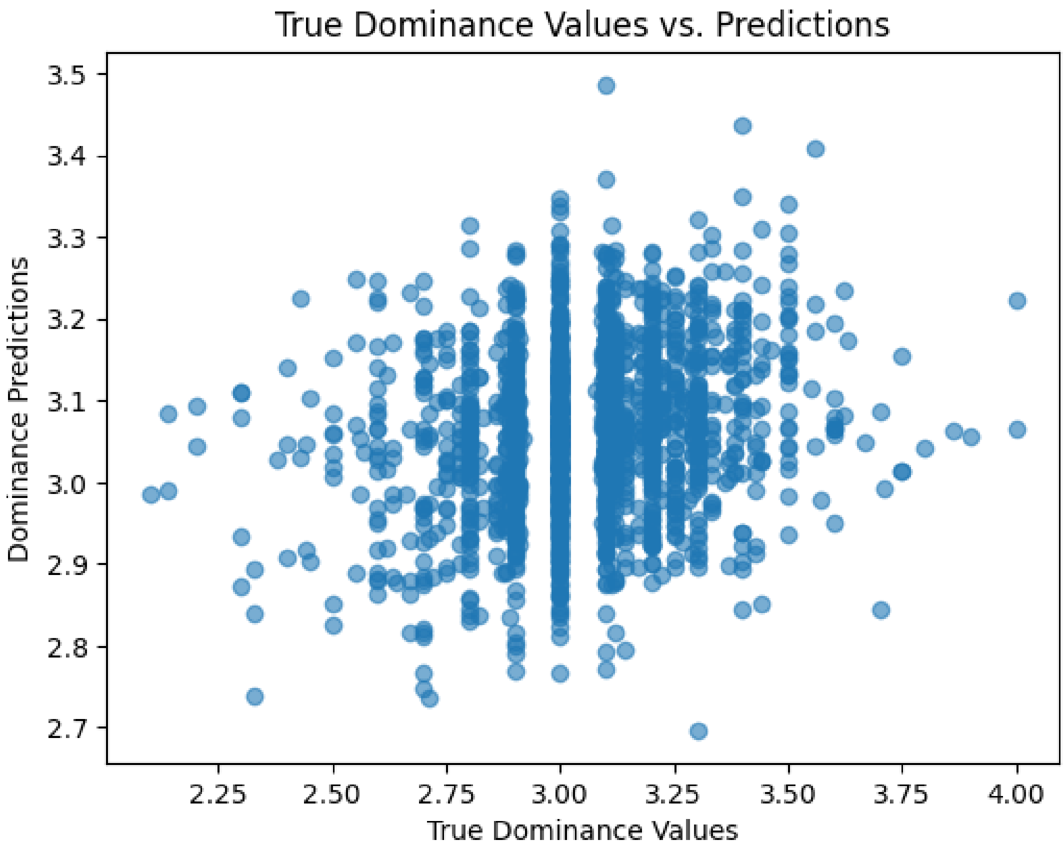
```
For model: (Ridge(), Ridge(), Ridge())
Mean Squared Error: 0.09026898665441754
```

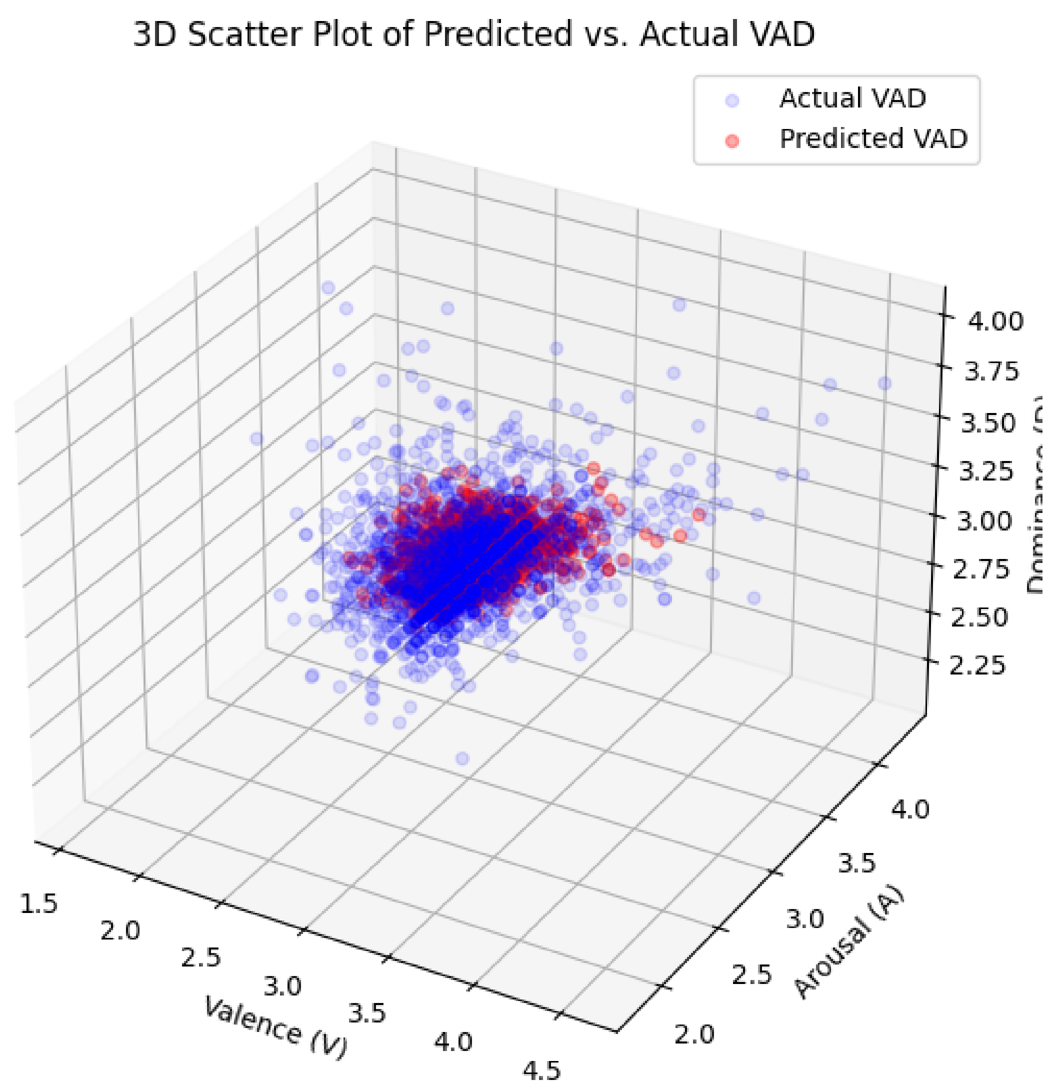



```
Mean Squared Error: 0.06376343645313226
```

