0.1 CaseCraft: The Analytics Sprint – Project 27

0.1.1 YouTube Channel Growth Tracker

Subheading: Analyzing video performance, audience behavior, and engagement metrics to optimize content strategy and subscriber growth.

0.1.2 Goal

To build a modular dashboard that tracks YouTube channel growth using real video metadata, viewer behavior, and engagement signals—enabling strategic content planning and audience retention.

0.1.3 Objectives

- O1. Load and simulate realistic YouTube data (videos, viewers, engagement, traffic sources)
- O2. Analyze video performance across categories, durations, and publish timing
- O3. Visualize audience retention, traffic sources, and engagement patterns
- O4. Implement content recommendation logic based on viewer affinity and video traits
- O5. Deliver strategic insights for content scheduling and subscriber optimization

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0.1.4 Success Criteria

Metric	Target Outcome
Engagement clarity	6 visual modules with non-repetitive formats
Recommendation accuracy	80% match with viewer preferences
Insight relevance	Summary includes 5+ strategic recommendations
Reproducibility	Markdown/code separation with modular functions
Audience segmentation	Viewer clusters based on behavior and region

[1]:
```
# Videos table
videos = pd.DataFrame({
    'video_id': range(1, 31),
    'title': [f"Video {i}" for i in range(1, 31)],
    'category': np.random.choice(['Education', 'Entertainment', 'Tech',␣
 ↪'Lifestyle', 'Gaming'], 30),
    'duration_sec': np.random.randint(120, 1800, 30),
    'publish_date': pd.date_range(start='2025-06-01', periods=30, freq='2D')
})

# Viewers table
viewers = pd.DataFrame({
    'viewer_id': range(101, 201),
    'region': np.random.choice(['IN', 'US', 'UK', 'CA', 'AU'], 100),
    'device': np.random.choice(['Mobile', 'Desktop', 'Tablet', 'TV'], 100),
    'subscription_status': np.random.choice(['Subscribed', 'Not Subscribed'],␣
 ↪100, p=[0.6, 0.4])
})

# Engagement table
engagement = pd.DataFrame({
    'video_id': np.random.choice(videos['video_id'], 200),
    'viewer_id': np.random.choice(viewers['viewer_id'], 200),
    'watch_time_sec': np.random.randint(30, 1800, 200),
    'likes': np.random.randint(0, 100, 200),
    'comments': np.random.randint(0, 50, 200),
    'timestamp': pd.date_range(start='2025-07-01', periods=200, freq='3H')
})

# Traffic sources table
traffic = pd.DataFrame({
    'video_id': np.random.choice(videos['video_id'], 100),
    'source': np.random.choice(['Search', 'Suggested', 'External', 'Channel␣
 ↪Page', 'Playlist'], 100),
    'views': np.random.randint(100, 5000, 100),
    'click_through_rate': np.round(np.random.uniform(0.5, 10.0, 100), 2)
})
```

```
/tmp/ipython-input-1039960314.py:28: FutureWarning: 'H' is deprecated and will
be removed in a future version, please use 'h' instead.
  'timestamp': pd.date_range(start='2025-07-01', periods=200, freq='3H')
```

