

Analyzing YouTube Video Engagement

A CASE STUDY OF MRBEAST

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Introduction

The purpose of this paper is to present a comprehensive analysis of video engagement using data scraped from MrBeast's English YouTube channels. The dataset used was populated from scraping the following channels: @MrBeast, @MrBeastGaming, @BeastReacts, and @BeastPhilanthropy. Every video on the selected channels had been scraped and cleaned to the following: Title, Duration, Upload Date, Upload Time, Like Count, Comment Count, View Count, Tags, and Category. My objective for this study is to provide a greater understanding of YouTube viewer interactions and an insight into factors affecting video engagement.

YouTube is an emerging platform with over 2 billion users consuming and creating video content. MrBeast's channels stand as a compelling case study due to his overall success. Each channel has a range of videos spanning various categories and engagement levels. By using Python as a web scraping and data analysis tool, we can get a better understanding of his YouTube engagement success.

The challenges addressed in this paper are for diving deeper into factors influencing video engagement on MrBeast's channels. As content creators continue to grow their platform, understanding the dynamics behind the success of audience attention for individual videos becomes increasingly pivotal for channel growth. By using data science, we can unveil the patterns, correlations, and trends that contribute to MrBeast's success.

Objectives:

This paper's goal is to achieve the following objectives:

1. Analyze the engagement metrics (View, Like, and Comment Counts) across each channel's videos.
2. Investigate potential patterns of video uploads and their impact on engagement.
3. Explore engagement levels with video duration.
4. Uncover potential outliers and anomalies for further examination.

Data Collection and Cleaning:

My analysis is formed based on a Python web scraping procedure I have programmed. This procedure involves using Python Selenium, an open-source web testing and automation framework, to automate scrolling through a YouTube channel's video page to dynamically load the channel's videos. Using BeautifulSoup, a Python library commonly used for web scraping and parsing HTML and XML documents, to extract the video links from the dynamically loaded video blocks. After the channel's video URLs are collected, each video ID is then passed to YouTube's Data API to retrieve detailed information about the video. When the video details are collected, they are properly cleaned. Video duration gets formatted to minutes. Video upload date is formatted as (Month day, year) with the time being split off into its own variable formatted to the 24-hour system. Category ID is mapped from a numeric value to its string

readable form. For both like and view count, if there is none, then a '0' will take its place. For both tags and category, if none is present then its value will be 'None'. After the data is cleaned, it's organized into columns and rows in a CSV file. Each row of the CSV file represents a video while the columns represent the video's details: Channel, Title, Duration, Upload Date, Upload Time, Likes, Comments, Views, Tags, Category ID, and URL. The collected information is then subjected to exploratory data analysis(EDA), enabling us to generate valuable insights.

Descriptive Analysis

Overview of Data:

The dataset scraped from each of MrBeast's channels forms the base of my analysis, allowing me to investigate the engagement dynamics of each video. This dataset shows a range of video attributes, shedding light on performance and view interaction patterns on MrBeast's content. These attributes offer multiple windows into viewing each video's engagement metrics.

The dataset's dates span from [August 12th, 2023] to [March 9th, 2012]. These dates capture a timeframe that allows exploration of temporal patterns, engagement over time, and potential trends. The dataset has a total of 1,133 videos, with the majority of videos (730) being uploaded onto MrBeast's main channel @MrBeast. Each video contributes to the understanding of video behaviors, content preferences, and the interaction between engagement factors.

Summary Statistics:

To establish a prior understanding of the engagement factors, I calculated the summary statistics for several of each channel's engagement metrics within the dataset. The engagement metrics include View Count, Like Count, Comment Count, and Duration of each video. These metrics provide a great overview of viewer engagement and video interactions.

| All Channels: | View Count | Like Count | Comment Count | Duration (M) |
|---------------|-------------|------------|---------------|--------------|
| Mean: | 33,505,792 | 827,530 | 30,754 | 15.61 |
| Median: | 6,254,769 | 148,565 | 6,623 | 8.40 |
| STD: | 54,192,378 | 1,597,083 | 79,962 | 87.23 |
| Minimum: | 36,169 | 0 | 0 | 0.03 |
| Maximum: | 484,181,090 | 27,894,142 | 1,902,448 | 1,428.12 |
| Quartile 25%: | 126,381 | 4,111 | 588 | 3.78 |
| Quartile 50%: | 6,254,769 | 148,565 | 6,623 | 8.40 |
| Quartile 75%: | 42,888,230 | 926,868 | 35,120 | 12.15 |

| @MrBeast: | View Count | Like Count | Comment Count | Duration (M) |
|---------------|-------------|------------|---------------|--------------|
| Mean: | 36,255,947 | 949,957 | 33,735 | 18.56 |
| Median: | 339,346 | 11,398 | 1,361 | 4.60 |
| STD: | 64,527,575 | 1,933,932 | 63,515 | 108.57 |
| Minimum: | 36,169 | 0 | 0 | 0.03 |
| Maximum: | 484,181,090 | 27,894,142 | 745,743 | 1428.12 |
| Quartile 25%: | 63,234 | 1,994 | 335 | 3.10 |
| Quartile 50%: | 339,346 | 11,398 | 1,361 | 4.60 |
| Quartile 75%: | 41,985,481 | 1,143,068 | 47,814 | 12.64 |

| @MrBeastGaming: | View Count | Like Count | Comment Count | Duration (M) |
|-----------------|-------------|------------|---------------|--------------|
| Mean: | 46,976,244 | 1,015,941 | 54,616 | 10.47 |
| Median: | 41,387,593 | 893,576 | 29,998 | 10.25 |
| STD: | 26,668,947 | 583,653 | 170,361 | 1.43 |
| Minimum: | 8,935,433 | 271,585 | 7,702 | 8.02 |
| Maximum: | 159,619,954 | 4,964,436 | 1,902,448 | 16.05 |
| Quartile 25%: | 26,872,324 | 681,816 | 20,455 | 9.98 |
| Quartile 50%: | 41,387,593 | 893,576 | 29,998 | 10.25 |
| Quartile 75%: | 62,571,842 | 1,234,235 | 41,496 | 11.05 |

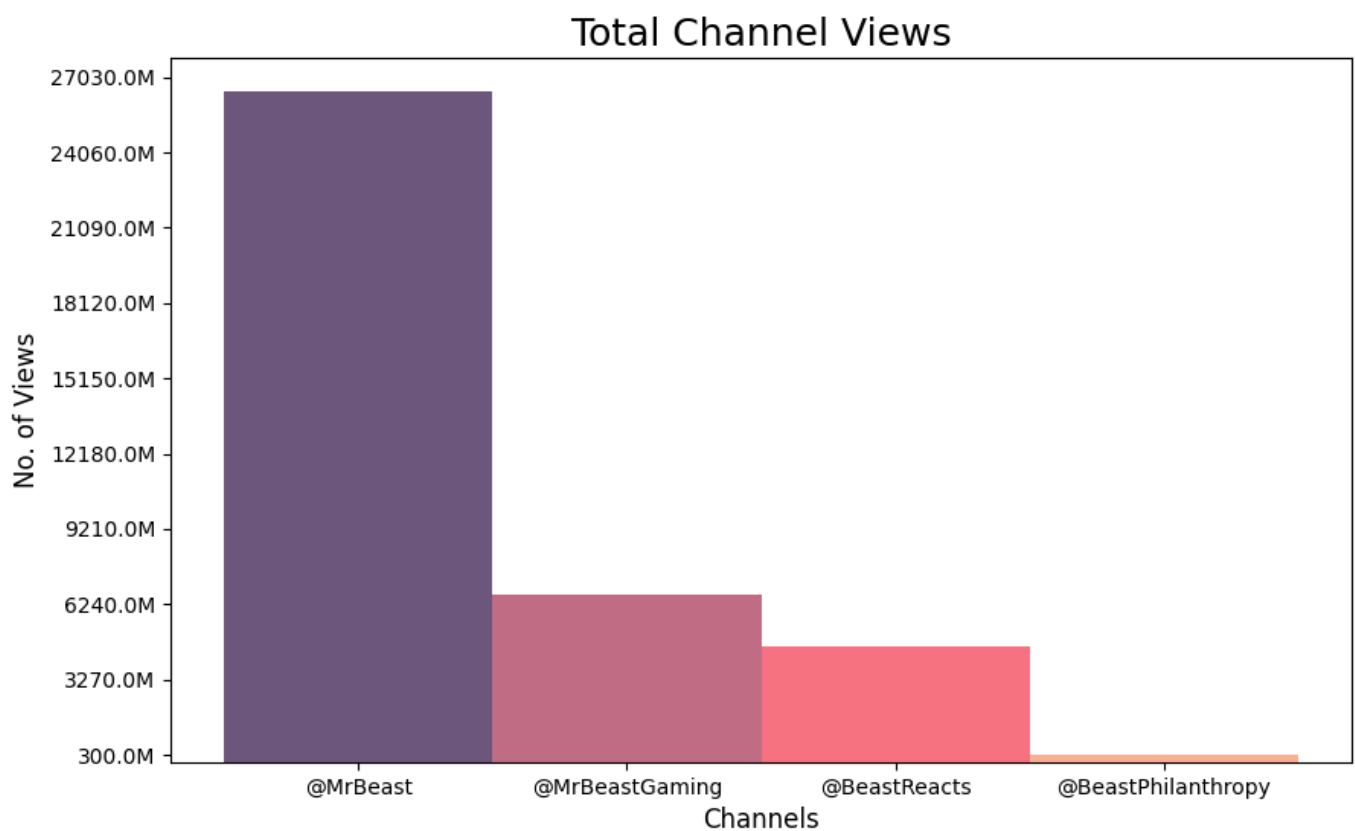
| @BeastReacts: | View Count | Like Count | Comment Count | Duration (M) |
|---------------|------------|------------|---------------|--------------|
| Mean: | 19,348,443 | 355,248 | 7,938 | 10.75 |
| Median: | 8,150,512 | 140,915 | 4,265 | 10.60 |
| STD: | 20,441,263 | 421,196 | 8,614 | 2.42 |
| Minimum: | 584,080 | 10,293 | 505 | 5.08 |
| Maximum: | 78,669,936 | 3,699,443 | 67,940 | 15.85 |
| Quartile 25%: | 2,507,426 | 38,654 | 1,881 | 8.25 |
| Quartile 50%: | 8,150,512 | 140,915 | 4,265 | 10.60 |
| Quartile 75%: | 34,803,122 | 623,104 | 12,099 | 12.47 |

| @BeastPhilanthropy: | View Count | Like Count | Comment Count | Duration (M) |
|---------------------|------------|------------|---------------|--------------|
| Mean: | 12,025,412 | 644,166 | 24,135 | 4.67 |
| Median: | 10,815,550 | 661,326 | 19,111 | 4.62 |
| STD: | 6,335,611 | 301,353 | 15,368 | 0.80 |
| Minimum: | 1,004,596 | 148,565 | 7,294 | 3.05 |
| Maximum: | 30,625,558 | 1,517,302 | 70,589 | 6.57 |
| Quartile 25%: | 7,812,994 | 407,995 | 10,868 | 4.18 |
| Quartile 50%: | 10,815,550 | 661,326 | 19,111 | 4.62 |
| Quartile 75%: | 15,252,932 | 763,079 | 33,652 | 5.33 |

