Load Dataset

Load the two csv files, parse the JSON data line by line and extract the part of ["_source"]["tweet"] that is relevant to the prediction only. Then convert the json file into csv file and reload it. Standardize the file type can simplifies the following steps.

In [1]:
```
import pandas as pd
import json

emotion_data = pd.read_csv('emotion.csv')
identification_data = pd.read_csv('data_identification.csv')
```

In [2]:
```
with open("tweets_DM.json", "r", encoding="utf-8") as file:
    tweets_data = pd.DataFrame(
        json.loads(line)["_source"]["tweet"]
        for line in file
    )

tweets_data.to_csv('tweets.csv', index=False)
```

In [3]:
```
tweet_data = pd.read_csv('tweets.csv')
```

Exploratory Data Analysis

This step is to making sure that the data is loaded correctly and helps to understand the data structure.

In [4]:
```
tweet_data.head()
```

Out[4]:

	hashtags	tweet_id	text
0	['Snapchat']	0x376b20	People who post "add me on #Snapchat" must be ...
1	['freepress', 'TrumpLegacy', 'CNN']	0x2d5350	@brianklaas As we see, Trump is dangerous to #...
2	['bibleverse']	0x28b412	Confident of your obedience, I write to you, k...
3	[]	0x1cd5b0	Now ISSA is stalking Tasha 😂😂😂 <LH>
4	[]	0x2de201	"Trust is not the same as faith. A friend is s...

In [5]:
```
emotion_data.head()
```

Out[5]:

	tweet_id	emotion
0	0x3140b1	sadness
1	0x368b73	disgust
2	0x296183	anticipation
3	0x2bd6e1	joy
4	0x2ee1dd	anticipation

In [6]:
```
identification_data.head()
```

Out[6]:

	tweet_id	identification
0	0x28cc61	test
1	0x29e452	train
2	0x2b3819	train
3	0x2db41f	test
4	0x2a2acc	train

In [7]:
```
tweet_data.shape
```

Out[7]:
```
(1867535, 3)
```

In [8]:
```
emotion_data.shape
```

Out[8]:
```
(1455563, 2)
```

In [9]:
```
identification_data.shape
```

Out[9]:
```
(1867535, 2)
```

Data Preprocessing

Check for Missing and Duplicate Data

This step is to make sure there are no missing values or duplicated data in the dataset. Based on the output there are no missing values nor duplicated data found so no need to perform any steps to handle missing value nor drop the duplicated data.

In [10]:
```
print("\033[1mMissing values by Column : \033[0m")
print("-"*30)
print(tweet_data.isna().sum())
print("-"*30)
print("Total Missing Values: ",tweet_data.isna().sum().sum())
```

```
Missing values by Column :
------------------------------
hashtags    0
tweet_id    0
text        0
dtype: int64
------------------------------
Total Missing Values:  0
```

In [11]:
```
print("\033[1mMissing values by Column : \033[0m")
print("-"*30)
print(emotion_data.isna().sum())
print("-"*30)
print("Total Missing Values: ",emotion_data.isna().sum().sum())
```

```
Missing values by Column :
------------------------------
tweet_id    0
emotion     0
dtype: int64
------------------------------
Total Missing Values:  0
```

In [12]:
```
print("\033[1mMissing values by Column : \033[0m")
print("-"*30)
print(identification_data.isna().sum())
print("-"*30)
print("Total Missing Values: ",identification_data.isna().sum().sum())
```

```
Missing values by Column :
------------------------------
tweet_id          0
identification    0
dtype: int64
------------------------------
Total Missing Values:  0
```

In [13]:
```
print("Duplicate tweet_id:")
print("Tweet Data:", tweet_data.duplicated(subset=['tweet_id']).sum())
print("Emotion Data:", emotion_data.duplicated(subset=['tweet_id']).sum())
print("Identification Data:", identification_data.duplicated(subset=['tweet_ic
```

```
Duplicate tweet_id:
Tweet Data: 0
Emotion Data: 0
Identification Data: 0
```

Merging Data

Identify the shape of the data before merging and ensure the same number of data is shown after merging. This merging is separate into test set merge and training set merge. They are merged separately as they have different data shape and different attributes. Train data has the emotion label to carry out supervised learning.

In [14]:
```
test_set = identification_data[identification_data['identification'] == 'test'
test_set.shape
```

Out[14]: (411972, 2)

In [15]:
```
# Merge to get test tweets
test_tweets = test_set.merge(tweet_data, on='tweet_id', how='inner')
test_tweets.shape
```

Out[15]: (411972, 4)

In [16]:
```
test_tweets.head()
```

Out[16]:

	tweet_id	identification	hashtags	text
0	0x28cc61	test	[]	@Habbo I've seen two separate colours of the e...
1	0x2db41f	test	[]	@FoxNews @KellyannePolls No serious self respe...
2	0x2466f6	test	['womendrivers']	Looking for a new car, and it says 1 lady owne...
3	0x23f9e9	test	['robbingmembers']	@cineworld “only the brave” just out and fount...
4	0x1fb4e1	test	[]	Felt like total dog 💩 going into open gym and ...

