video_features_exploration

April 14, 2025

1 Video lifetime performance prediction based on early engagement signals

1.1 I. Exploring the feature set

1.1.1 Dataset Structure and Feature Overview

This dataset is designed to capture video performance and early engagement signals around platform-specific impression milestones.

Key Feature Groups: - `video_id`, `channel_name`, `video_length`: basic identifiers and metadata - `*_1k`: engagement metrics when the video reaches 1,000 impressions (e.g., `views3s_1k`, `like_1k`, `comments_1k`) - `*_5k`: engagement metrics at the 5,000 impression milestone (e.g., `views3s_5k`, `like_5k`, `comments_5k`) - `*_final`: final outcome metrics used as regression targets (e.g., `views_final`, `like_final`, `comment_final`) - `reaches_5k`: boolean flag indicating whether the video truly reached 5k impressions

These features reflect the kind of early-stage metrics typically available in video performance forecasting workflows.

[3]:
```
# Import libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[4]:
```
# Load the dataset
file_path = '../data/Video_Timeseries.csv'
df = pd.read_csv(file_path)
df = df.dropna().reset_index(drop=True)
df.shape
```

[4]: (13806, 15)

[5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 13806 entries, 0 to 13805
Data columns (total 15 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
```

```
 0   video_id           13806 non-null  object
 1   channel_id         13806 non-null  object
 2   video_length       13806 non-null  int64
 3   views_final        13806 non-null  float64
 4   impressions_final  13806 non-null  float64
 5   like_final         13806 non-null  float64
 6   comment_final      13806 non-null  float64
 7   views3s_1k         13806 non-null  int64
 8   impressions_1k     13806 non-null  int64
 9   like_1k            13806 non-null  float64
 10  comments_1k        13806 non-null  float64
 11  views3s_5k         13806 non-null  float64
 12  impressions_5k     13806 non-null  float64
 13  like_5k            13806 non-null  float64
 14  comments_5k        13806 non-null  float64
dtypes: float64(10), int64(3), object(2)
memory usage: 1.6+ MB
```

[6]:

```
df.head()
```

[6]:

```
                                            video_id  \
0  58006937d7695b285f9854bf86a0d63a1476f578925275…
1  91423a16a2a5fc24cda7bd93403c52f1198dfb7a62ad0c…
2  ac4f4163917b5bb69c1b227a075817a830ee8afc93bef6…
3  061287596b4a02efaff23eacba6fc9ee2d31b6f6daebd6…
4  4250d891dfeba257ef2367c37e29865b4555120d26aa43…

                                          channel_id  video_length  \
0  bab3e0fb356b5dab60dfbfbc33a611547250e93830f6f0…           785
1  cd0c9afcf7a1c5c5f2e80747041df16c661074594493a1…           412
2  7687f7c22713a0ba4ce088fb9b5c32a2d9c03567759c28…           186
3  a45ac131cbca37a25a5527b76bb9910cc4ee9689670af0…           338
4  29a69f4cd31f2c5a88e7a5e16a621e8d2d3fd2971cbadb…           400

   views_final  impressions_final  like_final  comment_final  views3s_1k  \
0      60904.0            96520.0      1094.0           51.0         593
1     130986.0           286634.0       760.0          116.0        9471
2     886216.0          1160128.0     29008.0          184.0        2813
3     534100.0          1006887.0      7151.0          165.0       17679
4     203323.0           382255.0      2174.0          351.0        1643

   impressions_1k  like_1k  comments_1k  views3s_5k  impressions_5k  like_5k  \
0            1160     23.0          3.0      4002.0          6710.0    127.0
1           39359    185.0          7.0      9471.0         39359.0    185.0
2            3266    113.0          2.0      6029.0          8773.0    271.0
3           31591    494.0         27.0     17679.0         31591.0    494.0
4            2855     12.0          3.0      3424.0          7966.0     28.0
```

```
   comments_5k
0         11.0
1          7.0
2          5.0
3         27.0
4         12.0
```