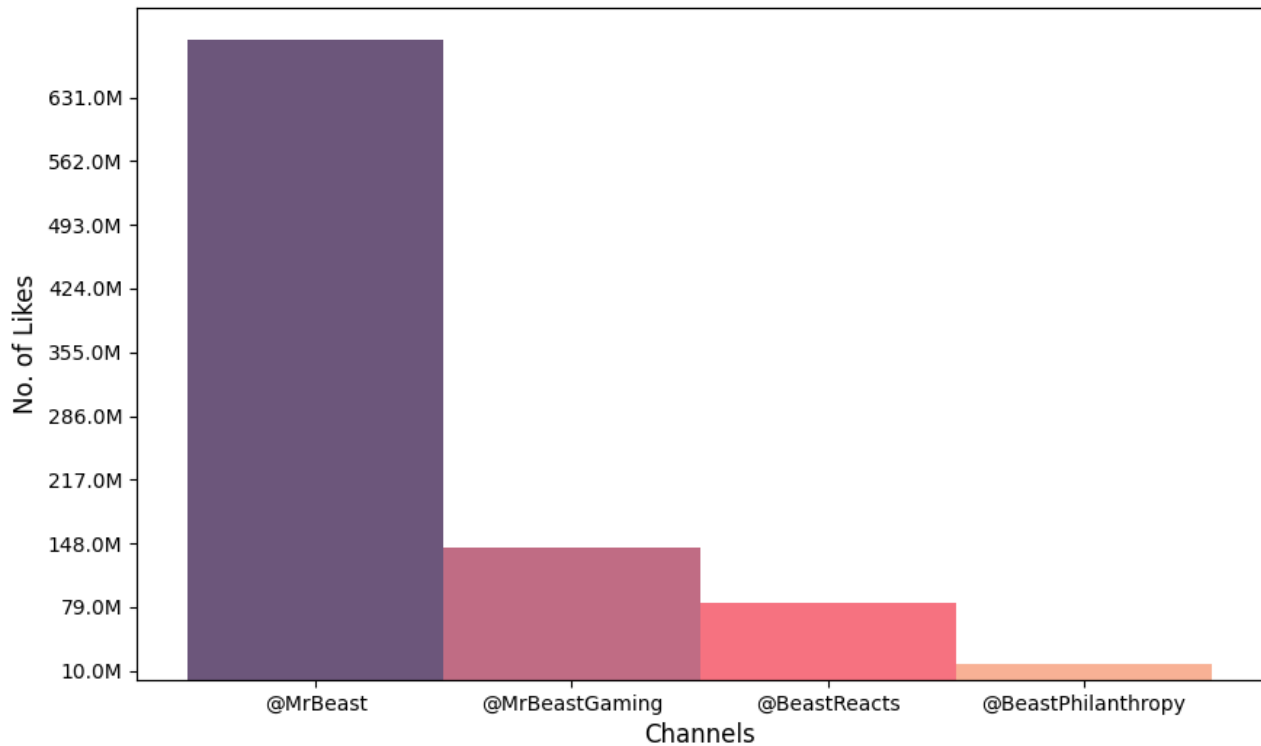
The view count's mean and median provide an understanding to the average video viewership spread across each channel. Analyzing these tables, you can say the @MrBeast channel on average gets more viewership than his other channels with its lowest averagely viewed being the @BeastPhilanthropy channel. But when analyzing the like and comment count's mean and median, you can say that the @BeastReacts channel has the lowest numbers averagely compared to every other channel. Each channel's mean and median for duration gives an insight into the typical length of each video, which can impact viewer engagement. This initial snapshot of the dataset's statistics serves as a great start for investigating engagement patterns and insights for the next sections.

Distribution Analysis:

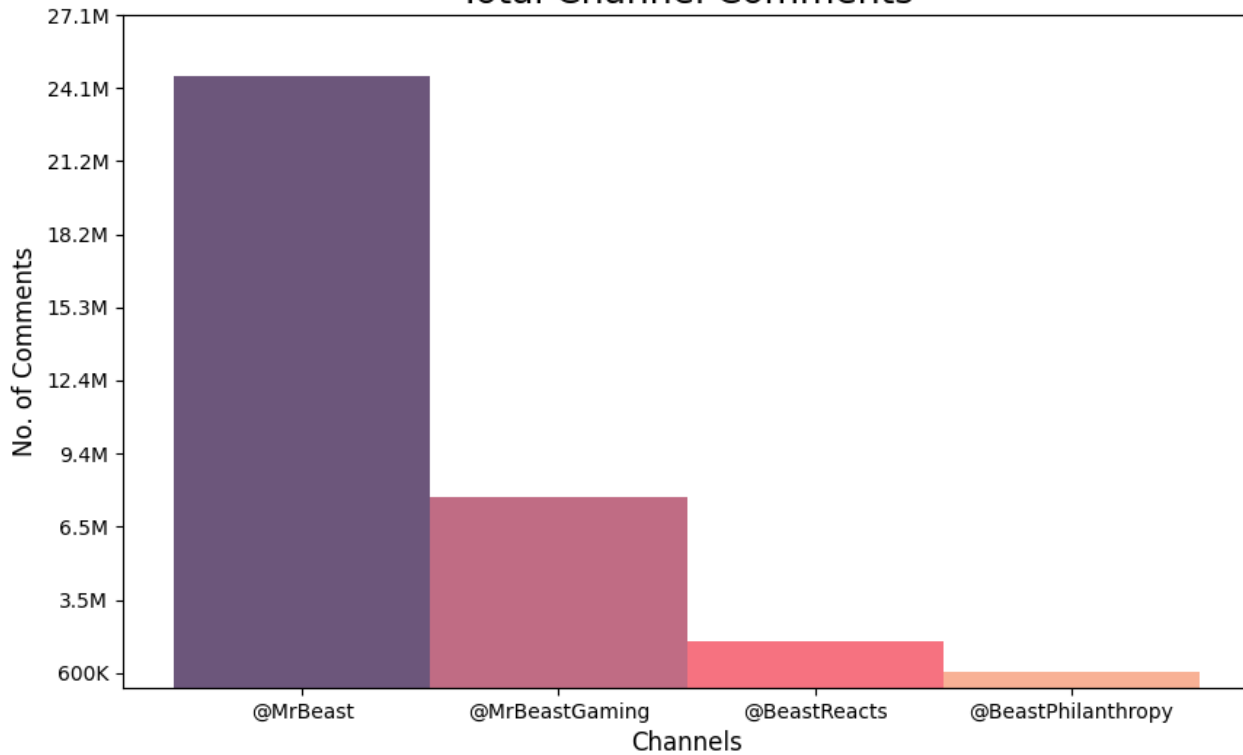
My distribution analysis helps see the spread of engagement metrics across each of the channels. Through bar graph visualizations, the variation in view, like, and comment counts, allow for insight into channel patterns.



Total Channel Likes



Total Channel Comments



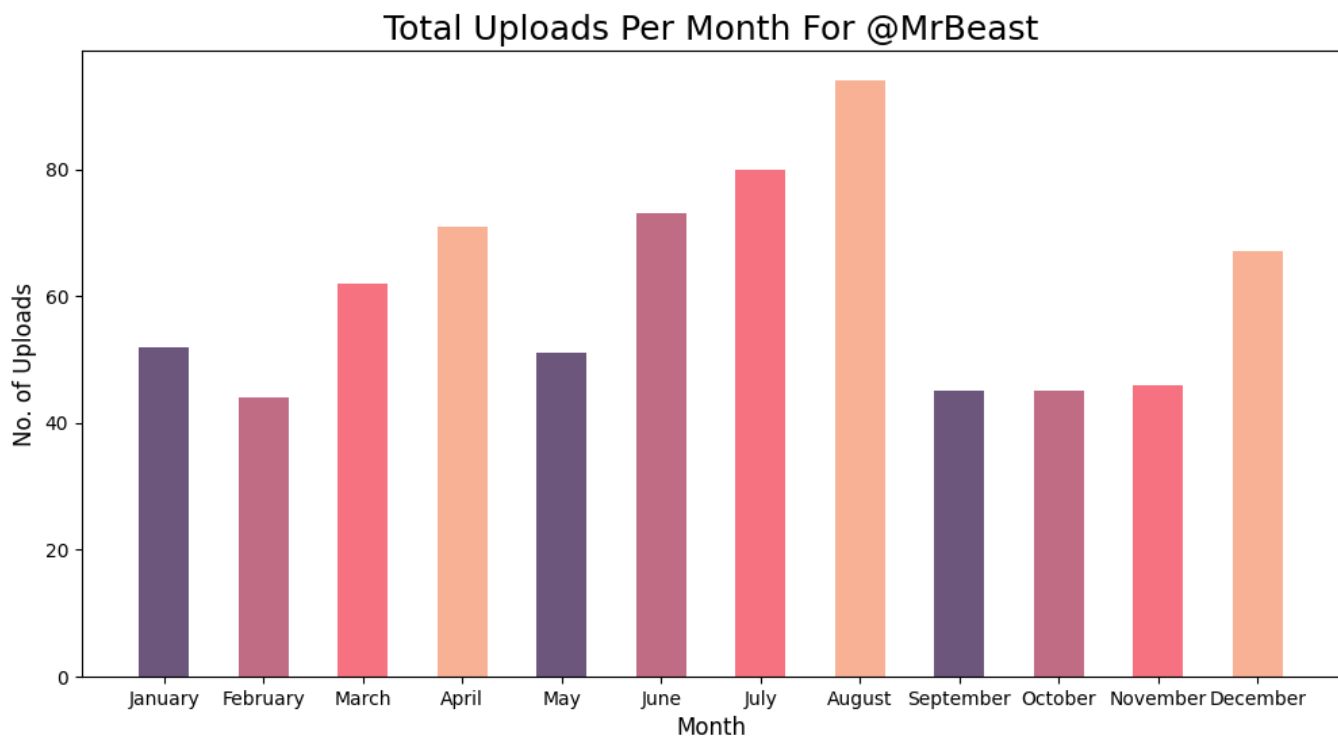
The bar graph depicting total channel views illustrates the varying levels of video viewership among MrBeast's channels. Channels with taller bars indicate channels with higher viewership compared to shorter bars that yield lower viewership compared to the others. Similarly, the graph for total like count across each channel shows the diversity in audience reactions to each

channel's videos. Elevated bars show channels with videos that resonate stronger with viewers, compared to the short bars which indicate modest feedback. The comment count graph unveils viewer interaction and engagement on videos. Channels with elevated bars reflect videos with more discussions and exchanges, while shorter bars signify lesser engagement.

