Step 1: Import Basic Libraries

1. json
2. numpy
3. pandas
4. matplotlib
5. seaborn
6. nltk

```
import json
import pandas as pd
import numpy as np
import nltk
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
```

Step 2: Data Preprocessing

Turn CSV files into dataframes

1. Load the tweets data into a dataframe
2. Load the emotions data into a dataframe
3. Load the identification data into a dataframe
4. Concatenate the dataframes into one dataframe
5. Remove the columns that are not needed
6. Split the data into training and testing data

```
data = []
with
open('/kaggle/input/dm-2024-isa-5810-lab-2-homework/tweets_DM.json',
'r') as f:
    for line in f:
        data.append(json.loads(line))

print(data[0])
f.close()
```

```
{'_score': 391, '_index': 'hashtag_tweets', '_source': {'tweet':
{'hashtags': ['Snapchat'], 'tweet_id': '0x376b20', 'text': 'People who
post "add me on #Snapchat" must be dehydrated. Cuz man.... that\'s
<LH>'}}, '_crawldate': '2015-05-23 11:42:47', '_type': 'tweets'}
```

```
flattened_data = [
    {
```

```
        "tweet_id": item["_source"]["tweet"]["tweet_id"],
        "index": item["_index"],
        "score": item["_score"],
        "hashtags": item["_source"]["tweet"]["hashtags"],
        "text": item["_source"]["tweet"]["text"],
        "crawldate": item["_crawldate"],
        "type": item["_type"]
    }
    for item in data
]

# Convert to DataFrame for analysis
tweets_df = pd.DataFrame(flattened_data)
tweets_df.head()
```

```
   tweet_id          index  score                          hashtags  \
0  0x376b20  hashtag_tweets    391                        [Snapchat]
1  0x2d5350  hashtag_tweets    433  [freepress, TrumpLegacy, CNN]
2  0x28b412  hashtag_tweets    232                      [bibleverse]
3  0x1cd5b0  hashtag_tweets    376                                []
4  0x2de201  hashtag_tweets    989                                []

                                                text
crawldate  \
0  People who post "add me on #Snapchat" must be ...  2015-05-23
11:42:47
1  @brianklaas As we see, Trump is dangerous to #...  2016-01-28
04:52:09
2  Confident of your obedience, I write to you, k...  2017-12-25
04:39:20
3                Now ISSA is stalking Tasha 😂😂😂 <LH>  2016-01-24
23:53:05
4  "Trust is not the same as faith. A friend is s...  2016-01-08
17:18:59

     type
0  tweets
1  tweets
2  tweets
3  tweets
4  tweets
```

```
emotion =
pd.read_csv('/kaggle/input/dm-2024-isa-5810-lab-2-homework/emotion.csv
')
emotion.head()
```

```
   tweet_id       emotion
0  0x3140b1       sadness
1  0x368b73       disgust
```

```
2  0x296183  anticipation
3  0x2bd6e1           joy
4  0x2ee1dd  anticipation
```

```python
data_identification = pd.read_csv('/kaggle/input/dm-2024-isa-5810-lab-2-homework/data_identification.csv')
data_identification.head()
```

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

```python
merged_df = tweets_df.merge(emotion, on="tweet_id", how="left")

final_df = merged_df.merge(data_identification, on="tweet_id", how="left")

final_df.head()
```

```
   tweet_id           index  score                        hashtags  \
0  0x376b20  hashtag_tweets    391                      [Snapchat]
1  0x2d5350  hashtag_tweets    433  [freepress, TrumpLegacy, CNN]
2  0x28b412  hashtag_tweets    232                    [bibleverse]
3  0x1cd5b0  hashtag_tweets    376                              []
4  0x2de201  hashtag_tweets    989                              []

                                                text
crawldate  \
0  People who post "add me on #Snapchat" must be ...  2015-05-23
11:42:47
1  @brianklaas As we see, Trump is dangerous to #...  2016-01-28
04:52:09
2  Confident of your obedience, I write to you, k...  2017-12-25
04:39:20
3                 Now ISSA is stalking Tasha 😂😂😂 <LH>  2016-01-24
23:53:05
4  "Trust is not the same as faith. A friend is s...  2016-01-08
17:18:59

     type       emotion identification
0  tweets  anticipation          train
1  tweets       sadness          train
2  tweets           NaN           test
3  tweets          fear          train
4  tweets           NaN           test
```

```python
final_df.drop('type', axis=1, inplace=True)
final_df.drop('index', axis=1, inplace=True)
```

