Imports

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Dataset

```
# Load dataset
file_path = "twitter_dataset.csv"
df = pd.read_csv(file_path)

# Convert Timestamp to datetime and extract features
df["Timestamp"] = pd.to_datetime(df["Timestamp"])
df["Hour"] = df["Timestamp"].dt.hour
df["Day"] = df["Timestamp"].dt.day
df["Tweet_Length"] = df["Text"].apply(len)
df["Word_Count"] = df["Text"].apply(lambda x: len(x.split()))
```

Data Viz.

```


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# Descriptive Statistics
print("Descriptive Statistics:\n", df.describe())
```
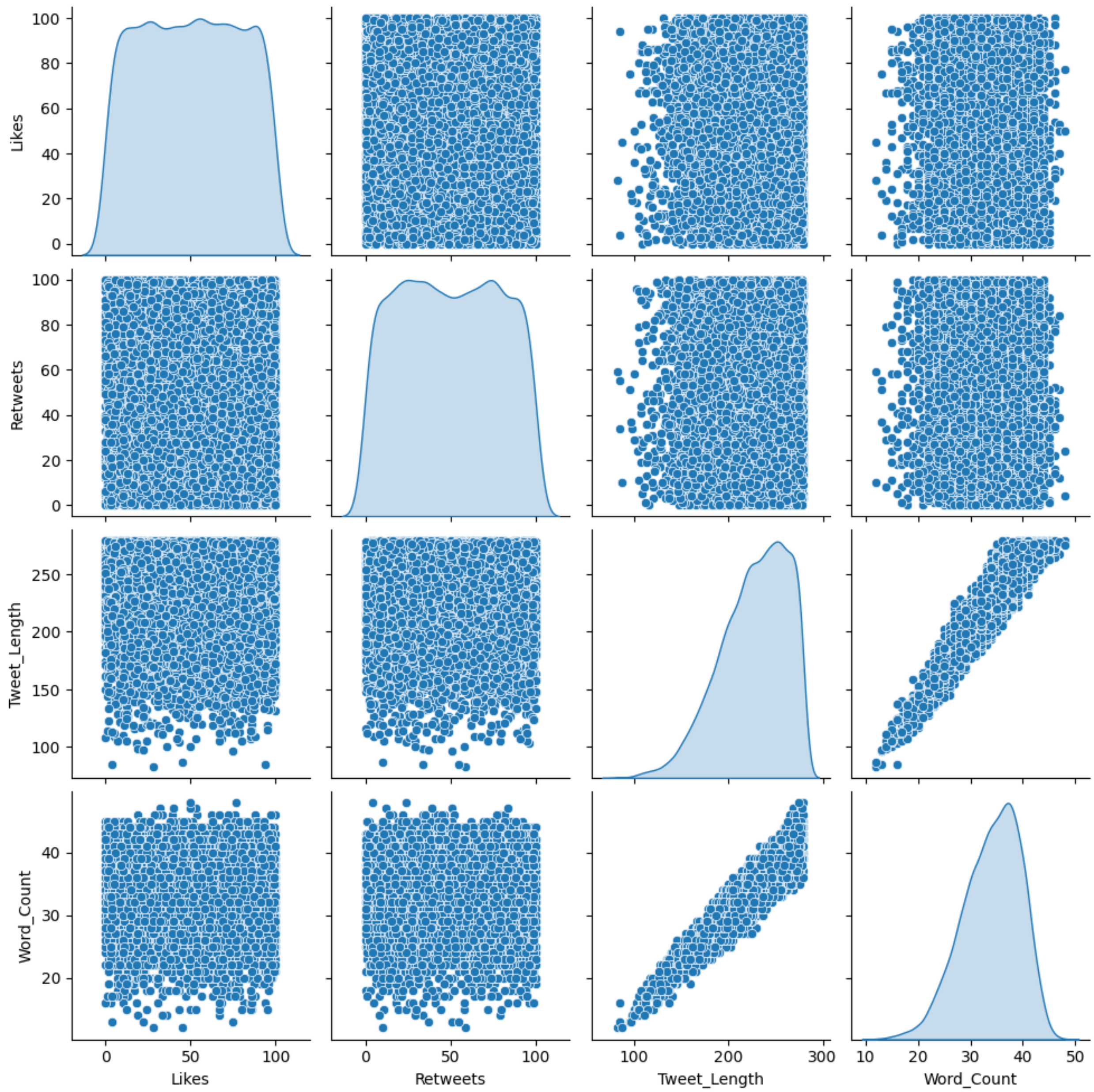

```
# Most liked and most retweeted tweets
most_liked = df.loc[df["Likes"].idxmax()]
most_retweeted = df.loc[df["Retweets"].idxmax()]
print("Most Liked Tweet:\n", most_liked)
print("Most Retweeted Tweet:\n", most_retweeted)

# Data Visualization
sns.pairplot(df, vars=["Likes", "Retweets", "Tweet_Length",
"Word_Count"], diag_kind="kde")
plt.show()

# Distribution of Likes and Retweets
fig, ax = plt.subplots(1, 2, figsize=(12, 5))
