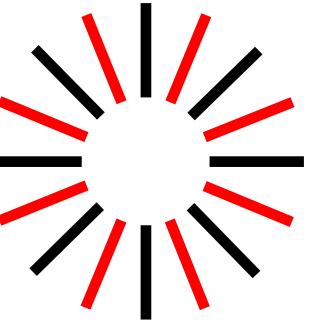


# **ANALYSIS ON TRENDING YOUTUBE VIDEOS**

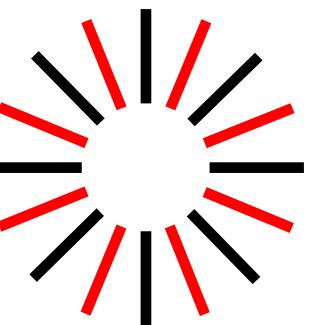


**BY DAVID ABRAHAM**



# AGENDA

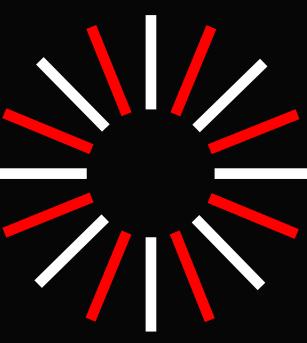
- Why I chose this topic
- Research Goal
- Dataset
- Implementation Pipeline
- Data Handling and EDA
- Key Insights
- Technologies Used
- Challenges



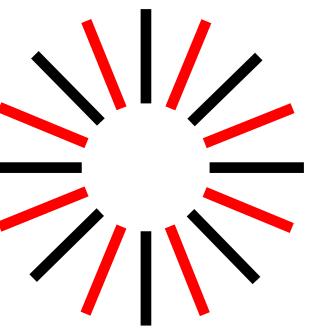
# WHY I CHOSE THIS TOPIC?

- Frequent YouTube user (commutes, chill-time activity).
- Curious if there are some insights common across high performing videos.





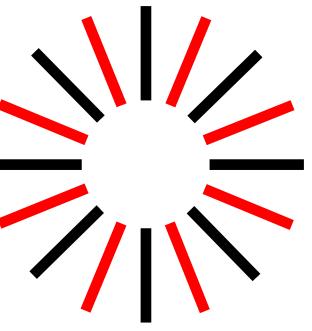
# WHAT PATTERNS AND FACTORS ARE PRESENT ON TRENDING VIDEOS?



# DATASET

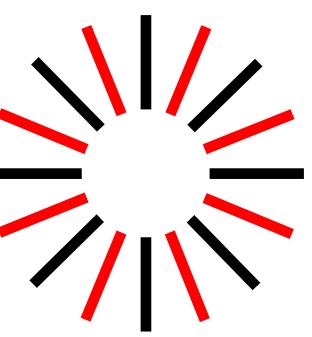


- Collected via YouTube API.
- Contains Daily snapshot of “Trending” list in the year 2019.
- Regions used: US, CA, GB (Major English-speaking markets) out of 10 available regions.
- Key fields: title, channel, publish time, tags, views, likes/dislikes, comments, description, category\_id.
- Why it fits: aligns directly with the question “what drives trending success?”



# DATA HANDLING AND EDA

- **Cleaning:** handle missing values, remove duplicates, correct data types, remove rows lacking vital information.
- **Wrangling:** merge only relevant data of US/CA/GB, map category\_id → category\_name, standardize time fields.
- **Feature engineering:** engagement\_rate, like\_ratio, comment\_rate, dislike\_ratio, days\_to\_trending.
- **EDA:** Descriptive Statistics on country/category/channel/videos, correlation matrix.
- **Added Video Performance Classification:** Explosive / High-Performing / Standard Trending.



