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]:
```python
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]:
```python
# 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]:
```python
# 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]:
```python
# 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
```

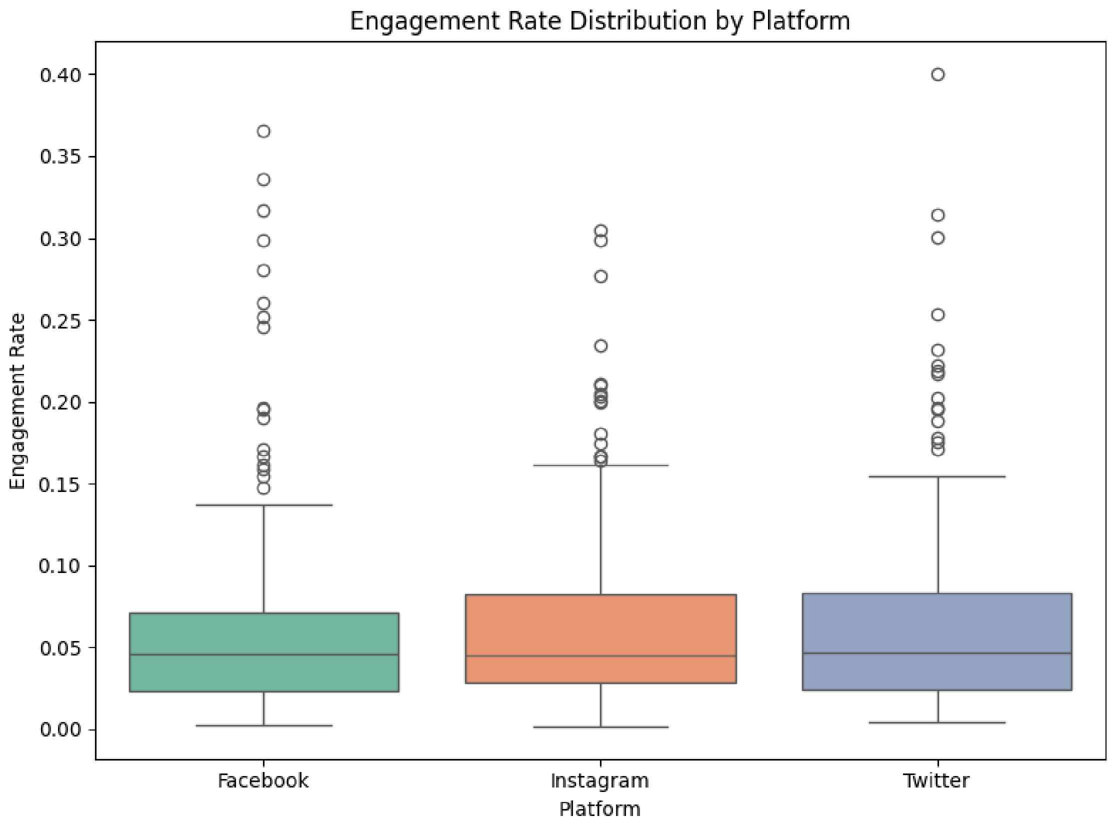
```
1   1292        212       85         19637       5742             267    Saturday
2   1461        172       13         19999      45421             149      Sunday
3    936        183       77          4778       7157             114      Sunday
4    680         87       79         11050      18203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