sns.histplot(df["Likes"], bins=30, kde=True, ax=ax[0], color='blue')
ax[0].set_title("Distribution of Likes")
sns.histplot(df["Retweets"], bins=30, kde=True, ax=ax[1],
color='green')
ax[1].set_title("Distribution of Retweets")
plt.show()

# Scatter plot of Tweet Length vs Likes
plt.figure(figsize=(8, 5))
sns.scatterplot(x=df["Tweet_Length"], y=df["Likes"], alpha=0.5)
plt.title("Tweet Length vs Likes")
plt.xlabel("Tweet Length")
plt.ylabel("Likes")
plt.show()

# Scatter plot of Tweet Length vs Retweets
plt.figure(figsize=(8, 5))
sns.scatterplot(x=df["Tweet_Length"], y=df["Retweets"], alpha=0.5,
color='red')
plt.title("Tweet Length vs Retweets")
plt.xlabel("Tweet Length")
plt.ylabel("Retweets")
plt.show()

# Time-Series Analysis: Engagement Trends Over Time
df.set_index("Timestamp", inplace=True)
df_resampled = df.resample("D").sum()

plt.figure(figsize=(12, 6))
plt.plot(df_resampled.index, df_resampled["Likes"], label="Likes",
color='blue')
plt.plot(df_resampled.index, df_resampled["Retweets"],
label="Retweets", color='green')
plt.xlabel("Date")
plt.ylabel("Engagement")
plt.title("Tweet Engagement Over Time")
```