In [17]:
```
train_set = identification_data[identification_data['identification'] == 'trai
train_data = train_set.merge(tweet_data, on='tweet_id', how='inner').merge(emo

train_data.shape
```

Out[17]: (1455563, 5)

In [18]:
```
train_data.head()
```

Out[18]:

	tweet_id	identification	hashtags	text	emotion
0	0x29e452	train	[]	Huge Respect👍 @JohnnyVegasReal talking about l...	joy
1	0x2b3819	train	['spateradio', 'app']	Yoooo we hit all our monthly goals with the ne...	joy
2	0x2a2acc	train	[]	@KIDSNTS @PICU_BCH @uhbcomms @BWCHBoss Well do...	trust
3	0x2a8830	train	['PUBG', 'GamersUnite', 'twitch', 'BeHealthy',...	Come join @ambushman27 on #PUBG while he striv...	joy
4	0x20b21d	train	['strength', 'bones', 'God']	@fanshixieen2014 Blessings!My #strength little...	anticipation

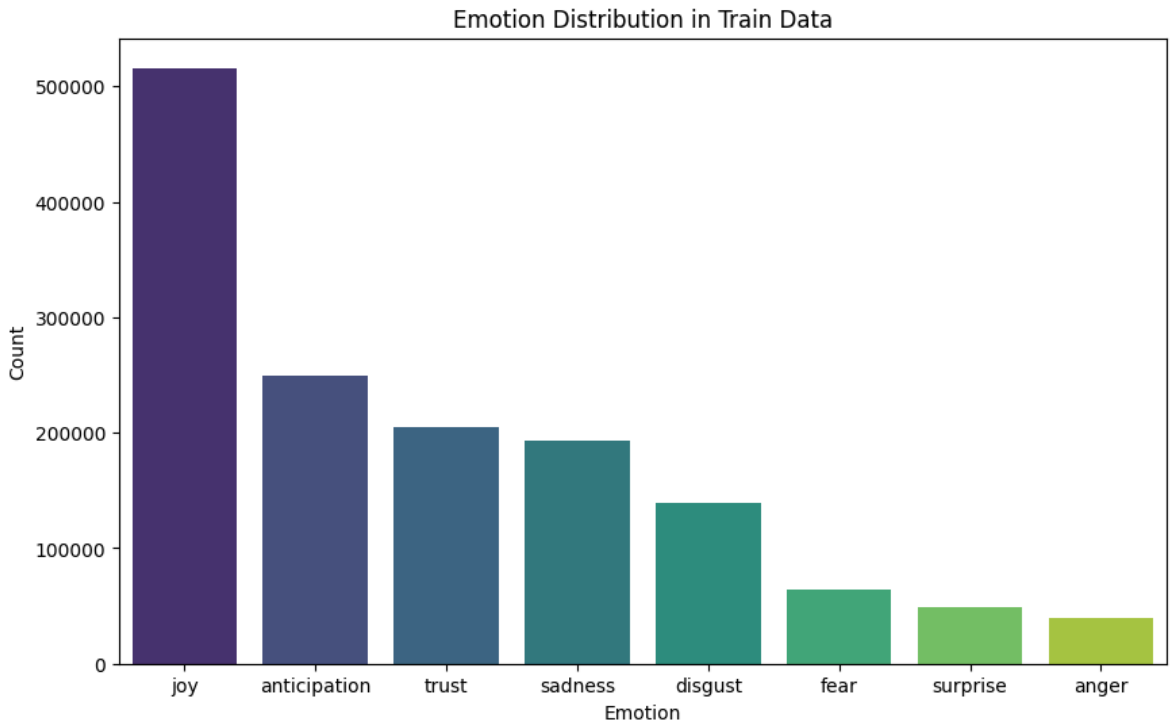
Data Visualization

A barplot is plotted to show the distribution of the emotion count in the train data. The visualization has shown that the number of joy has a huge difference from the other emotion. This shows that this is an imbalanced data.

In [20]:
```
import matplotlib.pyplot as plt
import seaborn as sns

emotion_count_train = train_data['emotion'].value_counts()

plt.figure(figsize=(10, 6))
sns.barplot(x=emotion_count_train.index, y=emotion_count_train.values, palette
plt.title("Emotion Distribution in Train Data")
plt.xlabel("Emotion")
plt.ylabel("Count")
plt.show()
```



In [21]:
```
emotion_count_train
```

Out[21]:
```
emotion
joy             516017
anticipation    248935
trust           205478
sadness         193437
disgust         139101
fear             63999
surprise         48729
anger            39867
Name: count, dtype: int64
```

Text Preprocessing

Stemming is carried out to stem the word in a sentence to its base word. This can help to increase accuracy. Besides, stopwords such as "a", "an", "the" will be removed. Tokenization also been carried out where the words are converted to lowercase. The preprocess_text function will tokenize the words in sentence with stemming and remove stopwords.