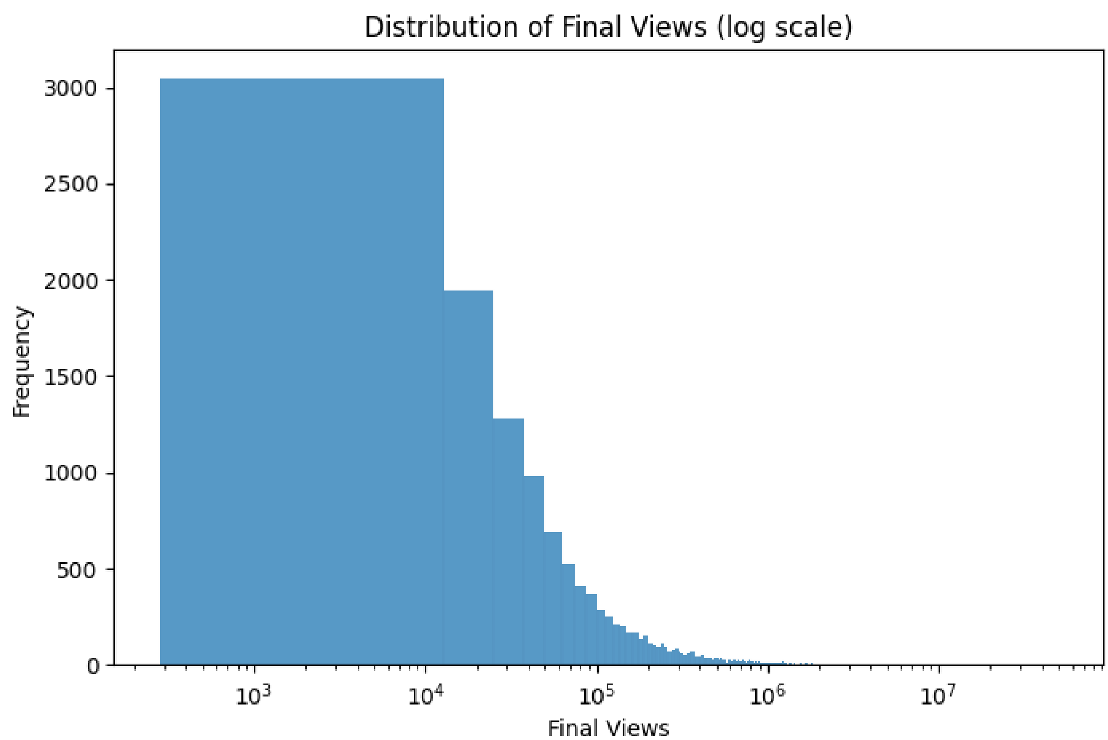
[7]:
```python
# normalizing the early engagement data based on impressions milestones
df['views3s_1k'] = df['views3s_1k'] * 1000 / df['impressions_1k']
df['like_1k'] = df['like_1k'] * 1000 / df['impressions_1k']
df['comments_1k'] = df['comments_1k'] * 1000 / df['impressions_1k']
df['views3s_5k'] = df['views3s_5k'] * 1000 / df['impressions_5k']
df['like_5k'] = df['like_5k'] * 1000 / df['impressions_5k']
df['comments_5k'] = df['comments_5k'] * 1000 / df['impressions_5k']

# drop the impressions columns
# df = df.drop(columns=['impressions_1k', 'impressions_5k'])
df.head()
```

[7]:
```
                                            video_id  \
0  58006937d7695b285f9854bf86a0d63a1476f578925275…
1  91423a16a2a5fc24cda7bd93403c52f1198dfb7a62ad0c…
2  ac4f4163917b5bb69c1b227a075817a830ee8afc93bef6…
3  061287596b4a02efaff23eacba6fc9ee2d31b6f6daebd6…
4  4250d891dfeba257ef2367c37e29865b4555120d26aa43…

                                          channel_id  video_length  \
0  bab3e0fb356b5dab60dfbfbc33a611547250e93830f6f0…           785
1  cd0c9afcf7a1c5c5f2e80747041df16c661074594493a1…           412
2  7687f7c22713a0ba4ce088fb9b5c32a2d9c03567759c28…           186
3  a45ac131cbca37a25a5527b76bb9910cc4ee9689670af0…           338
4  29a69f4cd31f2c5a88e7a5e16a621e8d2d3fd2971cbadb…           400

   views_final  impressions_final  like_final  comment_final  views3s_1k  \
0      60904.0            96520.0      1094.0           51.0  511.206897
1     130986.0           286634.0       760.0          116.0  240.631114
2     886216.0          1160128.0     29008.0          184.0  861.298224
3     534100.0          1006887.0      7151.0          165.0  559.621411
4     203323.0           382255.0      2174.0          351.0  575.481611

   impressions_1k    like_1k  comments_1k  views3s_5k  impressions_5k  \
0            1160  19.827586     2.586207  596.423249          6710.0
1           39359   4.700323     0.177850  240.631114         39359.0
2            3266  34.598898     0.612370  687.222159          8773.0
3           31591  15.637365     0.854674  559.621411         31591.0
4            2855   4.203152     1.050788  429.826764          7966.0
```

	like_5k	comments_5k
0	18.926975	1.639344
1	4.700323	0.177850
2	30.890231	0.569930
3	15.637365	0.854674
4	3.514938	1.506402