# SOME EDA RESULTS

```
=====
OVERALL STATISTICS
=====

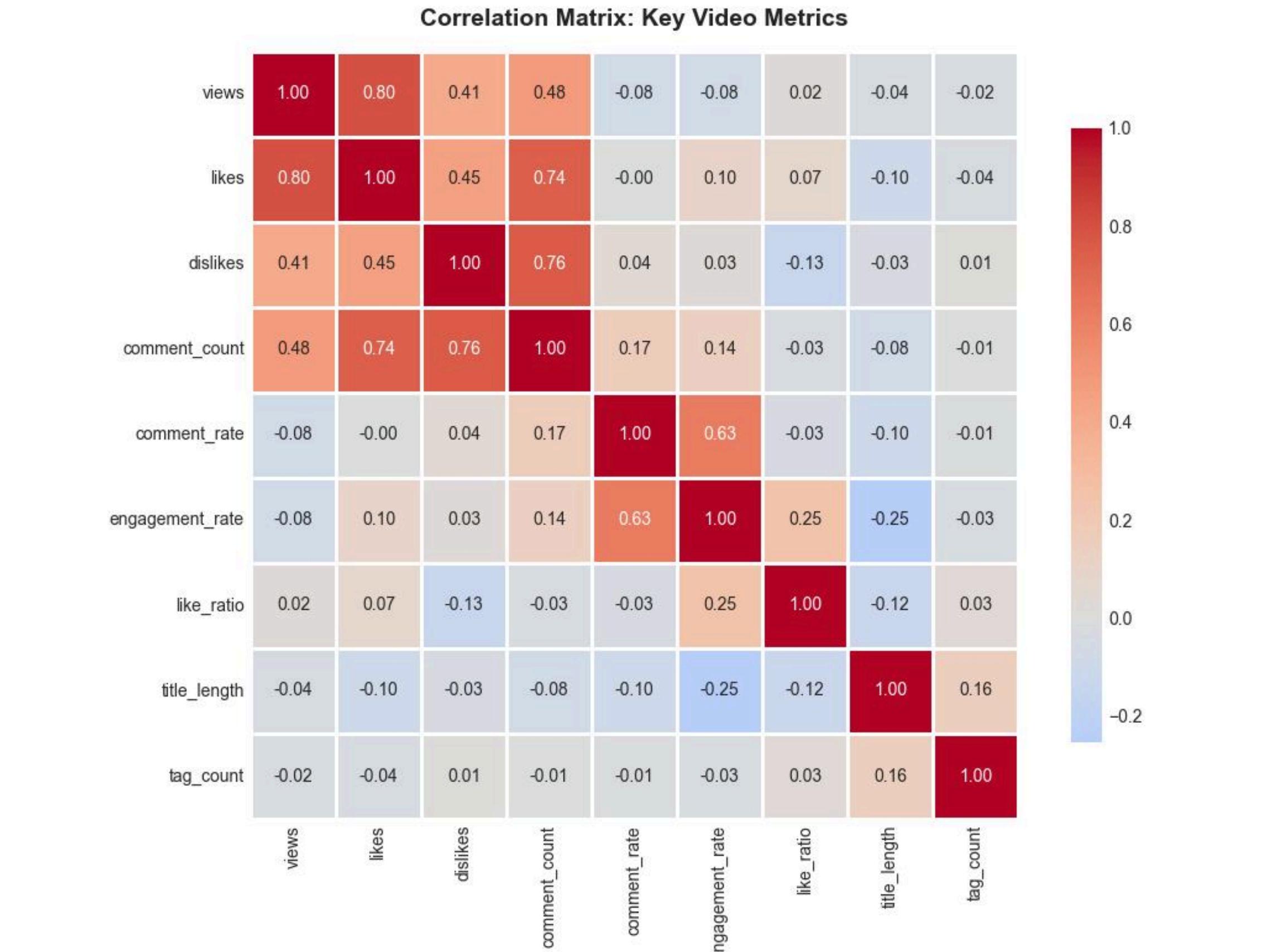
Total videos analyzed: 107,832
Countries: 3
Unique channels: 6,843
Categories: 18

=====
VIEW STATISTICS
=====

count      1.078320e+05
mean       2.852660e+06
std        1.183086e+07
min        5.490000e+02
25%        1.768340e+05
50%        5.241610e+05
75%        1.622088e+06
max        4.245389e+08
Name: views, dtype: float64
```

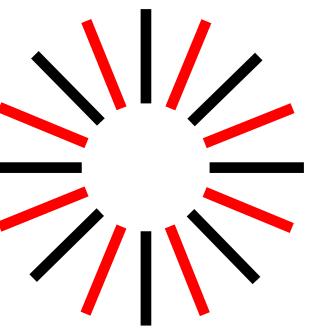
```
=====
CATEGORY ANALYSIS
=====

          Video Count   Avg Views  Median Views  Max Views \
category_name
Entertainment           29494  1732388.06    483142.5  169884583
Music                   20184  9343917.25  1897067.0  424538912
People & Blogs            9337  998784.42   320294.0  33627806
Comedy                  8054  1323810.48   698034.0  43460605
News & Politics           7437  550830.78   170848.0  18994966
Howto & Style             7358  818695.67   374955.5  54155921
Sports                  6409  1438113.80   394143.0  29090799
Film & Animation          5843  2344937.87   660906.0  54863912
Gaming                  3649  1249232.39   434156.0  18158133
Science & Technology        3584  1432483.36   553772.0  42799458
Education                 2855  681374.18   358602.0  12100921
Pets & Animals              1581  835070.88   442124.0  6416920
Travel & Events                835  690061.28   307812.0  23932421
Autos & Vehicles               810  987282.25   396856.5  25244097
Shows                     199  754829.82   631793.0  1709880
Unknown                   144  1518677.87  151952.0  26703269
Nonprofits & Activism            53  3187433.30  144532.0  24286474
Movies                      6  2853415.00  2906235.5  5661965
```