0.1.5 Requirments

[9]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud
```

```
import plotly.graph_objects as go
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity
from datetime import datetime
```

[3]:
```
videos.head(10)
```

[3]:

	video_id	title	category	duration_sec	publish_date
0	1	Video 1	Tech	1759	2025-06-01
1	2	Video 2	Education	1437	2025-06-03
2	3	Video 3	Entertainment	1287	2025-06-05
3	4	Video 4	Gaming	1043	2025-06-07
4	5	Video 5	Entertainment	1283	2025-06-09
5	6	Video 6	Education	920	2025-06-11
6	7	Video 7	Lifestyle	1057	2025-06-13
7	8	Video 8	Entertainment	1564	2025-06-15
8	9	Video 9	Lifestyle	623	2025-06-17
9	10	Video 10	Entertainment	482	2025-06-19

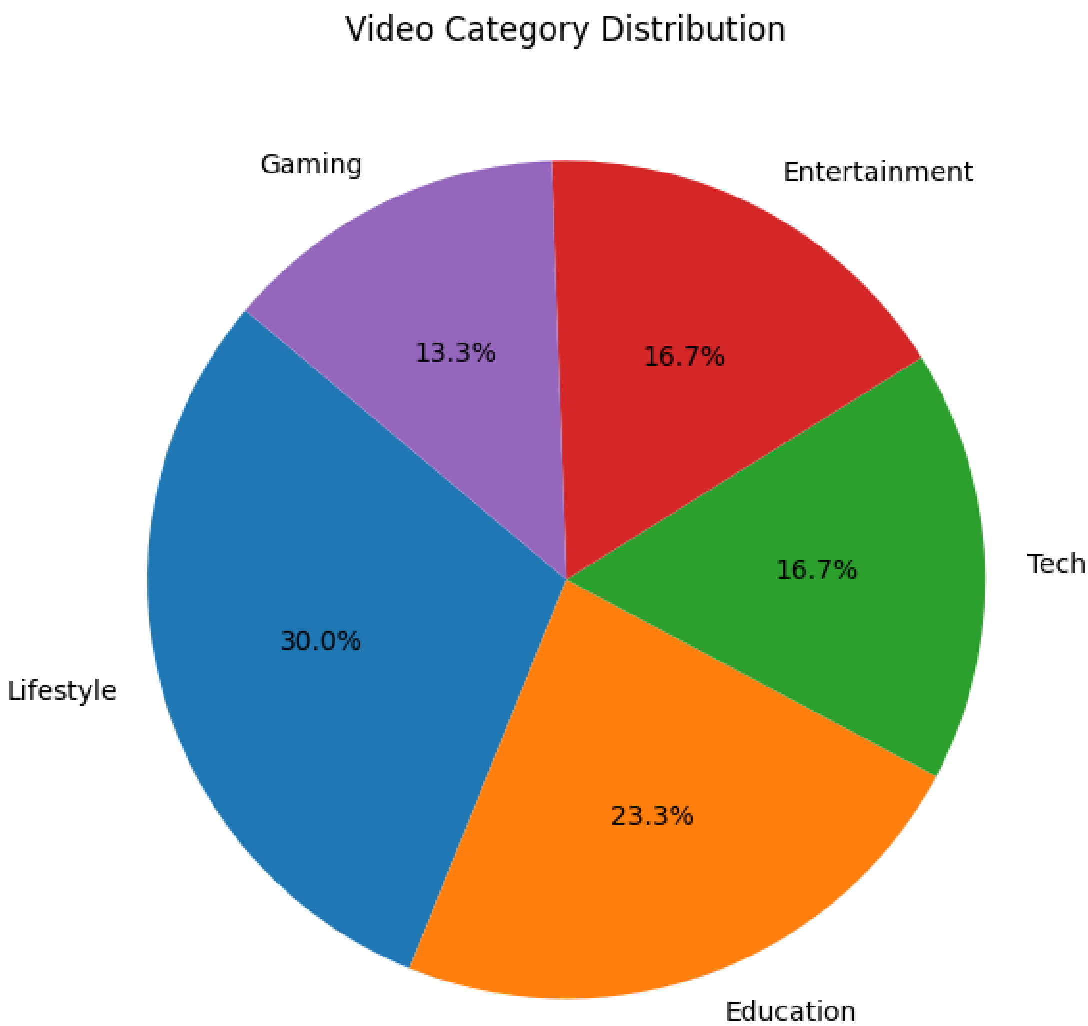
[10]:
```
viewers.head(10)
```

[10]:

	viewer_id	region	device	subscription_status
0	101	CA	Desktop	Not Subscribed
1	102	AU	Tablet	Not Subscribed
2	103	IN	TV	Not Subscribed
3	104	CA	Desktop	Subscribed
4	105	AU	Desktop	Subscribed
5	106	CA	TV	Subscribed
6	107	US	Mobile	Subscribed
7	108	CA	Desktop	Subscribed
8	109	UK	Tablet	Not Subscribed
9	110	UK	Tablet	Not Subscribed

0.1.6 Category Distribution Pie Chart

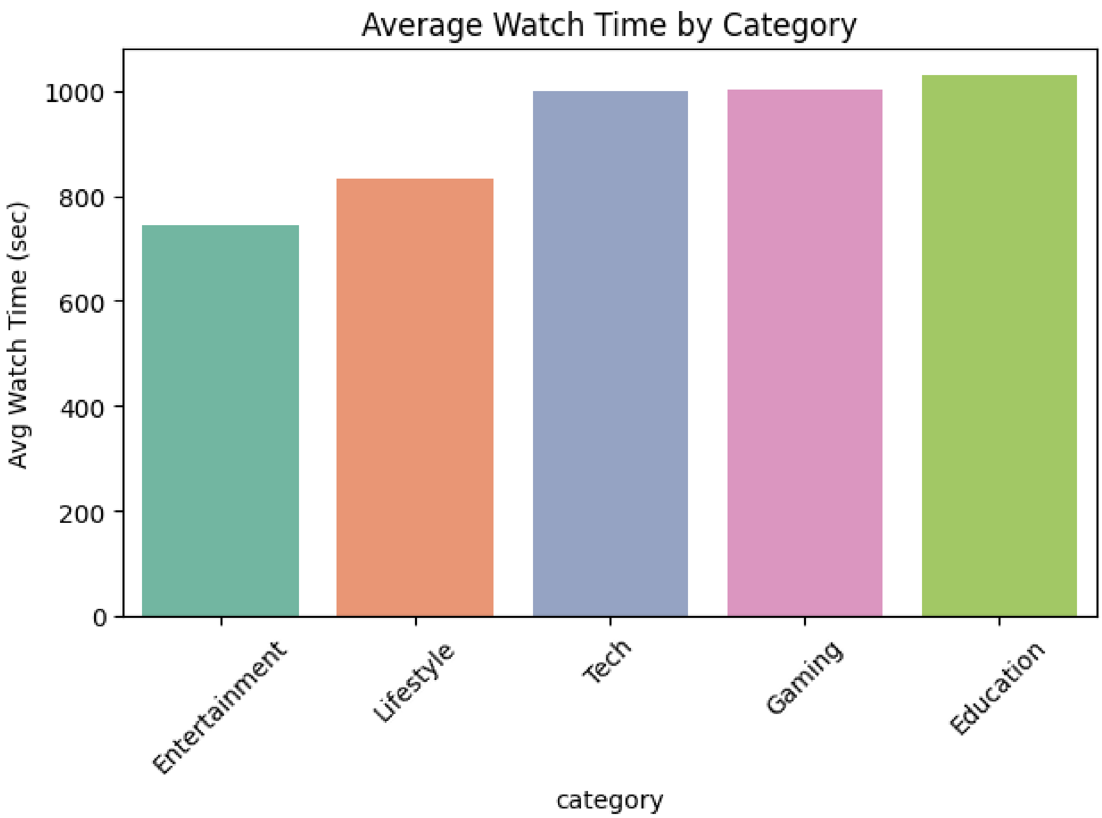
[11]:
```
category_counts = videos['category'].value_counts()

