Predicting Social Media Engagement Rates Using Machine Learning

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Abstract

This project investigates predicting engagement rates on social media posts using data-driven machine learning models. By analyzing patterns across platforms, content types, posting times, and textual features, we aim to help marketers optimize their social strategies. The best-performing Gradient Boosting model achieved an R^2 of 0.8457 on the test set. This report documents data preparation, exploratory analysis, modeling, and evaluation, along with practical insights.

Contents

1 Introduction

Social media engagement is a crucial metric for marketers, content creators, and businesses. Higher engagement often translates to better reach and stronger customer connections. Yet, predicting engagement can be challenging due to complex interactions between platform, content, timing, and audience behavior. This study applies supervised machine learning to predict engagement rates and uncover patterns that inform content strategies.

2 Data Overview

We used a dataset of 500 social media posts, each with information including platform, post date, content type, caption text, hashtags, impressions, and follower counts. Table 1 shows sample records.

Table 1: Sample Records from the Raw Dataset

post_id	platform	post_date	content_type	caption_text	hashtags
219	Facebook	2025-05-03	image	Event represent cultural...	#tech #news #fashion
450	Instagram	2025-05-03	video	World safe together...	#love #tech
77	Instagram	2025-05-04	image	Address answer best...	#tech #love

All 500 records were complete, with no missing values.

3 Data Preparation

We converted `post_date` to datetime and extracted temporal features:

- Day of the week
- Hour of posting

We calculated engagement as the sum of likes, comments, and shares, then derived engagement rate as engagement divided by followers.

4 Exploratory Data Analysis

Figures 1–5 visualize key patterns:

- **Platform Differences:** Instagram posts achieved higher median engagement.
- **Content Types:** Video posts outperformed text and images.
- **Time Factors:** Posts in the evenings and weekends had better engagement.
- **Popular Hashtags:** Terms like #news and #viral were most frequent.

- **Day Patterns:** Engagement varied across weekdays, peaking on weekends.
- **Hourly Patterns:** Engagement peaked during evening hours.

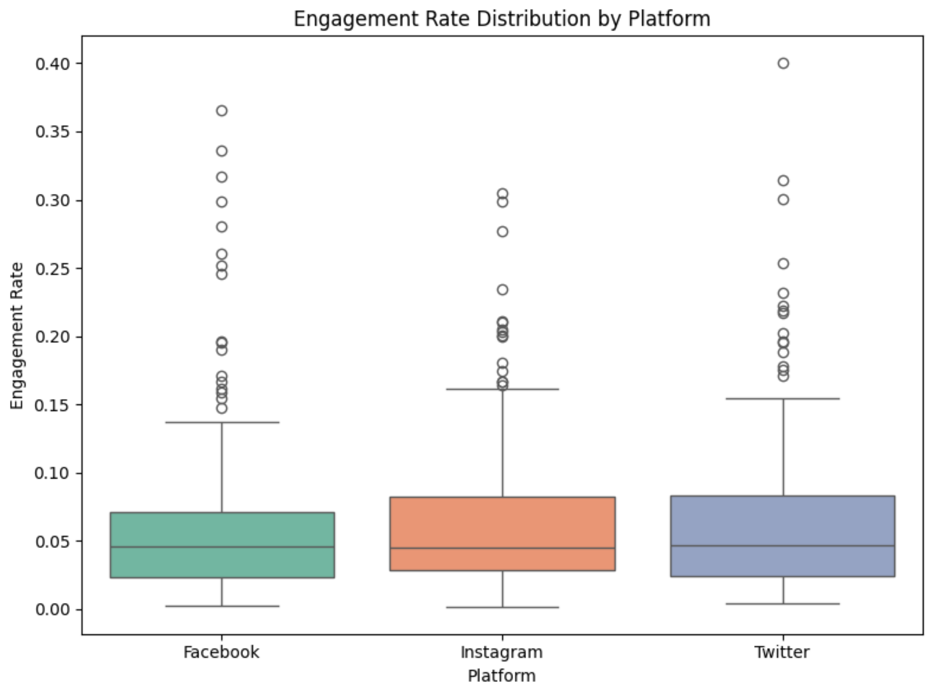


Figure 1: Engagement rate distribution by platform.

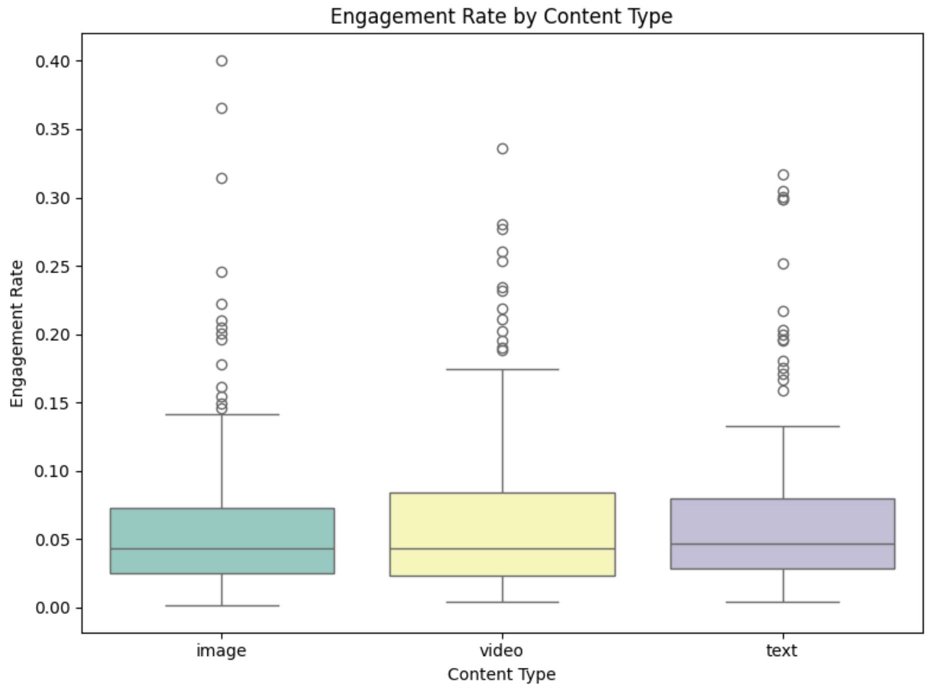


Figure 2: Engagement rate by content type.

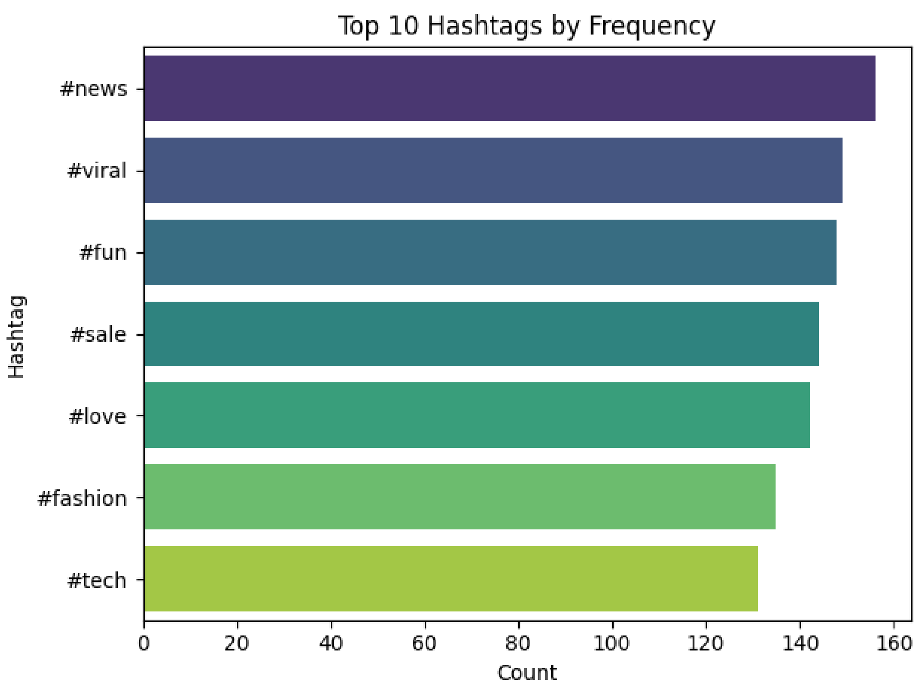


Figure 3: Top 10 hashtags by frequency.