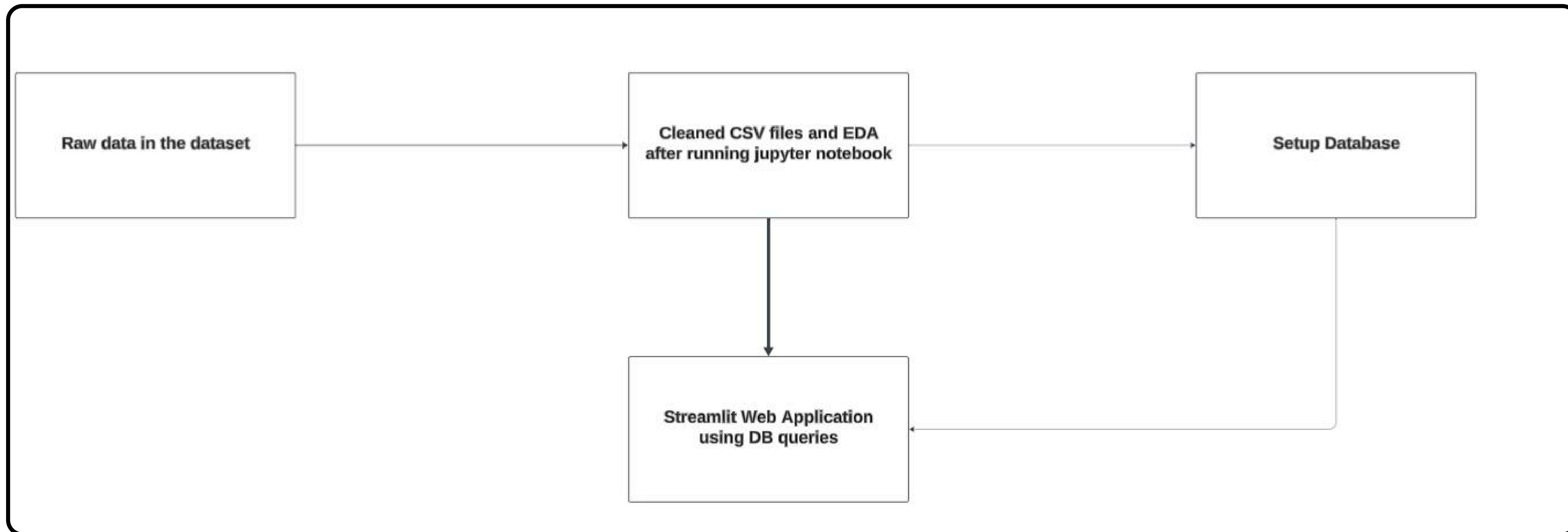


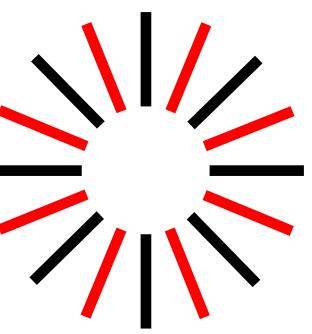
=====
COUNTRY COMPARISON
=====

	Videos	Avg Views	Avg Engagement %	Avg Days to Trending
country				
CA	35826	804318.71	3.98	2.97
GB	31279	5848696.06	3.84	43.40
US	40727	2353503.62	4.06	16.21



# IMPLEMENTATION PIPELINE



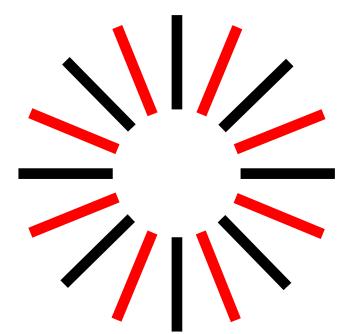


# Key Insights

- **Creator benefit = views, and views follow reactions:**

a. Likes, Dislikes and Comments Count have high positive correlation: Explains why creators have calls to action in the middle of videos.





# Video Performance Classification Rules

```
def classify_video_performance(df):
    """
    Classify trending videos based on views and speed-to-trending.
    Uses days_to_trending instead of engagement_rate to better capture viral growth patterns.

    Parameters:
    df (DataFrame): Video data with engagement metrics

    Returns:
    DataFrame: Data with performance classification
    """
    df_class = df.copy()

    # Calculate percentiles for classification
    view_75 = df_class['views'].quantile(0.75)
    view_90 = df_class['views'].quantile(0.90)
    days_25 = df_class['days_to_trending'].quantile(0.25) # Fast = LOW days
    days_50 = df_class['days_to_trending'].quantile(0.50)

    # Classification logic using if-elif-else structure
    def classify_video(row):
        views = row['views']
        days = row['days_to_trending']

        # Explosive: Top 10% views AND trended in bottom 25% time (fastest)
        if views >= view_90 and days <= days_25:
            return 'Explosive'
        # High-Performing: Top 25% views OR fast trending
        elif views >= view_75 or days <= days_50:
            return 'High-Performing'
        # Standard: Typical trending performance
        else:
            return 'Standard Trending'

    df_class['performance_class'] = df_class.apply(classify_video, axis=1)

    print("Performance classification complete:")
    print(df_class['performance_class'].value_counts())
    print(f"\nClassification thresholds:")
    print(f"  Explosive views threshold (90th percentile): {view_90:.0f}")
    print(f"  High-performing views threshold (75th percentile): {view_75:.0f}")
    print(f"  Fast trending threshold (25th percentile): {days_25:.1f} days")
    print(f"  Moderate trending threshold (50th percentile): {days_50:.1f} days")
    return df_class

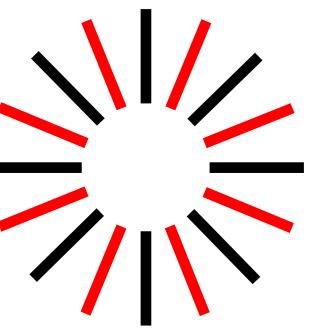
df_clean = classify_video_performance(df_clean)
```

- **Explosive Trending Videos :** Top 10% views AND in the Top 25% days to trending.
- **High-Performing Trending Videos :** Top 25% views OR top 50% days to trending.
- **Standard Trending Videos :** No extra classification criteria.

*Video performance is classified using total views and days to trending, because*