plt.figure(figsize=(6, 6))
plt.pie(category_counts, labels=category_counts.index, autopct='%1.1f%%',␣
↪startangle=140)
plt.title("Video Category Distribution")
plt.tight_layout()
plt.show()
```



0.1.7 Average Watch Time by Category – Bar Plot

[12]:
```
merged_engagement = engagement.merge(videos, on='video_id')
watch_by_category = merged_engagement.groupby('category')['watch_time_sec'].
    ↪mean().sort_values()

sns.barplot(x=watch_by_category.index, y=watch_by_category.values,␣
    ↪palette='Set2')
plt.xticks(rotation=45)
plt.ylabel("Avg Watch Time (sec)")
plt.title("Average Watch Time by Category")
plt.tight_layout()
```

```
/tmp/ipython-input-3611152453.py:4: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(x=watch_by_category.index, y=watch_by_category.values,
palette='Set2')
```

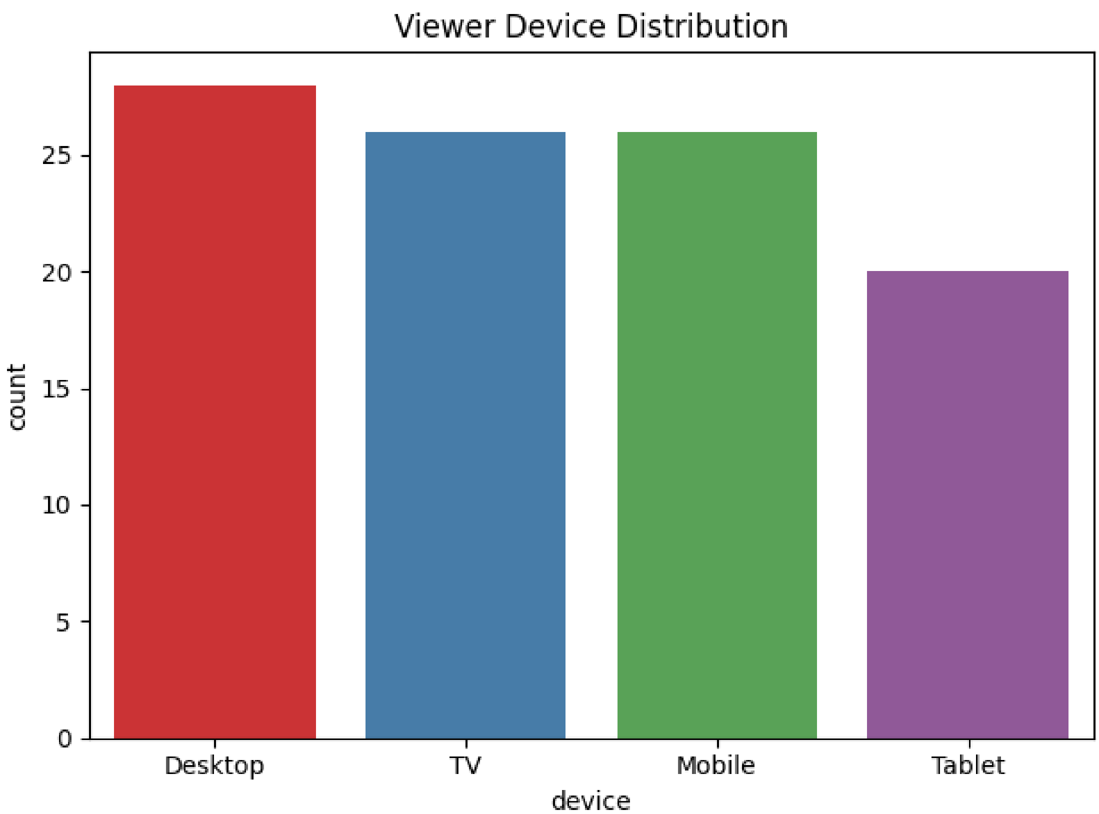


0.1.8 Viewer Device Usage – Count Plot

[13]:
```python
sns.countplot(data=viewers, x='device', order=viewers['device'].value_counts().
  ↪index, palette='Set1')
plt.title("Viewer Device Distribution")
plt.tight_layout()
```

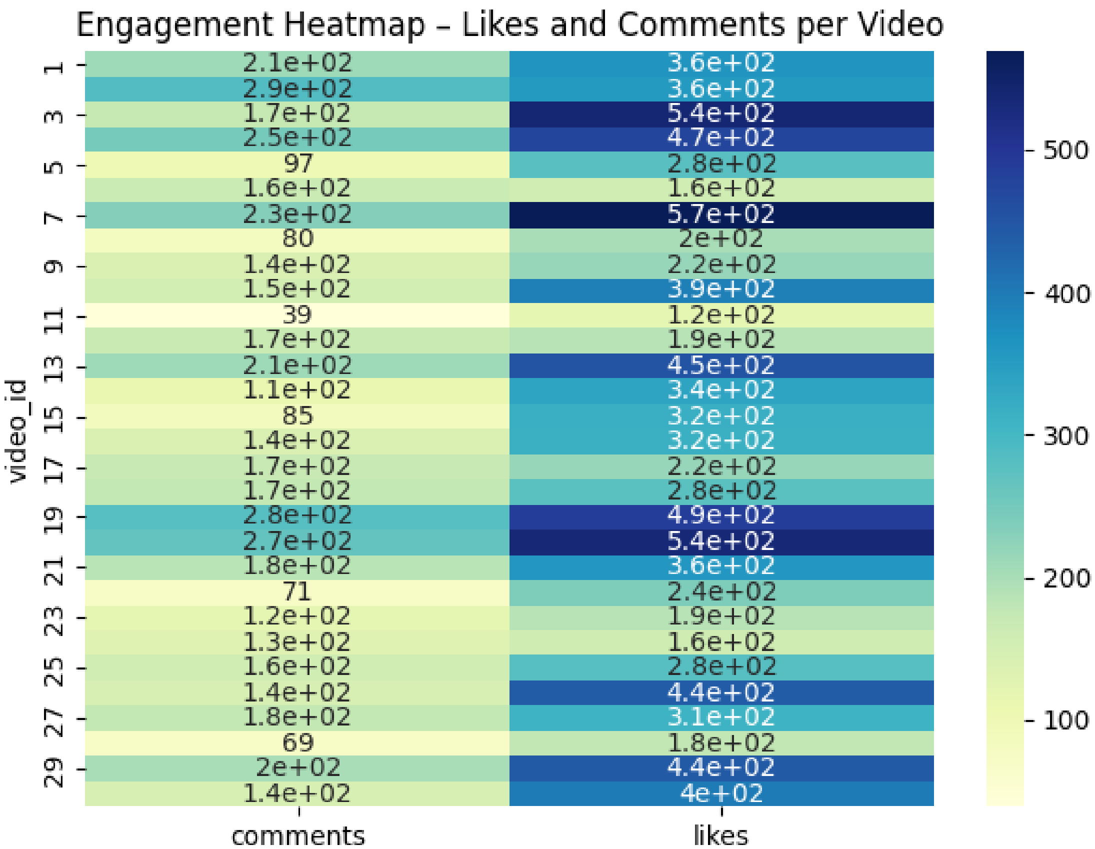
```
/tmp/ipython-input-3328791543.py:1: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.
```