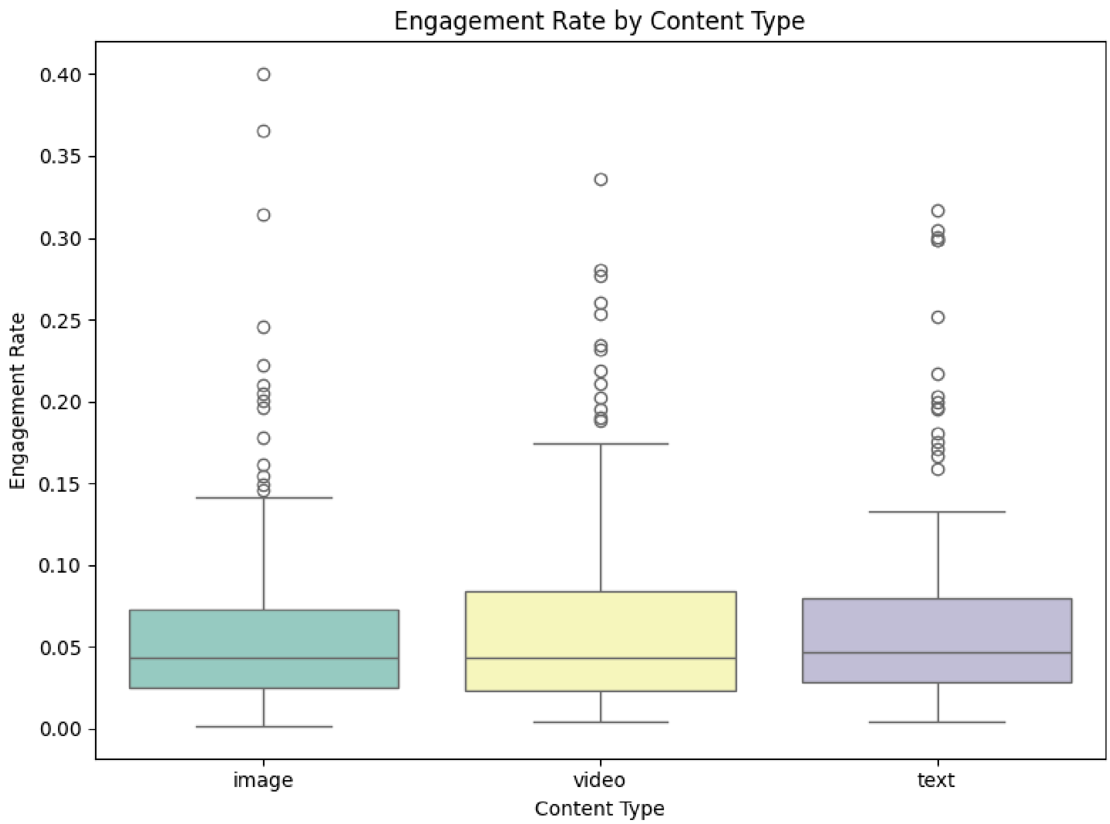
5 Exploratory Data Analysis

[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()
```

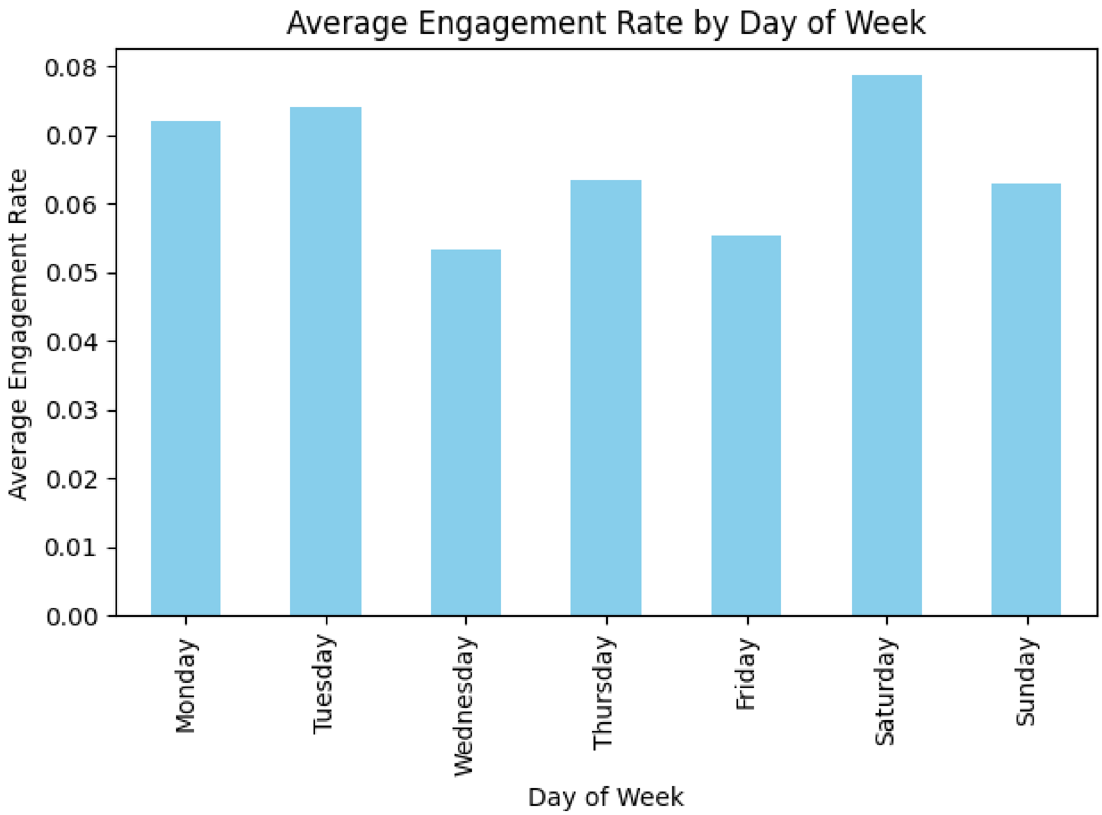


[10]:

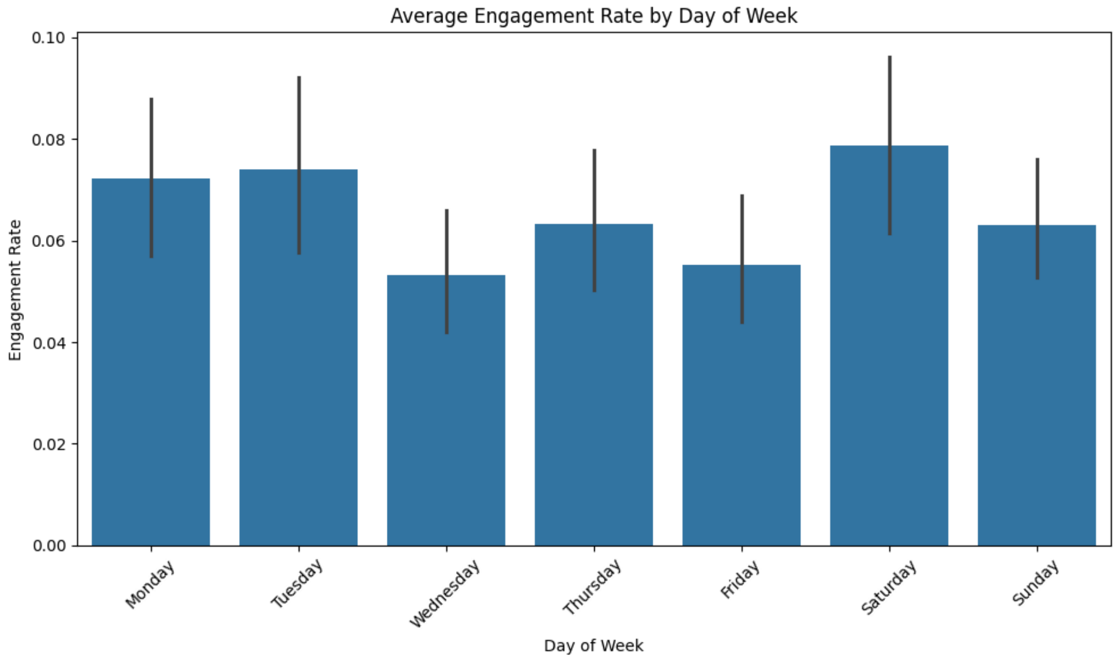
```
plt.figure(figsize=(8,6))
sns.boxplot(data=df, x='content_type', y='engagement_rate', palette='Set3', hue␣