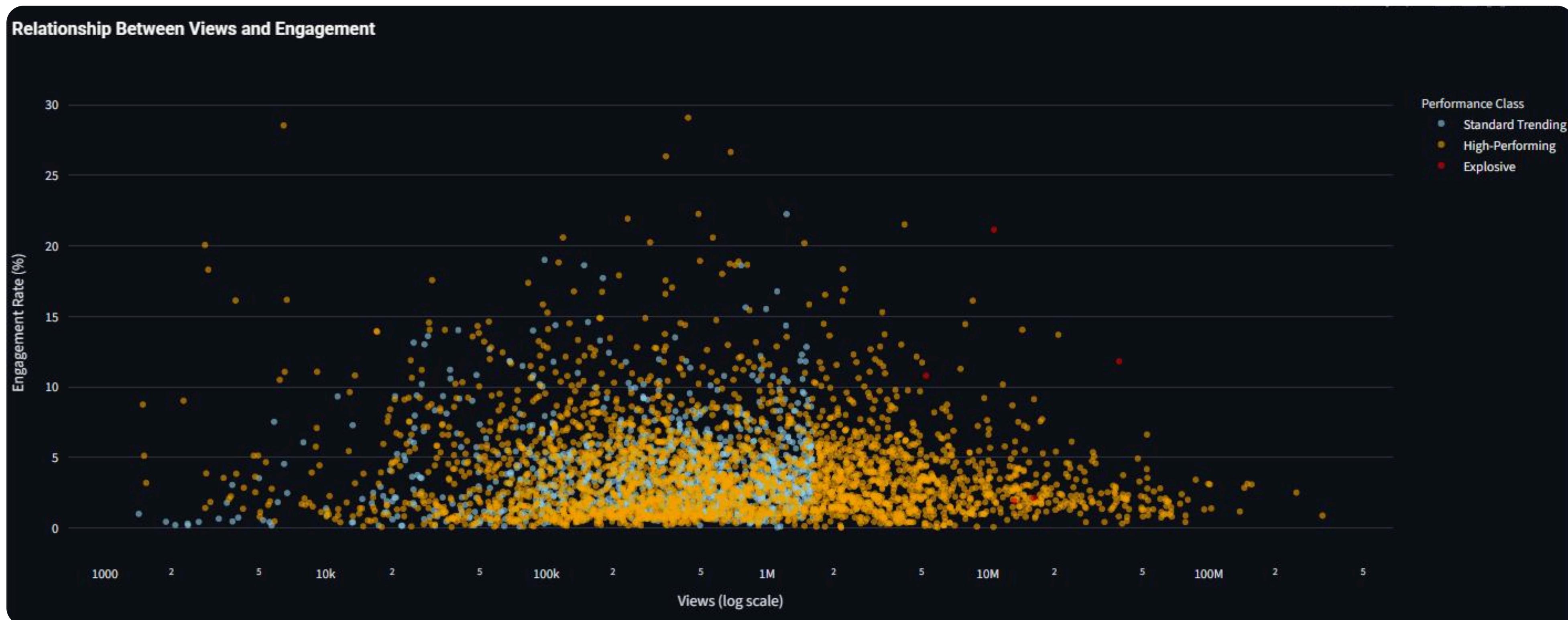
*together they capture both how large a video became and how fast it spread, which*

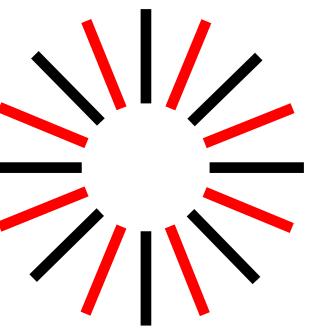
*reflects real-world viral success on YouTube.*



# Key Insights

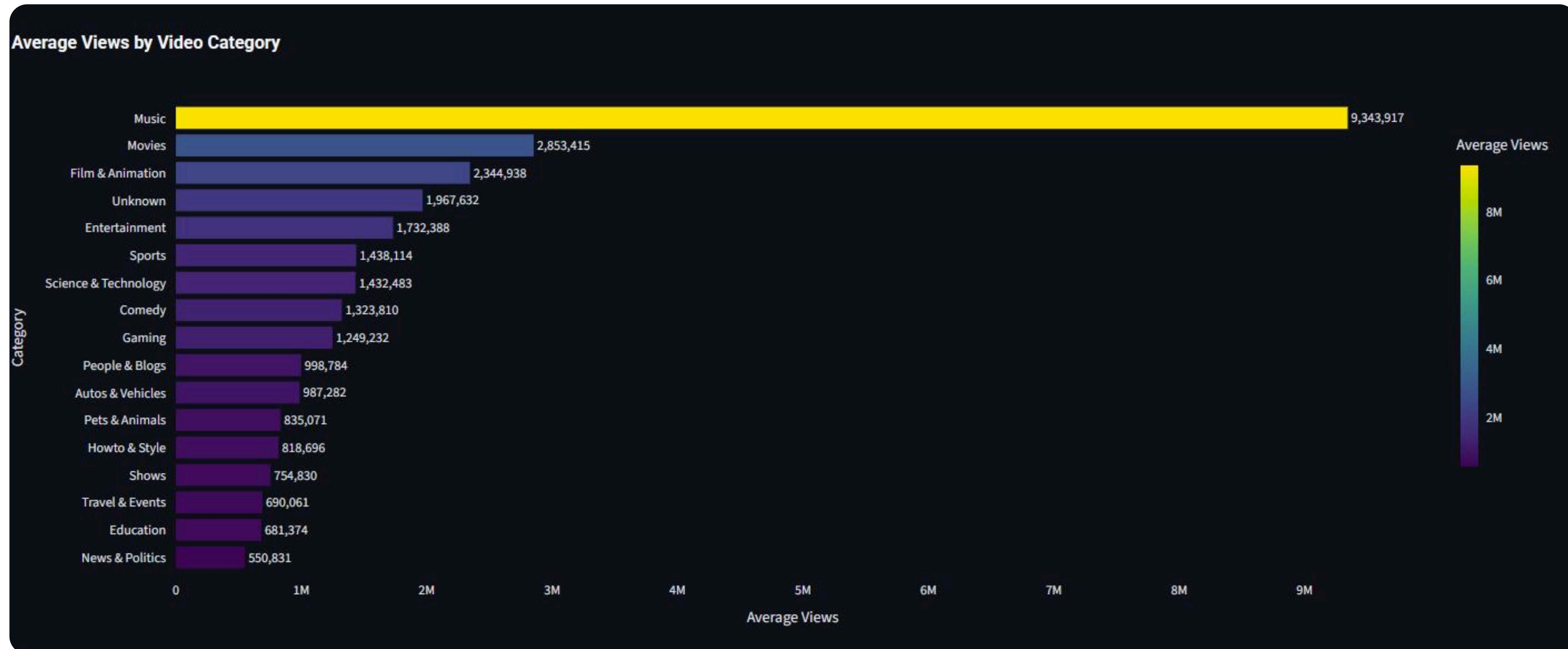
- **Views vs interaction on classified video performance**
  - a. Some Explosive Trending videos have high engagement rate but others don't.
  - b. Consistent with correlation matrix as majority of high view count videos have lower engagement.