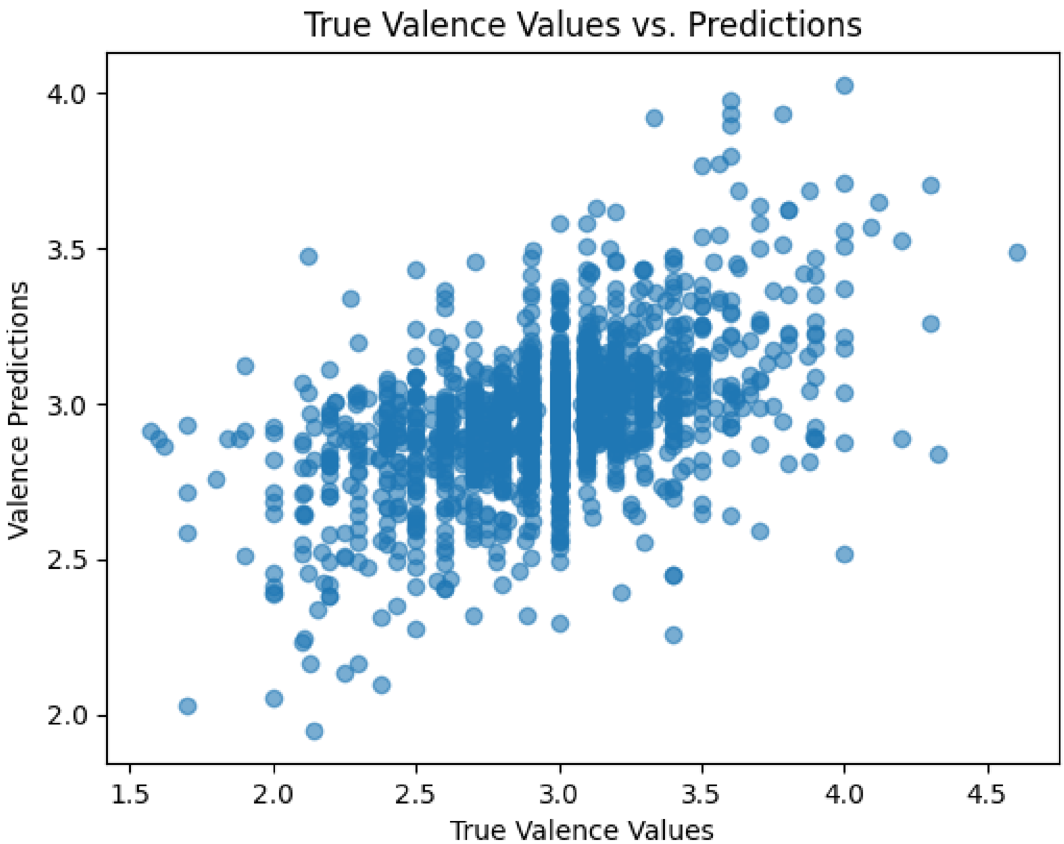


Mean Squared Error: 0.045870274582342704

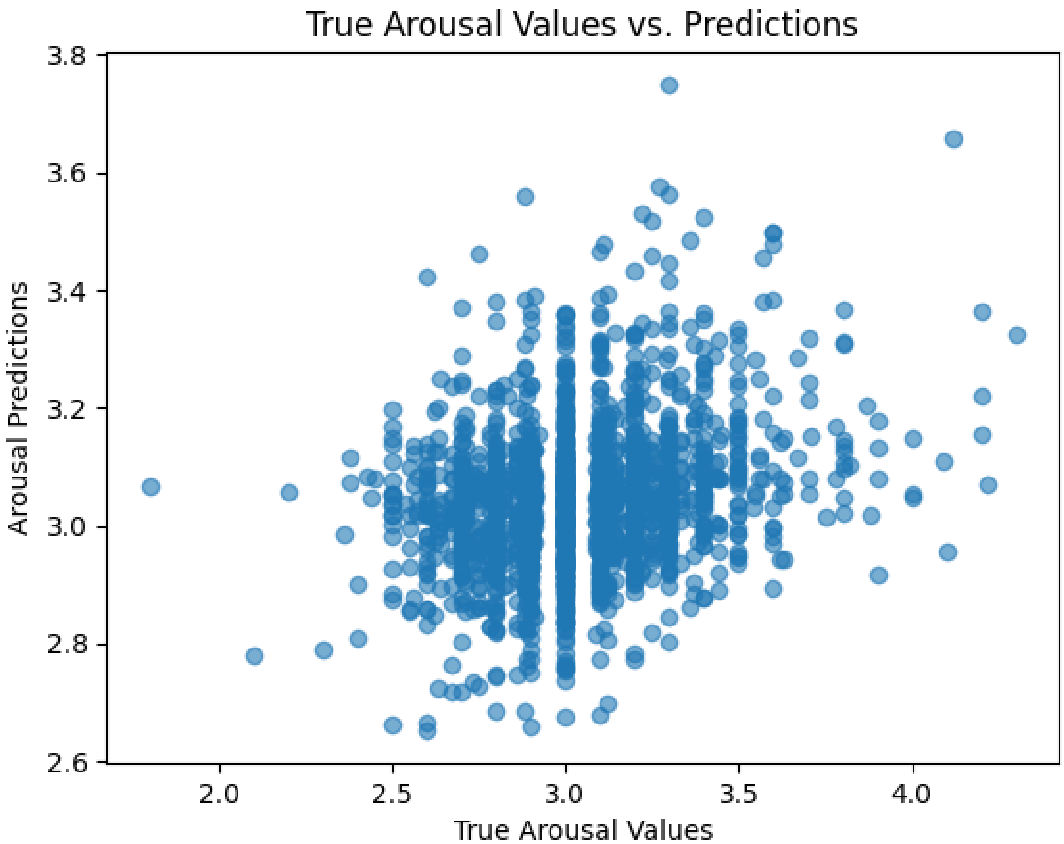

True Dominance Values vs. Predictions
Dominance Predictions
True Dominance Values
3.5
3.4
3.3
3.2
3.1
3.0
2.9
2.8
2.7
2.25
2.50
2.75
3.00
3.25
3.50
3.75
4.00



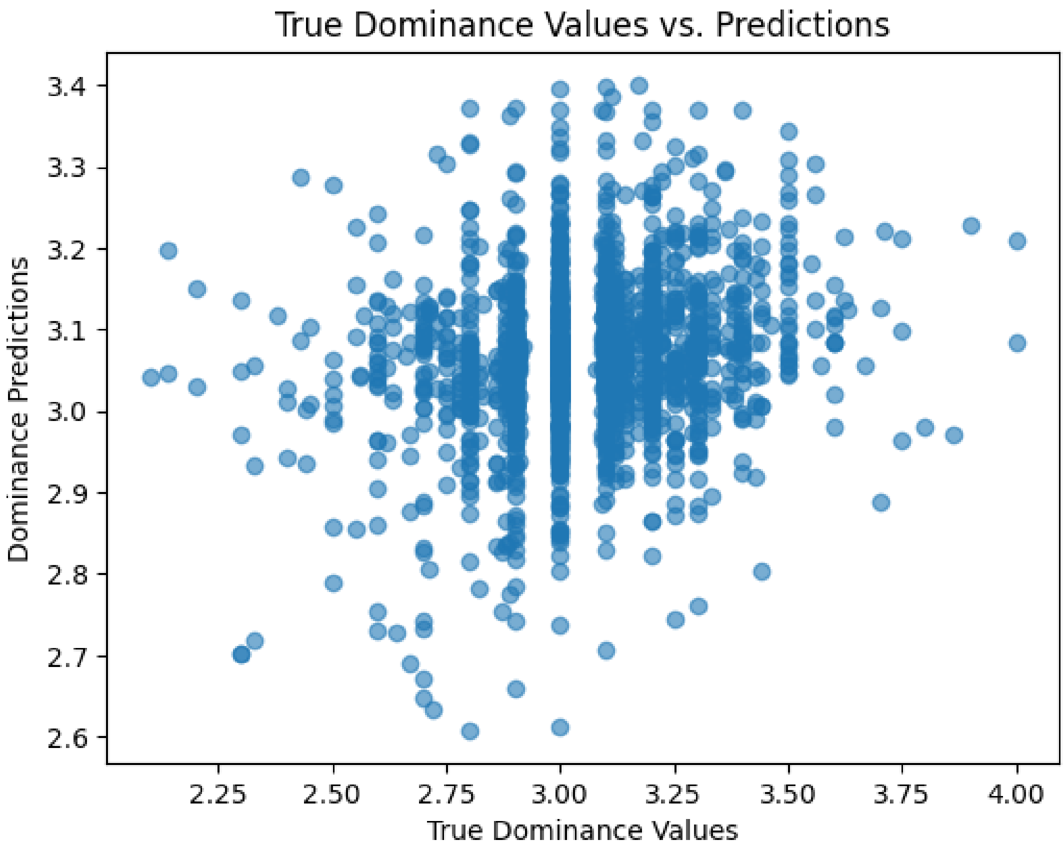

```
For model: (RandomForestRegressor(random_state=42),
RandomForestRegressor(random_state=42), RandomForestRegressor(random_state=42))
Mean Squared Error: 0.09408549925337421
```

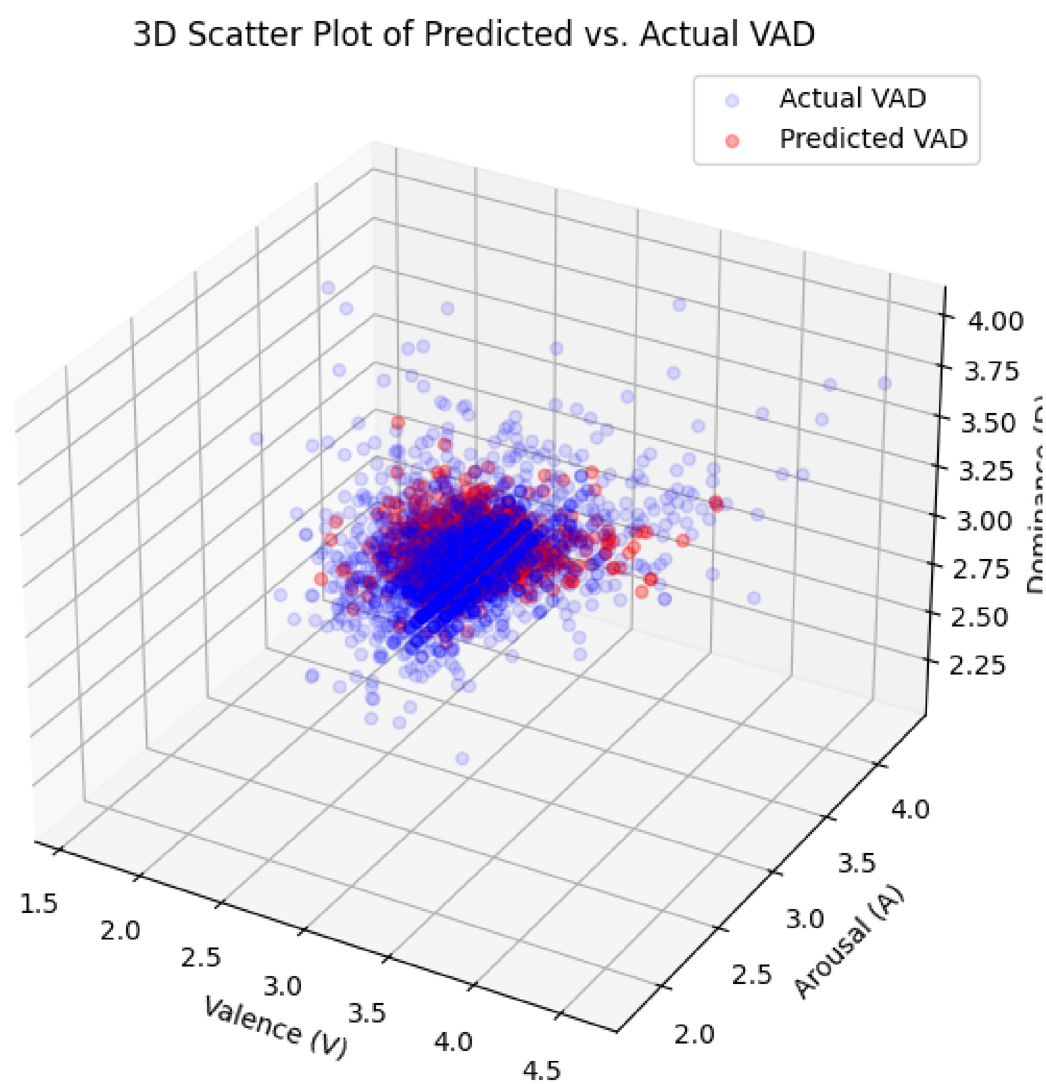



```
Mean Squared Error: 0.06432927849038828
```