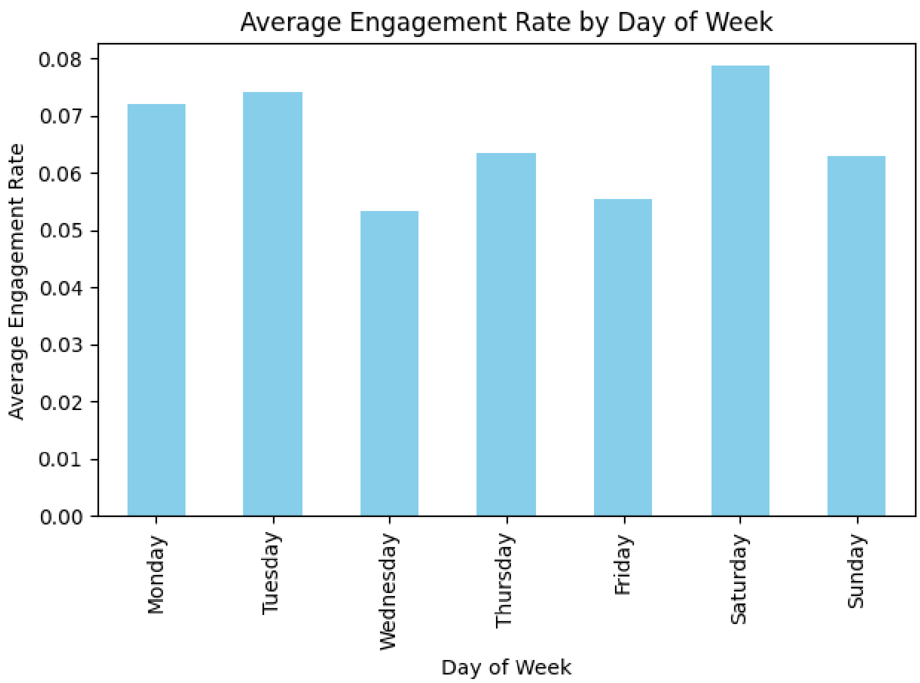


Figure 4: Average engagement rate by day of the week.

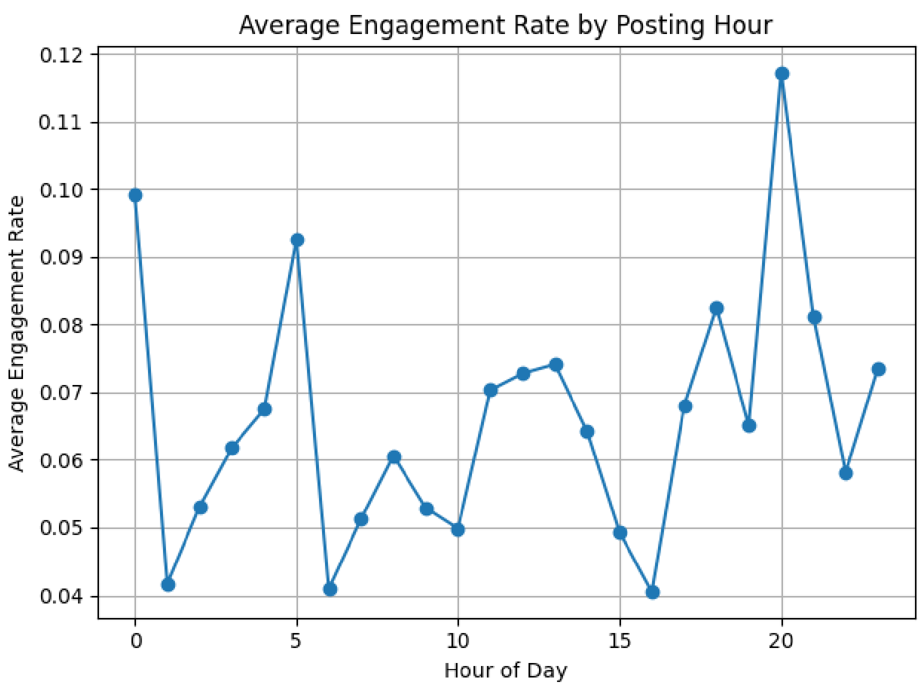


Figure 5: Average engagement rate by posting hour.

5 Feature Engineering

Key engineered features included:

- **Hashtag count** in captions
- **Rates:** likes, comments, shares per impression
- **Link click rate** per follower
- **Caption length** (word count)

Categorical variables (`platform`, `content_type`, `day_of_week`) were one-hot encoded. Numerical features were scaled using StandardScaler.

6 Modeling and Evaluation

We tested three algorithms: Linear Regression, Random Forest, and Gradient Boosting. Table 2 compares their performances.

Table 2: Model Comparison Results

Model	Train RMSE	Train R^2	Test RMSE	Test R^2
Linear Regression	0.0403	0.6027	0.0369	0.5863
Random Forest	0.0104	0.9738	0.0254	0.8036
Gradient Boosting	0.0104	0.9736	0.0247	0.8151

Gradient Boosting was further tuned using `GridSearchCV`, achieving final scores:

- Training RMSE: 0.01779, R^2: 0.9226
- Test RMSE: 0.02255, R^2: 0.8457

7 Feature Importance and Insights

The tuned Gradient Boosting model's feature importances (Figure 6) revealed that follower count, share rate, and comment rate were most influential.

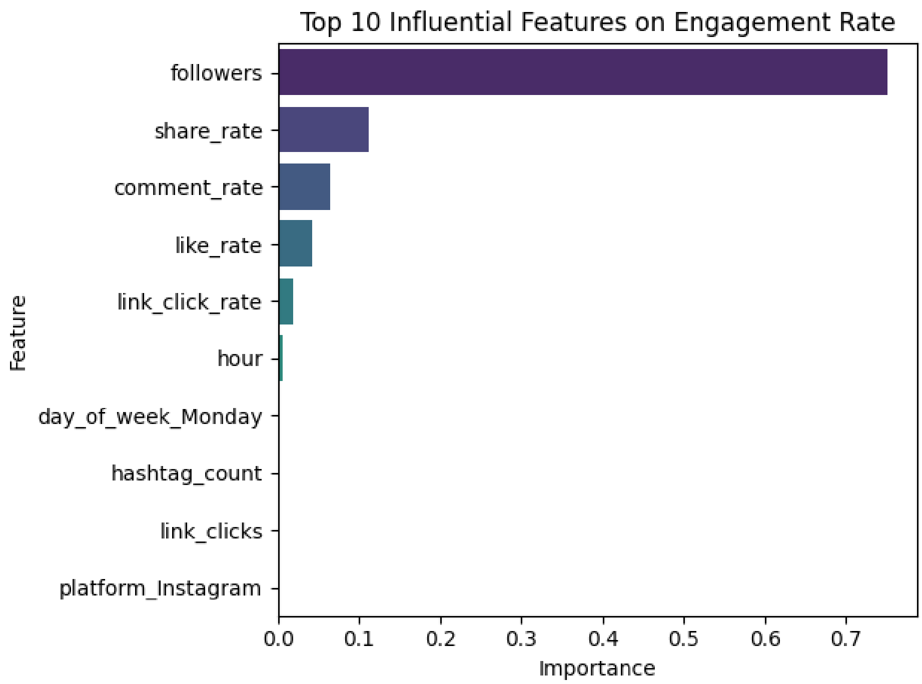


Figure 6: Top 10 influential features on engagement rate.