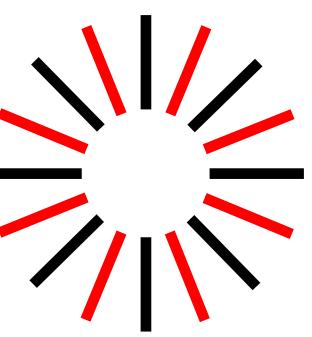




# Key Insights

- **Category effect:** Music dominates average views as majority of trending videos are music related.

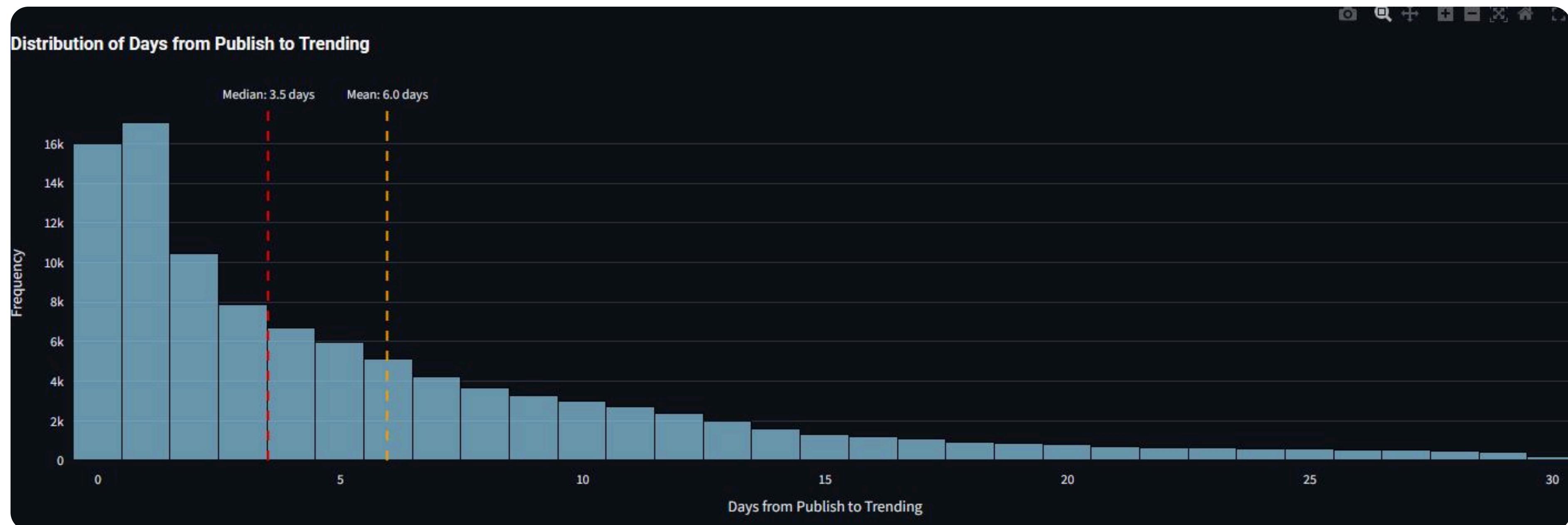


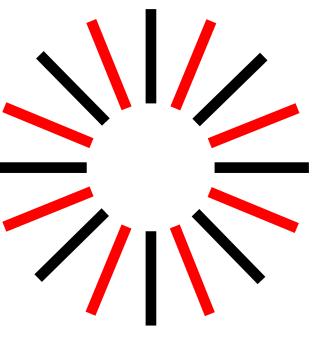


# Key Insights

- **Speed matters:** Trending is time-sensitive.

Most videos trend very close to the day of publishing so early momentum is pivotal!