↪= 'content_type')
plt.title('Engagement Rate by Content Type')
plt.ylabel('Engagement Rate')
plt.xlabel('Content Type')
plt.legend([],[], frameon=False)
plt.tight_layout()
plt.show()
```



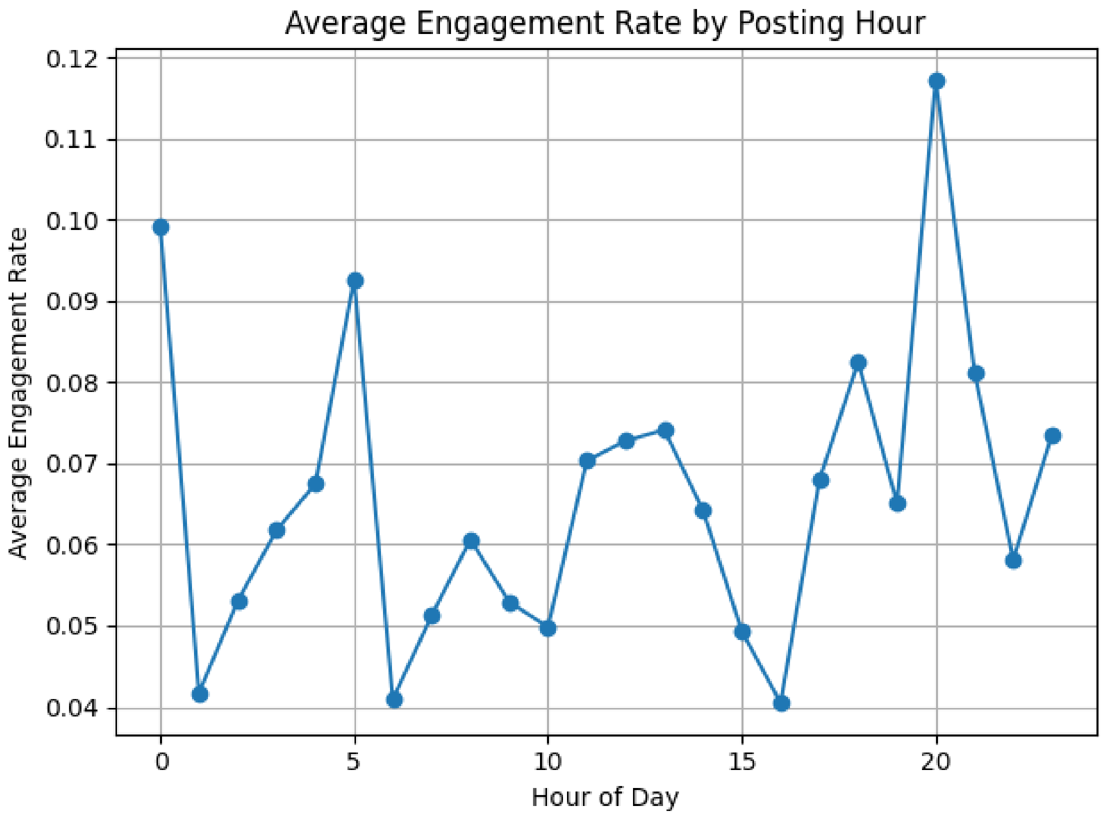
[11]:
```
avg_engagement_day = df.groupby('day_of_week')['engagement_rate'].mean().