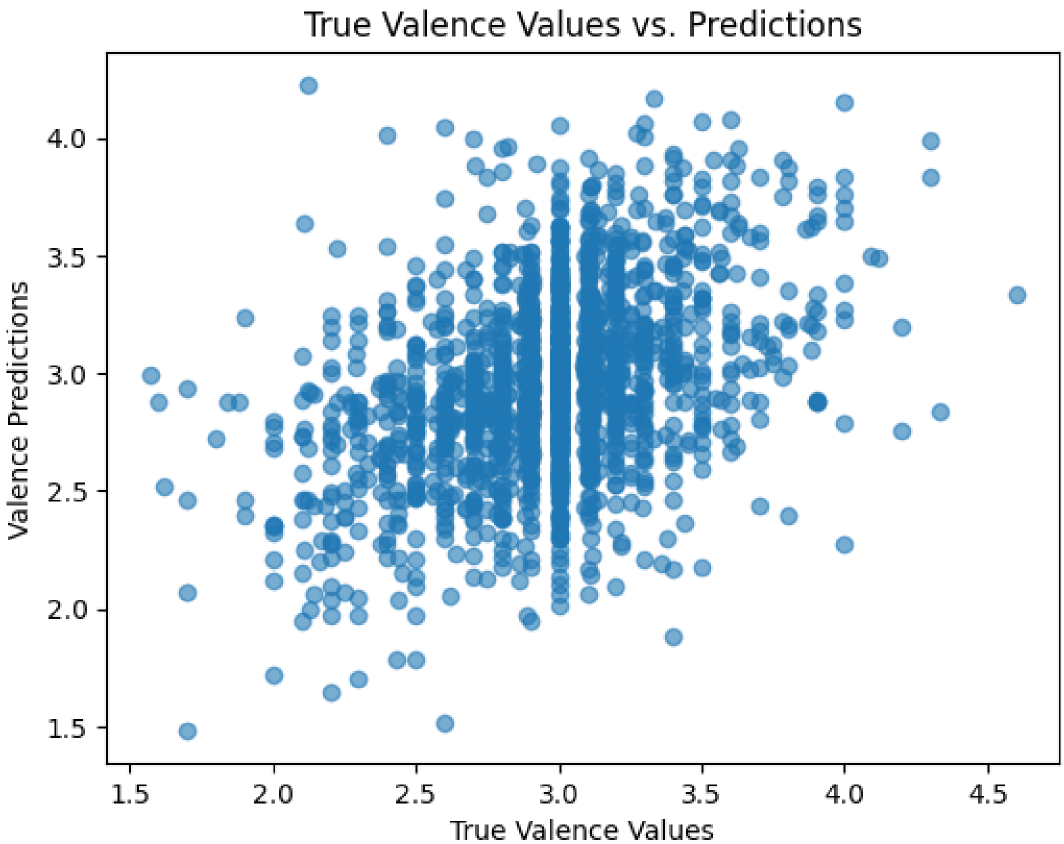


Mean Squared Error: 0.04517407402580452

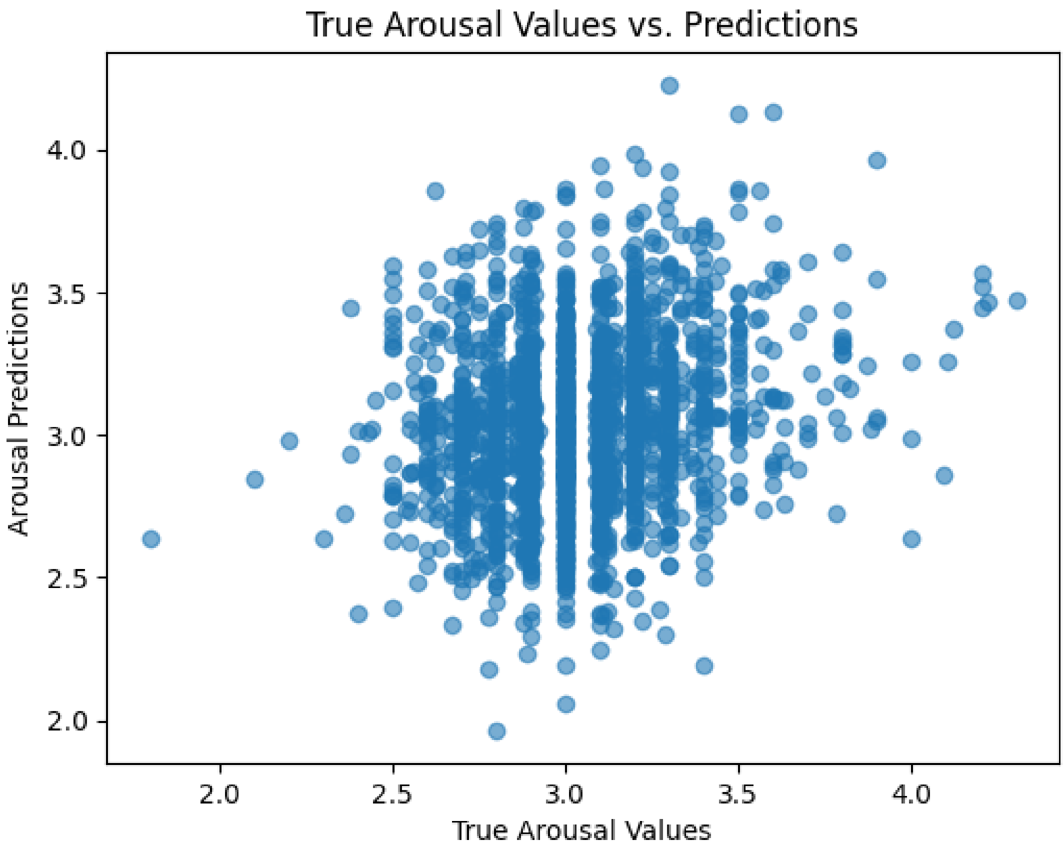

True Dominance Values vs. Predictions
Dominance Predictions
True Dominance Values
3.4
3.3
3.2
3.1
3.0
2.9
2.8
2.7
2.6
2.25
2.50
2.75
3.00
3.25
3.50
3.75
4.00



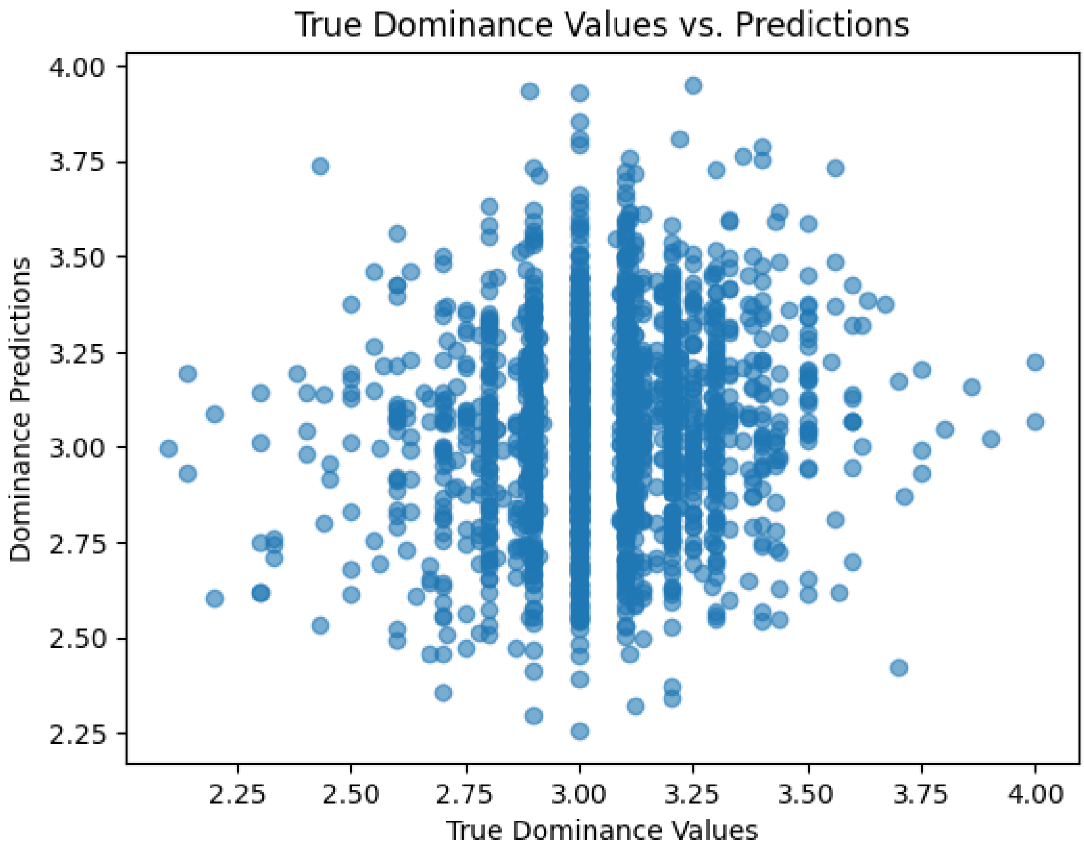

```
For model: (MLPRegressor(hidden_layer_sizes=(50, 30), max_iter=500,
random_state=42), MLPRegressor(hidden_layer_sizes=(50, 30), max_iter=500,
random_state=42), MLPRegressor(hidden_layer_sizes=(50, 30), max_iter=500,
random_state=42))
Mean Squared Error: 0.15841422693210777
```