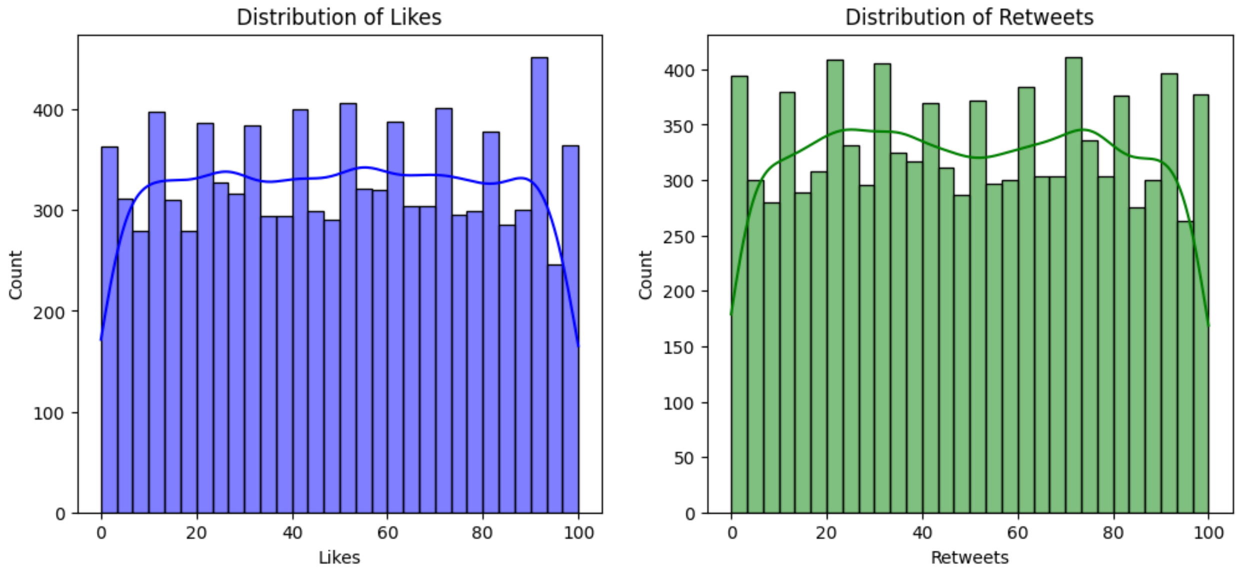
```
plt.legend()
plt.show()

# Identifying peak tweeting hours
plt.figure(figsize=(10, 5))
sns.barplot(x=df.groupby("Hour")["Likes"].mean().index,
y=df.groupby("Hour")["Likes"].mean(), color='blue', alpha=0.7)
plt.xlabel("Hour of the Day")
plt.ylabel("Average Likes")
plt.title("Average Likes by Hour")
plt.show()

plt.figure(figsize=(10, 5))
sns.barplot(x=df.groupby("Hour")["Retweets"].mean().index,
y=df.groupby("Hour")["Retweets"].mean(), color='green', alpha=0.7)
plt.xlabel("Hour of the Day")
plt.ylabel("Average Retweets")
plt.title("Average Retweets by Hour")
plt.show()
```