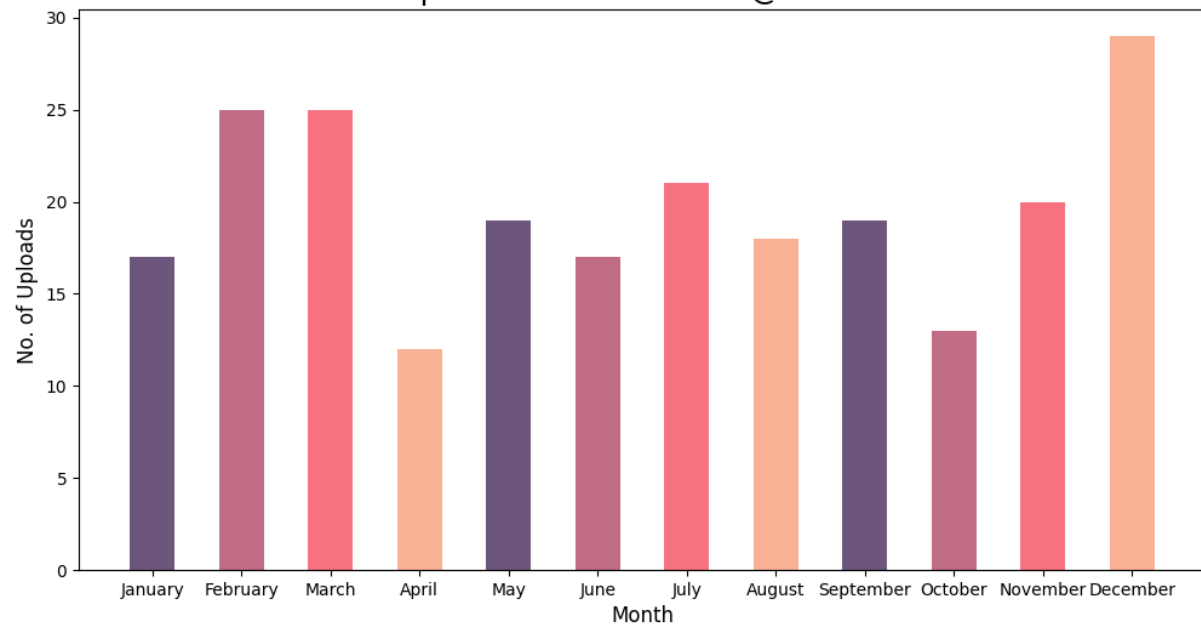
Analyzing these graphs, you can see which channel receives a greater amount of video engagement compared to the others. The @MrBeast channel in every graph towers the other channels, while the @BeastPhilanthropy has the smallest bar. Even though the @BeastPhilanthropy channel is the smallest, its numbers for total views and likes are still above one million with its total comments above 600 thousand. The @MrBeastGaming and @BeastReacts share a similar relationship in engagement for viewer and like count. But when it comes to total comment count, the @MrBeastGaming channel outperforms @BeastReacts in comment engagement. Does the size of your channel result in more viewer interactions or does the content you post matter the most for engagement?

Temporal Patterns:

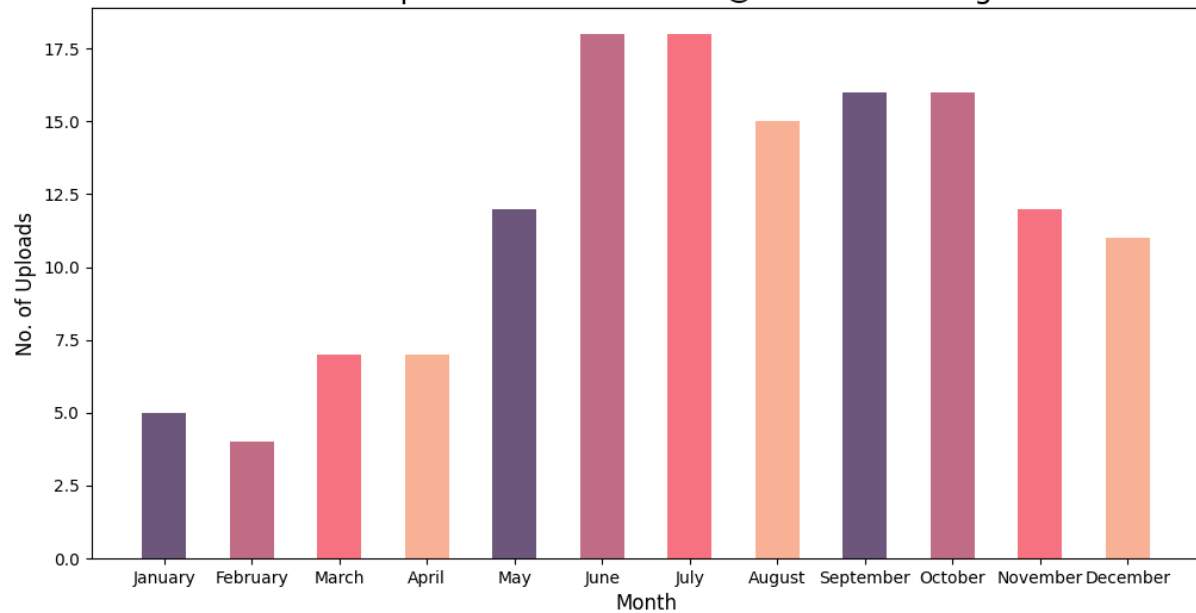
Temporal patterns show an insight into video upload timing and frequencies across each of the channels. The following bar graphs show monthly upload frequencies for each channel. Providing an overview of each channel's content release schedules.



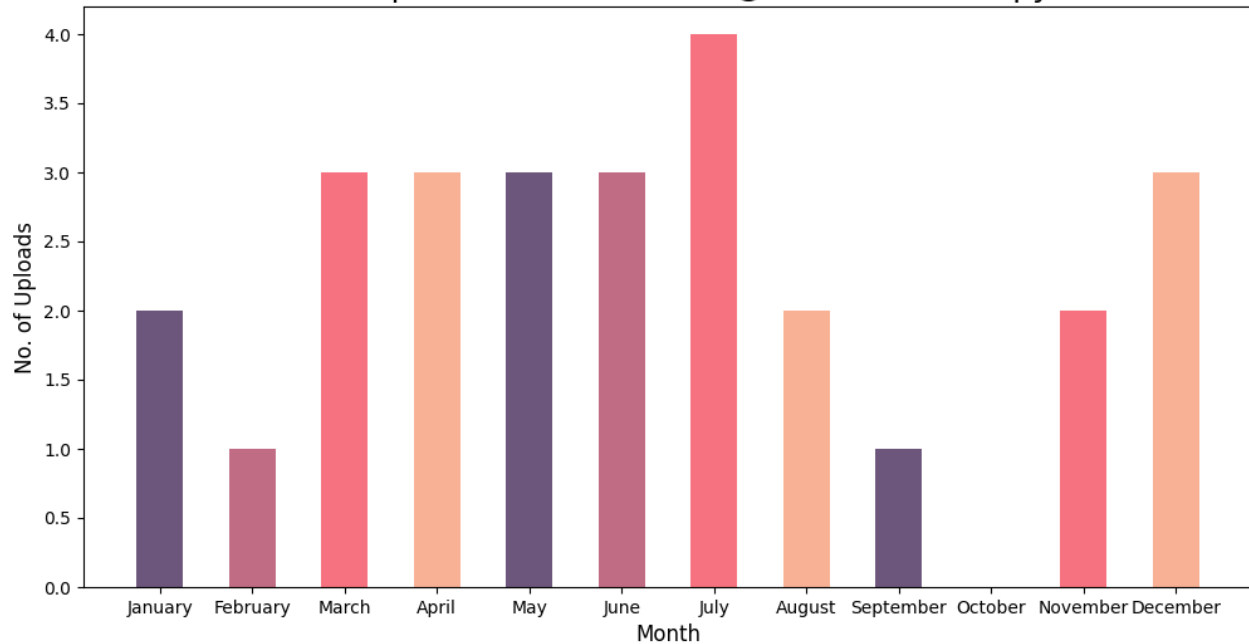
Total Uploads Per Month For @BeastReacts



Total Uploads Per Month For @MrBeastGaming



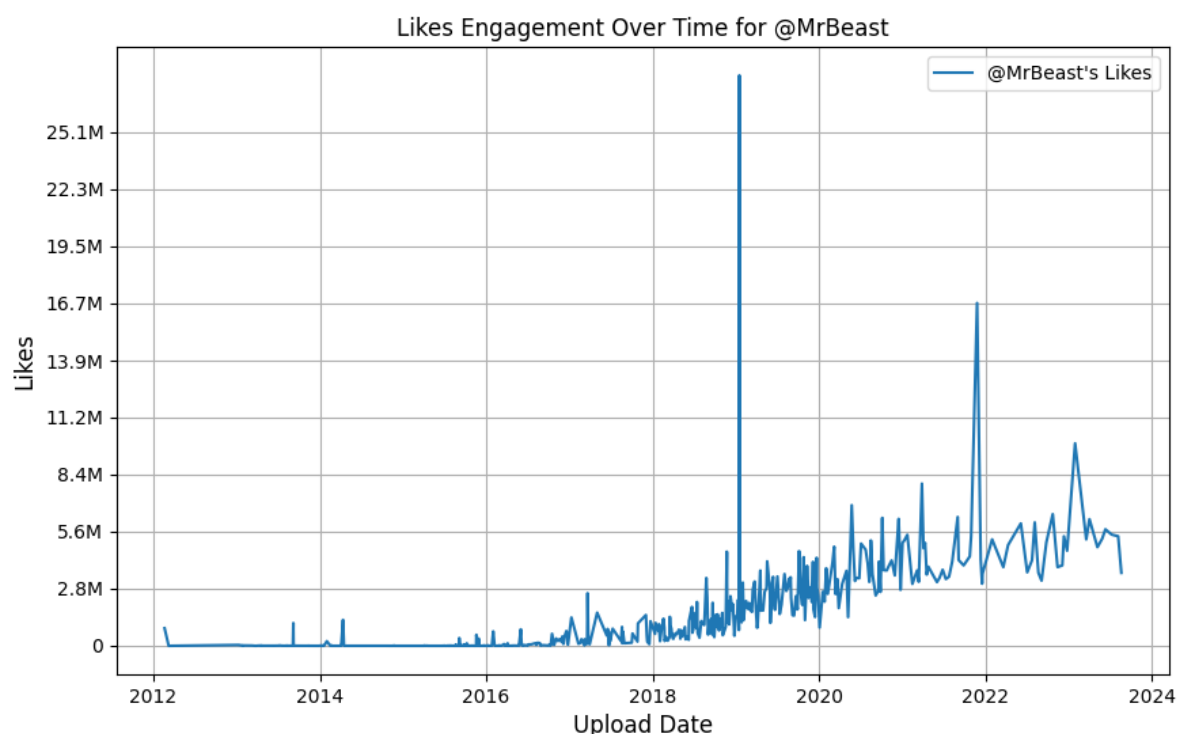
Total Uploads Per Month For @BeastPhilanthropy