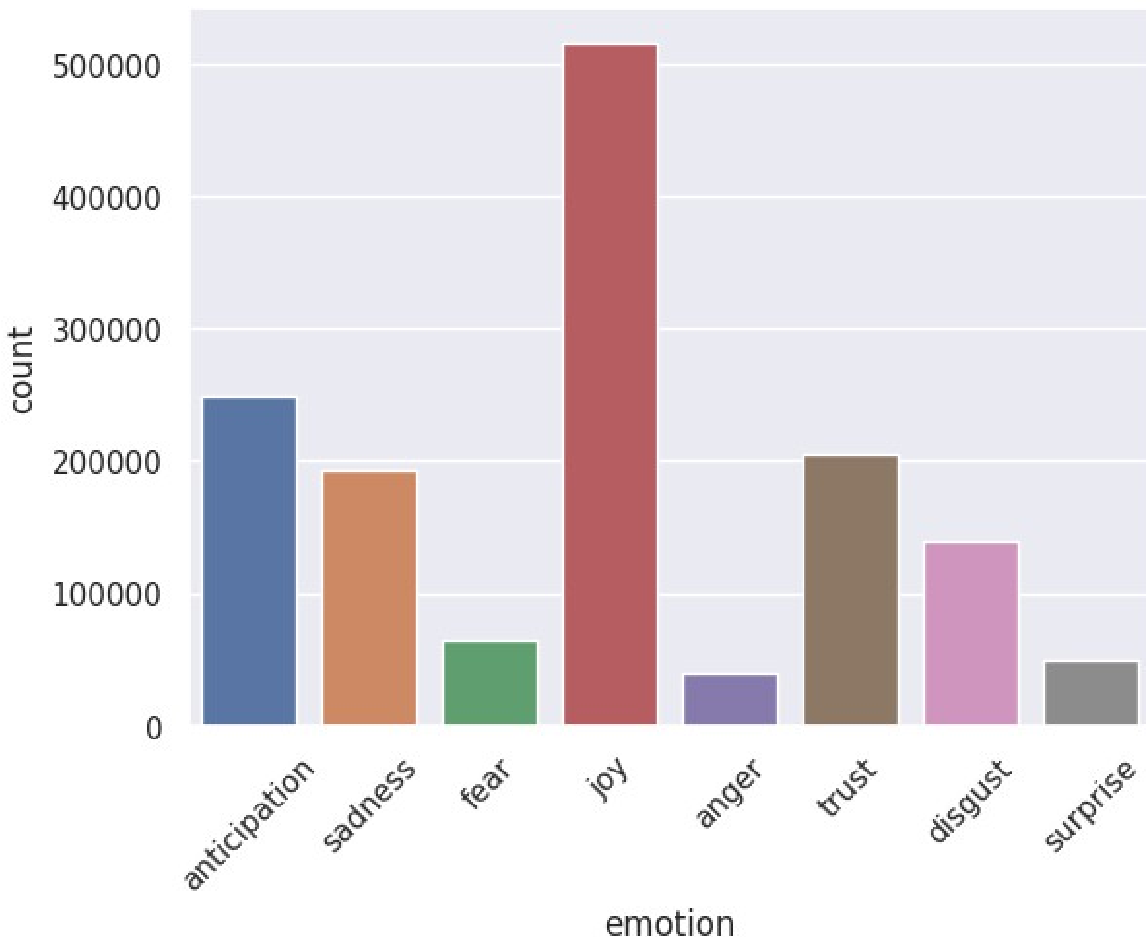
```python
final_df.drop('score', axis=1, inplace=True)
final_df.drop('hashtags', axis=1, inplace=True)
final_df.drop('crawldate', axis=1, inplace=True)

train_df = final_df[final_df['identification'] == 'train']
test_df = final_df[final_df['identification'] == 'test']

print(f"Train set size: {len(train_df)}")
print(f"Test set size: {len(test_df)}")
```

```
Train set size: 1455563
Test set size: 411972
```

Undersampling to Deal with Class Imbalance

From the plot above, we know that the data is imbalanced. We will use undersampling to deal with this issue.