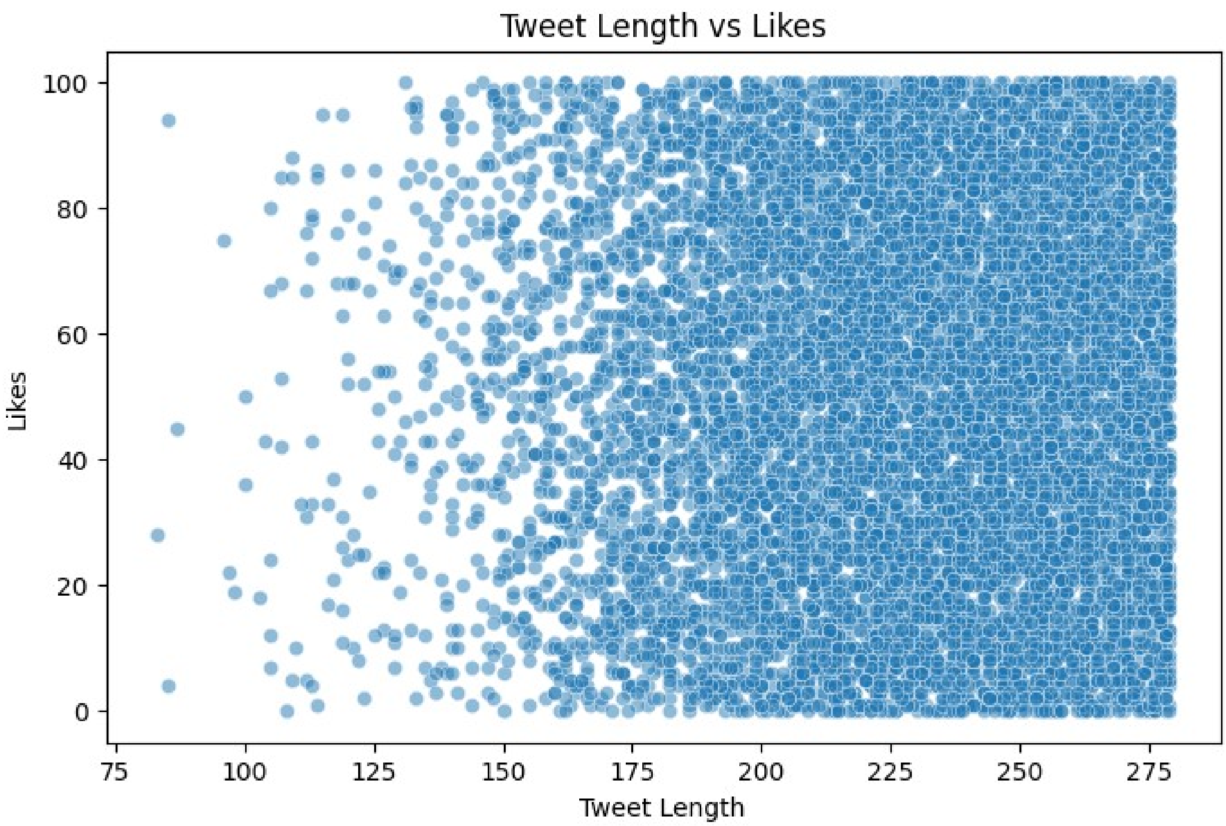
```
Descriptive Statistics:
           Tweet_ID      Retweets         Likes
Timestamp  \
count  10000.00000  10000.000000  10000.000000
10000
mean    5000.50000     49.721200     49.929300  2023-03-08
19:55:00.845099776
min        1.00000      0.000000      0.000000            2023-01-01
00:01:15
25%     2500.75000     25.000000     25.000000     2023-02-02
18:35:42.500000
50%     5000.50000     49.000000     50.000000     2023-03-08
17:56:55.500000
75%     7500.25000     75.000000     75.000000  2023-04-11
09:22:33.750000128
max    10000.00000    100.000000    100.000000            2023-05-15
12:32:09
std     2886.89568     28.948856     28.877193
NaN

               Hour           Day  Tweet_Length    Word_Count
count  10000.000000  10000.000000   10000.00000  10000.000000
mean      11.472900     14.550200     226.89360     33.985300
min        0.000000      1.000000      83.00000     12.000000
25%        5.000000      7.000000     203.00000     30.000000
50%       11.000000     14.000000     232.00000     35.000000
75%       17.000000     22.000000     255.00000     38.000000
max       23.000000     31.000000     279.00000     48.000000
std        6.917648      8.611695      35.53295      5.530908
Most Liked Tweet:
```