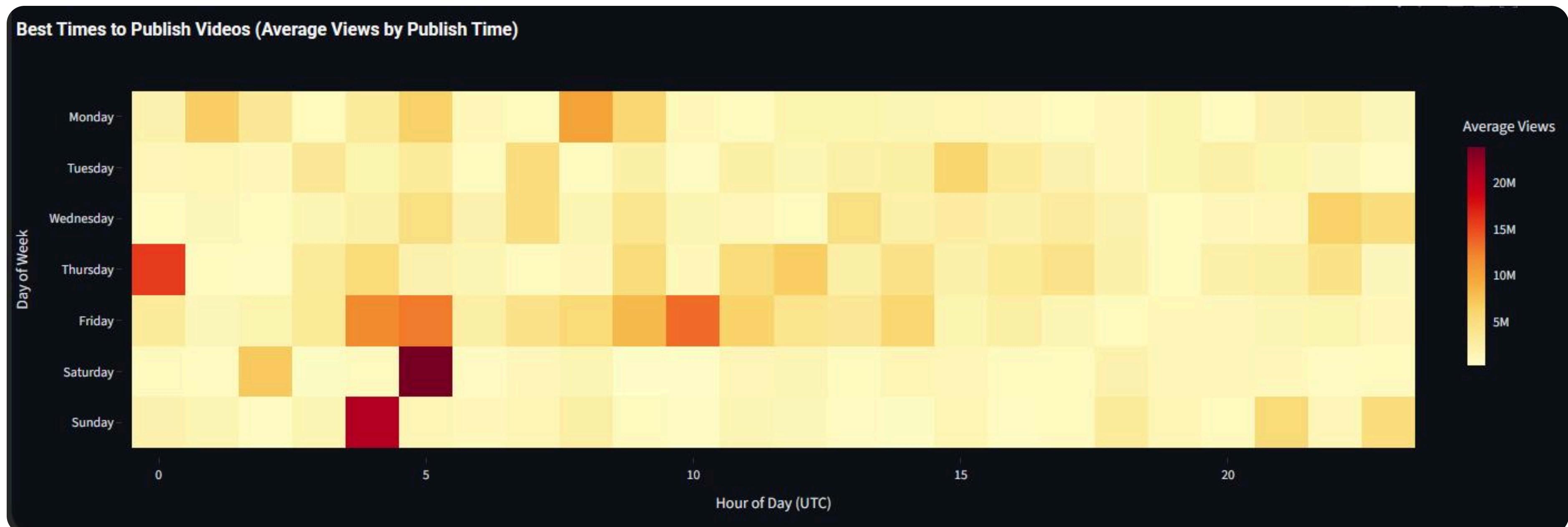


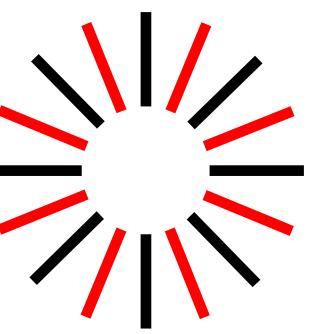


# Key Insights

- **Publishing strategy:** Upload timing affects performance

**Early-morning UTC and weekend windows show highest average views.**

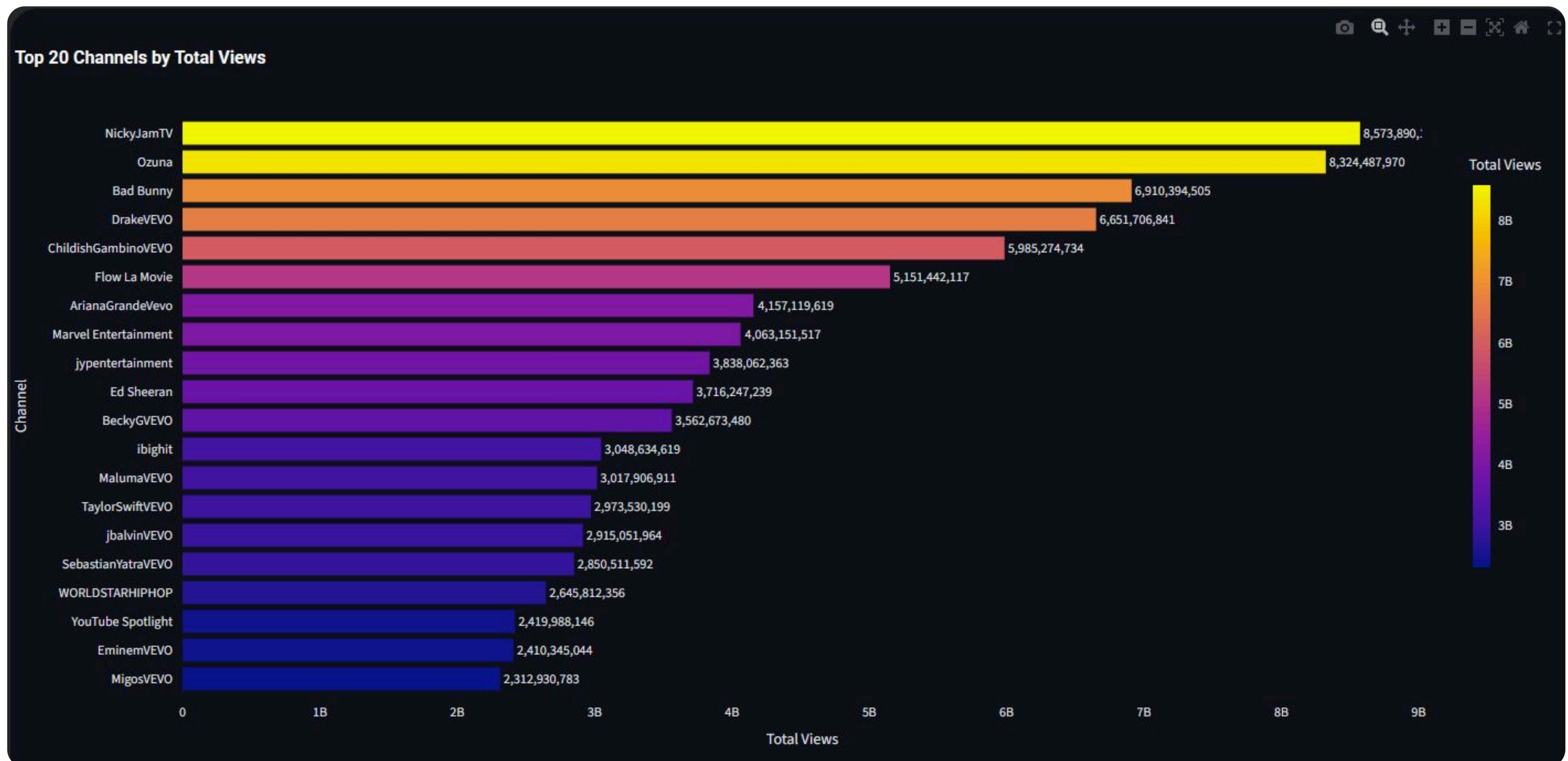