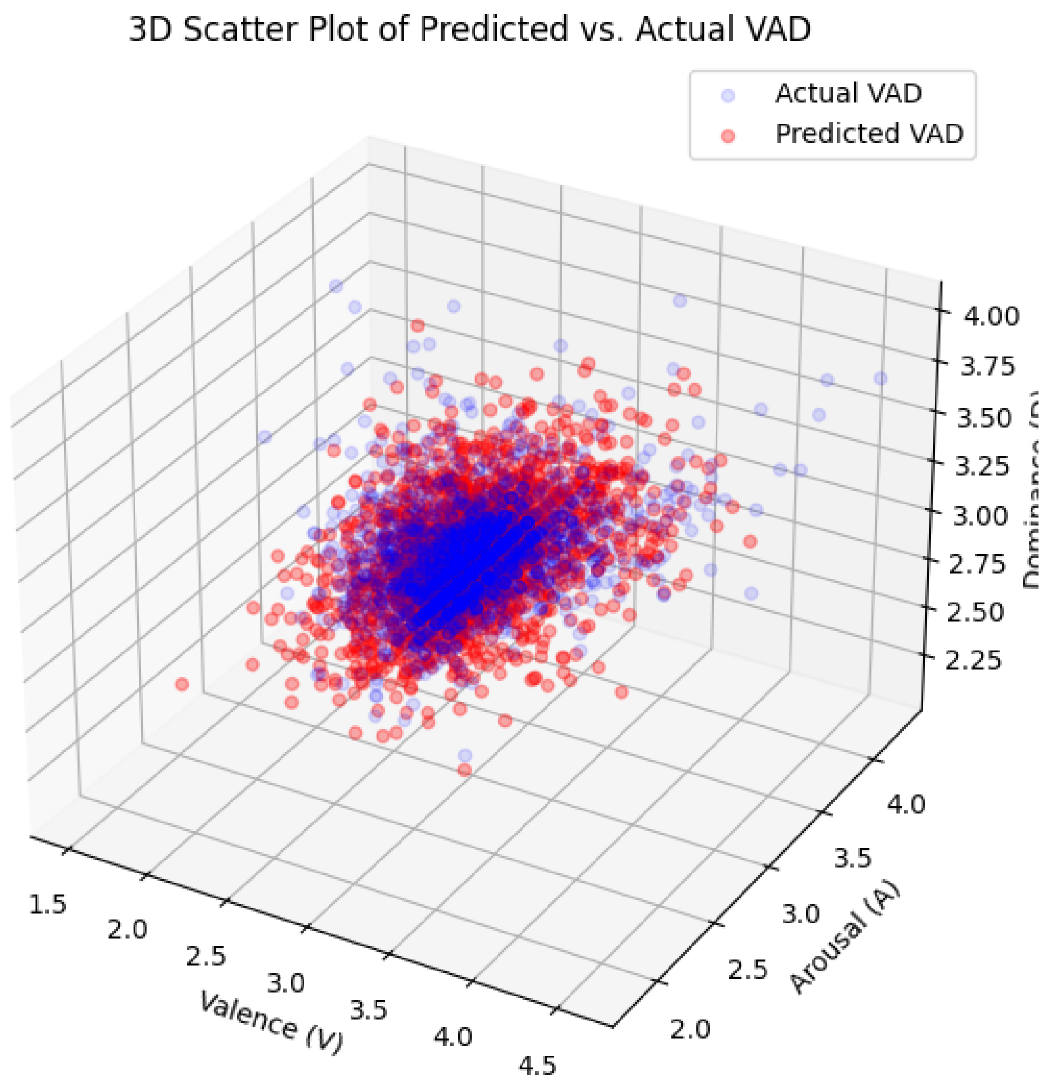



```
Mean Squared Error: 0.1201529828397856
```




```
Mean Squared Error: 0.09289542334051358
```


True Dominance Values vs. Predictions
Dominance Predictions
True Dominance Values
4.00
3.75
3.50
3.25
3.00
2.75
2.50
2.25
2.25
2.50
2.75
3.00
3.25
3.50
3.75
4.00



[ ]:
```
# To Do: Plot R-Squared, MSE, and MAE
```

8 Step7: Making Predictions

[15]:
```
def predict(message, model):
    (model_v, model_a, model_d) = model
    v = model_v.predict(message)
    a = model_a.predict(message)
    d = model_d.predict(message)
    return v, a, d
```

```
[16]: # Get a few sample texts from the test data for prediction
sampled_data = test_data.sample(10)
messages = sampled_data['text'].values

# --- Handling specific instances ---

# If using LDA:
# input_message = lda.transform(count_vectorizer.transform(messages))

# If using TF-IDF:
input_message = tfidf_vectorizer.transform(messages)

# If using Word2Vec:
# input_message = np.array([get_word2vec_embedding(text) for text in messages])


for model in models:
    print(f"For model:", model)
    (model_v, model_a, model_d) = model

    # Get predictions for the new messages
    v_pred, a_pred, d_pred = predict(input_message, model)

    # Display results for each message
    for i, msg in enumerate(messages):
        print(f"Message: {msg}")
        print(f"Predicted Valence: {v_pred[i]:.2f}, Arousal: {a_pred[i]:.2f},␣
↪Dominance: {d_pred[i]:.2f}")
        print(f"Actual Valence: {sampled_data['V'].values[i]:.2f}, Arousal:␣
↪{sampled_data['A'].values[i]:.2f}, Dominance: {sampled_data['D'].values[i]:.
↪2f}\n")

    # Create a 3D plot
    fig = plt.figure(figsize=(10, 7))
    ax = fig.add_subplot(111, projection='3d')

    # Actual VAD values for the 5 sampled messages
    v_actual = sampled_data['V'].values
    a_actual = sampled_data['A'].values
    d_actual = sampled_data['D'].values

    # Scatter actual values
    ax.scatter(v_actual, a_actual, d_actual, color='blue', label='Actual VAD',␣
↪alpha=0.6, s=100)

    # Scatter predicted values
```

```python
    ax.scatter(v_pred, a_pred, d_pred, color='red', label='Predicted VAD',␣
↪alpha=0.6, s=100)

    # Set labels and title
    ax.set_xlabel('Valence (V)')
    ax.set_ylabel('Arousal (A)')
    ax.set_zlabel('Dominance (D)')
    ax.set_title('3D Scatter Plot of Predicted vs. Actual VAD for Sampled␣
↪Messages')

    # Add a legend
    ax.legend()

    # Show the plot
    plt.show()
```

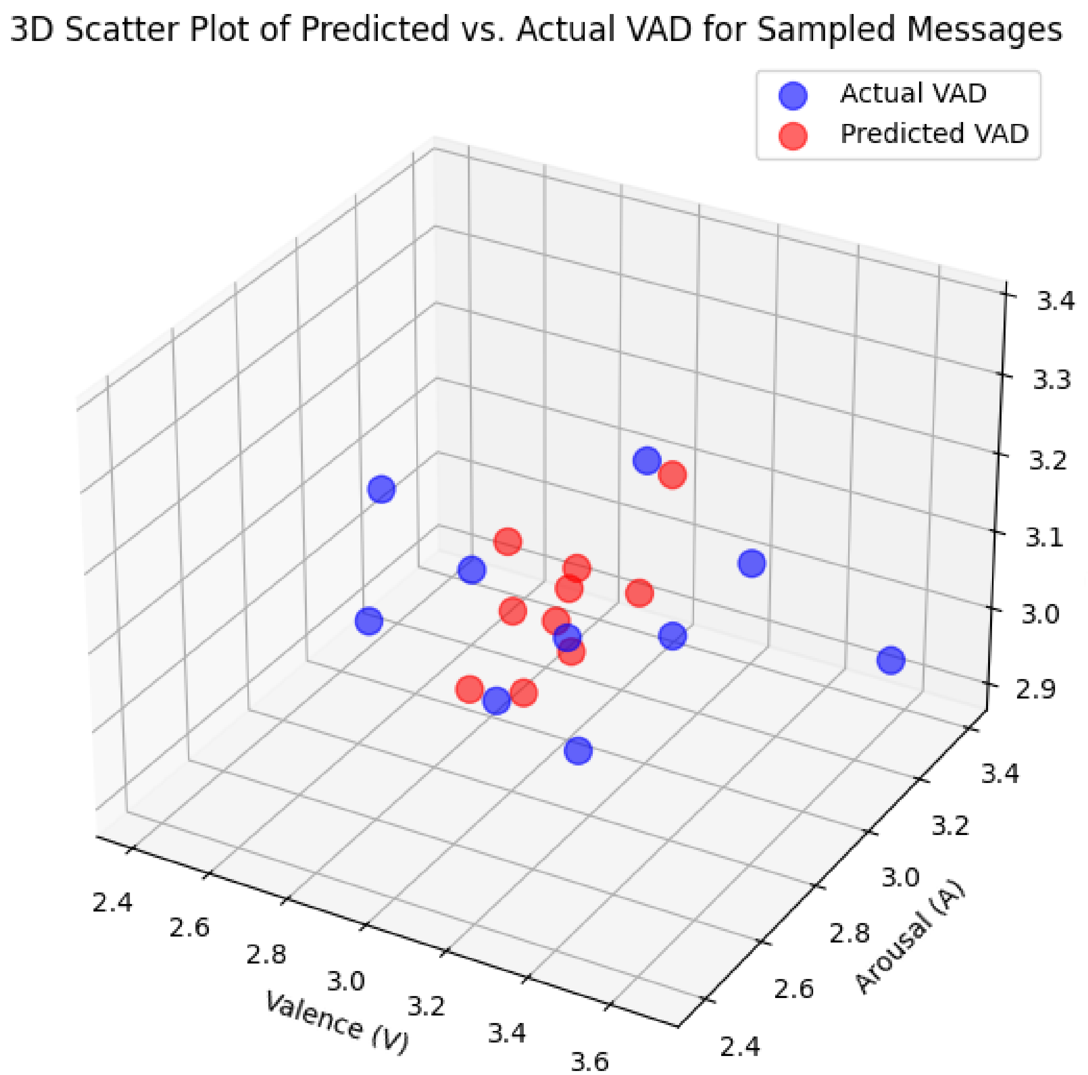
```
For model: (Ridge(), Ridge(), Ridge())
Message: Body Shop's Roddick has Hepatitis C
Predicted Valence: 2.76, Arousal: 3.11, Dominance: 3.06
Actual Valence: 2.40, Arousal: 3.10, Dominance: 2.90

Message: Minaya obtained Floyd from the Florida Marlins on July 11, only two
weeks after he stunned baseball by acquiring Bartolo Colon from Cleveland.
Predicted Valence: 2.76, Arousal: 2.98, Dominance: 2.90
Actual Valence: 3.00, Arousal: 3.00, Dominance: 3.00

Message: Midden seems to be marked in some olfactory way, since removing midden
from nests makes them more likely to be invaded by other species (Gordon, 35).
Predicted Valence: 3.03, Arousal: 3.00, Dominance: 3.09
Actual Valence: 2.82, Arousal: 2.91, Dominance: 3.09

Message: We took his rental car back to the motel where he was staying.
Predicted Valence: 2.91, Arousal: 2.93, Dominance: 3.04
Actual Valence: 3.00, Arousal: 2.75, Dominance: 3.00

Message: Until thirty seconds ago, I didn’t believe in magic or any of that kind
of …weirdness."
Predicted Valence: 2.93, Arousal: 3.05, Dominance: 3.00
Actual Valence: 3.20, Arousal: 3.40, Dominance: 3.00

Message: Mother: Lohan is doing 'great' in rehab
Predicted Valence: 3.04, Arousal: 3.20, Dominance: 3.00
Actual Valence: 3.67, Arousal: 3.22, Dominance: 3.00

Message: It is the intent of this language to make clear the congressional
support for the holding in Granholm-prohibiting state laws that allow an in-
state winery to do something a similarly situated out-of-state winery cannot do.
```