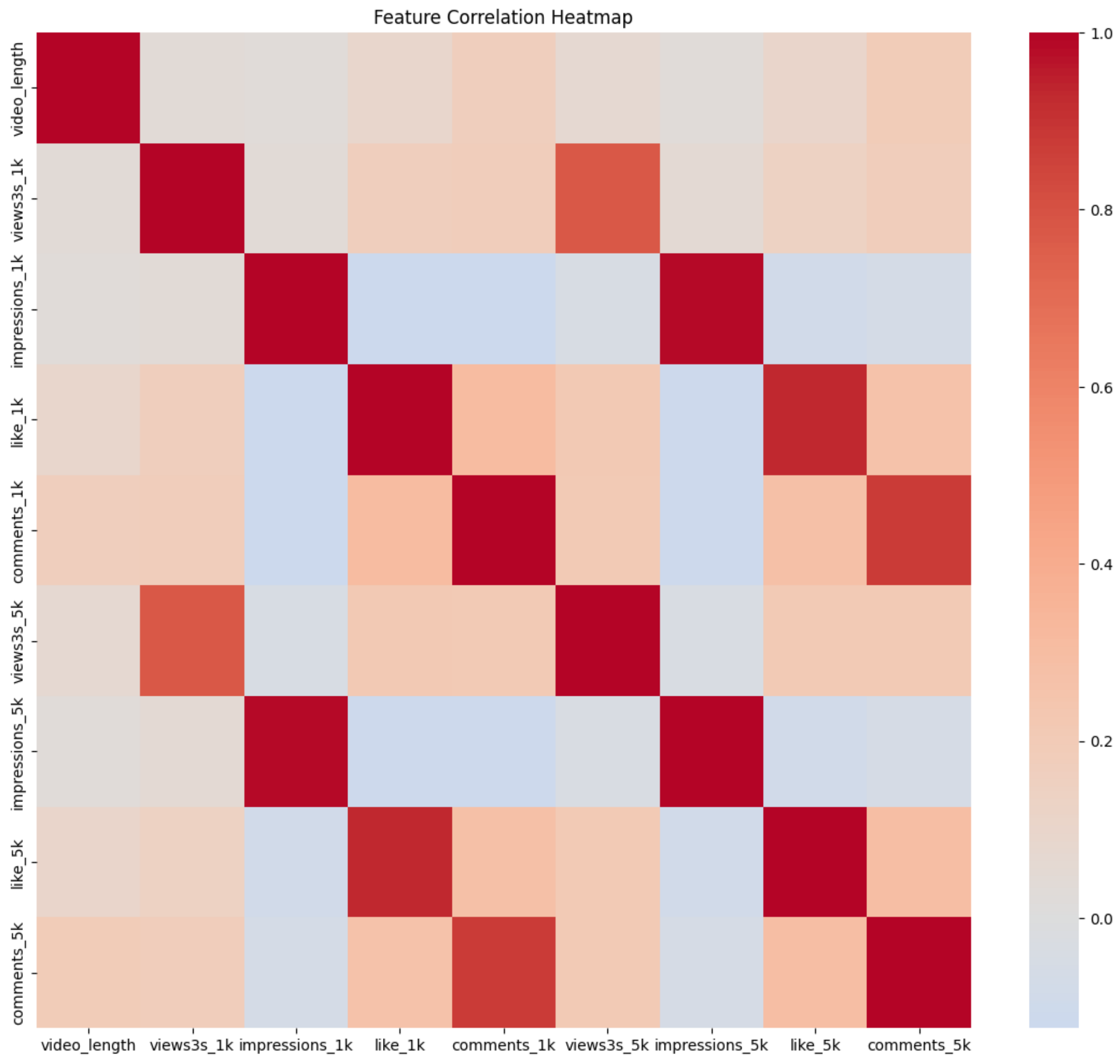
1.2 II. Exploring the target distribution

[8]:
```
# Histogram of final views
plt.figure(figsize=(8, 5))
sns.histplot(df['views_final'])
plt.xscale("log")
plt.title("Distribution of Final Views (log scale)")
plt.xlabel("Final Views")
plt.ylabel("Frequency")
plt.show()
```



1.3 III. Testing which features are tied closely to final outcome with correlations

[9]:
```
# Feature correlation heatmap
numeric_cols = [col for col in df.columns if df[col].dtype != 'object' and␣
↪'final' not in col]
corr = df[numeric_cols].corr()

plt.figure(figsize=(14, 12))
sns.heatmap(corr, cmap="coolwarm", center=0)
plt.title("Feature Correlation Heatmap")
plt.show()
```



1.4 IV. Training a regression model

1.4.1 Initial Model Training: Baseline Approach

We begin with a single Random Forest model trained on log-transformed `views_final`. This gives us a baseline against which to compare more advanced techniques like lifespan-aware modeling.