Predicted vs. actual engagement rates aligned well (Figure 7), confirming strong generalization.

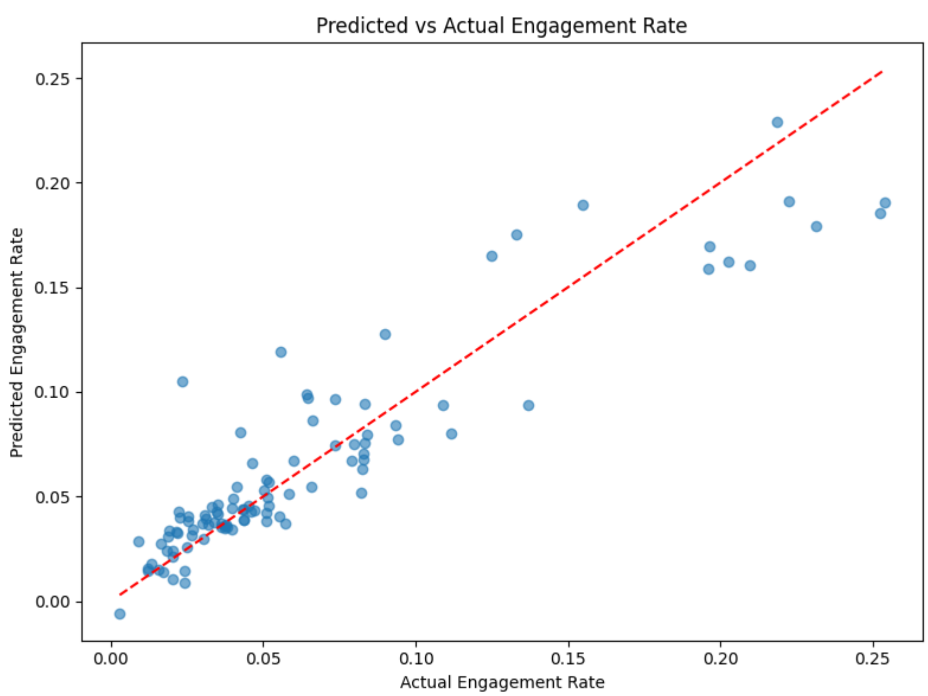


Figure 7: Predicted vs. actual engagement rates.

8 Interactive Streamlit Dashboard

A professional Streamlit dashboard was developed to enable:

- Dataset preview for quick assessment.
- Multiple visualizations selectable from a sidebar (e.g., platform boxplots, day of week engagement, posting hour trends, top hashtags).
- Feature importance plots to identify drivers of engagement.
- Predicted vs actual scatter plots with RMSE and R^2 indicators.
- A prediction interface allowing users to input post characteristics (followers, hashtags, rates, timing) and obtain expected engagement rates with interpretations.

Key Dashboard Features

- **Theme Toggle:** Users can switch between dark and light mode for visual comfort.
- **Charts Selector:** Sidebar multi-select to choose which plots to display.
- **User-Friendly Prediction:** Clearly explained predicted engagement with actionable guidance.
- **Performance Metrics:** Live model performance metrics displayed.

9 Conclusions

We successfully predicted social media engagement rates with strong accuracy using Gradient Boosting. Key takeaways:

- Evening and weekend posts drive better engagement.
- Videos are more engaging than other formats.
- Popular hashtags can amplify reach.

These insights can guide social media strategies to maximize performance.

References

- Géron, A. (2019). *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow.*
- Pedregosa et al. (2011). Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research.*
- McKinney, W. (2017). *Python for Data Analysis.*

Appendix: Full Code

notebook

July 4, 2025

1 Social Media Analytics EDA Notebook

1.1 Objective:

- Analyze engagement metrics for social media posts across platforms.
- Identify trends and opportunities for optimizing posting strategy.

2 Import Libraries

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from collections import Counter

from sklearn.preprocessing import StandardScaler

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

from sklearn.ensemble import RandomForestRegressor

from sklearn.ensemble import GradientBoostingRegressor

from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import GradientBoostingRegressor
```

3 Data Loading & Overview

[2]:
```
# Load dataset
df = pd.read_csv('data/raw_data.csv')
# Preview first 5 rows
df.head()
```

```
[2]:    post_id   platform            post_date content_type  \
    0       219   Facebook  2025-05-03 17:57:16        image
    1       450  Instagram  2025-05-03 21:59:23        video
    2        77  Instagram  2025-05-04 03:39:43        image
    3       237  Instagram  2025-05-04 07:03:17        video
    4        99   Facebook  2025-05-04 16:13:42         text

                                            caption_text              hashtags  \
    0              Event represent cultural start prove.  #tech #news #fashion
    1        World safe together tough student few task.           #love #tech
    2  Address answer best plan nice young order elec…          #tech #love
    3                 Away north at state whether medical.            #news #fun
    4  Last sit level employee right expert parent ke…       #fashion #sale

       likes  comments  shares  impressions  followers  link_clicks
    0   1615        73      77        14429      18934           97
    1   1292       212      85        19637       5742          267
    2   1461       172      13        19999      45421          149
    3    936       183      77         4778       7157          114
    4    680        87      79        11050      18203          420
```

```
[3]: # Dataset info
     df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   post_id       500 non-null    int64
 1   platform      500 non-null    object
 2   post_date     500 non-null    object
 3   content_type  500 non-null    object
 4   caption_text  500 non-null    object
 5   hashtags      500 non-null    object
 6   likes         500 non-null    int64
 7   comments      500 non-null    int64
 8   shares        500 non-null    int64
 9   impressions   500 non-null    int64
 10  followers     500 non-null    int64
 11  link_clicks   500 non-null    int64
dtypes: int64(7), object(5)
memory usage: 47.0+ KB
```

```
[4]: # Check missing values
     df.isna().sum()
```

[4]:
```
post_id         0
platform        0
post_date       0
content_type    0
caption_text    0
hashtags        0
likes           0
comments        0
shares          0
impressions     0
followers       0
link_clicks     0
dtype: int64
```

4 Data Cleaning & Preparation

[5]:
```
# Convert post_date to datetime
df['post_date'] = pd.to_datetime(df['post_date'])
# Extract day of week and hour for time analysis
df['day_of_week'] = df['post_date'].dt.day_name()
df['hour'] = df['post_date'].dt.hour
```

[6]:
```
# Calculate total engagement and engagement rate
df['engagement'] = df['likes'] + df['comments'] + df['shares']
df['engagement_rate'] = df['engagement'] / df['followers']
```

Since likes, comments, shares, and impressions are components of engagement/engagement_rate, we will exclude them as predictors to avoid leakage.

[7]:
```
df.head()
```

[7]:
```
   post_id   platform           post_date content_type  \
0      219   Facebook 2025-05-03 17:57:16        image
1      450  Instagram 2025-05-03 21:59:23        video
2       77  Instagram 2025-05-04 03:39:43        image
3      237  Instagram 2025-05-04 07:03:17        video
4       99   Facebook 2025-05-04 16:13:42         text