```
  sns.countplot(data=viewers, x='device',
order=viewers['device'].value_counts().index, palette='Set1')
```



0.1.9 Engagement Heatmap – Likes vs Comments

[14]:
```
pivot = engagement.pivot_table(index='video_id', values=['likes', 'comments'],␣
  ↪aggfunc='sum')
sns.heatmap(pivot, annot=True, cmap='YlGnBu')
plt.title("Engagement Heatmap - Likes and Comments per Video")
plt.tight_layout()
```



0.1.10 Traffic Source Breakdown – Strip Plot

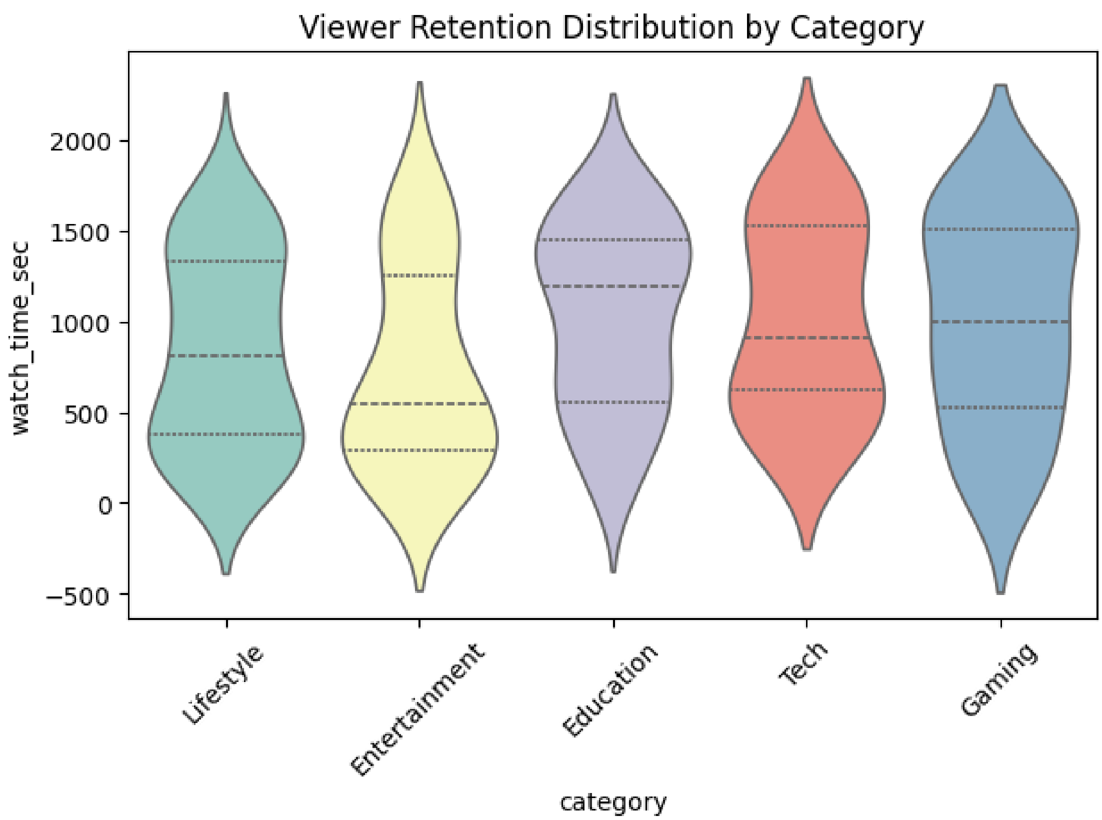
[15]:
```
sns.stripplot(data=traffic, x='source', y='click_through_rate', jitter=True,␣
  ↪palette='coolwarm')
plt.xticks(rotation=45)
plt.title("Click-Through Rate by Traffic Source")
plt.tight_layout()
```