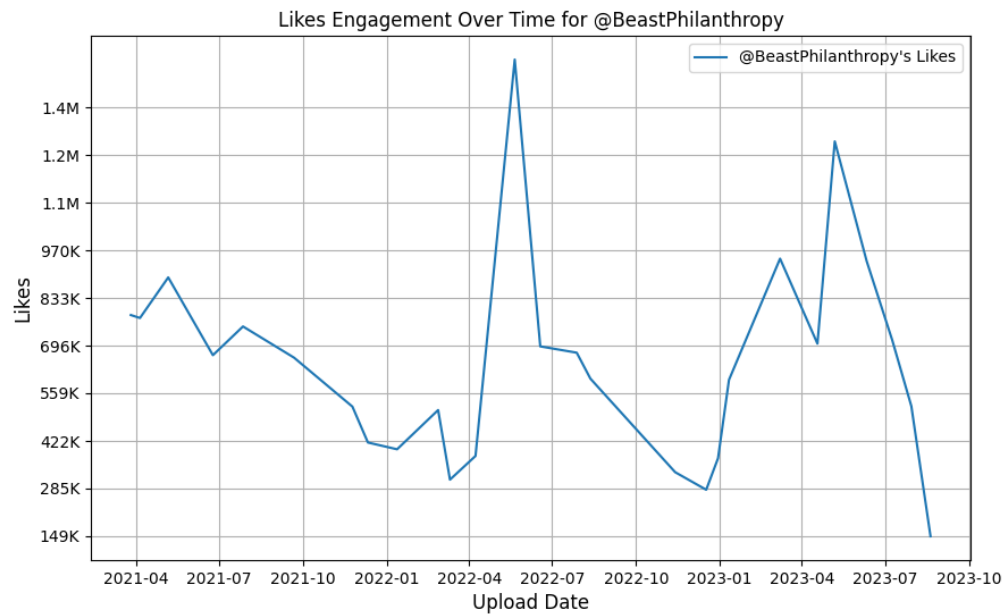
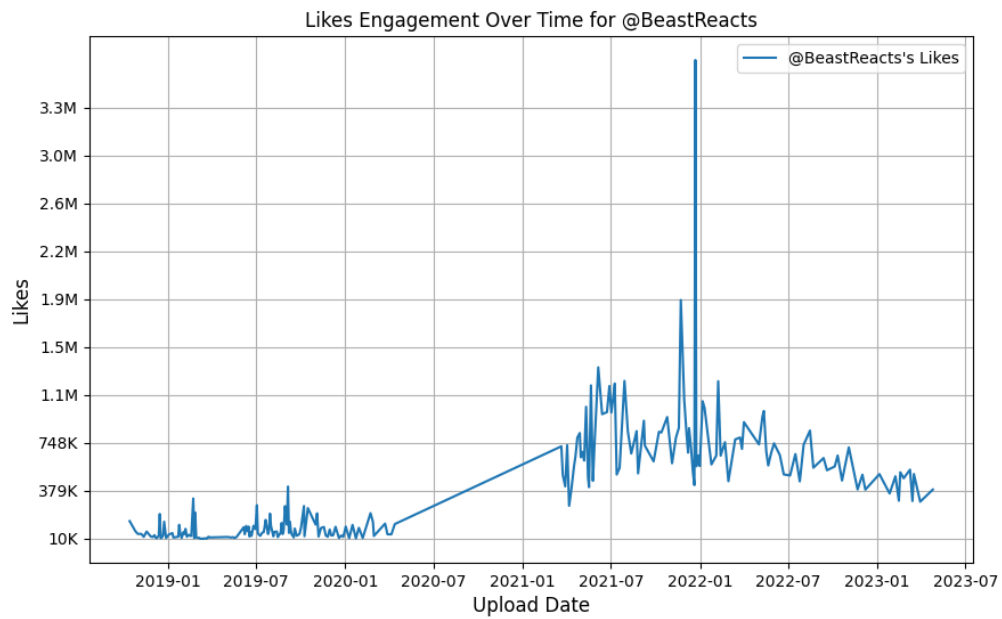
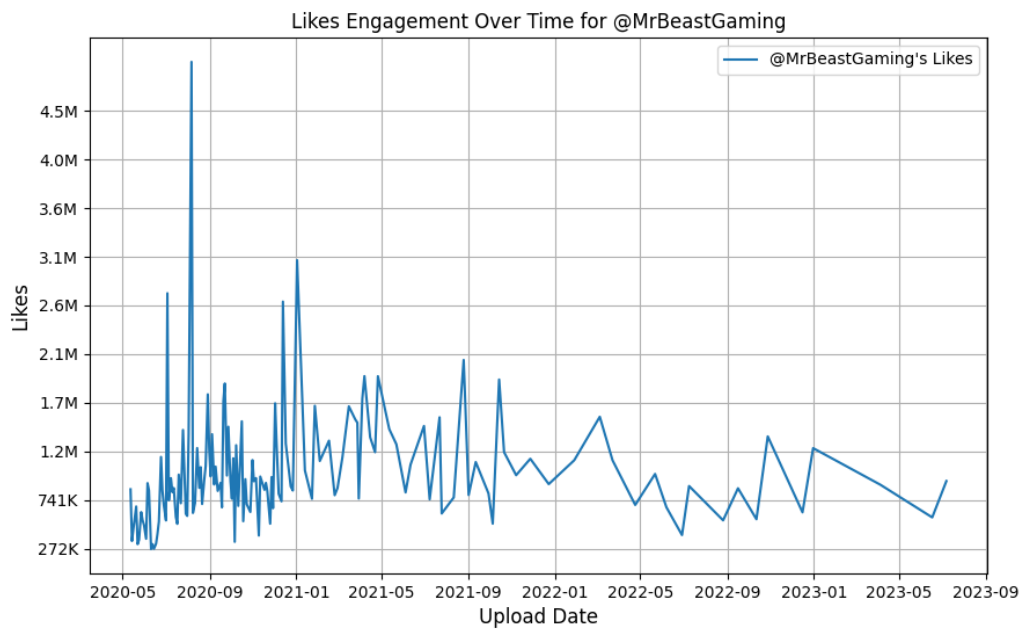


Analyzing these graphs, you can see how each channel's upload schedule differs from each other. You can infer from each channel that the summer season is the most popular time to upload. @MrBeast most frequent upload month is August, @BeastReacts is December, @MrBeastGaming is tied for June and July, and @BeastPhilanthropy is July. For each channel besides the @BeastReacts channel, you see a decrease in uploads during winter with a rise in spring. Each channel frequencies stagger throughout the months, but two of the channels maintain a constant frequency for more than 3 months. @BeastPhilanthropy maintains a constant schedule for the months March through June. While @MrBeast maintains a constant schedule for the months September through November. There is one outlier with zero uploads in a month, @BeastPhilanthropy, containing no uploads during the month of October. There could be many factors affecting the results of upload frequencies including the year, season, and total video uploads for each channel, but the results of this analysis help pave a path for further investigation.

Engagement Over Time:

Diving further into our temporal patterns, let's take a look at how viewer engagement changes over time. In order to understand viewer response on each channel we can see how it has changed from videos uploaded years ago compared to videos uploaded today. Keep in mind that many viewers tend to go back and rewatch former uploaded videos, changing how the engagement data originally did when it was first uploaded, but still paints a big picture. Using the like count for each channel, this line graph showcases the trajectory of likes over time. The x-axis represents time, while y-axis indicates the like counts for the videos posted.



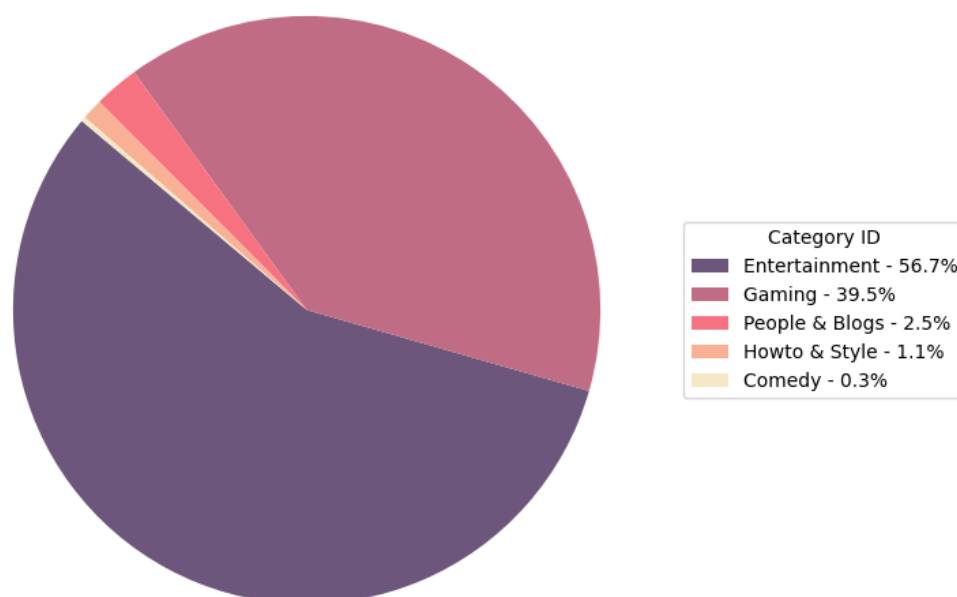


Analyzing these graphs, you can see how viewer engagement can never be guaranteed for every video a channel uploads. Each channel has its ups and downs with like engagement, but you are able to see multiple spikes during different time periods. You can infer that these spikes are videos going viral on YouTube, gaining more like interactions. One outlier, on the channel @MrBeast, during the periods of 2018 to 2020, had a video with the biggest spike going from an average 2 million likes all the way up to a little over 25 million likes. Looking back on the summary static data we can assume that this video was his channel maximum of 27,894,142 likes. The next biggest spike for the @MrBeast channel wasn't until late 2019 jumping from an estimated average of 3 million likes to a little over 27 million. Looking at the @MrBeastGaming you can see massive engagement at the start of the channel during 2020, but with a slow decline throughout 2022. Did covid-19's quarantine play an affect on video engagement? For @MrBeast we can't assume this is the case as this channel has had a positive incline since 2018 and the @BeastPhilanthropy channel having its first upload in early 2021. But for the @MrBeastGaming and @BeastReacts channels both had a positive incline start in 2020, with a slow decline in late 2021, when a lot of covid-19 public restrictions were lifted in the United States. After analyzing like engagement over time, patterns are starting to form with viewer interaction throughout the years.