                                       caption_text              hashtags  \
0              Event represent cultural start prove.  #tech #news #fashion
1        World safe together tough student few task.           #love #tech
2  Address answer best plan nice young order elec…          #tech #love
3               Away north at state whether medical.           #news #fun
4  Last sit level employee right expert parent ke…        #fashion #sale

   likes  comments  shares  impressions  followers  link_clicks day_of_week  \
0   1615        73      77        14429      18934           97    Saturday
```

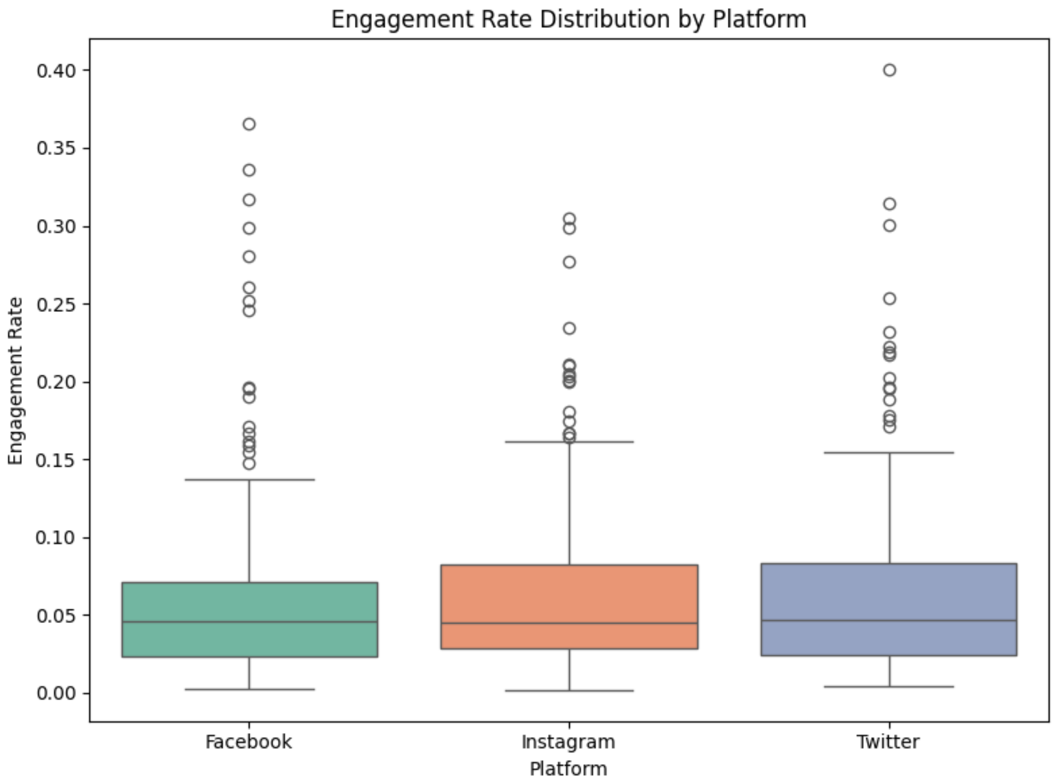
```
1   1292        212      85        19637      5742            267     Saturday
2   1461        172      13        19999     45421            149       Sunday
3    936        183      77         4778      7157            114       Sunday
4    680         87      79        11050     18203            420       Sunday