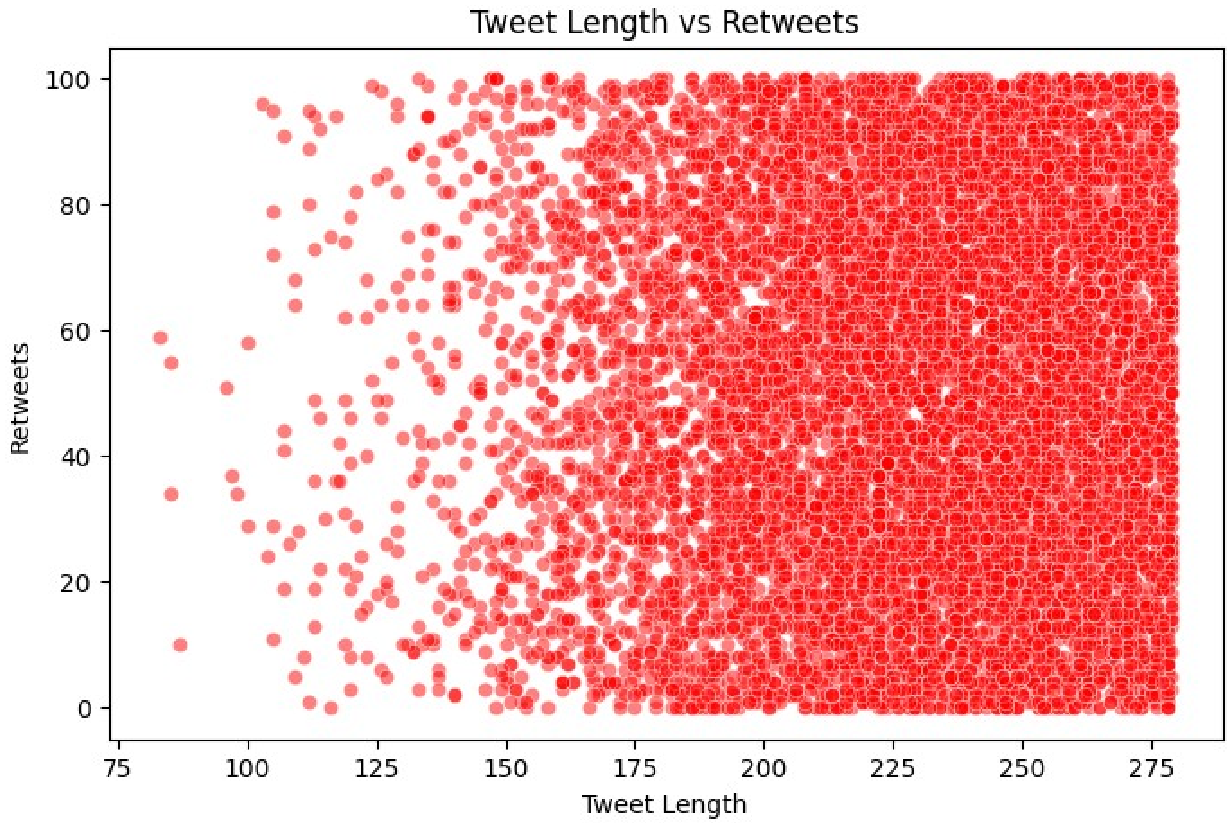
```
 Tweet_ID                                                     117
Username                                                  ojordan
Text            West appear important not billion serve father...
Retweets                                                       24
Likes                                                         100
Timestamp                                     2023-04-08 20:03:49
Hour                                                           20
Day                                                             8
Tweet_Length                                                  197
Word_Count                                                     29
Name: 116, dtype: object
Most Retweeted Tweet:
 Tweet_ID                                                     167
Username                                              scottandrea
Text            Part despite its south develop building. Food ...
Retweets                                                      100
Likes                                                          20
Timestamp                                     2023-01-02 04:48:29
Hour                                                            4
Day                                                             2
Tweet_Length                                                  264
Word_Count                                                     42
Name: 166, dtype: object
```