In [22]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import PorterStemmer

stemmer = PorterStemmer()
stop_words = set(stopwords.words('english'))

def preprocess_text(text):
    # tokenization
    word_tokens = word_tokenize(text)
    # stemming
    filtered_sentence = [stemmer.stem(w.lower()) for w in word_tokens if w.low
    return ' '.join(filtered_sentence)

train_data['processed_text'] = train_data['text'].apply(preprocess_text)

vectorizer = TfidfVectorizer()

X = vectorizer.fit_transform(train_data['processed_text'])
```

Splitting Data into Training and Testing Sets

The train data is splitted into training and testing sets where 80% of it is used for training and the other 20% is used for testing. This step is important to build model. Each model will use the X_train and y_train to evaluate the performance on X_test and y_test.

In [23]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, train_data['emotion'],
```

Build Classification Model

Linear Support Vector Classifier

There are two models built using Linear Support Vector Classifier. One model is without class weight balancing while the another one is with class weight balancing. The model without the class weight balancing gets a higher overall accuracy. The recall of anger and surprise from the model without balancing is much lower comapred to the other emotion. This is because they are the minority classes in the data and is hard for the model to classify them correctly. The emotion joy has the highest recall as it is the majority class and the model can train well to classify it correctly. On the other hand, the recall of each emotion is more balance in the model with class weight balancing. Both the recall of anger and sadness have increased, however the recall of joy has a slight decrease as all the classes are balanced and the performance spread across all classes.

In [24]:
```
from sklearn.svm import LinearSVC
from sklearn.metrics import classification_report, accuracy_score

svc = LinearSVC()
svc.fit(X_train, y_train)
y_pred = svc.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.5492437644488566
              precision    recall  f1-score   support

       anger       0.55      0.24      0.33      7964
anticipation       0.60      0.55      0.57     49725
     disgust       0.48      0.40      0.43     27892
        fear       0.64      0.39      0.49     12955
         joy       0.55      0.79      0.65    103089
     sadness       0.52      0.46      0.49     38835
    surprise       0.56      0.23      0.32      9750
       trust       0.53      0.32      0.40     40903

    accuracy                           0.55    291113
   macro avg       0.55      0.42      0.46    291113
weighted avg       0.55      0.55      0.53    291113
```

In [25]:
```
from sklearn.svm import LinearSVC
from sklearn.metrics import classification_report, accuracy_score

svc = LinearSVC(class_weight='balanced')
svc.fit(X_train, y_train)
y_pred = svc.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.5168851957830808
              precision    recall  f1-score   support

       anger       0.22      0.43      0.29      7964
anticipation       0.59      0.57      0.58     49725
     disgust       0.42      0.45      0.43     27892
        fear       0.37      0.52      0.43     12955
         joy       0.64      0.61      0.63    103089
     sadness       0.50      0.45      0.47     38835
    surprise       0.25      0.35      0.29      9750
       trust       0.48      0.39      0.43     40903

    accuracy                           0.52    291113
   macro avg       0.43      0.47      0.44    291113
weighted avg       0.53      0.52      0.52    291113
```

Logistic Regression

There are two models built using Logistic Regression. One model is without class weight balancing while the another one is with class weight balancing. The results of both models are almost the same as the Linear Support Vector Classifier. However, logistic regression without class weight balance gets a slightly higher acccuracy compared to LinearSVC without class weight balance. This is because logistic regression can handle imbalance data better as it is probabilistic based which normalizes probabilities across all classes. LinearSVC is sensitive to class imbalance and will cause the minority class to have low performance.

In [26]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score

lr = LogisticRegression(max_iter=1000)
lr.fit(X_train, y_train)
y_pred = lr.predict(X_test)

print("Accuracy:", accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
C:\Users\User\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklea
rn\linear_model\_logistic.py:458: ConvergenceWarning: lbfgs failed to converg
e (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://sciki
t-learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regres
sion (https://scikit-learn.org/stable/modules/linear_model.html#logistic-regr
ession)
  n_iter_i = _check_optimize_result(