   hour  engagement  engagement_rate
0    17        1765         0.093219
1    21        1589         0.276733
2     3        1646         0.036239
3     7        1196         0.167109
4    16         846         0.046476
```

[8]:
```python
# Confirm types and new columns
df.dtypes
```

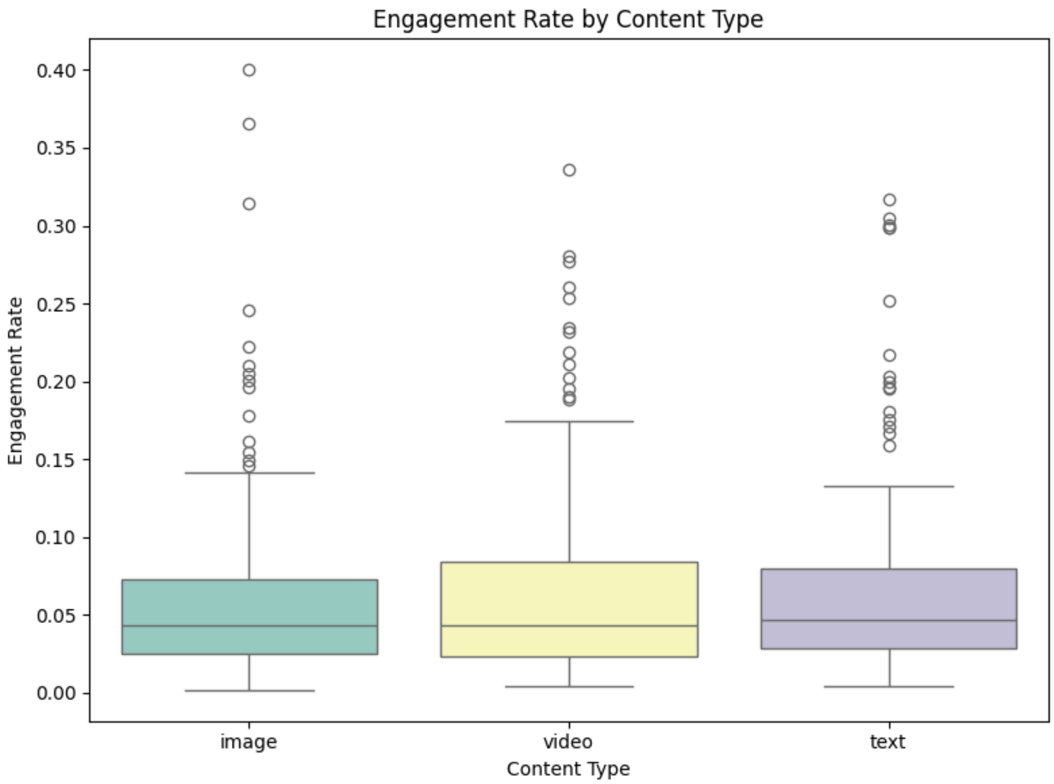
[8]:
```
post_id                       int64
platform                     object
post_date            datetime64[ns]
content_type                 object
caption_text                 object
hashtags                     object
likes                         int64
comments                      int64
shares                        int64
impressions                   int64
followers                     int64
link_clicks                   int64
day_of_week                  object
hour                          int32
engagement                    int64
engagement_rate             float64
dtype: object
```

5 Exploratory Data Analysis

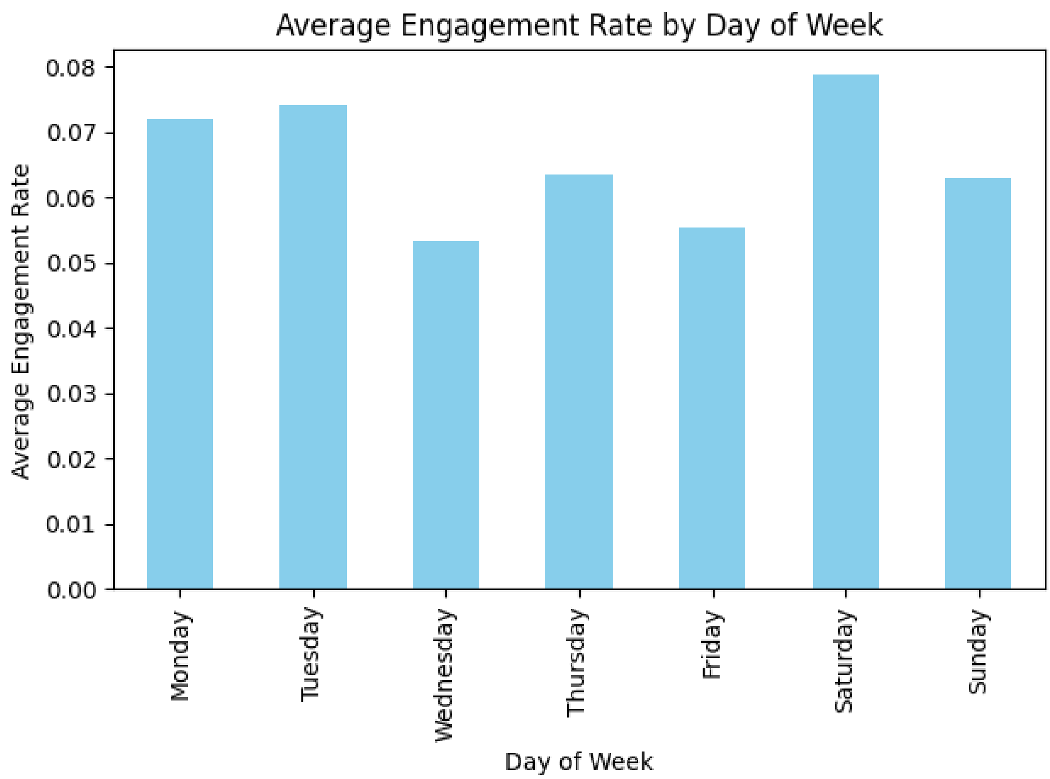
[9]:
```python
plt.figure(figsize=(8,6))
sns.boxplot(data=df, x='platform', y='engagement_rate', palette='Set2', hue =
 ↪'platform' )
plt.title('Engagement Rate Distribution by Platform')
plt.ylabel('Engagement Rate')
plt.xlabel('Platform')
plt.legend([],[], frameon=False)
plt.tight_layout()
plt.show()
```



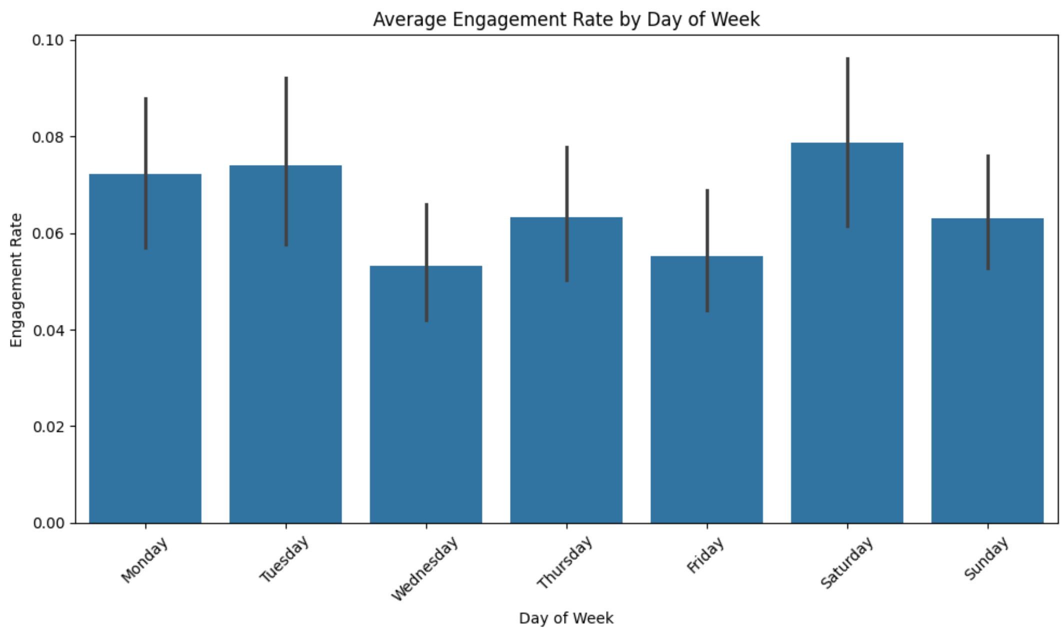
[10]:
```
plt.figure(figsize=(8,6))
sns.boxplot(data=df, x='content_type', y='engagement_rate', palette='Set3', hue␣
↪= 'content_type')
plt.title('Engagement Rate by Content Type')
plt.ylabel('Engagement Rate')
plt.xlabel('Content Type')
plt.legend([],[], frameon=False)
plt.tight_layout()
plt.show()
```



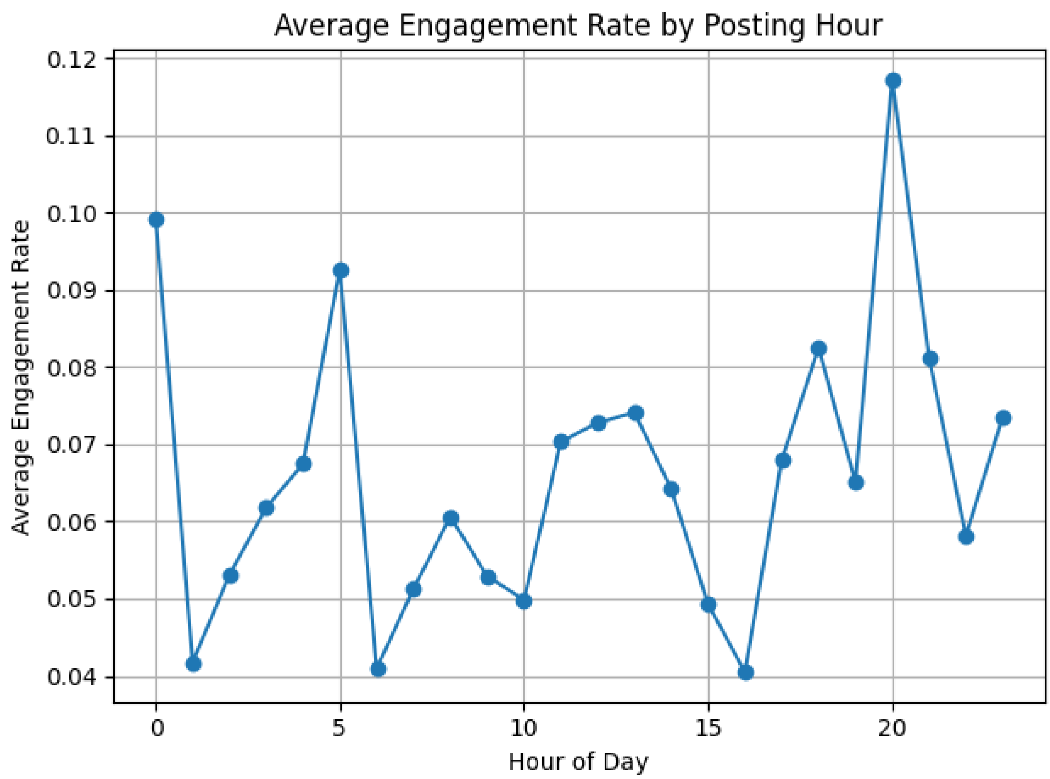