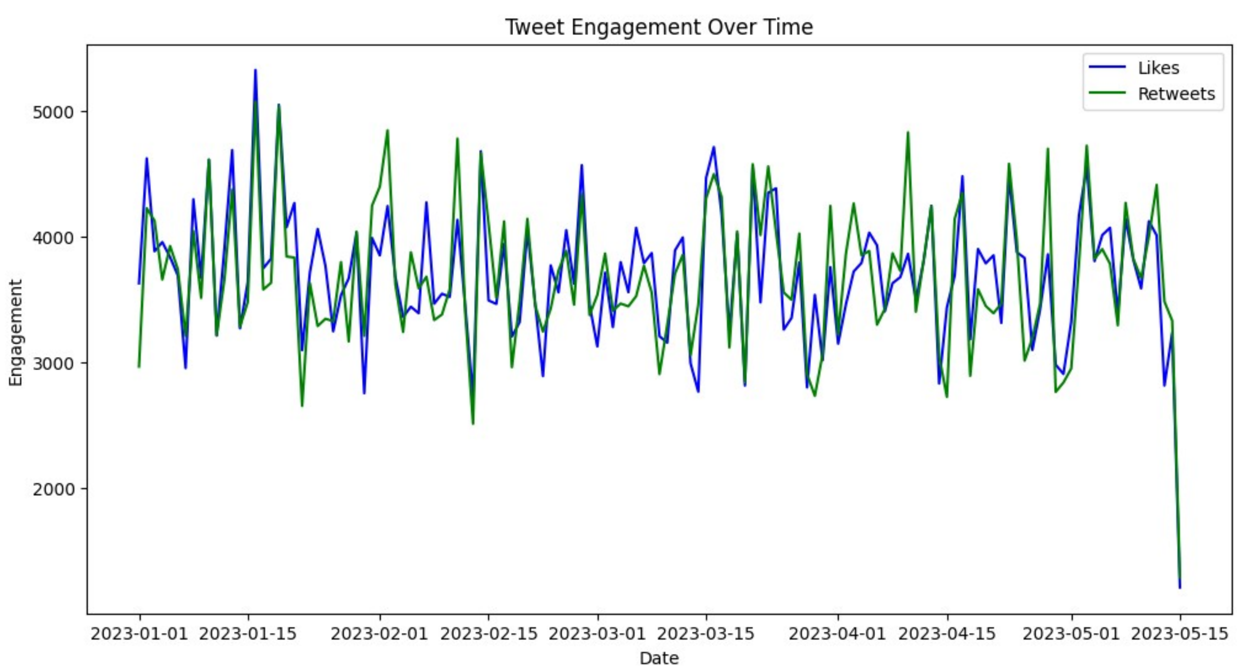


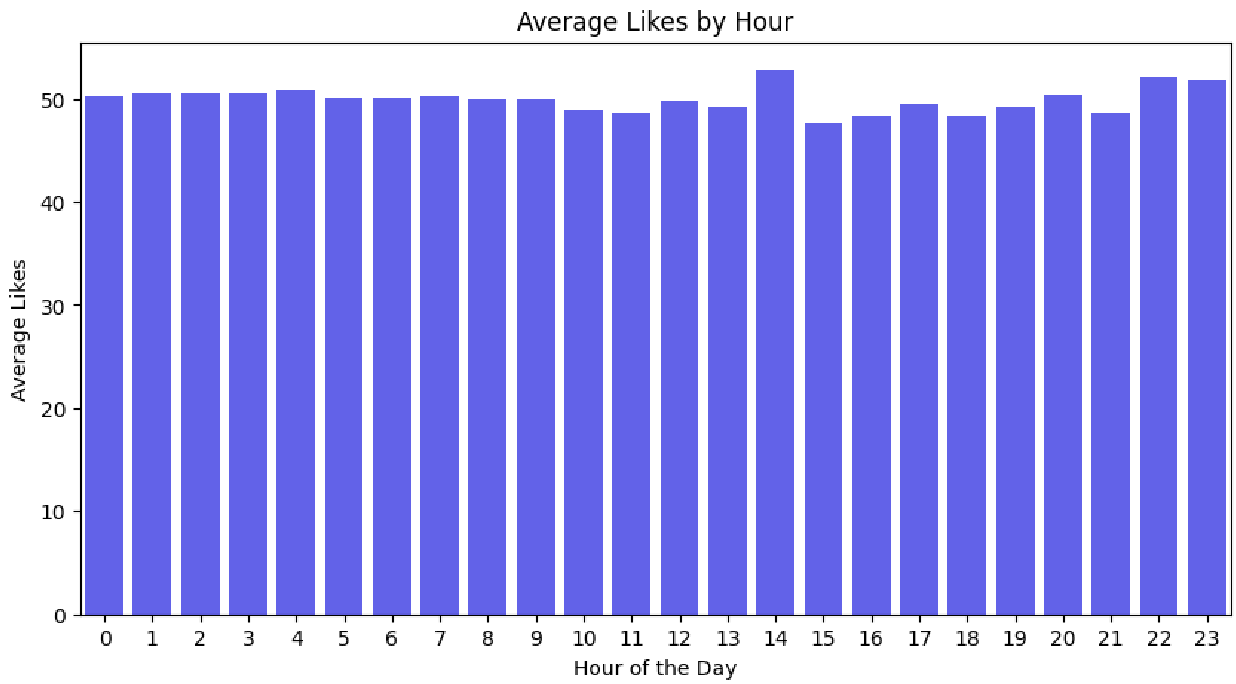
Likes
Retweets
Tweet_Length
Word_Count

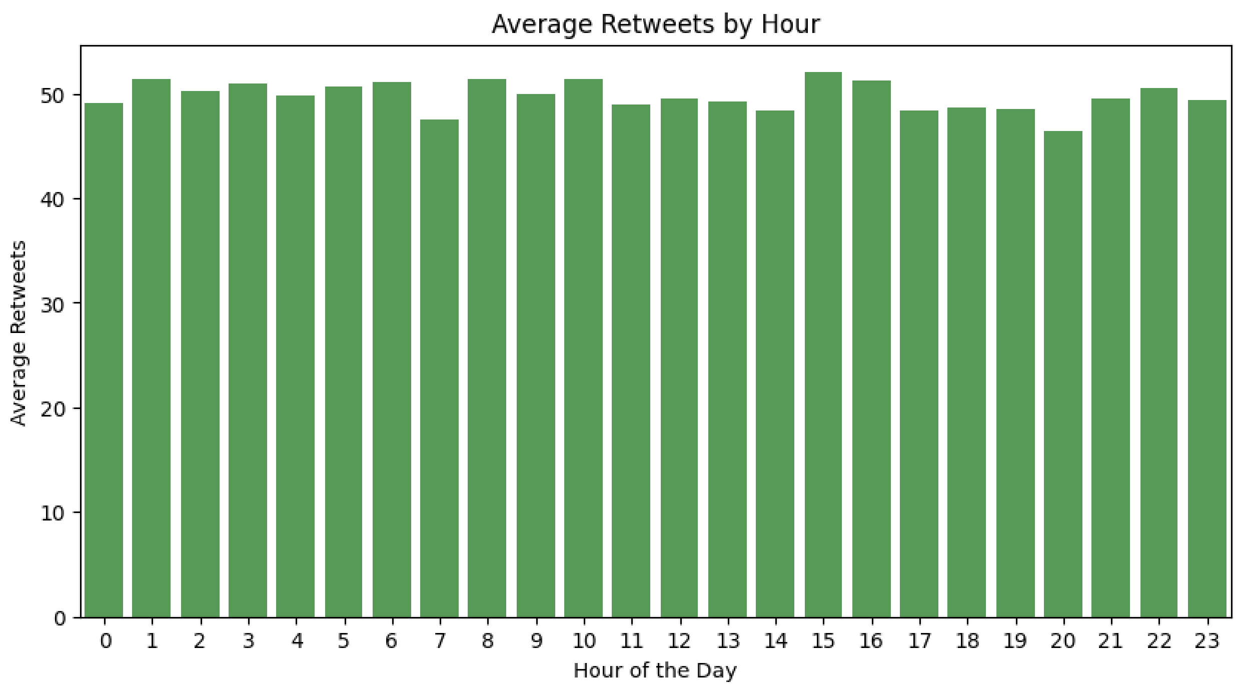

Distribution of Likes
Count
Likes
0
100
200
300
400
0
20
40
60
80
100
Distribution of Retweets
Count
Retweets
0
50
100
150
200
250
300
350
400
0
20
40
60
80
100


Tweet Length vs Likes
Likes
Tweet Length
0
20
40
60
80
100
75
100
125
150
175
200
225
250
275


Tweet Length vs Retweets
Retweets
Tweet Length
0
20
40
60
80
100
75
100
125
150
175
200
225
250
275


Tweet Engagement Over Time
Likes
Retweets
Engagement
Date
2000
3000
4000
5000
2023-01-01
2023-01-15
2023-02-01
2023-02-15
2023-03-01
2023-03-15
2023-04-01
2023-04-15
2023-05-01
2023-05-15