[10]:
```python
# Train a basic regression model
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_absolute_percentage_error
```

[11]:
```python
# Select early features
features = [
    'views3s_1k', 'like_1k', 'comments_1k',
    'views3s_5k', 'like_5k', 'comments_5k',
    # 'video_length'
]
```

[12]:
```python
# Create X and y and split the data
import numpy as np

X = df[features]
y_log = np.log1p(df['views_final'])

X_train, X_test, y_train, y_test = train_test_split(X, y_log, test_size=0.2,␣
 ↪random_state=42)
```

[13]:
```python
# Fit the model
model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)
```

[13]:
```
RandomForestRegressor(random_state=42)
```

[14]:
```python
# Evaluate
mae = mean_absolute_error(y_test, model.predict(X_test))
mape = mean_absolute_percentage_error(y_test, model.predict(X_test))

print(f"MAE: {mae:.2f}")
print(f"MAPE: {mape:.4f}")
```

```
MAE: 1.22
MAPE: 0.1137
```

1.5 V. Introduce cluster-specific modelling

[15]:
```
# # Estimate alpha-lifespan and cluster
# def classify_lifespan(row, alpha=0.5):
#     if pd.isna(row['views3s_5k']):
#         return 'short'
#     ratio = row['views3s_5k'] / row['views_final']
#     return 'long' if ratio >= alpha else 'short'

# df['lifespan_group'] = df.apply(classify_lifespan, axis=1)
```

[16]:
```
# df['lifespan_group'].value_counts()
```

[19]:
```
# engineering velocity features for clustering

df['velocity_1'] = df['impressions_1k'] / 1000
df['velocity_5'] = df['impressions_5k'] / df['impressions_1k']
```

[21]:
```
from sklearn.cluster import KMeans

# We create two velocity features.
# velocity_1 = impressions_1k normalized by 1000.
df['velocity_1'] = df['impressions_1k'] / 1000.0
# velocity_5 = impressions_5k / impressions_1k (handle division-by-zero).
df['velocity_5'] = df['impressions_5k'] / df['impressions_1k']

clust_features = ['velocity_1', 'velocity_5']
X_clust = df[clust_features].values

# Perform K-means clustering (using k=3 clusters; adjust if needed).
k = 3
kmeans = KMeans(n_clusters=k, random_state=42)
df['cluster'] = kmeans.fit_predict(X_clust)
print("\nCluster counts based on engineered velocity features:")
print(df['cluster'].value_counts())
```

```

Cluster counts based on engineered velocity features:
cluster
0    11479
1     1736
2      591
Name: count, dtype: int64
```

[22]:
```
# Train separate models for each lifespan group
models = {}
metrics = {}
```

```python
for group in df['cluster'].unique():
    group_df = df[df['cluster'] == group]
    X = group_df[features]
    y_log = np.log1p(group_df['views_final'])

    X_train, X_test, y_train, y_test = train_test_split(X, y_log, test_size=0.
 ↪2, random_state=42)
    model = RandomForestRegressor(n_estimators=100, random_state=42)
    model.fit(X_train, y_train)

    y_pred = model.predict(X_test)
    y_pred_exp = np.expm1(y_pred)
    y_test_exp = np.expm1(y_test)

    mae = mean_absolute_error(y_test_exp, y_pred_exp)
    mape = mean_absolute_percentage_error(y_test_exp, y_pred_exp)

    models[group] = model
    metrics[group] = {'MAE': mae, 'MAPE': mape}
```

[24]:

```python
# Compare specialized models
for group, metric in metrics.items():
    print(f"Cluster {group}: MAE = {metric['MAE']:.2f}, MAPE = {metric['MAPE']:.
 ↪4f}")
```

```
Cluster 0: MAE = 242283.33, MAPE = 2.2707
Cluster 1: MAE = 356563.88, MAPE = 2.0435
Cluster 2: MAE = 263131.78, MAPE = 0.9407
```