Language that bars facial discrimination is included in the bill to codify this prohibition"
Predicted Valence: 3.03, Arousal: 2.98, Dominance: 2.99
Actual Valence: 3.10, Arousal: 2.90, Dominance: 2.90

Message: The savings are counted in more ways than dollars and cents, however.
Predicted Valence: 3.16, Arousal: 3.15, Dominance: 3.19
Actual Valence: 3.00, Arousal: 2.38, Dominance: 3.38

Message: In an effort to provide yet one more thing to bet on, players are imported from Spain to take part in this lightning-fast Basque ball game.
Predicted Valence: 2.97, Arousal: 3.06, Dominance: 3.04
Actual Valence: 3.00, Arousal: 3.29, Dominance: 3.14

Message: Photography took over as a means of portraiture for the bourgeois and the upper class and despite the fact that it was possible to color the photographs, for the most part they were left in black and white because it was seen as more "natural".
Predicted Valence: 2.97, Arousal: 2.89, Dominance: 2.96
Actual Valence: 3.20, Arousal: 3.10, Dominance: 3.00



For model: (RandomForestRegressor(random_state=42),
RandomForestRegressor(random_state=42), RandomForestRegressor(random_state=42))
Message: Body Shop's Roddick has Hepatitis C
Predicted Valence: 2.75, Arousal: 3.22, Dominance: 2.99
Actual Valence: 2.40, Arousal: 3.10, Dominance: 2.90

Message: Minaya obtained Floyd from the Florida Marlins on July 11, only two
weeks after he stunned baseball by acquiring Bartolo Colon from Cleveland.
Predicted Valence: 2.85, Arousal: 3.08, Dominance: 2.98
Actual Valence: 3.00, Arousal: 3.00, Dominance: 3.00

Message: Midden seems to be marked in some olfactory way, since removing midden
from nests makes them more likely to be invaded by other species (Gordon, 35).

Predicted Valence: 3.03, Arousal: 3.02, Dominance: 3.11
Actual Valence: 2.82, Arousal: 2.91, Dominance: 3.09

Message: We took his rental car back to the motel where he was staying.
Predicted Valence: 2.77, Arousal: 3.04, Dominance: 3.05
Actual Valence: 3.00, Arousal: 2.75, Dominance: 3.00

Message: Until thirty seconds ago, I didn't believe in magic or any of that kind of …weirdness."
Predicted Valence: 2.77, Arousal: 2.99, Dominance: 3.08
Actual Valence: 3.20, Arousal: 3.40, Dominance: 3.00

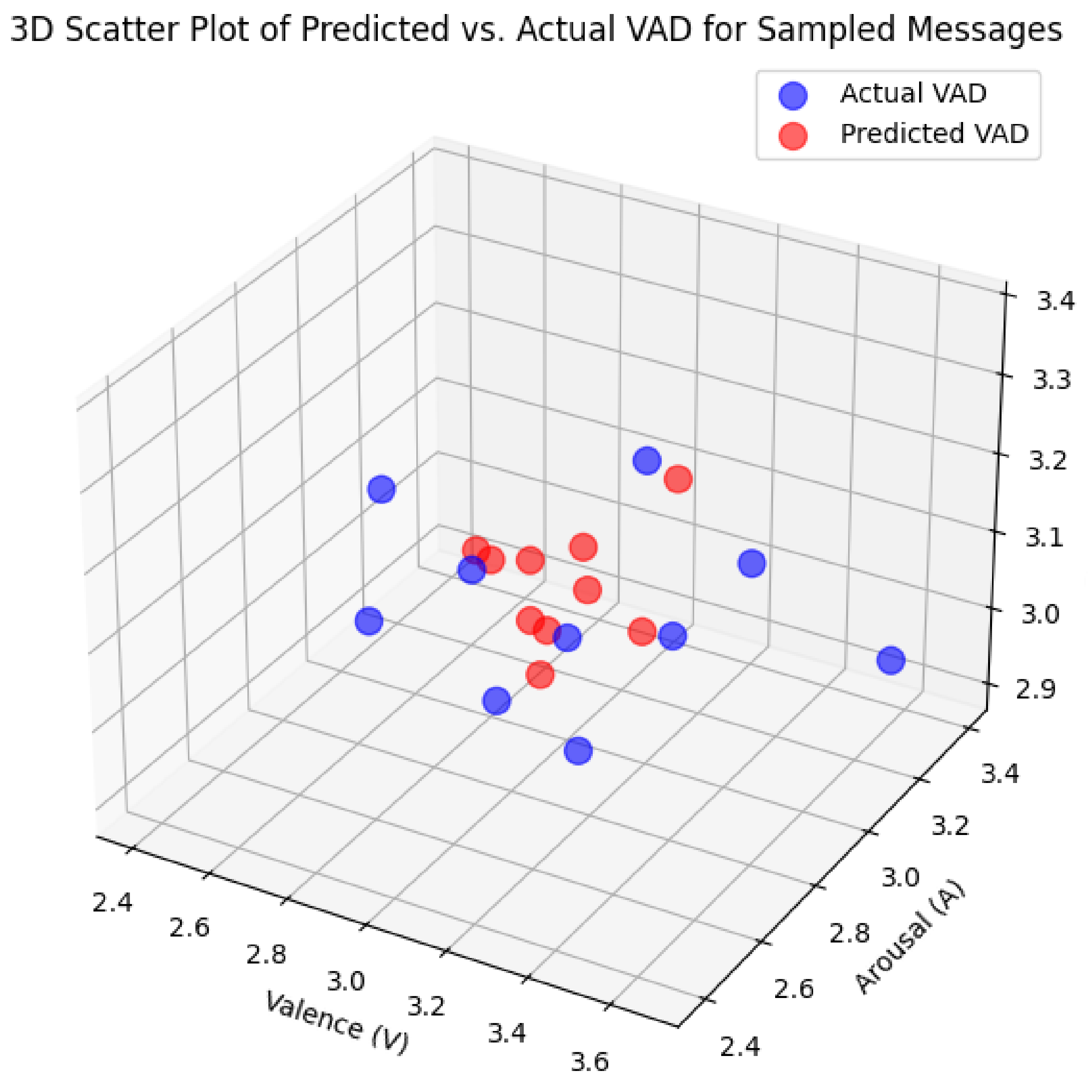
Message: Mother: Lohan is doing 'great' in rehab
Predicted Valence: 3.09, Arousal: 3.14, Dominance: 2.98
Actual Valence: 3.67, Arousal: 3.22, Dominance: 3.00

Message: It is the intent of this language to make clear the congressional support for the holding in Granholm-prohibiting state laws that allow an in-state winery to do something a similarly situated out-of-state winery cannot do. Language that bars facial discrimination is included in the bill to codify this prohibition"
Predicted Valence: 3.04, Arousal: 3.02, Dominance: 3.06
Actual Valence: 3.10, Arousal: 2.90, Dominance: 2.90

Message: The savings are counted in more ways than dollars and cents, however.
Predicted Valence: 3.20, Arousal: 3.12, Dominance: 3.20
Actual Valence: 3.00, Arousal: 2.38, Dominance: 3.38

Message: In an effort to provide yet one more thing to bet on, players are imported from Spain to take part in this lightning-fast Basque ball game.
Predicted Valence: 2.95, Arousal: 2.97, Dominance: 2.95
Actual Valence: 3.00, Arousal: 3.29, Dominance: 3.14

Message: Photography took over as a means of portraiture for the bourgeois and the upper class and despite the fact that it was possible to color the photographs, for the most part they were left in black and white because it was seen as more "natural".
Predicted Valence: 3.01, Arousal: 2.91, Dominance: 3.04
Actual Valence: 3.20, Arousal: 3.10, Dominance: 3.00




```
For model: (MLPRegressor(hidden_layer_sizes=(50, 30), max_iter=500,
random_state=42), MLPRegressor(hidden_layer_sizes=(50, 30), max_iter=500,
random_state=42), MLPRegressor(hidden_layer_sizes=(50, 30), max_iter=500,
random_state=42))
Message: Body Shop's Roddick has Hepatitis C
Predicted Valence: 2.70, Arousal: 3.21, Dominance: 3.07
Actual Valence: 2.40, Arousal: 3.10, Dominance: 2.90

Message: Minaya obtained Floyd from the Florida Marlins on July 11, only two
weeks after he stunned baseball by acquiring Bartolo Colon from Cleveland.
Predicted Valence: 2.06, Arousal: 2.72, Dominance: 2.26
Actual Valence: 3.00, Arousal: 3.00, Dominance: 3.00
```