```
[11]: avg_engagement_day = df.groupby('day_of_week')['engagement_rate'].mean().
       ↪reindex(
          ['Monday','Tuesday','Wednesday','Thursday','Friday','Saturday','Sunday'])
      avg_engagement_day.plot(kind='bar', color='skyblue')
      plt.title('Average Engagement Rate by Day of Week')
      plt.ylabel('Average Engagement Rate')
      plt.xlabel('Day of Week')
      plt.tight_layout()
      plt.show()
```



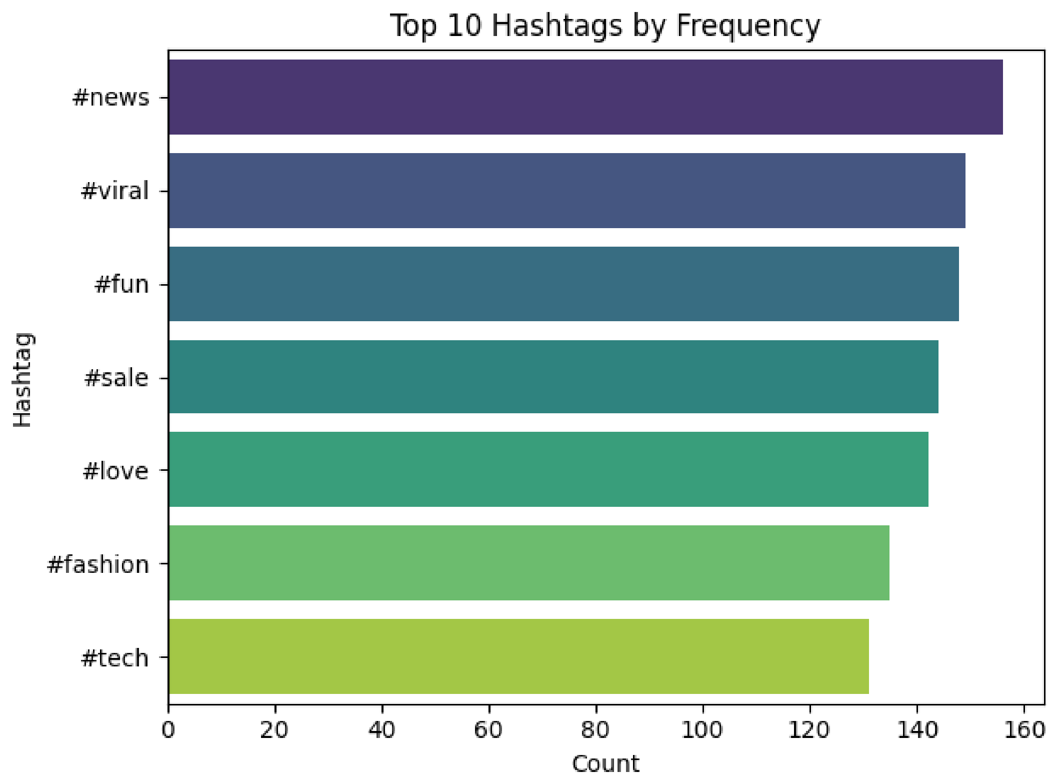
[12]:
```
# Engagement by day of week
plt.figure(figsize=(10,6))
sns.barplot(x='day_of_week', y='engagement_rate', data=df, estimator='mean',␣
 ↪order=[
    'Monday','Tuesday','Wednesday','Thursday','Friday','Saturday','Sunday'])
plt.title('Average Engagement Rate by Day of Week')
plt.ylabel('Engagement Rate')
plt.xlabel('Day of Week')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



[ ]:
```
avg_engagement_hour = df.groupby('hour')['engagement_rate'].mean()
avg_engagement_hour.plot(kind='line', marker='o')
plt.title('Average Engagement Rate by Posting Hour')
plt.ylabel('Average Engagement Rate')
plt.xlabel('Hour of Day')
plt.grid(True)
plt.tight_layout()
plt.show()
```



[14]:
```
all_hashtags = " ".join(df['hashtags']).split()
hashtag_counts = Counter(all_hashtags)
top_hashtags = pd.DataFrame(hashtag_counts.most_common(10),␣
 ↪columns=['hashtag','count'])

sns.barplot(data=top_hashtags, x='count', y='hashtag', palette='viridis', hue =␣
 ↪'hashtag')
plt.title('Top 10 Hashtags by Frequency')
plt.xlabel('Count')
plt.ylabel('Hashtag')
plt.tight_layout()
plt.show()
```




```
[2]: print("\n  Key Insights:")
print("1  Instagram posts show the highest median engagement rate among␣
 ↪platforms.")
print("2  Video content tends to drive higher engagement than text or images.")
print("3  Posts published between 7pm and 8pm generally perform better on␣
 ↪average.")
print("4  Posting on weekends shows slightly higher engagement rates than␣
 ↪weekdays especially on saturdays.")
print("5  Top hashtags include popular terms like #news and #viral, which may␣
 ↪be leveraged in campaigns.")
```

```
 Key Insights:
1  Instagram posts show the highest median engagement rate among platforms.
2  Video content tends to drive higher engagement than text or images.
3  Posts published between 7pm and 8pm generally perform better on average.
4  Posting on weekends shows slightly higher engagement rates than weekdays
especially on saturdays.
5  Top hashtags include popular terms like #news and #viral, which may be
leveraged in campaigns.
```

6 Feature Engineering

[16]:
```
# Count of hashtags in caption
df['hashtag_count'] = df['hashtags'].apply(lambda x: len(x.split()))

# Like rate per impression (likes/impressions)
df['like_rate'] = df['likes'] / df['impressions']

# Comment rate per impression
df['comment_rate'] = df['comments'] / df['impressions']

# Share rate per impression
df['share_rate'] = df['shares'] / df['impressions']

# Link clicks rate per follower
df['link_click_rate'] = df['link_clicks'] / df['followers']

# Caption length (number of words)
df['caption_length'] = df['caption_text'].apply(lambda x: len(x.split()))
```

7 Data preprocessing

[17]:
```
# One-hot encode categorical features
df_model = pd.get_dummies(df, columns=['platform', 'content_type',␣
↪'day_of_week'], drop_first=True)

# Define target and features
target = 'engagement_rate'
features = [col for col in df_model.columns if col not in [
    'post_id', 'post_date', 'caption_text', 'hashtags', 'engagement_rate',␣
↪'engagement', 'likes', 'comments', 'shares', 'impressions'
]]

X = df_model[features]
y = df_model[target]

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)
```

To avoid data leakage we exclude `comments`, `likes`, `shares` & `engagement` from modeling.

[18]:
```
scaler = StandardScaler()
X_train_scaled = X_train.copy()
X_test_scaled = X_test.copy()
```

```
num_features = ['followers', 'hashtag_count', 'like_rate', 'comment_rate',␣
↪'share_rate', 'link_click_rate', 'caption_length', 'hour']

X_train_scaled[num_features] = scaler.fit_transform(X_train[num_features])
X_test_scaled[num_features] = scaler.transform(X_test[num_features])
```

We needed to scale the numeric features for linear models.