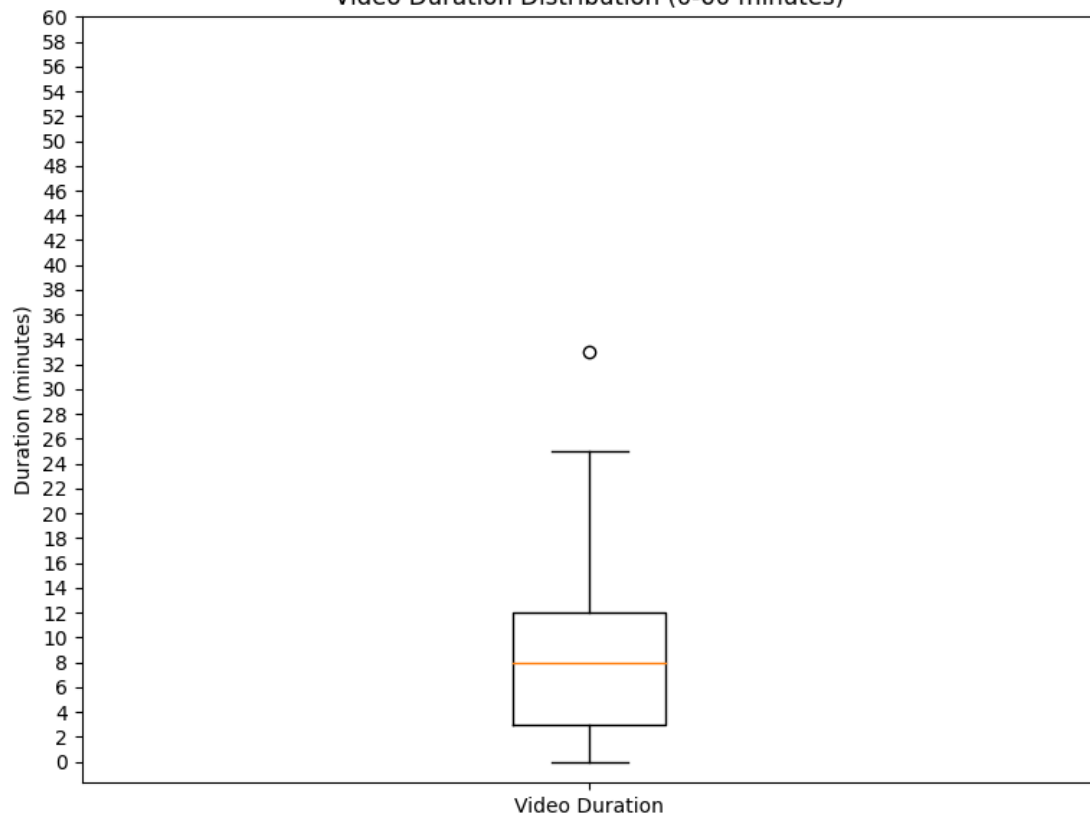
Category Distribution:

Understanding how video categories are distributed between each channel can recognize content diversity and viewer preferences. The pie chart illustrating each category usage percentage showcases each channel's topics. Does selecting the right category mean anything for viewer engagement?

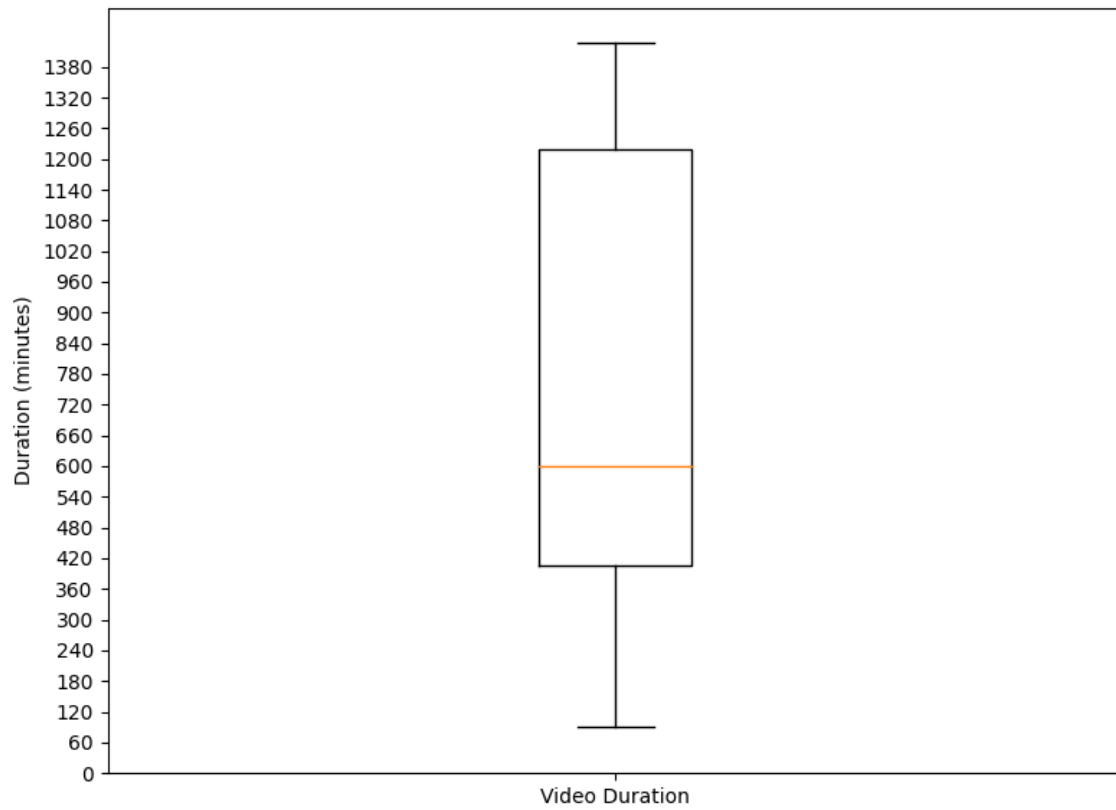
Combined Video Category Distribution



Video Duration Distribution (0-60 minutes)



Video Duration Distribution (Above 60 minutes)



Analyzing these graphs, the median for videos below 60 minutes are around eight minutes while videos above 60 minutes are ten hours long. Majority of those videos below 60 minutes have a range from 1 minute to 26 minutes with one outlier at 34 minutes. The majority of the videos above 60 minutes have a range from two hours to above 23 hours with no outliers. Investigating the graph for videos below 60 minutes, you can assume videos in the range of four to twelve minutes are a popular choice as they lie between the 25% and 75% quartile. back at the summary statics we can see that the 25% quartile is 3.78 and the 75% quartile is 12.15 even including the ones above 60 minutes. With that we can infer viewers prefer videos in that range.

Initial Observations:

The initial analysis performed on each of MrBeast's channel's video details has compelling insights into viewer engagement, preferences of content, and temporal factors. These initial observations have set the stage for a better understanding of every channel's performance.

Out of each channel, the one with the most viewer interactions is the @MrBeast channel. The channel outperforms every other channel in view, like, and comment count, while maintaining a positive incline in like engagement over the span of the channel's life. By analyzing the monthly upload frequency, we can assume the best months for viewer engagement rise in the spring, max out in the summer, and drop during fall. Across the channels, popular video categories are the entertainment and gaming category. With the most used tags reflecting potential viewer search results. Also, video duration ranging from four minutes to twelve can lead to retaining viewer attention, which has the possibility to lead to more viewer engagement.

These initial observations provide a framework for the following sections. Where a deeper analysis can be formed to investigate furth into these initially seen patterns in viewer engagement and channel performance.

Temporal Analysis

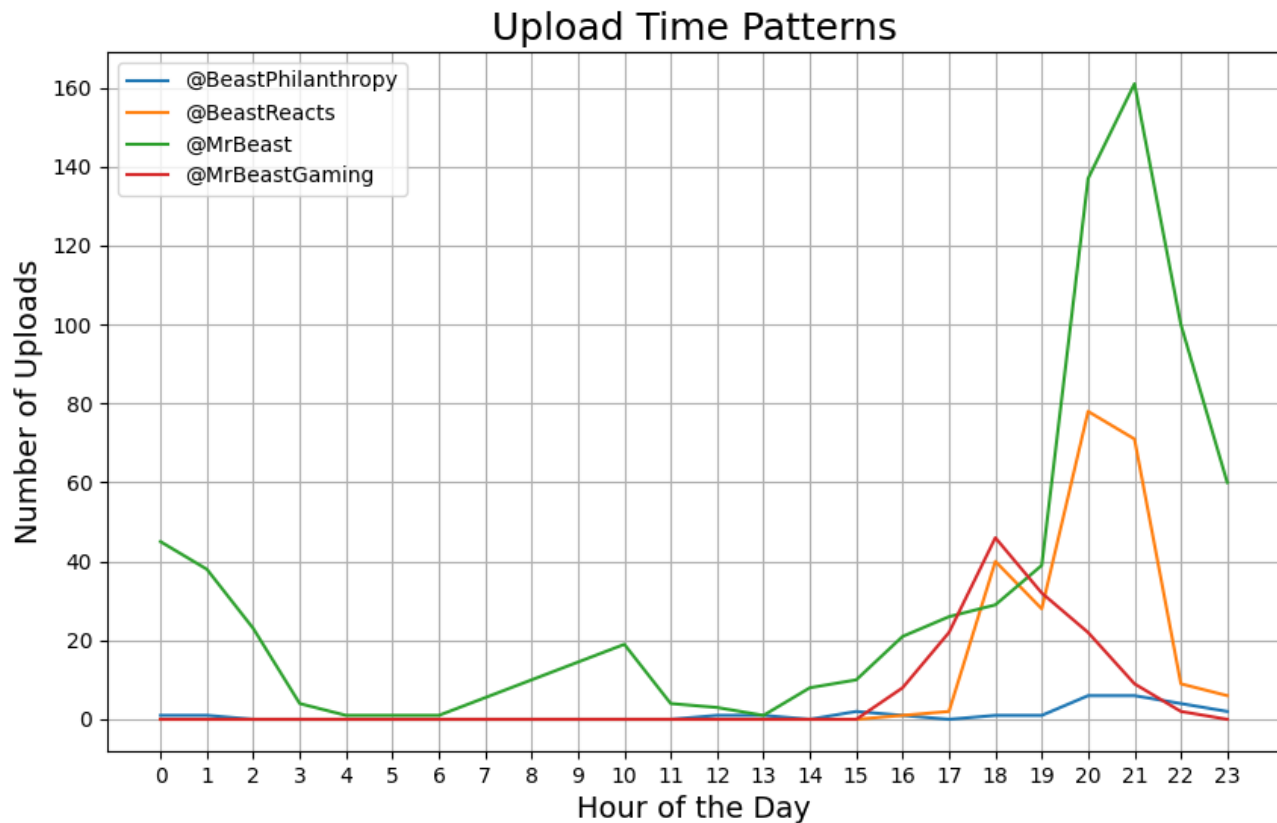
Overview of Section:

This section explores the temporal dynamic of video uploads across each of MrBeast's channels. Through investigating upload frequencies and upload time patterns we can see the potential impacts on viewer engagement. Allowing an insight into MrBeast's strategic content distribution and its continuity with audience behavior.