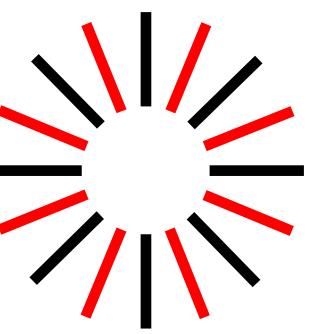


# Key Insights

- **Trending is winner-takes-most:** The same top channels appear repeatedly

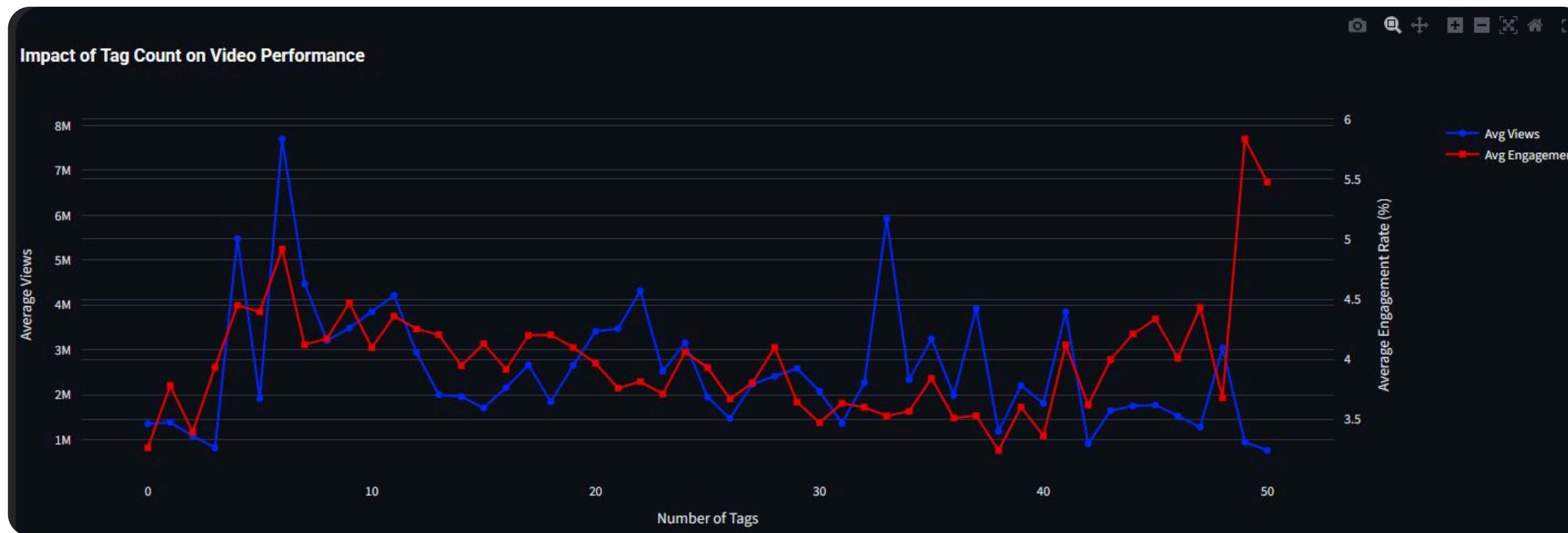
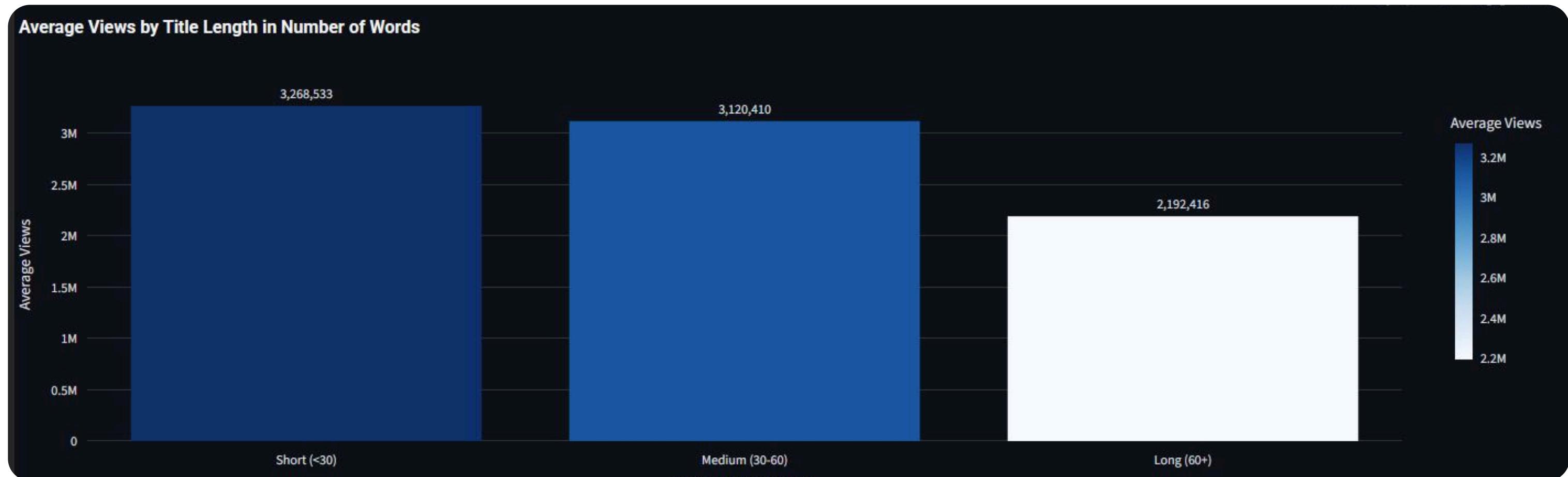
Once you go viral it's easier to get another hit.