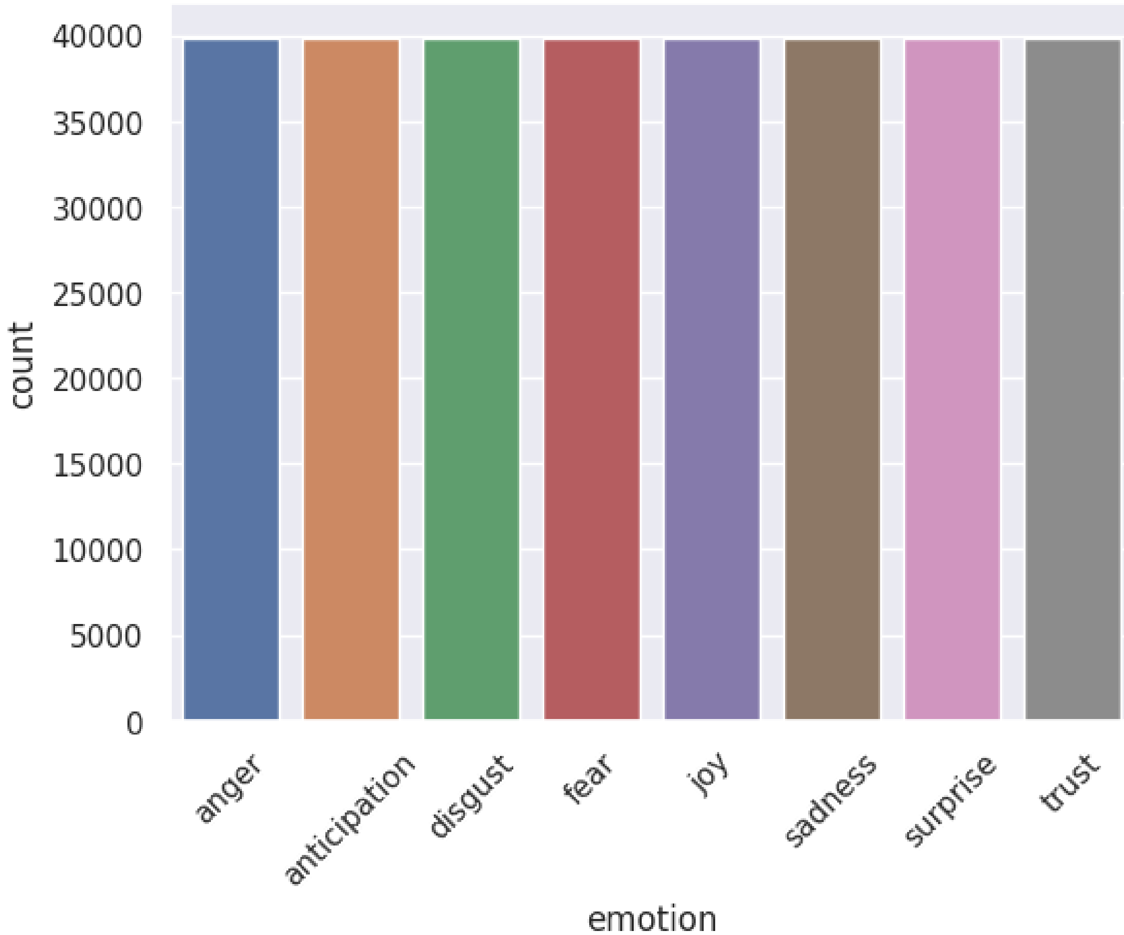
```python
sns.countplot(x='emotion', data=final_df)
plt.xticks(rotation=45)
plt.show()
```



Why Use Random Undersampling?

- In imbalanced datasets, the model may become biased toward the majority class.
- Random undersampling reduces this bias by creating a balanced dataset, improving the model's ability to learn patterns for minority classes.
- However, it can remove potentially useful data, so it's often used with caution.

```
import imblearn
from imblearn.under_sampling import RandomUnderSampler

undersample = RandomUnderSampler(random_state=42)

X = train_df.drop('emotion', axis=1)
y = train_df.emotion

X_over, y_over = undersample.fit_resample(X, y)

sns.countplot(x=y_over, data=train_df)
plt.xticks(rotation=45)
plt.show()
```



Plot Word Frequency for Top 30 Words in Train/Test Dataset

Here we can find out the distribution of words in two datesets:

1. There are many stop words in the plots we drawn
2. There are many non-words like '&' in the plots we drawn.

```
from collections import Counter

import matplotlib.pyplot as plt

def plot_top_words_frequency(df, title):
    all_words = ' '.join(df['text']).split()
    word_freq = Counter(all_words)
    common_words = word_freq.most_common(30)
    words, counts = zip(*common_words)

    plt.figure(figsize=(10, 8))
    plt.barh(words, counts)
```

```
    plt.gca().invert_yaxis()
    plt.title(title)
    plt.xlabel('Frequency')
    plt.show()
plot_top_words_frequency(train_df, 'Top 30 Words in Training Dataset')
plot_top_words_frequency(test_df, 'Top 30 Words in Testing Dataset')
```

Remove Stop Words and Non-Words

Use `re` to remove URLs, mentions, hashtags, and special characters

```
import re
def clean_text(text):
    text = re.sub(r"http\S+|www\S+|https\S+", '', text,
flags=re.MULTILINE)  # Remove URLs
    text = re.sub(r'\@\w+|\#', '', text)  # Remove mentions and
hashtags
    text = re.sub(r"[^a-zA-Z\s]", '', text)  # Remove special
characters
    return text.lower().strip()

train_df['text'] = train_df['text'].apply(clean_text)
test_df['text'] = test_df['text'].apply(clean_text)
```

For this part we encode the emotions into numerical values.

```
from sklearn.preprocessing import LabelEncoder

label_encoder = LabelEncoder()
train_df['emotion_encoded'] =
label_encoder.fit_transform(train_df['emotion'])
```

Step 3: Model Training

BERT (Don't to try to run this, it is very time consuming)

```
train_X = train_df['text']
train_y = train_df['emotion_encoded']
test_X = test_df['text']
```

1. Load the tokenizer and model
2. Prepare train and test data
3. Compile model
4. Train the model

```
from transformers import BertTokenizer,
TFBertForSequenceClassification
import tensorflow as tf

tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
model = TFBertForSequenceClassification.from_pretrained('bert-base-
uncased', num_labels=8)

train_encodings = tokenizer(list(train_X), truncation=True,
padding=True, max_length=128, return_tensors='tf')
test_encodings = tokenizer(list(test_X), truncation=True,
padding=True, max_length=128, return_tensors='tf')

model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=5e-5),

loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])

model.fit(train_encodings['input_ids'], train_y, batch_size=32,
epochs=1)
```

1. Use tokenizer to turn test data into encodings.
2. Use the trained model to predict.
3. Turn the prediction into emotion labels.
4. Transform and save the predicated labels.

```
from transformers import BertTokenizer,
TFBertForSequenceClassification
import pandas as pd
import numpy as np

test_encodings = tokenizer(list(test_X), truncation=True,
padding=True, max_length=128, return_tensors='tf')

test_predictions = model.predict(test_encodings['input_ids'])[0]
predicted_labels = np.argmax(test_predictions, axis=1)

test_df['predicted_emotion'] =
label_encoder.inverse_transform(predicted_labels)

submission = pd.DataFrame({
    'id': test_df['tweet_id'],
    'emotion': test_df['predicted_emotion']
})
submission.to_csv('/kaggle/working/submission_bert.csv', index=False)
```

Logistic Regression (This is the model I used in the competition)

```
train_X = train_df['text']
train_y = train_df['emotion_encoded']

test_X = test_df['text']
```

The purpose of this process is to convert raw text data into numerical feature matrices that can be used by machine learning models. TF-IDF emphasizes words that are both frequent in a document and unique to it, which helps capture the semantic relevance of words in text data.

```
from sklearn.feature_extraction.text import TfidfVectorizer

tfidf = TfidfVectorizer(max_features=5000)
X_train_vec = tfidf.fit_transform(train_X)
X_test_vec = tfidf.transform(test_X)
```

- Preprocessing: Standardizes the TF-IDF features to ensure efficient and stable training of the logistic regression model.
- Training: Trains a logistic regression model on the scaled TF-IDF features to predict the class labels for a text classification task (e.g., spam detection, sentiment analysis).
- Prediction: Uses the trained model to predict the labels for the test data.

```
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler(with_mean=False)  # TF-IDF vectors are sparse, so use `with_mean=False`
X_train_scaled = scaler.fit_transform(X_train_vec)
X_test_scaled = scaler.transform(X_test_vec)

model = LogisticRegression(max_iter=1000, random_state=42)

model.fit(X_train_scaled, train_y)

test_predictions = model.predict(X_test_scaled)
```

- Decoding Predictions:

  Converts numerical predictions (test_predictions) back to their original categorical labels (e.g., "happy," "sad") using label_encoder.inverse_transform.