Upload Time Patterns:

The timing of when a video is uploaded during the day can play a crucial role in capturing viewer attention and engagement. Analyzing upload time patterns provides an insight into when MrBeast releases a video, potentially aligning with the availability and preferences of the

viewers. The line graph illustrates upload time patterns, indicating when videos are uploaded across each hour of the day. Each line represents a specific channel's upload timing trend.

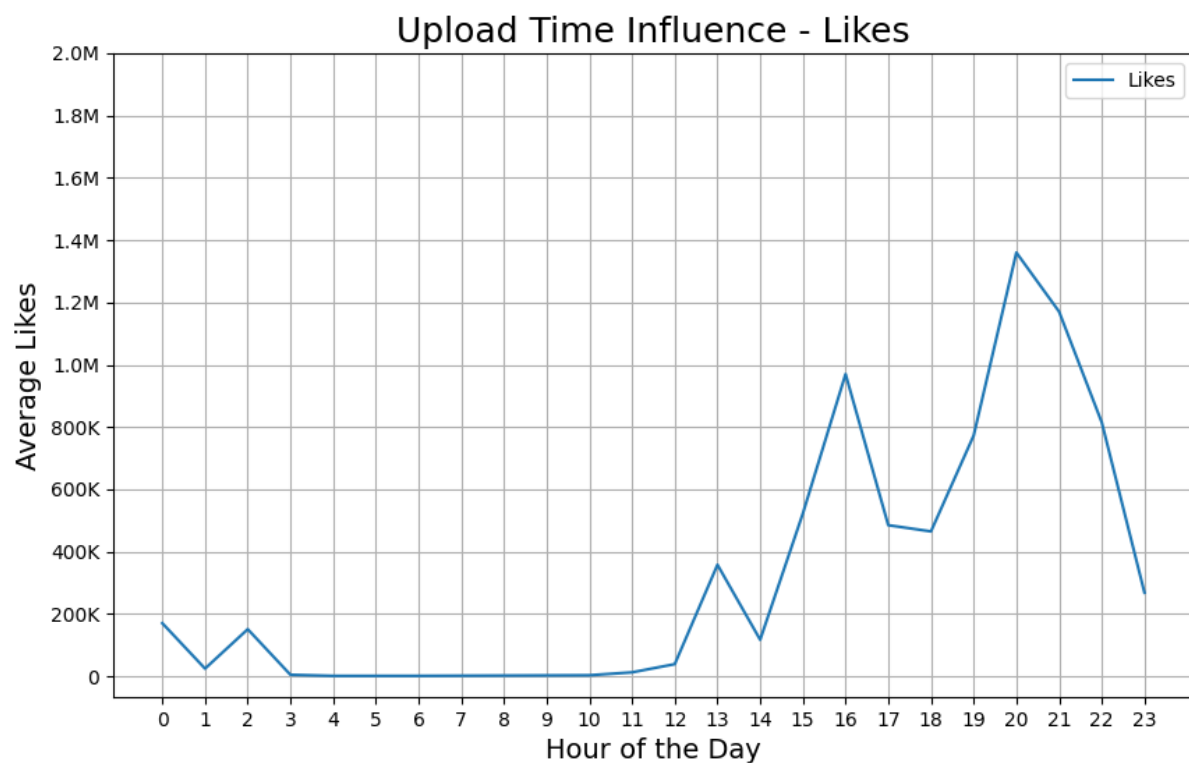
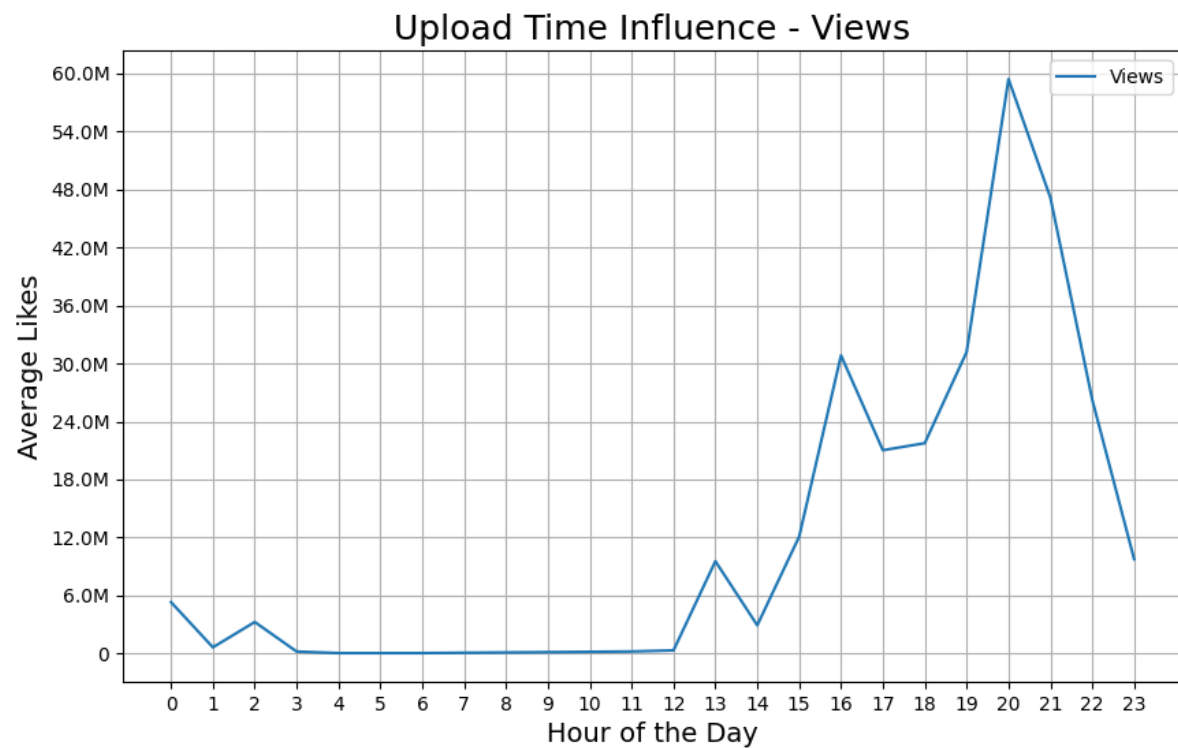


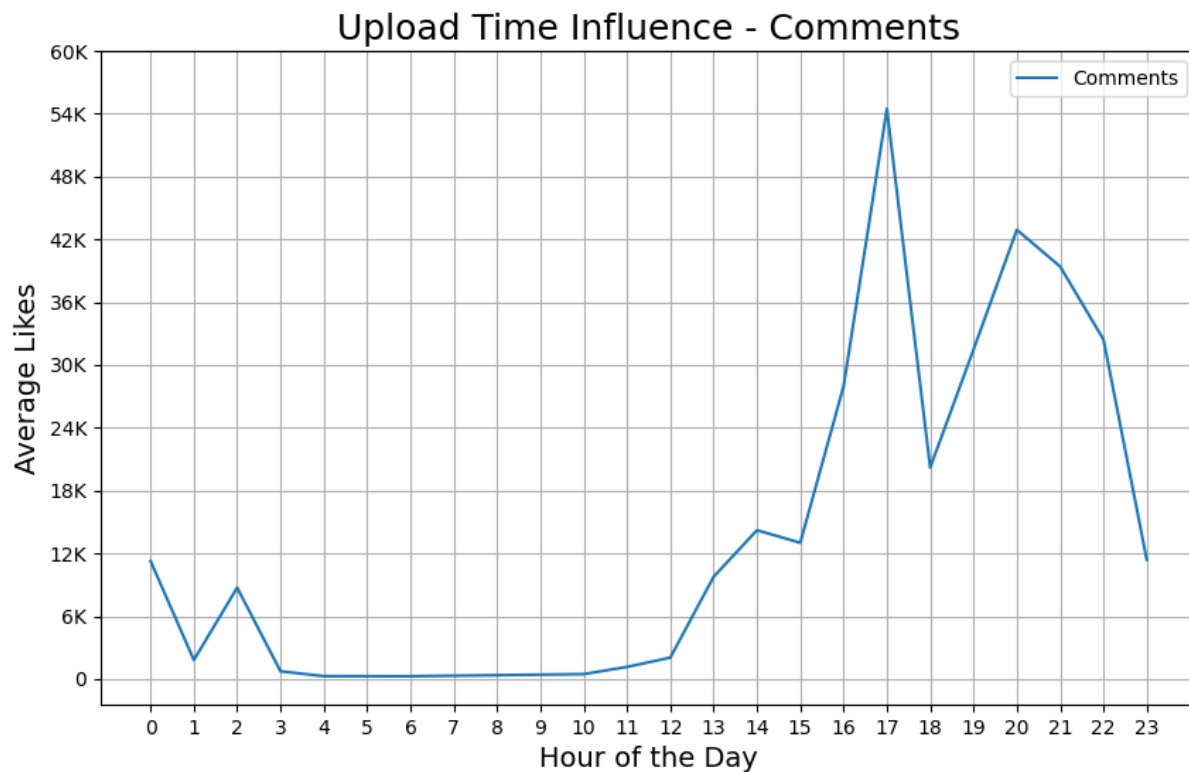
Analyzing this graph, the peak upload hours are between 6pm to 9pm Eastern Standard Time. For each channel the time of day they upload the most is varied but similar. The @MrBeast channel mainly uploads at 9pm, @BeastReacts is 8pm, @MrBeastGaming is 6pm, and @BeastPhilanthropy is 8pm. These also correlated with Pacific Standard Time of 3pm to 6pm. You can estimate MrBeast uploads are reflected for when school is out for younger viewers and when older viewers are off of work, for both the West and East coast. One outlier is the @MrBeast channel peaking at 10am EST. This could result from an older schedule before 2019 as the newer channels only start peaking around 4pm EST. The same thing can be said for the hours between 12am to 2am EST for the @MrBeast channel.

Upload Time Influence:

Do videos released during a specific hour of day receive higher engagement? The pattern between upload timings and viewer engagement is crucial aspect of content distribution. Understanding the impact on engagement metric for specific upload times gains an insight into audience behavior and interactions. The following line graphs illustrate the relationship

between upload time and engagement metrics in terms of likes, comments, and views. These graphs uncover trends in engagement based on the time-of-day videos are released.