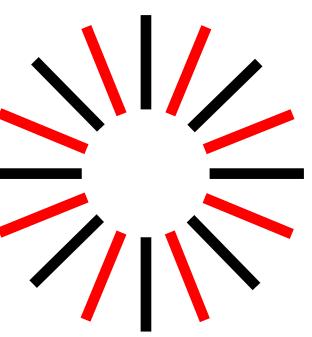




# Key Insights

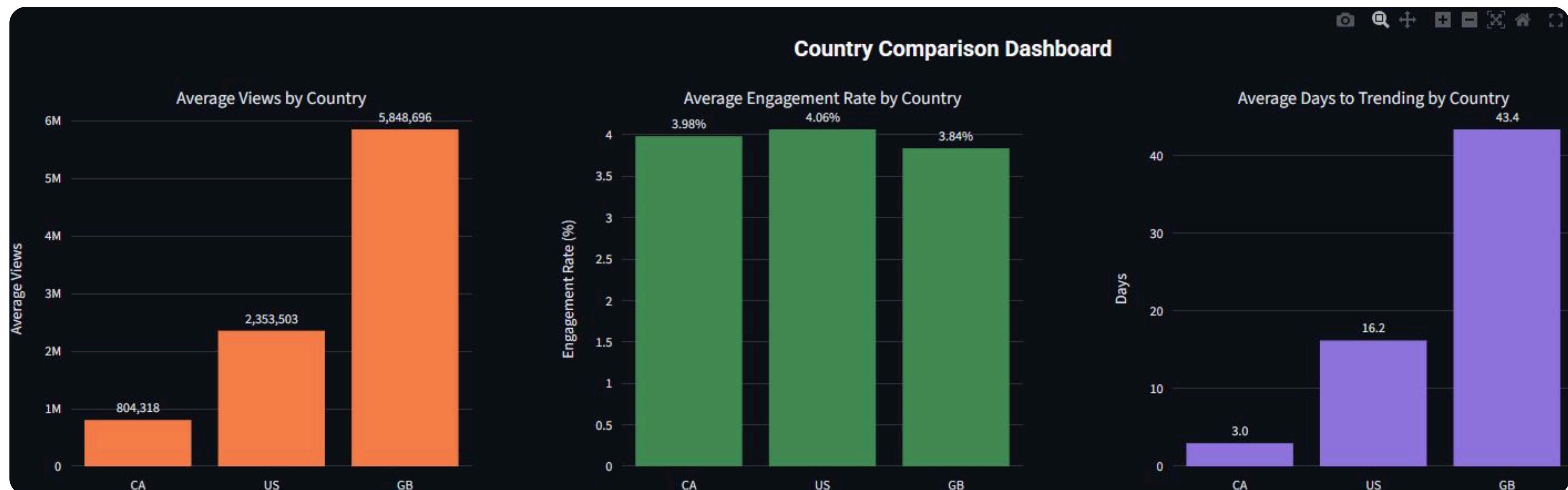
- **Metadata isn't a cheat code:** Title length and Video Tags play a minor role but have their own optimal counts.

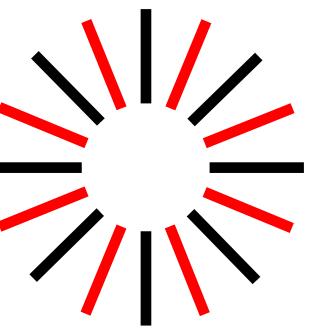




# Key Insights

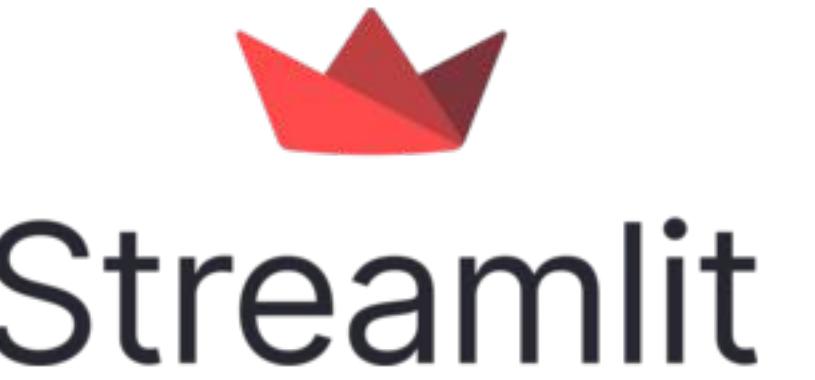
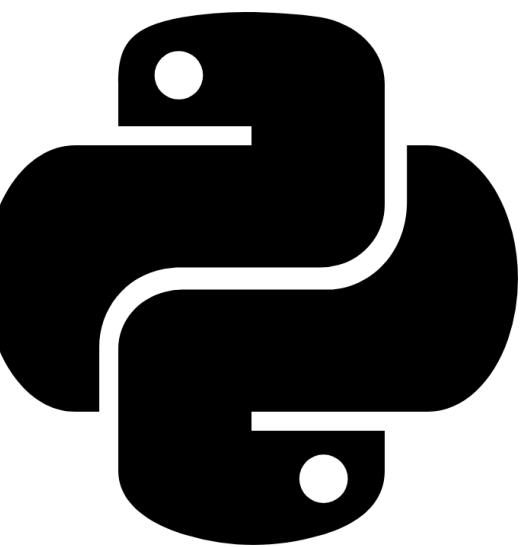
- **Cross Country Market dynamics:**
  - a. Engagement rate similar across US/CA/GB.
  - b. The Britain Paradox.

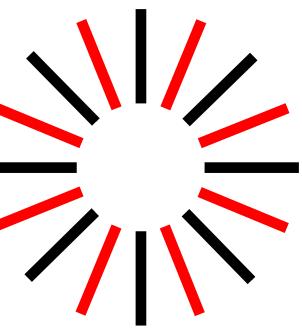




# Technologies Used

- **Python:** data loading, cleaning, wrangling, database related scripts.
- **Visualization:** Matplotlib + Seaborn and Plotly (Plots, distributions, correlations).
- **SQL / Storage:** SQLite database for structured querying using sqlite3 library in python.
- **Web App Frontend:** Streamlit app for interactive exploration + insights





# Challenges

- **Defining a valid classification rule for my project because all videos had already trended.**
- **Choosing which option to take for building the web app Streamlit vs Django.**
  - a. Had more experience with Django but needed to assess its suitability for my project.
  - b. Looked into Streamlit Community templates to see its applications.

# **THANK YOU!**