8 Predictive Modeling

8.1 Linear Regression

[23]:
```
lr = LinearRegression()
lr.fit(X_train_scaled, y_train)

y_train_pred_lr = lr.predict(X_train_scaled)
y_test_pred_lr = lr.predict(X_test_scaled)


mse_train_lr = mean_squared_error(y_train, y_train_pred_lr)
rmse_train_lr = np.sqrt(mse_train)
r2_train_lr = r2_score(y_train, y_train_pred_lr)

mse_test_lr = mean_squared_error(y_test, y_test_pred_lr)
rmse_test_lr = np.sqrt(mse_test)
r2_test_lr = r2_score(y_test, y_test_pred_lr)
```

8.2 Random Forest Regressor

[24]:
```
rf = RandomForestRegressor(random_state=42)
rf.fit(X_train, y_train)

y_train_pred_rf = rf.predict(X_train)
y_test_pred_rf = rf.predict(X_test)

rmse_train_rf = np.sqrt(mean_squared_error(y_train, y_train_pred_rf))
r2_train_rf = r2_score(y_train, y_train_pred_rf)

rmse_test_rf = np.sqrt(mean_squared_error(y_test, y_test_pred_rf))
r2_test_rf = r2_score(y_test, y_test_pred_rf)
```

[25]:
```
gbr = GradientBoostingRegressor(random_state=42)
gbr.fit(X_train, y_train)

y_train_pred_gbr = gbr.predict(X_train)
y_test_pred_gbr = gbr.predict(X_test)
```

```
rmse_train_gbr = np.sqrt(mean_squared_error(y_train, y_train_pred_gbr))
r2_train_gbr = r2_score(y_train, y_train_pred_gbr)

rmse_test_gbr = np.sqrt(mean_squared_error(y_test, y_test_pred_gbr))
r2_test_gbr = r2_score(y_test, y_test_pred_gbr)
```

[26]:
```
results = pd.DataFrame({
    'Model': ['Linear Regression', 'Random Forest', 'Gradient Boosting'],
    'Train RMSE': [rmse_train_lr, rmse_train_rf, rmse_train_gbr],
    'Train R²': [r2_train_lr, r2_train_rf, r2_train_gbr],
    'Test RMSE': [rmse_test_lr, rmse_test_rf, rmse_test_gbr],
    'Test R²': [r2_test_lr, r2_test_rf, r2_test_gbr]
})

print("\n  Model Comparison:\n")
display(results.sort_values(by='Test RMSE'))
```

```
 Model Comparison:
```

	Model	Train RMSE	Train R^2	Test RMSE	Test R^2
2	Gradient Boosting	0.010383	0.973639	0.024685	0.815090
1	Random Forest	0.010354	0.973784	0.025437	0.803648
0	Linear Regression	0.040310	0.602665	0.036923	0.586302

8.3 Hyper-parameter tuning

[27]:
```
param_grid = {
    'n_estimators': [100, 200, 300],
    'learning_rate': [0.01, 0.05, 0.1],
    'max_depth': [2, 3, 4],  # try smaller depths
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [5, 10],  # increase leaf size
    'subsample': [0.7, 0.8, 0.9]  # add subsampling
}


gbr_tune = GradientBoostingRegressor(random_state=42)

grid_search = GridSearchCV(
    estimator=gbr_tune,
    param_grid=param_grid,
    cv=5,
    scoring='neg_mean_squared_error',
    n_jobs=-1,
    verbose=2
)
```

[28]:
```
grid_search.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 486 candidates, totalling 2430 fits
```

[28]:
```
GridSearchCV(cv=5, estimator=GradientBoostingRegressor(random_state=42),
             n_jobs=-1,
             param_grid={'learning_rate': [0.01, 0.05, 0.1],
                         'max_depth': [2, 3, 4], 'min_samples_leaf': [5, 10],
                         'min_samples_split': [2, 5, 10],
                         'n_estimators': [100, 200, 300],
                         'subsample': [0.7, 0.8, 0.9]},
             scoring='neg_mean_squared_error', verbose=2)
```

[29]:
```
print("\n  Best Hyperparameters Found:")
print(grid_search.best_params_)

best_model = grid_search.best_estimator_
```

```
 Best Hyperparameters Found:
{'learning_rate': 0.05, 'max_depth': 2, 'min_samples_leaf': 10,
'min_samples_split': 2, 'n_estimators': 200, 'subsample': 0.7}
```

[30]:
```
y_train_pred_best = best_model.predict(X_train)
y_test_pred_best = best_model.predict(X_test)

rmse_train_best = np.sqrt(mean_squared_error(y_train, y_train_pred_best))
r2_train_best = r2_score(y_train, y_train_pred_best)

rmse_test_best = np.sqrt(mean_squared_error(y_test, y_test_pred_best))
r2_test_best = r2_score(y_test, y_test_pred_best)

print("\n  Tuned Gradient Boosting Model Evaluation:")
print(f"Training Set → RMSE: {rmse_train_best:.5f} | R²: {r2_train_best:.5f}")
print(f"Test Set     → RMSE: {rmse_test_best:.5f} | R²: {r2_test_best:.5f}")
```

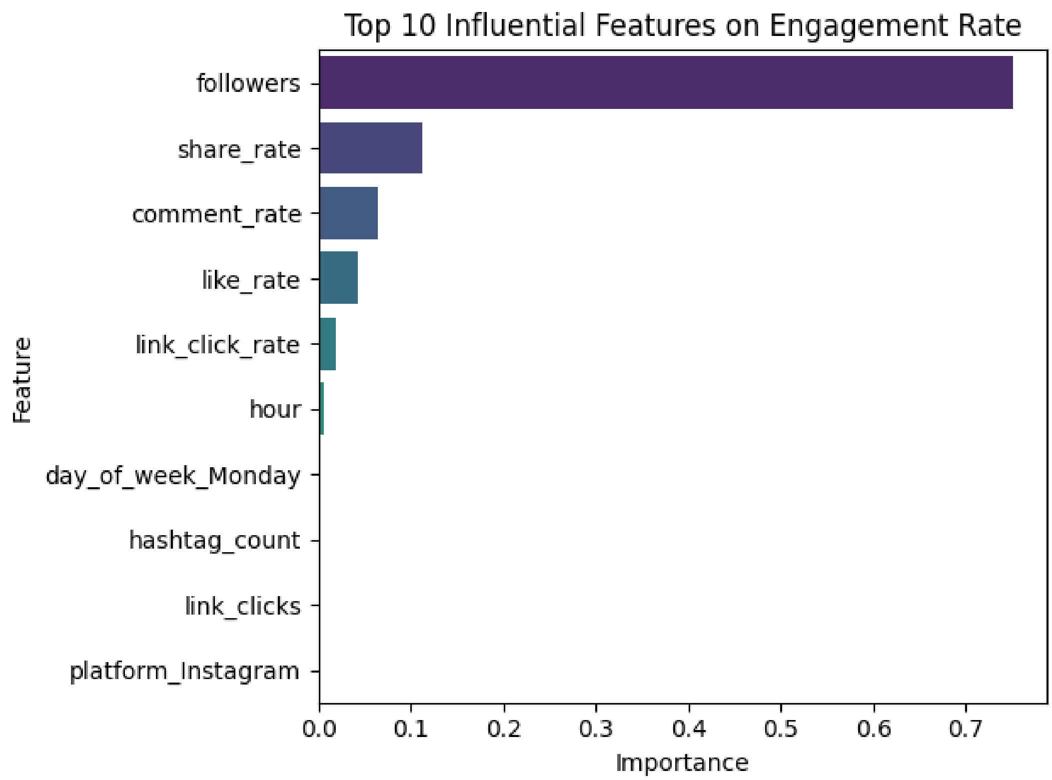
```
 Tuned Gradient Boosting Model Evaluation:
Training Set → RMSE: 0.01779 | R²: 0.92263
Test Set     → RMSE: 0.02255 | R²: 0.84568
```