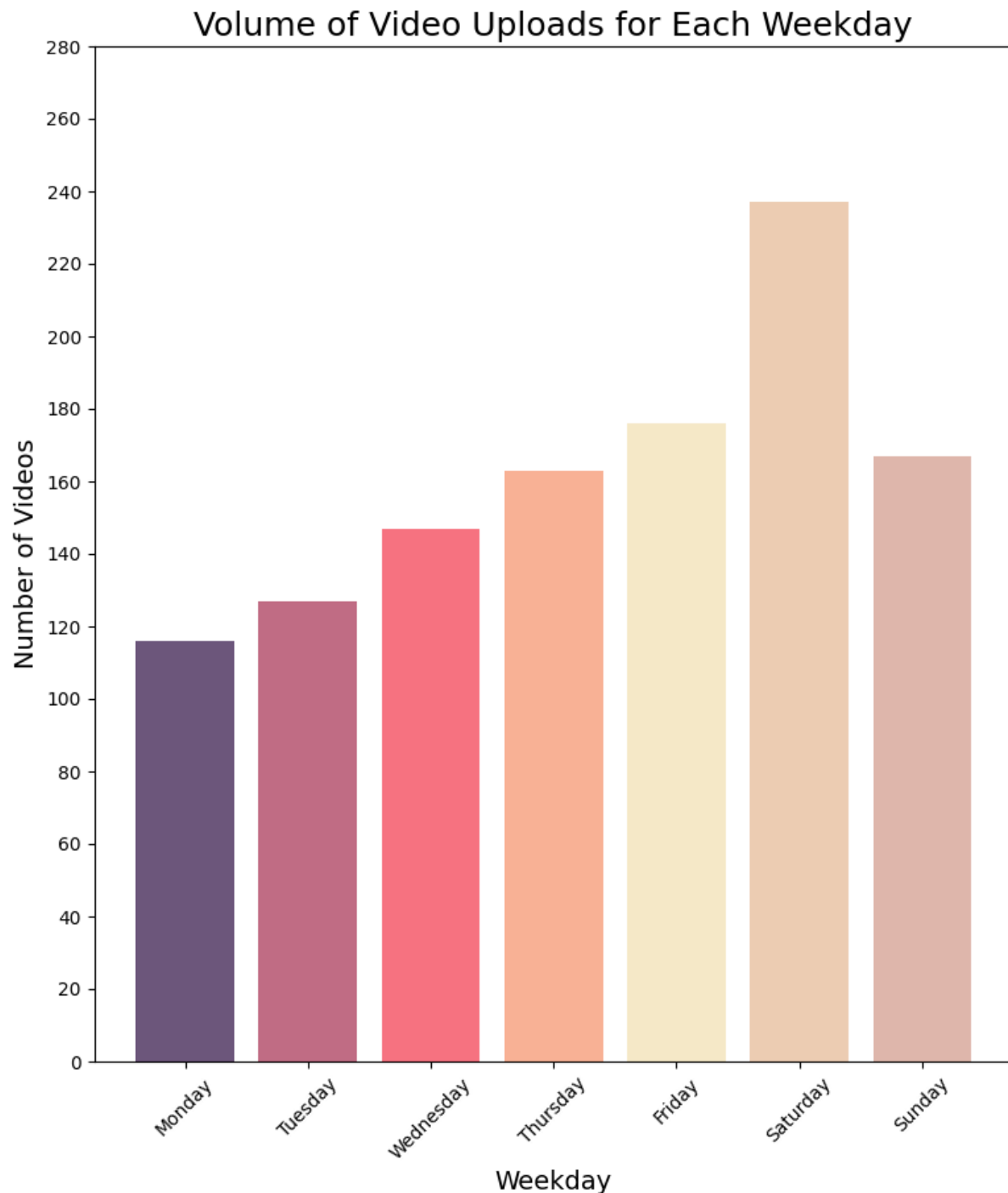




Analyzing these graphs, the peak upload hours are between 4pm to 10pm Eastern Standard Time. For each engagement metric, the time of day is similar to the time of day it rises and falls. For both views and likes the peak hours of the day are from 4pm to 9pm EST with the highest peak at 8pm EST. For comments the peak hour of day is from 4pm to 10pm EST with the highest peak at 5pm EST. Suboptimal times for engagement across all metrics are from 3am to 11am EST with a similar slight rise at 12pm EST. One common pattern between each graph is a decrease in engagement at 6pm EST and a slight peak at 2am EST. Matching the engagement peak upload hours of 4pm to 10pm EST to MrBeast's channels peak upload hours, you can see why MrBeast uploads between 6pm to 9pm. Overall, the optimal time of posting regarding MrBeast's engagement hours is 8pm EST for views and likes and 5pm EST for comment engagement.

Upload Day Patterns:

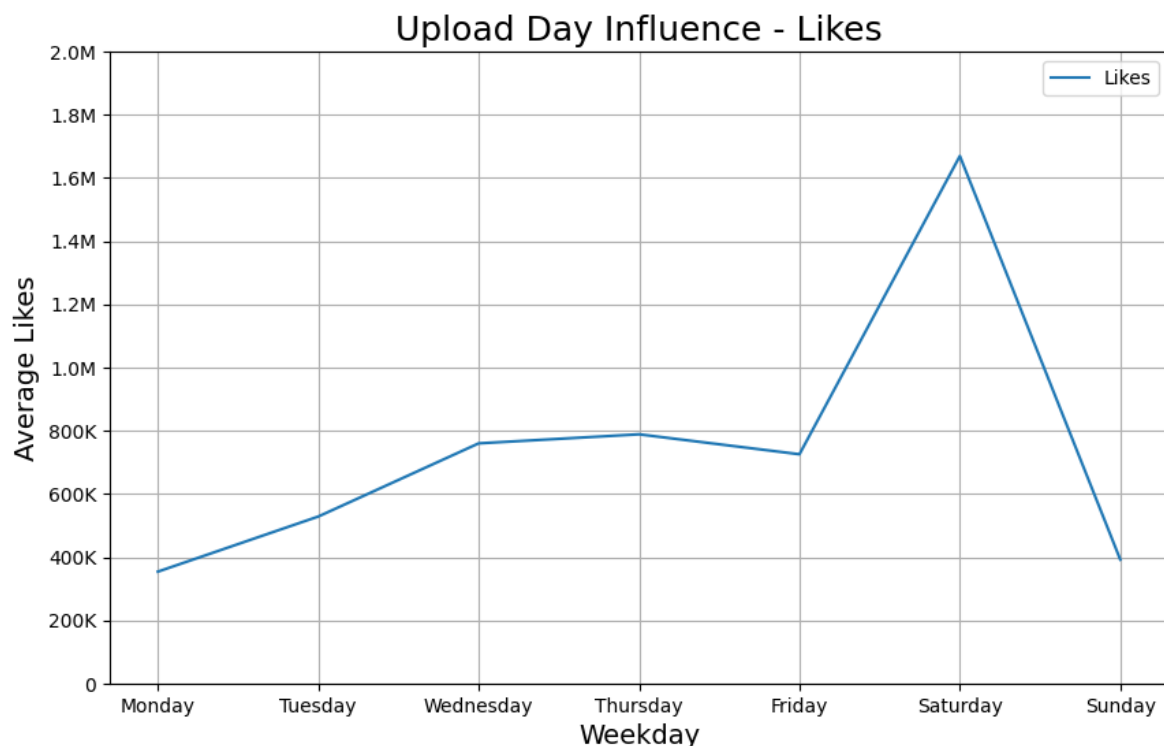
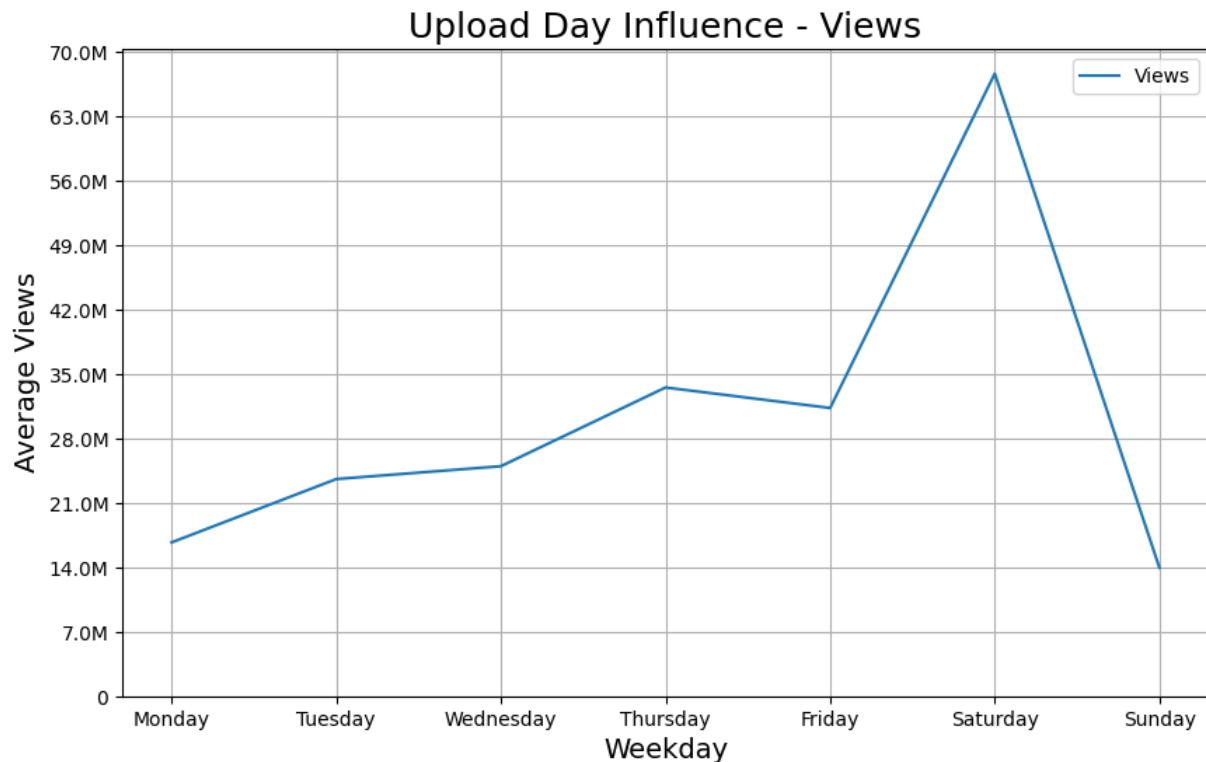
Analyzing what day of the week to upload can be crucial to gaining more insight into understanding audience behavior throughout the week. Investigating the distribution of video uploads for each day of the week offers an insight into MrBeast's scheduling strategy with potential of unraveling viewer engagement patterns. The bar graph illustrates the volume of video uploads for each weekday. Each bar represents a specific weekday, illustrating the number of videos released on that day.

