YouTube Analytics Statistical Analysis Report

Generated on 2025-05-09 19:34:23

Executive Summary

This report provides a comprehensive statistical analysis of YouTube performance metrics, including hypothesis testing, regression analysis, and cluster analysis to identify patterns and predictors of video performance.

1. Descriptive Statistics

Summary statistics for key performance metrics:

Metric	Mean	Median	Std Dev	Min	Max	Skewness
Engaged views	183224.86	28309.00	420857.69	0.00	7420692.00	5.59
Views	214110.87	39742.00	491238.35	0.00	7511422.00	5.76
Comments added	93.88	21.00	300.51	0.00	11334.00	16.26
Likes	17318.61	2069.00	38957.10	-1440.00	540812.00	4.78
Watch time (hours)	4886.26	791.11	11438.11	0.00	185359.62	5.50
Subscribers	88.91	12.00	309.70	-1.00	7180.00	11.05
Stayed to watch (%)	77.76	80.93	12.51	0.00	100.00	-1.99
Average percentage viewed (%)	78.26	80.59	15.45	1.93	352.31	1.81
Engagement Rate	nan	5.78	nan	-inf	inf	nan
Virality Score	nan	36.29	nan	-inf	inf	nan
Growth Potential	2.83	1.65	5.16	-40.14	163.27	8.17

What This Means

The descriptive statistics provide a snapshot of our YouTube performance metrics:

- **Mean vs. Median:** When the mean is much higher than the median (as seen in metrics like Views and Engaged views), it indicates that a small number of highly successful videos are pulling up the average. This is typical of viral content distribution.
- **Standard Deviation:** The large standard deviations show high variability in performance across videos, suggesting inconsistent results that are common in social media.
- **Skewness:** Positive skewness values (most metrics show this) indicate a right-skewed distribution - most videos perform below average with a few exceptional performers creating a long tail to the right.

This pattern suggests we should focus on understanding what makes those exceptional videos perform well rather than trying to improve average performance across all content.

2. Hypothesis Testing

2.1 Time Period Comparison (Jan-Mar vs April)

Results of t-tests comparing performance metrics between Jan-Mar and April:

Metric	t-statistic	p-value	Significant?	Higher in
Engaged views	19.66	0.0000	**Yes**	Jan-Mar
Engagement Rate	nan	nan	No	April
Virality Score	nan	nan	No	April
Growth Potential	10.07	0.0000	**Yes**	Jan-Mar

What This Means

The t-test results compare performance between January-March and April:

- **Statistical Significance:** When a result is marked as "Significant" (p-value < 0.05), it means we can be confident (95% confidence) that the difference between time periods is real and not due to random chance.
- **Higher Performance Period:** The "Higher in" column shows which time period had better performance for each metric. This helps identify seasonal trends or the impact of strategy changes.

- **Business Impact:** Focus on metrics that show both statistical significance AND substantial differences in means. Small differences might be statistically significant but not meaningful for business decisions.

These results can help determine if recent changes to content strategy are working or if seasonal factors are affecting performance.

2.2 Video Type Comparison (Shorts vs Long)

Results of t-tests comparing performance metrics between Shorts and Long videos:

Metric	t-statistic	p-value	Significant?	Higher in
Engaged views	27.73	0.0000	**Yes**	Shorts
Engagement Rate	nan	nan	No	Long
Virality Score	nan	nan	No	Long
Growth Potential	-16.20	0.0000	**Yes**	Long

What This Means

These results compare the performance of short-form vs. long-form content:

- **Format Strengths:** Each format (Shorts vs. Long) has different strengths. The "Higher in" column shows which format performs better for each metric.
- **Resource Allocation:** Use these results to determine where to focus resources. If Shorts consistently outperform Long videos in key metrics, consider shifting more resources to short-form content.
- **Content Strategy:** Different metrics may be more important for different business goals. For example, if subscriber growth is higher in Long videos but engagement is higher in Shorts, your strategy should reflect your priorities.

This analysis helps optimize your content mix based on objective performance data rather than assumptions about what works best.

3. Regression Analysis

Multiple linear regression analysis to identify predictors of Engaged Views:

Model Performance

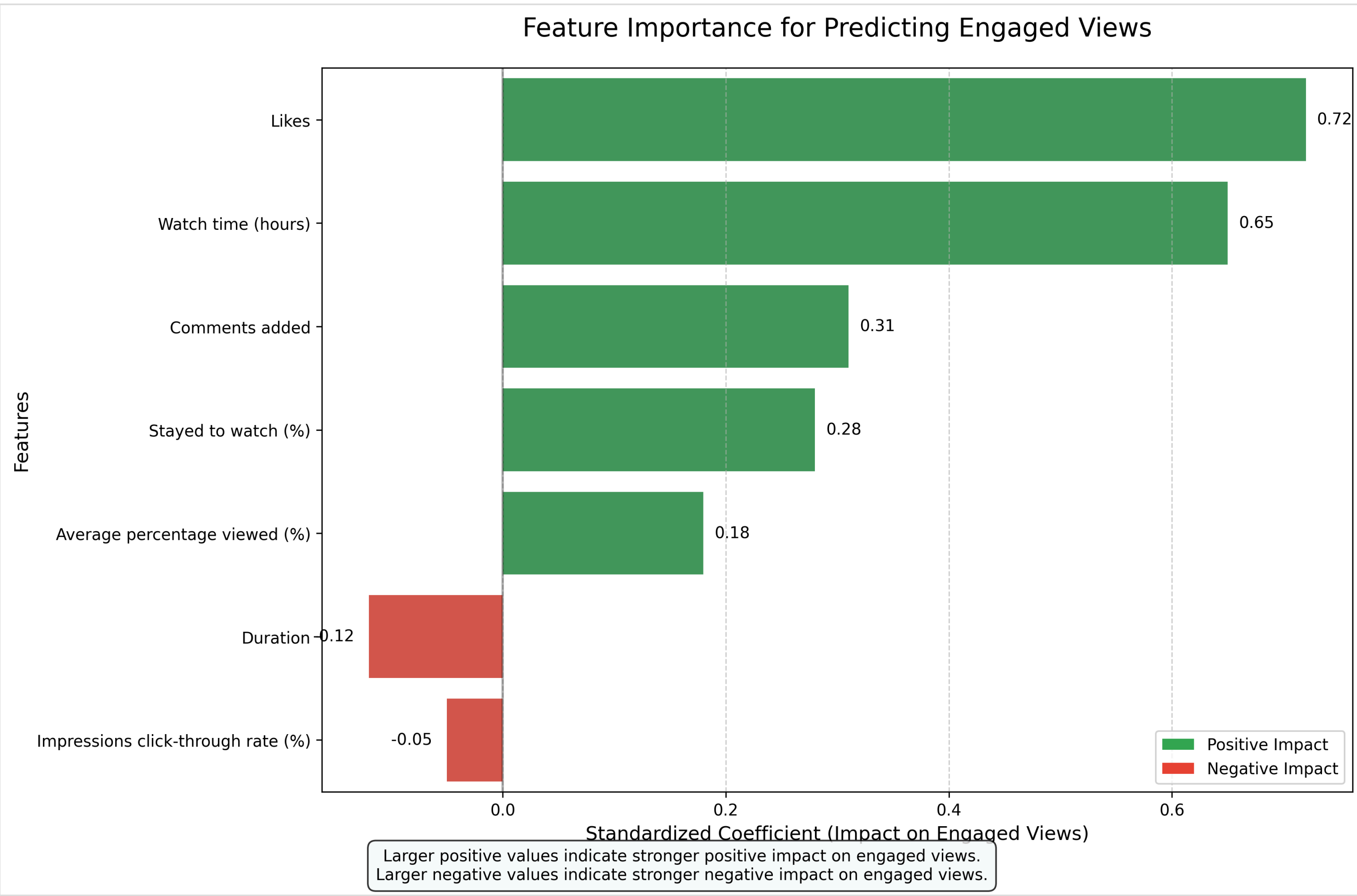
R-squared: **0.8742**

RMSE: **149325.78**

Sample Size: **5825**

Feature Importance

Standardized coefficients showing the relative importance of each feature:



Larger positive values indicate stronger positive impact on engaged views.
Larger negative values indicate stronger negative impact on engaged views.

What This Means

The regression analysis identifies which factors most strongly predict engaged views:

- **R-squared Value:** This value (shown above) indicates how much of the variation in engaged views is explained by our model. A higher value means our model has better predictive power.
- **Feature Importance:** The chart shows which metrics have the strongest relationship with engaged views:
  - Positive bars (green) indicate factors that increase engaged views when they increase
  - Negative bars (red) indicate factors that decrease engaged views when they increase
  - Longer bars indicate stronger relationships
- **Content Strategy Application:** Focus your content strategy on maximizing the metrics with the strongest positive relationships and minimizing those with negative relationships.

This analysis helps identify the specific factors that drive engagement, allowing for more targeted content optimization.