- Preparing Submission:

  Constructs a DataFrame with the id of each tweet and its predicted emotion.

- Saving as CSV:

  Exports the DataFrame to a CSV file.

```
test_df['predicted_emotion'] =
label_encoder.inverse_transform(test_predictions)

submission = pd.DataFrame({
    'id': test_df['tweet_id'],
    'emotion': test_df['predicted_emotion']
})
submission.to_csv('/kaggle/working/submission2.csv', index=False)
```

```
/tmp/ipykernel_24/3646833079.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  test_df['predicted_emotion'] =
label_encoder.inverse_transform(test_predictions)
```

XGBC Model

```
train_X = train_df['text']
train_y = train_df['emotion_encoded']

test_X = test_df['text']
```

This part is the same as the Logistic Regression

```
from sklearn.feature_extraction.text import TfidfVectorizer

tfidf = TfidfVectorizer(max_features=5000)
X_train_vec = tfidf.fit_transform(train_X)
X_test_vec = tfidf.transform(test_X)
```

Here we use XGBClassifer to train and fit the model.

```
from xgboost import XGBClassifier

xgb_model = XGBClassifier(n_estimators=100, max_depth=8,
random_state=42, objective='multi:softmax', num_class=8)
xgb_model.fit(X_train_vec, train_y)

test_predictions = xgb_model.predict(X_test_vec)
```

This part is to inverse the labels and save the result.

```
test_df['predicted_emotion'] =
label_encoder.inverse_transform(test_predictions)
```

```
submission = pd.DataFrame({
    'id': test_df['tweet_id'],
    'emotion': test_df['predicted_emotion']
})
submission.to_csv('/kaggle/working/submission_xgbc.csv', index=False)
```

Final Comments

Data Preprocessing

I tried to use `nltk` to preprocess the text data, so that i can remove the stopwords and punktuations before model training. It turned out that the result did not improve, so I removed this method before the competition.

```
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
import nltk

# Download required resources
nltk.download('stopwords')
nltk.download('punkt')

def remove_stopwords(df):
    stop_words = set(stopwords.words('english'))
    df['text'] = df['text'].apply(
        lambda text: ' '.join([word for word in word_tokenize(text) if
word.lower() not in stop_words])
    )
remove_stopwords(train_df)
remove_stopwords(test_df)
```

Undersampling

From the result, the undersampling for preprocessing did not work as much as i predicted, I believe the reason might be that the undersampling technique removed too many important examples from the majority class, which led to a loss of valuable information. This could have affected the model's ability to generalize effectively, especially if the remaining data did not adequately represent the majority class's distribution.

Model Comparison

1. BERT
    - Pros: A pretrained model with contextual understanding of inputs, capturing complex patterns in text.
    - Cons: Too time-consuming and computationally intensive; unable to finish training before the deadline.
2. Logistic Regression

- Pros: Achieved the best accuracy among the models tested; simple to implement and fast to train.
- Cons: Limited capacity to capture non-linear relationships in data, making it less effective for complex patterns.

3. XGBC (Extreme Gradient Boosting Classifier)

   - Pros: Handles imbalanced data well and provides robust performance with efficient computation.
   - Cons: Requires careful hyperparameter tuning, which can be time-consuming, and its performance is slightly lower than Logistic Regression in this specific task.

Where can I Improve

1. Hyperparameter Tuning

   Experiment with different settings for models like Logistic Regression and XGBC to optimize their performance.

2. Try Clustering

   Use clustering techniques (e.g., K-Means, DBSCAN) to group similar data points and potentially enhance feature engineering or preprocessing.

3. Data Augmentation

   Increase dataset size and diversity by creating synthetic samples or augmenting existing data, especially for the minority class.

4. Explore Other Models

   Test advanced models like Random Forest or Support Vector Machines to compare performance.

5. Evaluate Different Metrics

   Focus on precision, recall, and F1-score to better assess model performance, particularly in imbalanced datasets.