Message: Midden seems to be marked in some olfactory way, since removing midden from nests makes them more likely to be invaded by other species (Gordon, 35).
Predicted Valence: 2.91, Arousal: 2.97, Dominance: 2.81
Actual Valence: 2.82, Arousal: 2.91, Dominance: 3.09

Message: We took his rental car back to the motel where he was staying.
Predicted Valence: 2.89, Arousal: 2.78, Dominance: 2.96
Actual Valence: 3.00, Arousal: 2.75, Dominance: 3.00

Message: Until thirty seconds ago, I didn't believe in magic or any of that kind of …weirdness."
Predicted Valence: 2.93, Arousal: 3.19, Dominance: 3.09
Actual Valence: 3.20, Arousal: 3.40, Dominance: 3.00

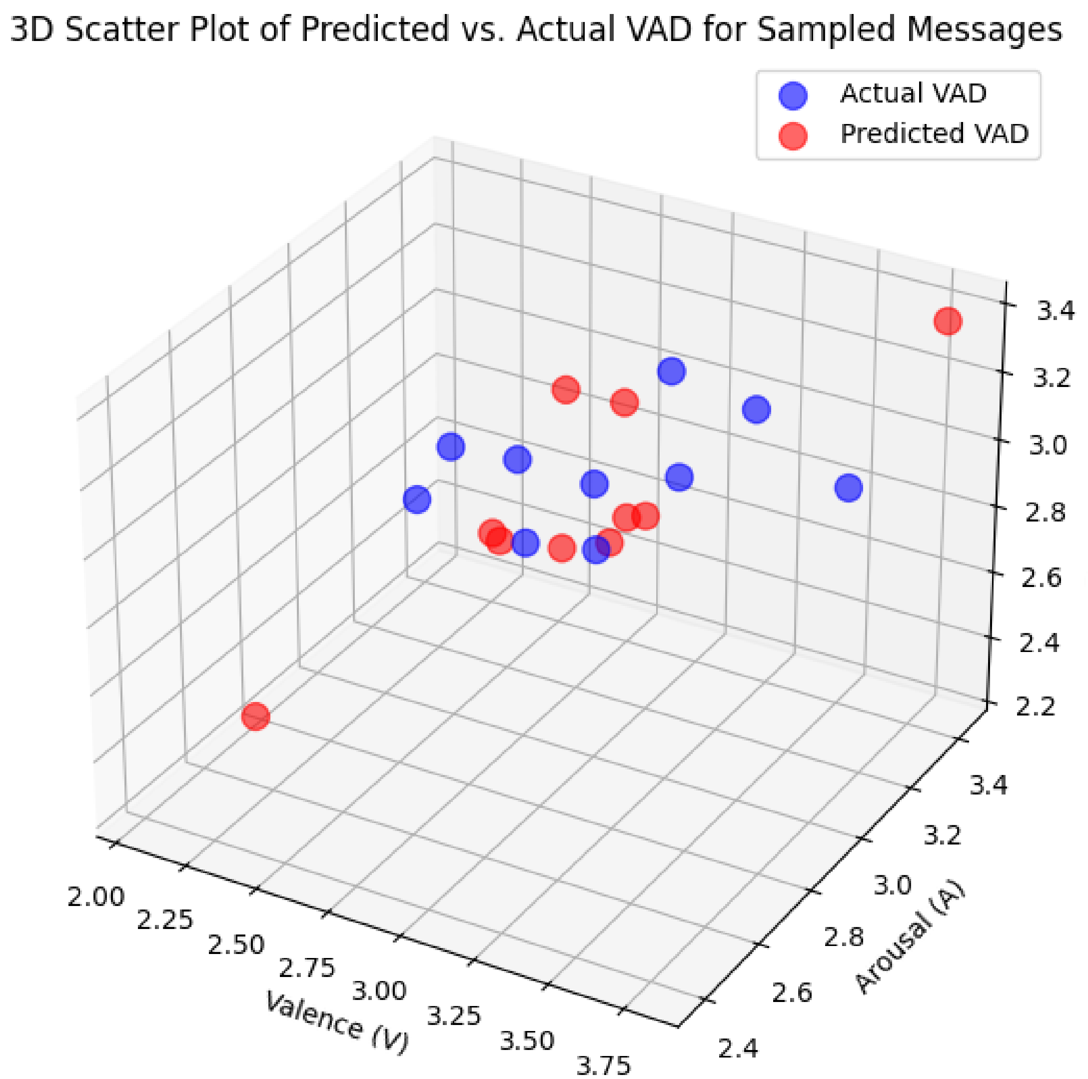
Message: Mother: Lohan is doing 'great' in rehab
Predicted Valence: 3.01, Arousal: 3.11, Dominance: 2.83
Actual Valence: 3.67, Arousal: 3.22, Dominance: 3.00

Message: It is the intent of this language to make clear the congressional support for the holding in Granholm-prohibiting state laws that allow an in-state winery to do something a similarly situated out-of-state winery cannot do. Language that bars facial discrimination is included in the bill to codify this prohibition"
Predicted Valence: 3.21, Arousal: 2.97, Dominance: 2.98
Actual Valence: 3.10, Arousal: 2.90, Dominance: 2.90

Message: The savings are counted in more ways than dollars and cents, however.
Predicted Valence: 3.80, Arousal: 3.44, Dominance: 3.37
Actual Valence: 3.00, Arousal: 2.38, Dominance: 3.38

Message: In an effort to provide yet one more thing to bet on, players are imported from Spain to take part in this lightning-fast Basque ball game.
Predicted Valence: 2.86, Arousal: 2.78, Dominance: 2.97
Actual Valence: 3.00, Arousal: 3.29, Dominance: 3.14

Message: Photography took over as a means of portraiture for the bourgeois and the upper class and despite the fact that it was possible to color the photographs, for the most part they were left in black and white because it was seen as more "natural".
Predicted Valence: 3.08, Arousal: 2.97, Dominance: 2.87
Actual Valence: 3.20, Arousal: 3.10, Dominance: 3.00



9 Step8: Infering Emotions

9.1 (Merhabian VAD)

[17]:
```
def normalize_vad(v, a, d):
    """Normalize VAD values from EmoBank's 1-5 scale to -1 to 1 scale"""
    return (v - 3) / 2, (a - 3) / 2, (d - 3) / 2

emotion_coords = {
    'joy': (0.76, 0.48, 0.35),
    'anger': (-0.51, 0.59, 0.25),
    'fear': (-0.64, 0.60, -0.43),
```

```
    'sadness': (-0.63, -0.27, -0.33),
    'surprise': (0.40, 0.67, -0.13),
    'disgust': (-0.60, 0.35, 0.11),
    'contentment': (0.82, -0.18, 0.21),
    'boredom': (-0.65, -0.62, -0.33),
    'acceptance': (0.46, -0.09, -0.19)
}

def infer_emotion_mehrabian(v, a, d):
    v_norm, a_norm, d_norm = normalize_vad(v, a, d)
    vad = np.array([v_norm, a_norm, d_norm])

    distances = {emotion: np.linalg.norm(vad - np.array(coords))
                 for emotion, coords in emotion_coords.items()}

    return min(distances, key=distances.get)

# Function to get the PAD values for a given emotion
def get_pad_values(emotion):
    if emotion in emotion_coords:
        return emotion_coords[emotion]
    else:
        return None

# Function to find the closest emotions given PAD values
def find_closest_emotions(v, a, d, n=3):
    v_norm, a_norm, d_norm = normalize_vad(v, a, d)
    vad = np.array([v_norm, a_norm, d_norm])

    distances = {emotion: np.linalg.norm(vad - np.array(coords))
                 for emotion, coords in emotion_coords.items()}

    sorted_emotions = sorted(distances.items(), key=lambda x: x[1])
    return [emotion for emotion, _ in sorted_emotions[:n]]
```

[18]:

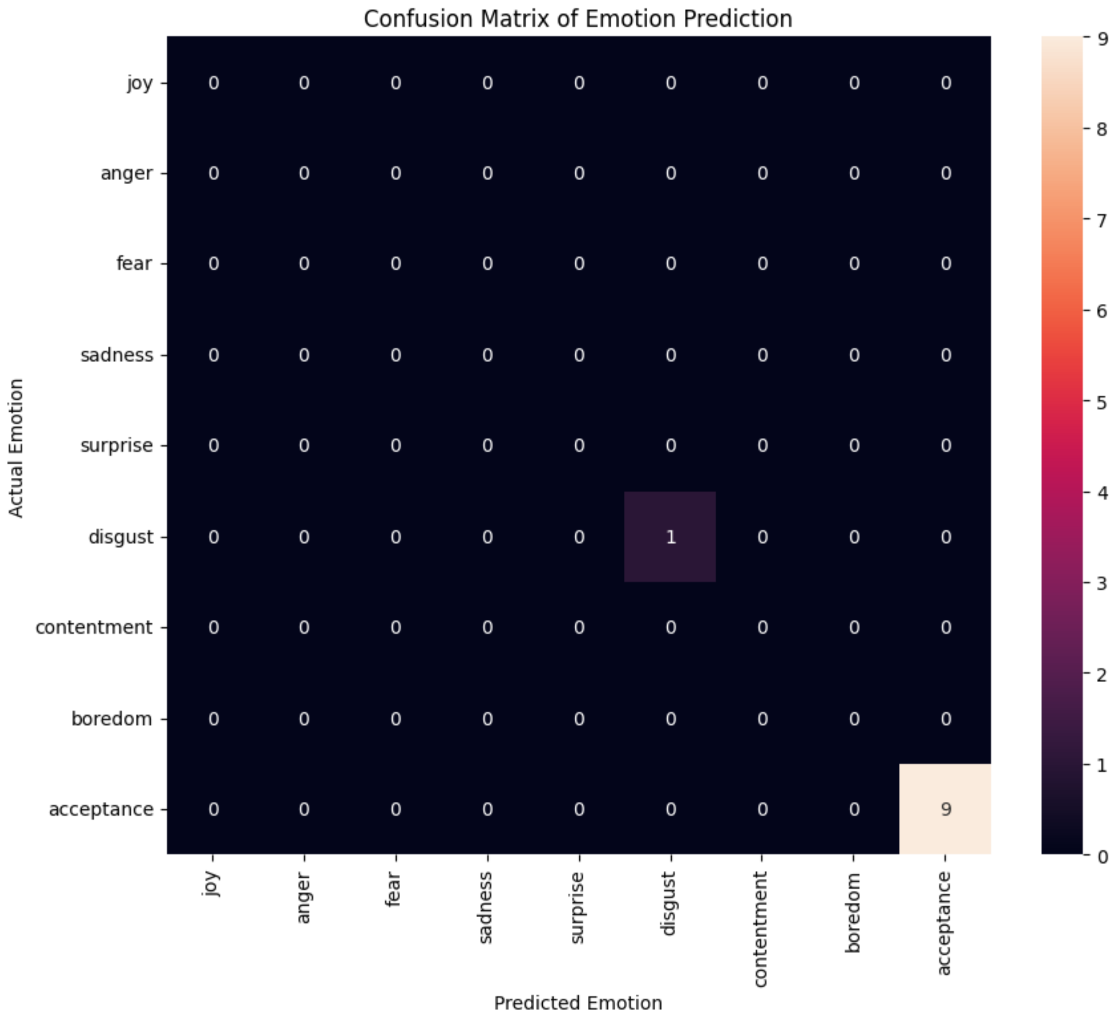
```
for model in models:
    v_pred, a_pred, d_pred = predict(input_message, model)

    # Create a DataFrame to store the results
    results = pd.DataFrame({
        'Message': sampled_data['text'].values,
        'Actual_V': sampled_data['V'].values,
        'Actual_A': sampled_data['A'].values,
        'Actual_D': sampled_data['D'].values,
        'Predicted_V': v_pred,
        'Predicted_A': a_pred,
        'Predicted_D': d_pred
```

```
    })

    # Infer emotions and find closest emotions for actual and predicted VAD␣
↪values
    results['Actual_Emotion'] = results.apply(lambda row:␣
↪infer_emotion_mehrabian(row['Actual_V'], row['Actual_A'], row['Actual_D']),␣
↪axis=1)
    results['Predicted_Emotion'] = results.apply(lambda row:␣
↪infer_emotion_mehrabian(row['Predicted_V'], row['Predicted_A'],␣
↪row['Predicted_D']), axis=1)
    results['Actual_Top3'] = results.apply(lambda row:␣
↪find_closest_emotions(row['Actual_V'], row['Actual_A'], row['Actual_D']),␣
↪axis=1)
    results['Predicted_Top3'] = results.apply(lambda row:␣
↪find_closest_emotions(row['Predicted_V'], row['Predicted_A'],␣
↪row['Predicted_D']), axis=1)

    # Display the results
    pd.set_option('display.max_colwidth', None)
    print(results[['Message', 'Actual_Emotion', 'Predicted_Emotion',␣
↪'Actual_Top3', 'Predicted_Top3']])

    # Calculate accuracy
    accuracy = (results['Actual_Emotion'] == results['Predicted_Emotion']).
↪mean()
    print(f"\nAccuracy of emotion prediction: {accuracy:.2%}")

    # Calculate top-3 accuracy
    top3_accuracy = results.apply(lambda row: row['Actual_Emotion'] in␣
↪row['Predicted_Top3'], axis=1).mean()
    print(f"Top-3 accuracy of emotion prediction: {top3_accuracy:.2%}")

    from sklearn.metrics import confusion_matrix

    cm = confusion_matrix(results['Actual_Emotion'],␣
↪results['Predicted_Emotion'], labels=list(emotion_coords.keys()))
    plt.figure(figsize=(10, 8))
    sns.heatmap(cm, annot=True, fmt='d', xticklabels=emotion_coords.keys(),␣
↪yticklabels=emotion_coords.keys())
    plt.title('Confusion Matrix of Emotion Prediction')
    plt.xlabel('Predicted Emotion')
    plt.ylabel('Actual Emotion')
    plt.show()
```

```
                                                              Message
\
0
```

```
Body Shop's Roddick has Hepatitis C
1
Minaya obtained Floyd from the Florida Marlins on July 11, only two weeks after
he stunned baseball by acquiring Bartolo Colon from Cleveland.
2
Midden seems to be marked in some olfactory way, since removing midden from
nests makes them more likely to be invaded by other species (Gordon, 35).
3
We took his rental car back to the motel where he was staying.
4
Until thirty seconds ago, I didn’t believe in magic or any of that kind of
…weirdness."
5
Mother: Lohan is doing 'great' in rehab
6  It is the intent of this language to make clear the congressional support for
the holding in Granholm-prohibiting state laws that allow an in-state winery to
do something a similarly situated out-of-state winery cannot do. Language that
bars facial discrimination is included in the bill to codify this prohibition"
7
The savings are counted in more ways than dollars and cents, however.
8
In an effort to provide yet one more thing to bet on, players are imported from
Spain to take part in this lightning-fast Basque ball game.
9
Photography took over as a means of portraiture for the bourgeois and the upper
class and despite the fact that it was possible to color the photographs, for
the most part they were left in black and white because it was seen as more
"natural".

  Actual_Emotion Predicted_Emotion                           Actual_Top3  \
0        disgust           disgust           [disgust, sadness, anger]
1     acceptance        acceptance       [acceptance, disgust, sadness]
2     acceptance        acceptance       [acceptance, disgust, sadness]
3     acceptance        acceptance       [acceptance, sadness, disgust]
4     acceptance        acceptance      [acceptance, surprise, disgust]
5     acceptance        acceptance  [acceptance, surprise, contentment]
6     acceptance        acceptance       [acceptance, sadness, disgust]
7     acceptance        acceptance   [acceptance, sadness, contentment]
8     acceptance        acceptance      [acceptance, disgust, surprise]
9     acceptance        acceptance      [acceptance, surprise, disgust]

                     Predicted_Top3
0     [disgust, acceptance, anger]
1   [acceptance, disgust, sadness]
2   [acceptance, disgust, sadness]
3   [acceptance, disgust, sadness]
4   [acceptance, disgust, sadness]
5  [acceptance, disgust, surprise]
```

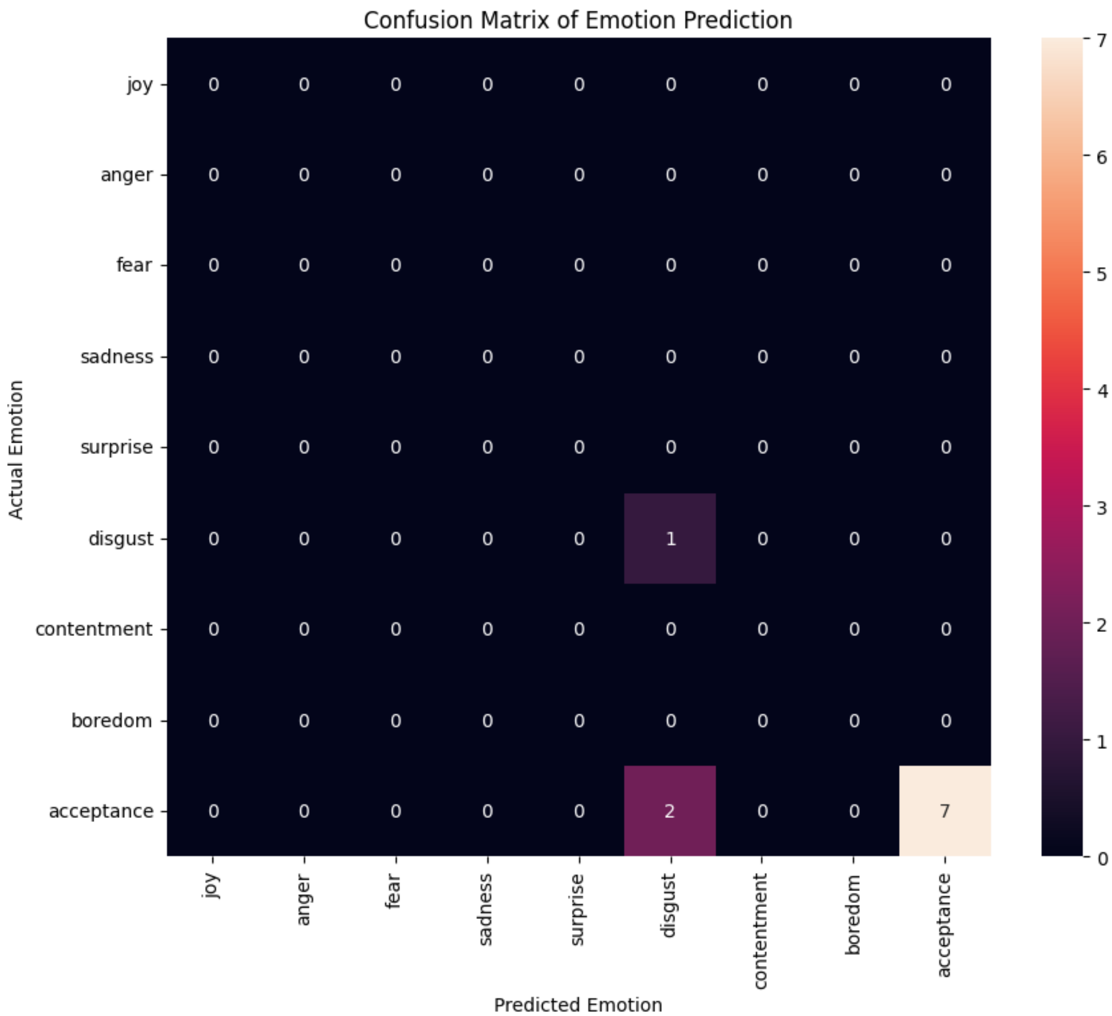
```
6   [acceptance, disgust, sadness]
7  [acceptance, surprise, disgust]
8   [acceptance, disgust, sadness]
9   [acceptance, sadness, disgust]

Accuracy of emotion prediction: 100.00%
Top-3 accuracy of emotion prediction: 100.00%
```




```
                                                                 Message
\
0
Body Shop's Roddick has Hepatitis C
1
Minaya obtained Floyd from the Florida Marlins on July 11, only two weeks after
he stunned baseball by acquiring Bartolo Colon from Cleveland.
2
```