Preprocessing

```
# TF-IDF Vectorization
vectorizer = TfidfVectorizer(max_features=1000)
tfidf_features = vectorizer.fit_transform(df["Text"]).toarray()
tfidf_df = pd.DataFrame(tfidf_features, columns=[f"TFIDF_{i}" for i in
```

```
range(tfidf_features.shape[1])])

# Remove duplicate columns and reset index
df = df.loc[:, ~df.columns.duplicated()]
df = df.reset_index(drop=True)  # Ensure unique index

# Identifying categorical features
categorical_features = df.select_dtypes(include=["object",
"category"]).columns.tolist()
if "Text" in categorical_features:
    categorical_features.remove("Text")  # Exclude text column as it's
already vectorized

# One-hot encoding categorical features
if categorical_features:
    encoder = OneHotEncoder(handle_unknown="ignore",
sparse_output=False)
    X_categorical = encoder.fit_transform(df[categorical_features])
    X_categorical_df = pd.DataFrame(X_categorical,
columns=encoder.get_feature_names_out(categorical_features))
    df = df.drop(columns=categorical_features)
else:
    X_categorical_df = pd.DataFrame()

# Combine features
X = pd.concat([df[["Hour", "Day", "Tweet_Length", "Word_Count"]],
tfidf_df], axis=1)
y_likes = df["Likes"]
y_retweets = df["Retweets"]

# Scaling numerical features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X = pd.DataFrame(X_scaled, columns=X.columns)

# Splitting data into training and testing sets
X_train, X_test, y_train_likes, y_test_likes = train_test_split(X,
y_likes, test_size=0.2, random_state=42)
X_train, X_test, y_train_retweets, y_test_retweets =
train_test_split(X, y_retweets, test_size=0.2, random_state=42)
```

- Scaling
- Encoding

Training

```
# Train Linear Regression models
lr_likes = LinearRegression().fit(X_train, y_train_likes)
lr_retweets = LinearRegression().fit(X_train, y_train_retweets)

# Train Random Forest models
rf_likes = RandomForestRegressor(n_estimators=100,
random_state=42).fit(X_train, y_train_likes)
rf_retweets = RandomForestRegressor(n_estimators=100,
random_state=42).fit(X_train, y_train_retweets)
```

Evaluation

```
# Predictions
y_pred_likes_lr = lr_likes.predict(X_test)
y_pred_retweets_lr = lr_retweets.predict(X_test)
y_pred_likes_rf = rf_likes.predict(X_test)
y_pred_retweets_rf = rf_retweets.predict(X_test)

# Evaluate models
def evaluate_model(y_true, y_pred, model_name):
    mae = mean_absolute_error(y_true, y_pred)
    mse = mean_squared_error(y_true, y_pred)
    rmse = np.sqrt(mse)
    r2 = r2_score(y_true, y_pred)
    return {
        "Model": model_name,
        "MAE": mae,
        "MSE": mse,
        "RMSE": rmse,
        "R2 Score": r2
    }

results = [
    evaluate_model(y_test_likes, y_pred_likes_lr, "Linear Regression
(Likes)"),
    evaluate_model(y_test_retweets, y_pred_retweets_lr, "Linear
Regression (Retweets)"),
    evaluate_model(y_test_likes, y_pred_likes_rf, "Random Forest
(Likes)"),
    evaluate_model(y_test_retweets, y_pred_retweets_rf, "Random Forest
(Retweets)")
]

# Convert results to DataFrame
results_df = pd.DataFrame(results)
results_df
```

	Model	MAE	MSE	RMSE	R2 Score
0	Linear Regression (Likes)	25.994415	941.765505	30.688198	-0.108938
1	Linear Regression (Retweets)	26.890601	989.434553	31.455279	-0.161465
2	Random Forest (Likes)	25.469810	871.734287	29.525147	-0.026476
3	Random Forest (Retweets)	25.783640	888.662090	29.810436	-0.043172