Accuracy: 0.5553788391449368
              precision    recall  f1-score   support

       anger       0.63      0.23      0.33      7964
anticipation       0.63      0.53      0.58     49725
     disgust       0.50      0.40      0.44     27892
        fear       0.72      0.37      0.49     12955
         joy       0.54      0.83      0.65    103089
     sadness       0.53      0.47      0.49     38835
    surprise       0.65      0.21      0.32      9750
       trust       0.58      0.30      0.39     40903

    accuracy                           0.56    291113
   macro avg       0.60      0.42      0.46    291113
weighted avg       0.57      0.56      0.53    291113
```

In [27]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score

lr = LogisticRegression(max_iter=1000, class_weight='balanced')
lr.fit(X_train, y_train)
y_pred = lr.predict(X_test)

print("Accuracy:", accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
C:\Users\User\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklea
rn\linear_model\_logistic.py:458: ConvergenceWarning: lbfgs failed to converg
e (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://sciki
t-learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regres
sion (https://scikit-learn.org/stable/modules/linear_model.html#logistic-regr
ession)
  n_iter_i = _check_optimize_result(

Accuracy: 0.48955903721235394
              precision    recall  f1-score   support

       anger       0.20      0.49      0.28      7964
anticipation       0.59      0.57      0.58     49725
     disgust       0.40      0.48      0.44     27892
        fear       0.33      0.55      0.41     12955
         joy       0.71      0.48      0.57    103089
     sadness       0.51      0.43      0.47     38835
    surprise       0.21      0.42      0.28      9750
       trust       0.43      0.47      0.45     40903

    accuracy                           0.49    291113
   macro avg       0.42      0.49      0.43    291113
weighted avg       0.55      0.49      0.50    291113
```

Multinomial Naive Bayes

The low accuracy but high recall of the majority class joy shows that the model tends to overpredict joy bacause it is the largest class. The minority classes which are the anger and surprise have a perfect precision and very low recall. This is because they have less data and cause less prediction to be done on them and just nice all the predictions are correct resulting a perfect precision score. Imbalance data making this model not suitable to be used as this model assume feature independence and might not match with the feature here as each feature might be realated to express an emotion. Besides, this model cannot distinguish feature overlap such as angry and frustrating.

In [28]:
```
# multionomial naive bayes
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import classification_report, accuracy_score

nb = MultinomialNB()
nb.fit(X_train, y_train)
y_pred = nb.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.46355538914442157
              precision    recall  f1-score   support

       anger       1.00      0.08      0.15      7964
anticipation       0.76      0.32      0.45     49725
     disgust       0.69      0.09      0.16     27892
        fear       0.98      0.07      0.14     12955
         joy       0.41      0.97      0.58    103089
     sadness       0.59      0.28      0.38     38835
    surprise       1.00      0.08      0.15      9750
       trust       0.83      0.08      0.15     40903

    accuracy                           0.46    291113
   macro avg       0.78      0.25      0.27    291113
weighted avg       0.64      0.46      0.38    291113
```

Output csv file

The model that output the highest accuracy which is the logisic regression without class weight balance is chosen to output the csv file. Firstly, preprocess the text in test_tweets which will remove the punctuation, remove stopwords and covnert the text into lowercase. Then, vectorize the text into numerical feature and then the trained logistic model is used to predict the emotion.

In [30]:
```
from sklearn.linear_model import LogisticRegression
import pandas as pd

test_tweets['processed_text'] = test_tweets['text'].apply(preprocess_text)

X_test_final = vectorizer.transform(test_tweets['processed_text'])

y_pred_test = lr.predict(X_test_final)

submission_df = pd.DataFrame({
    'id': test_tweets['tweet_id'],
    'emotion': y_pred_test
})

submission_df.to_csv('sampleSubmission.csv', index=False)

print("Successfully save the file")
```

```
Successfully save the file
```

Other Method

Since the method of using class weight balance does not increase the accuracy, I have tried to use SMOTE to balance the data however, the accuracy drops a lot. This might be due to the k-neighbors tuning used does not work well with the data. I have tried to perform hyperparameter tuning on the Logistic Regression and found out the best model is liblinear. Grid Search CV is used to tune the model and it increases the accuracy.

Ranking

69	▲ 2	Yan Xin	0.41774	4	3d

Submission

I have submitted 4 times where the first time I am using Multinomial Naive Bayes, second time using Linear Support Vector Classifier, third and fourth time using Logistic Regression. Logistic Regression gets the best result because it can handle high dimensional text data while Multinomial Naive Bayes has the lowest accuracy as it assumes feature independence and cannot capture the semantic between features. Linear SVC gets an average result as it cannot handle class overlapping such as good and great.

Submission and Description	Private Score	Public Score
sampleSubmission.csv Complete · 3d ago	**0.41774**	**0.43416**
sampleSubmission.csv Complete · 4d ago	**0.41774**	**0.43416**
sampleSubmission.csv Complete · 4d ago	**0.41413**	**0.42914**
sampleSubmission.csv Complete · 5d ago	**0.39742**	**0.41260**