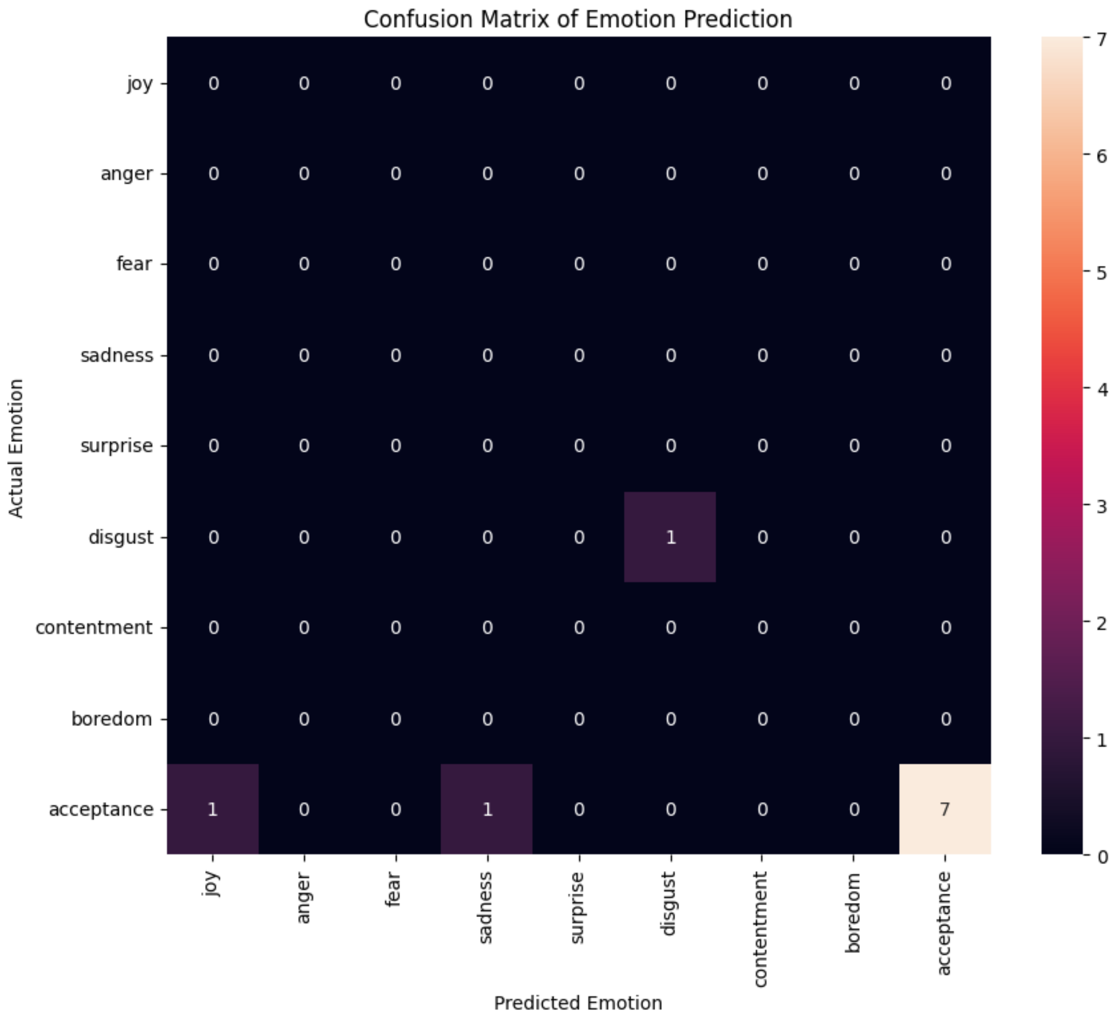
```
Midden seems to be marked in some olfactory way, since removing midden from
nests makes them more likely to be invaded by other species (Gordon, 35).
3
We took his rental car back to the motel where he was staying.
4
Until thirty seconds ago, I didn’t believe in magic or any of that kind of
…weirdness."
5
Mother: Lohan is doing 'great' in rehab
6  It is the intent of this language to make clear the congressional support for
the holding in Granholm-prohibiting state laws that allow an in-state winery to
do something a similarly situated out-of-state winery cannot do. Language that
bars facial discrimination is included in the bill to codify this prohibition"
7
The savings are counted in more ways than dollars and cents, however.
8
In an effort to provide yet one more thing to bet on, players are imported from
Spain to take part in this lightning-fast Basque ball game.
9
Photography took over as a means of portraiture for the bourgeois and the upper
class and despite the fact that it was possible to color the photographs, for
the most part they were left in black and white because it was seen as more
"natural".

  Actual_Emotion Predicted_Emotion                           Actual_Top3  \
0        disgust           disgust             [disgust, sadness, anger]
1     acceptance        acceptance       [acceptance, disgust, sadness]
2     acceptance        acceptance       [acceptance, disgust, sadness]
3     acceptance           disgust       [acceptance, sadness, disgust]
4     acceptance           disgust      [acceptance, surprise, disgust]
5     acceptance        acceptance  [acceptance, surprise, contentment]
6     acceptance        acceptance       [acceptance, sadness, disgust]
7     acceptance        acceptance   [acceptance, sadness, contentment]
8     acceptance        acceptance      [acceptance, disgust, surprise]
9     acceptance        acceptance      [acceptance, surprise, disgust]

                     Predicted_Top3
0     [disgust, acceptance, anger]
1   [acceptance, disgust, sadness]
2  [acceptance, disgust, surprise]
3   [disgust, acceptance, sadness]
4   [disgust, acceptance, sadness]
5  [acceptance, surprise, disgust]
6  [acceptance, disgust, surprise]
7  [acceptance, surprise, disgust]
8   [acceptance, disgust, sadness]
9   [acceptance, disgust, sadness]
```

```
Accuracy of emotion prediction: 80.00%
Top-3 accuracy of emotion prediction: 100.00%
```




```
                                                               Message
\
0
Body Shop's Roddick has Hepatitis C
1
Minaya obtained Floyd from the Florida Marlins on July 11, only two weeks after
he stunned baseball by acquiring Bartolo Colon from Cleveland.
2
Midden seems to be marked in some olfactory way, since removing midden from
nests makes them more likely to be invaded by other species (Gordon, 35).
3
We took his rental car back to the motel where he was staying.
4
```

```
Until thirty seconds ago, I didn’t believe in magic or any of that kind of
…weirdness."
5
Mother: Lohan is doing 'great' in rehab
6  It is the intent of this language to make clear the congressional support for
the holding in Granholm-prohibiting state laws that allow an in-state winery to
do something a similarly situated out-of-state winery cannot do. Language that
bars facial discrimination is included in the bill to codify this prohibition"
7
The savings are counted in more ways than dollars and cents, however.
8
In an effort to provide yet one more thing to bet on, players are imported from
Spain to take part in this lightning-fast Basque ball game.
9
Photography took over as a means of portraiture for the bourgeois and the upper
class and despite the fact that it was possible to color the photographs, for
the most part they were left in black and white because it was seen as more
"natural".

  Actual_Emotion Predicted_Emotion                          Actual_Top3  \
0        disgust           disgust            [disgust, sadness, anger]
1     acceptance           sadness       [acceptance, disgust, sadness]
2     acceptance        acceptance       [acceptance, disgust, sadness]
3     acceptance        acceptance       [acceptance, sadness, disgust]
4     acceptance        acceptance      [acceptance, surprise, disgust]
5     acceptance        acceptance  [acceptance, surprise, contentment]
6     acceptance        acceptance       [acceptance, sadness, disgust]
7     acceptance               joy   [acceptance, sadness, contentment]
8     acceptance        acceptance      [acceptance, disgust, surprise]
9     acceptance        acceptance      [acceptance, surprise, disgust]

                        Predicted_Top3
0         [disgust, anger, acceptance]
1          [sadness, boredom, disgust]
2       [acceptance, sadness, disgust]
3       [acceptance, sadness, disgust]
4         [acceptance, disgust, anger]
5      [acceptance, disgust, surprise]
6  [acceptance, surprise, contentment]
7          [joy, acceptance, surprise]
8       [acceptance, sadness, disgust]
9       [acceptance, disgust, sadness]

Accuracy of emotion prediction: 80.00%
Top-3 accuracy of emotion prediction: 90.00%
```


Confusion Matrix of Emotion Prediction
Actual Emotion
joy
anger
fear
sadness
surprise
disgust
contentment
boredom
acceptance
Predicted Emotion
joy
anger
fear
sadness
surprise
disgust
contentment
boredom
acceptance
0
1
2
3
4
5
6
7