↪reindex(
    ['Monday','Tuesday','Wednesday','Thursday','Friday','Saturday','Sunday'])
avg_engagement_day.plot(kind='bar', color='skyblue')
plt.title('Average Engagement Rate by Day of Week')
plt.ylabel('Average Engagement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



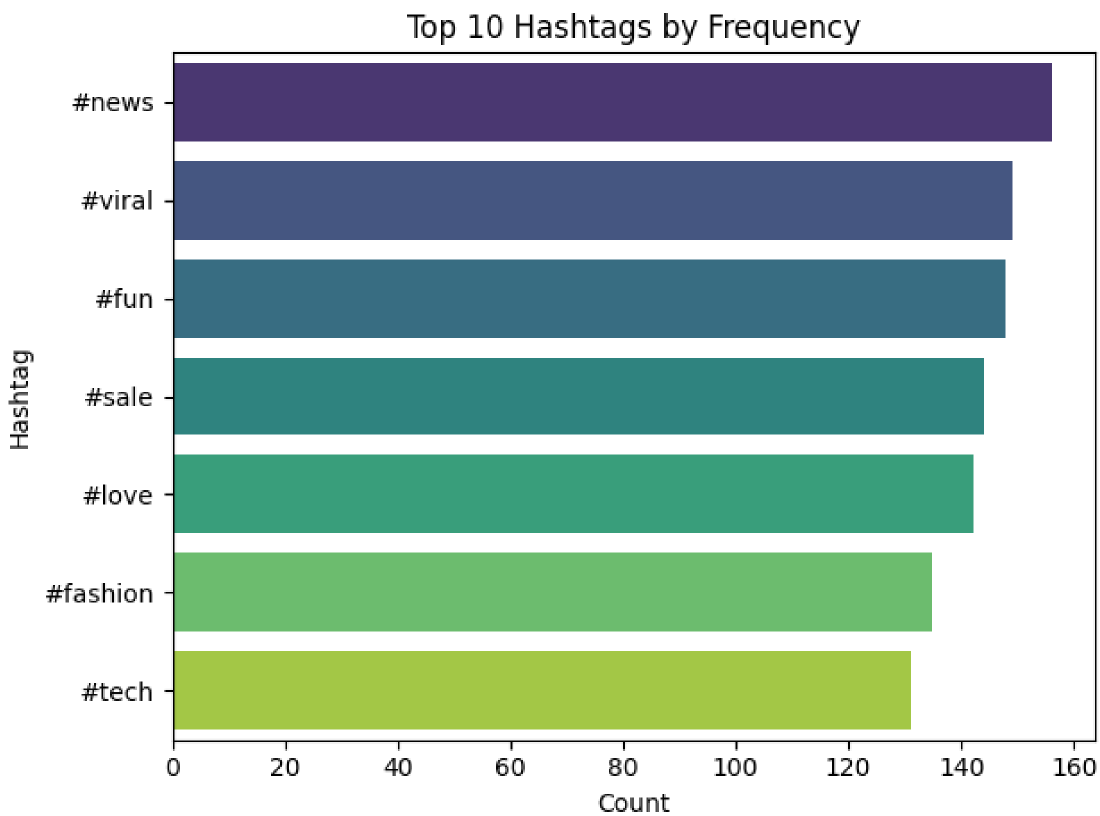
[12]:
```
# Engagement by day of week
plt.figure(figsize=(10,6))
sns.barplot(x='day_of_week', y='engagement_rate', data=df, estimator='mean',␣
  ↪order=[