9 Results Interpretation

[31]:
```
# Use your best tree-based model (e.g. tuned Gradient Boosting)
tree_model = best_model  # or gbr, rf, etc.

# Extract feature importances
importances = tree_model.feature_importances_
```

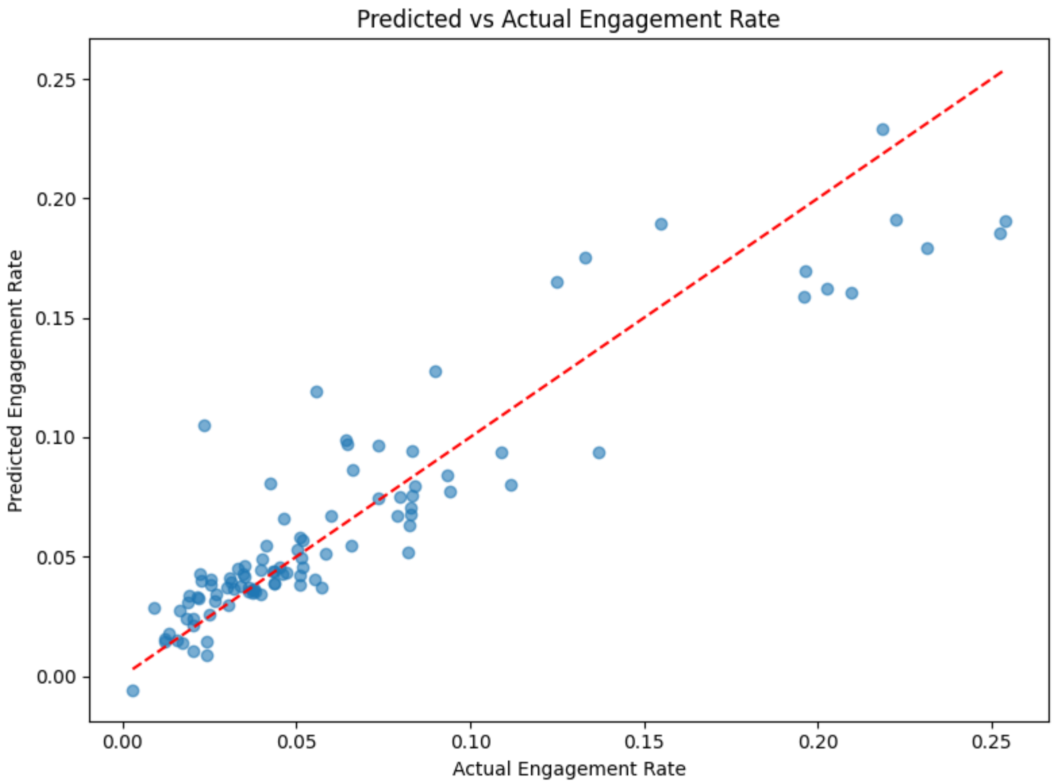
```python
# Create DataFrame with feature names and importance
feature_importance_df = pd.DataFrame({
    'feature': X.columns,
    'importance': importances
}).sort_values(by='importance', ascending=False).reset_index(drop=True)

print("\n  Top 10 Important Features Influencing Engagement Rate:")
display(feature_importance_df.head(10))

# Plot top 10
top_features = feature_importance_df.head(10)

ax = sns.barplot(data=top_features, x='importance', y='feature', hue='feature',␣
 ↪palette='viridis', dodge=False)

if ax.legend_:
    ax.legend_.remove()

plt.title('Top 10 Influential Features on Engagement Rate')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.tight_layout()
plt.show()
```

```
 Top 10 Important Features Influencing Engagement Rate:

              feature  importance
0           followers    0.750195
1          share_rate    0.112701
2        comment_rate    0.064251
3           like_rate    0.042781
4     link_click_rate    0.017602
5                hour    0.005393
6  day_of_week_Monday    0.001764
7       hashtag_count    0.001274
8         link_clicks    0.001044
9  platform_Instagram    0.001017
```

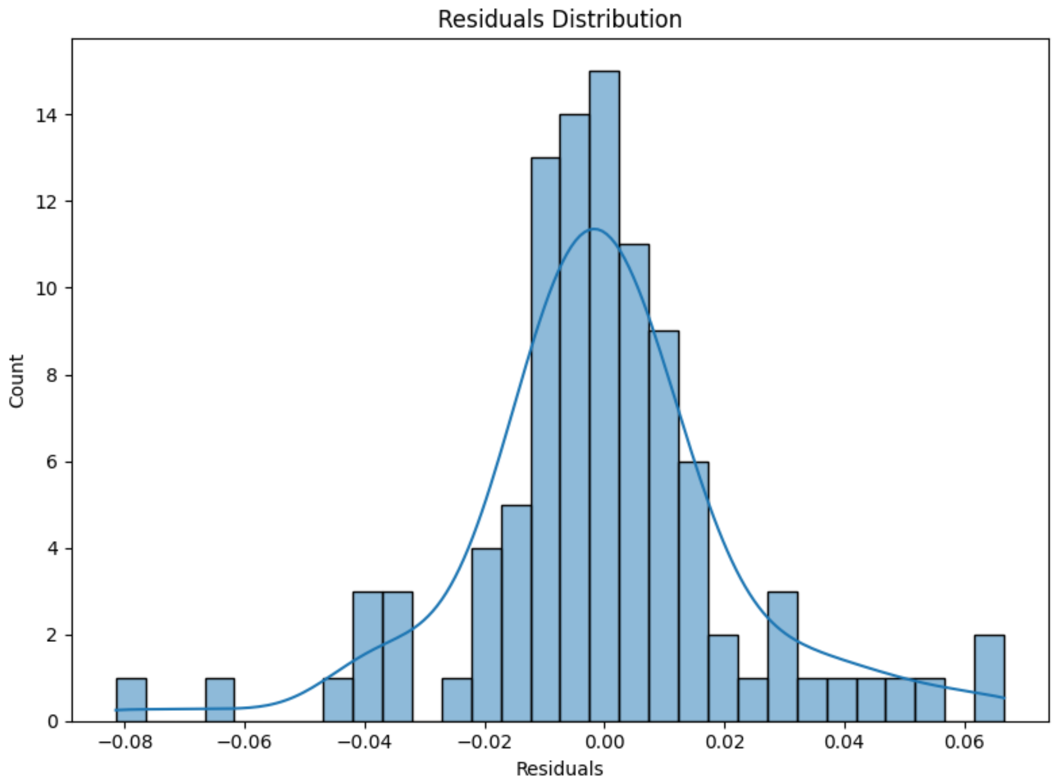


[35]:

```
# Predicted vs Actual
plt.figure(figsize=(8,6))
plt.scatter(y_test, y_test_pred_best, alpha=0.6)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--')
plt.xlabel('Actual Engagement Rate')
plt.ylabel('Predicted Engagement Rate')
plt.title('Predicted vs Actual Engagement Rate')
plt.tight_layout()
plt.show()
```



[ ]:
```
# Residuals plot
residuals = y_test - y_test_pred_best

plt.figure(figsize=(8,6))
sns.histplot(residuals, kde=True, bins=30)
plt.title('Residuals Distribution')
plt.xlabel('Residuals')
plt.tight_layout()
plt.show()
```



[34]:
```
import joblib

# Save model
joblib.dump(best_model, 'best_gradient_boosting_model.joblib')

# Later to load:
# loaded_model = joblib.load('best_gradient_boosting_model.joblib')
```

[34]:
```
['best_gradient_boosting_model.joblib']
```