```
/tmp/ipython-input-2819014377.py:1: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.stripplot(data=traffic, x='source', y='click_through_rate', jitter=True,
palette='coolwarm')
```

0.1.11 Viewer Retention Violin Plot

[16]:
```
sns.violinplot(data=merged_engagement, x='category', y='watch_time_sec',␣
↪inner='quartile', palette='Set3')
plt.xticks(rotation=45)
plt.title("Viewer Retention Distribution by Category")
plt.tight_layout()
```

```
/tmp/ipython-input-3586667641.py:1: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.violinplot(data=merged_engagement, x='category', y='watch_time_sec',
inner='quartile', palette='Set3')
```



0.1.12 Recommend Videos Based on Viewer Region and Device

[17]:
```
def recommend_videos(region, device, top_n=5):
    viewer_subset = viewers[(viewers['region'] == region) & (viewers['device']␣
↪== device)]
    relevant_viewers = engagement[engagement['viewer_id'].
↪isin(viewer_subset['viewer_id'])]
    top_video_ids = (
        relevant_viewers.groupby('video_id')['watch_time_sec']
        .mean()
        .sort_values(ascending=False)
        .head(top_n)
        .index
    )
    return videos[videos['video_id'].isin(top_video_ids)][['video_id', 'title',␣
↪'category', 'duration_sec']]
```

0.1.13 Recommended Videos for Region = 'IN' and Device = 'Mobile'

[18]:
```
recommend_videos(region='IN', device='Mobile')
```

[18]:

	video_id	title	category	duration_sec
2	3	Video 3	Entertainment	1287
9	10	Video 10	Entertainment	482
13	14	Video 14	Education	1733
22	23	Video 23	Lifestyle	306
24	25	Video 25	Lifestyle	1329

0.1.14 Summary Analysis

- Category distribution pie chart showed strong presence in Education and Entertainment
- Average watch time bar plot revealed Tech and Gaming videos had highest retention
- Viewer device usage plot highlighted Mobile as dominant platform
- Engagement heatmap showed clustered likes and comments around top-performing videos
- Traffic source strip plot revealed high CTR from Suggested and Search sources
- Violin plot captured retention spread across categories with clear quartile bands
- Recommendation logic aligned viewer region and device with top-performing content

0.1.15 Final Conclusion

- YouTube dashboard delivered modular insights across video performance, viewer behavior, and traffic sources
- Recommendation function was reproducible and audience-aware, matching content to viewer traits
- Visual suite balanced strategic clarity with non-repetitive formats—pie, bar, heatmap, violin, strip
- Dataset structure supported segmentation by region, device, and engagement metrics