    'Monday','Tuesday','Wednesday','Thursday','Friday','Saturday','Sunday'])
plt.title('Average Engagement Rate by Day of Week')
plt.ylabel('Engagement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

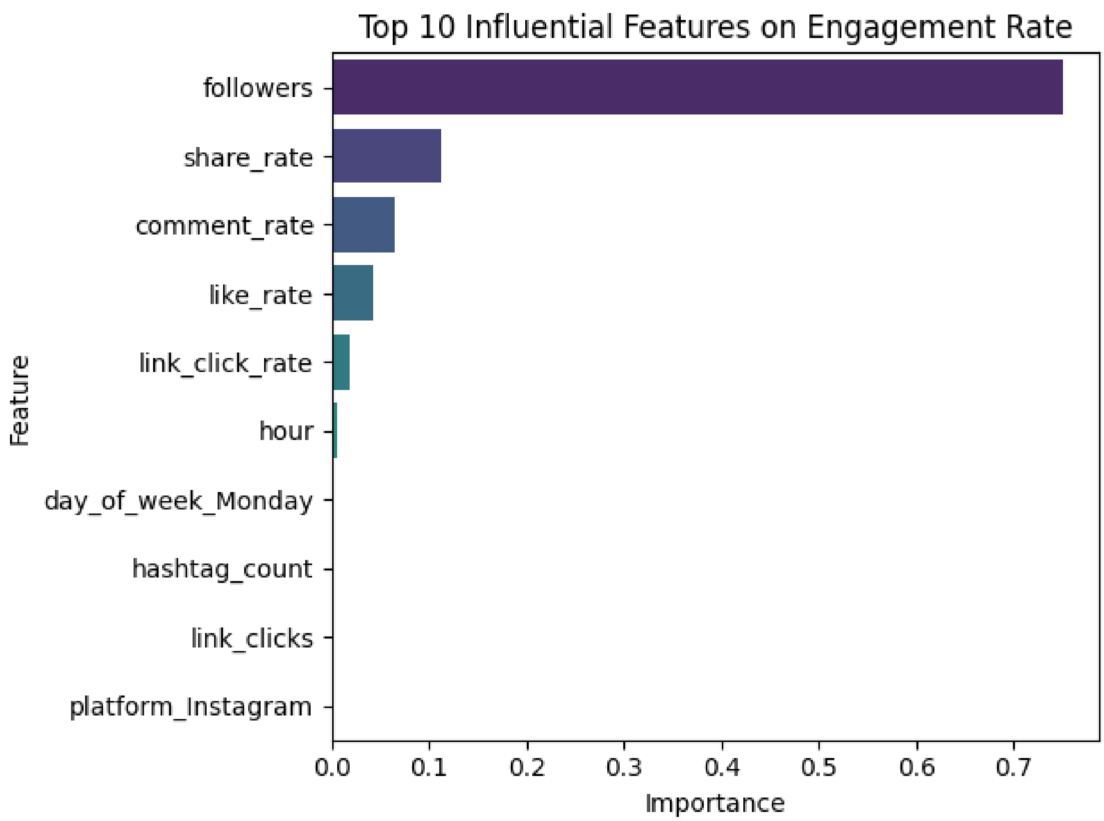
```

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

9 Results Interpretation

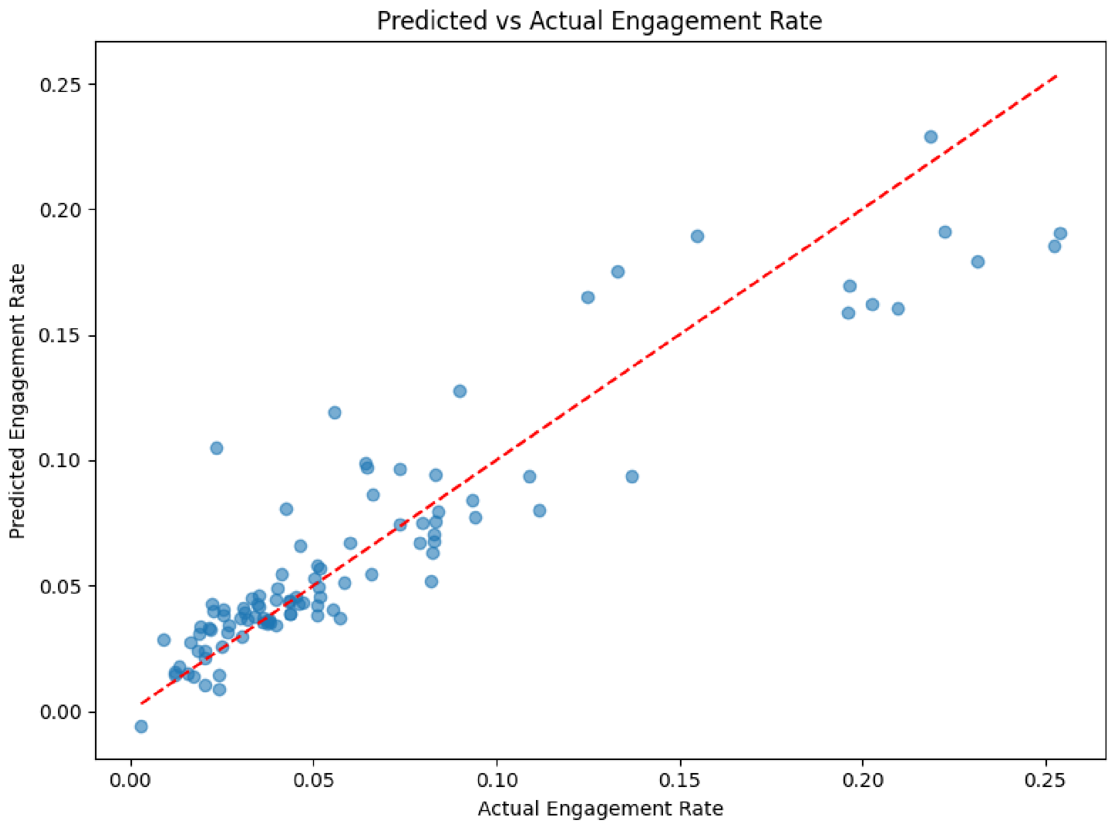
[31]:
```
# Use your best tree-based model (e.g. tuned Gradient Boosting)
tree_model = best_model  # or gbr, rf, etc.