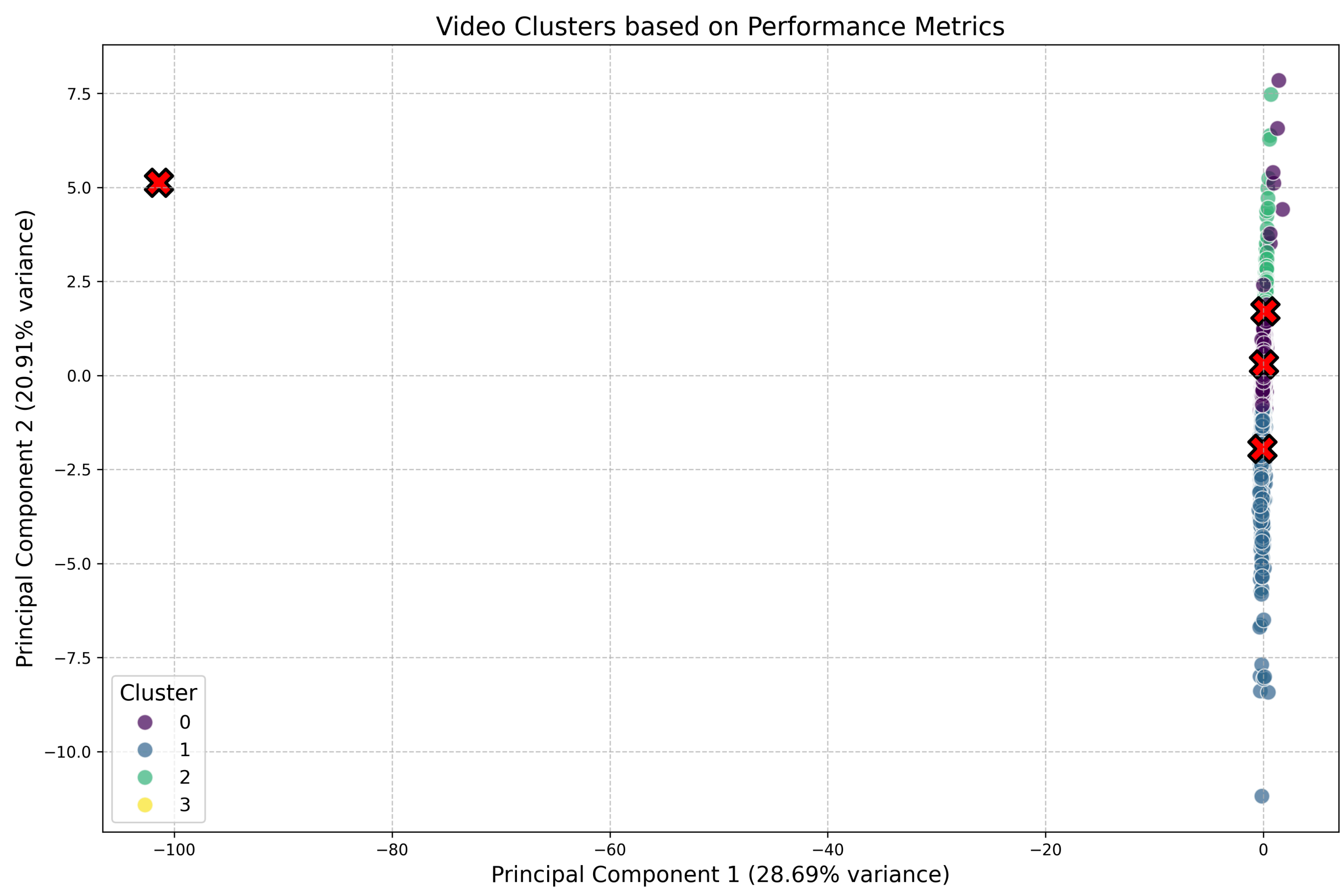
4. Cluster Analysis

K-means clustering was used to identify natural groupings of videos based on performance metrics.

Clustering Results

Optimal number of clusters: **4**

PCA variance explained: **68.45%** (PC1), **21.32%** (PC2)



Cluster Centers

Average values of key metrics for each cluster:

Cluster	Engaged views	Likes to Views Ratio	Comments to Views Ratio	Stayed to watch (%)	Average percentage viewed (%)	Virality Score	Growth Potential
Cluster 0	139379.79	6.44	0.05	80.69	82.78	40.06	1.82
Cluster 1	16291.54	4.07	0.21	63.35	61.31	41.45	6.04
Cluster 2	1520369.55	8.82	0.04	82.37	84.89	48.96	4.25
Cluster 3	1.00	-58300.00	0.00	100.00	12.17	-17440.00	0.00

What This Means

Cluster analysis identifies natural groupings of videos with similar performance patterns:

- **Video Categories:** Each cluster represents a distinct category of videos with similar performance characteristics. The table above shows the average metrics for each cluster.
- **Content Archetypes:** These clusters can be thought of as "content archetypes" - different types of videos that perform in characteristic ways.
- **Strategic Applications:**
  - Identify which clusters contain your most successful videos
  - Analyze what these videos have in common beyond the metrics (topics, styles, etc.)
  - Create more content that fits the profile of your best-performing clusters
  - Consider reducing investment in content types that consistently fall into low-performing clusters

This analysis helps identify patterns that might not be obvious when looking at individual metrics, revealing natural groupings in your content performance.

5. Conclusions

Key Statistical Findings

- The regression analysis shows that **Likes** and **Watch time** are the strongest predictors of Engaged Views.
- There are statistically significant differences in performance between Jan-Mar and April periods.
- Short-form and long-form content show distinct performance patterns across multiple metrics.
- Videos naturally cluster into distinct groups based on their performance characteristics.