# 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
```

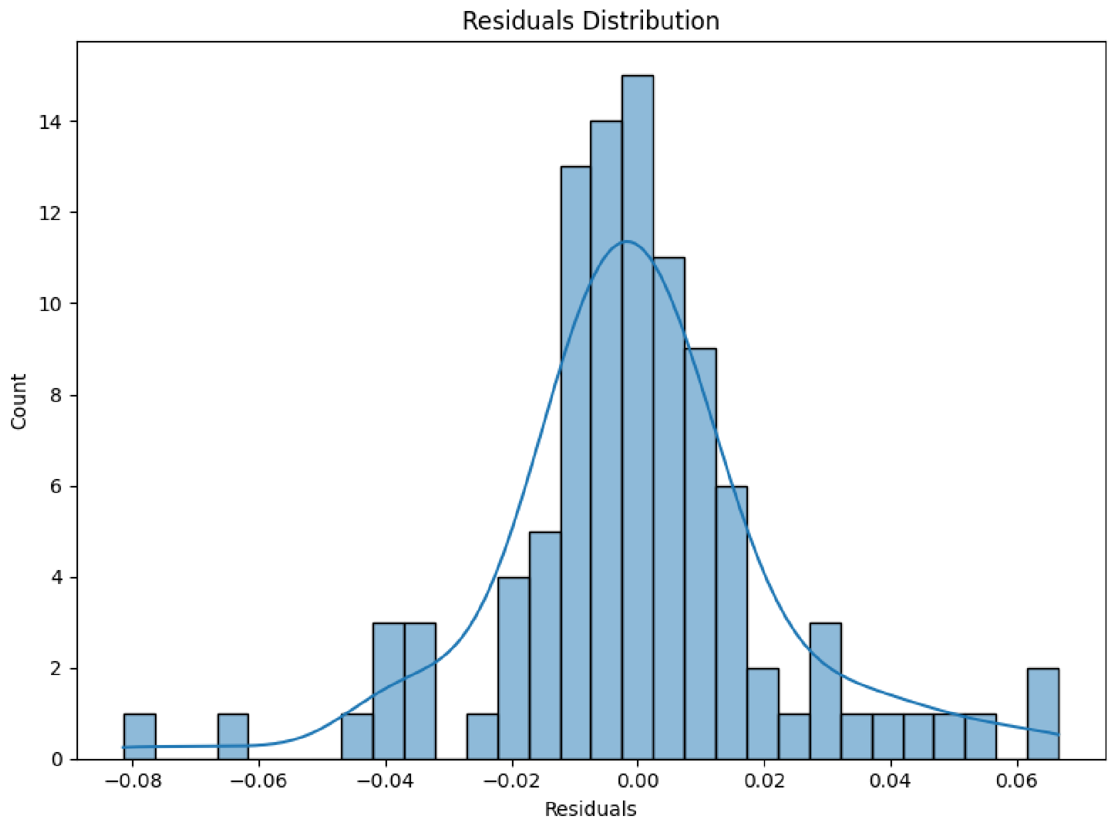


[35]:
```
# Predicted vs Actual
plt.figure(figsize=(8,6))
plt.scatter(y_test, y_test_pred_best, alpha=0.6)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--')
plt.xlabel('Actual Engagement Rate')
plt.ylabel('Predicted Engagement Rate')
plt.title('Predicted vs Actual Engagement 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']