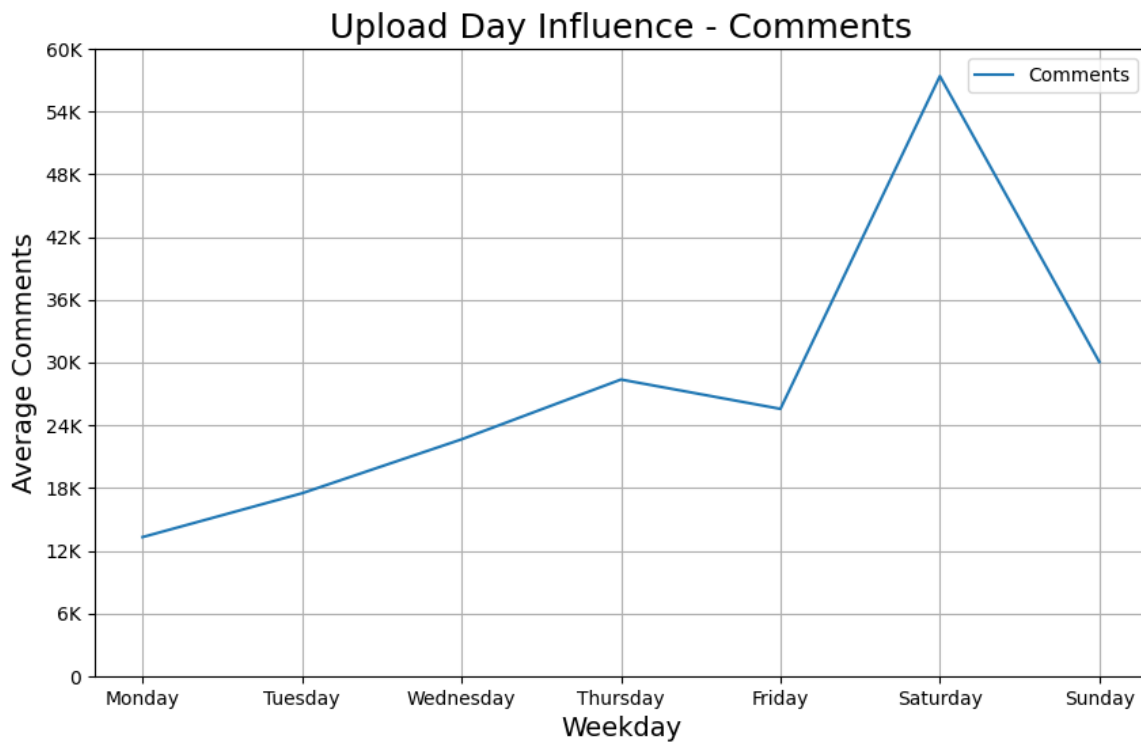


Analyzing the graph, you can see the day with the most uploads is Saturday. The numbers of uploads rise each day of the week until hitting its peak on Saturday. Each day of the week does have over 100 uploads, but Thursday through Sunday have over 160 uploads. The only outlier in this graph is Saturday with a massive peak of almost 100 uploads. This could mean that MrBeast scheduling strategy works around audiences having Saturday off from school and work. The decrease of uploads from Saturday to Sunday could be a result of engagement decrease on Sunday compared to Saturday for a weekend upload. Also, Friday has more uploads than Sunday even though Friday is during the school and work week. This could be a result of MrBeast scheduling around audiences becoming active after ending their last school or workday.

Upload Day Influence:

Does picking a perfect day of the week to upload result in more engagement? The pattern between an upload day and viewer engagement is a crucial aspect of content distribution. Analyzing engagement metrics based on weekdays provides an insight into audience behavior and engagement performances throughout the week. These line graphs illustrate engagement metrics in terms of likes, comments, and views across each different day of the week.





Analyzing these graphs, the peak day for all engagements is Saturday. All engagements see a similar pattern, where engagement rise from Monday to Thursday, dipping on Friday, and reaching a high peak on Saturday. For both view and like engagement, Sunday has a massive decrease dropping to below or the same engagement levels as Monday. For comment engagement, Sunday still has a drop from Saturday, but it stays above the rest of the weekdays. The peak on Saturday can be a result of heightened audience activity on the weekend, but this can't be said for Sunday. Matching these graphs to the volume of video uploads each weekday graph you can see the trend in audience engagement matching the number of uploads per each day. The one outlier in lining up the two graphs would be Friday. Where in the volume of uploads graph, Friday is the second highest peaking day for MrBeast's upload schedule, but engagement levels show Friday is below Thursday for audience attention.

Implications and Considerations:

The insights obtained from the in-depth temporal analysis of MrBeast's channels offer an insight into the implications of content creators and strategies wanting to optimize towards audience behavior for peak viewer engagement. These findings express the decision making regarding MrBeast's content scheduling and video distribution. Through understanding viewer habits and audience behavior, channels can tailor content scheduling to create a lasting connection and enhance viewer loyalty.

MrBeast schedule utilizes Saturday as the best day of the week across all channels. Investigating the engagement levels for the week, Saturday outperforms every other day for all engagement metrics. MrBeast distributes channel content between an average of 6pm to 9pm Eastern Standard Time. MrBeast understands that the peak hours of each channel's engagements are from 4pm to 10pm EST. Knowing when to release content with peak engagement hours and days optimizes visibility and interaction. Tailoring content distribution strategies to audience

behavior can maximize a channel’s engagement outcome. Building viewer loyalty through strategic timing can foster connections and anticipation.

This analysis highlights the strategic role of timing in content distribution. Exemplifying how a content creator can create a lasting connection through well-timed releases. Maximizing on peak engagement for the perfect hour and day of the week.

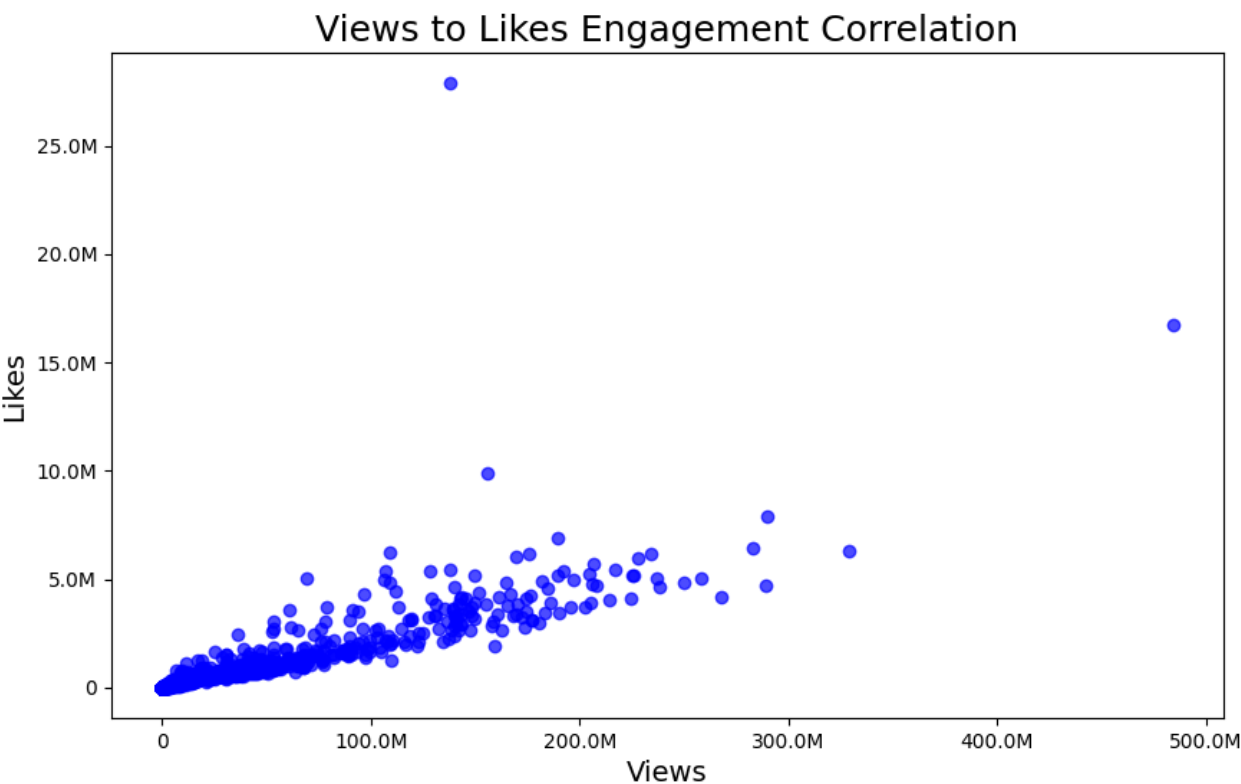
Engagement Pattern Analysis

Overview of Section:

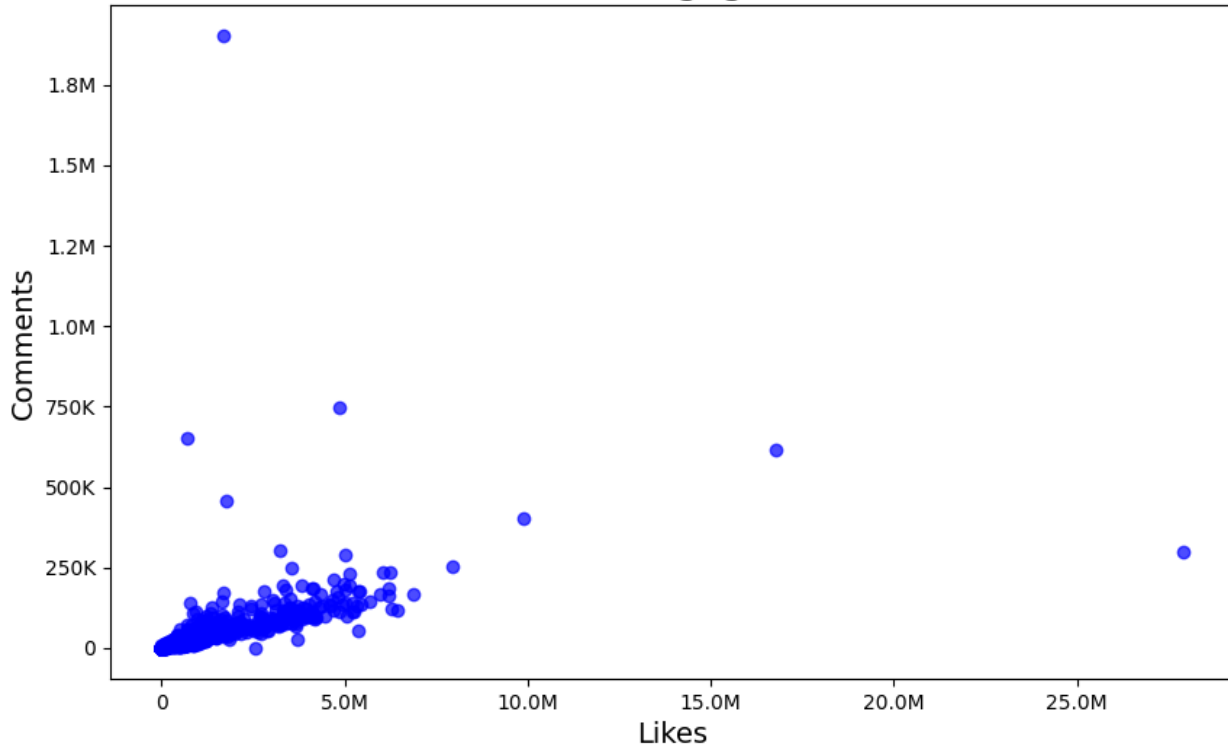
This section explores the interaction between engagement metrics and each metric’s correlation with video release patterns each year. Investigating how engagement metrics grow and fall over time allows an insight into the change of audience interaction and potential factors influencing engagement trends.

Engagement Metric Correlation:

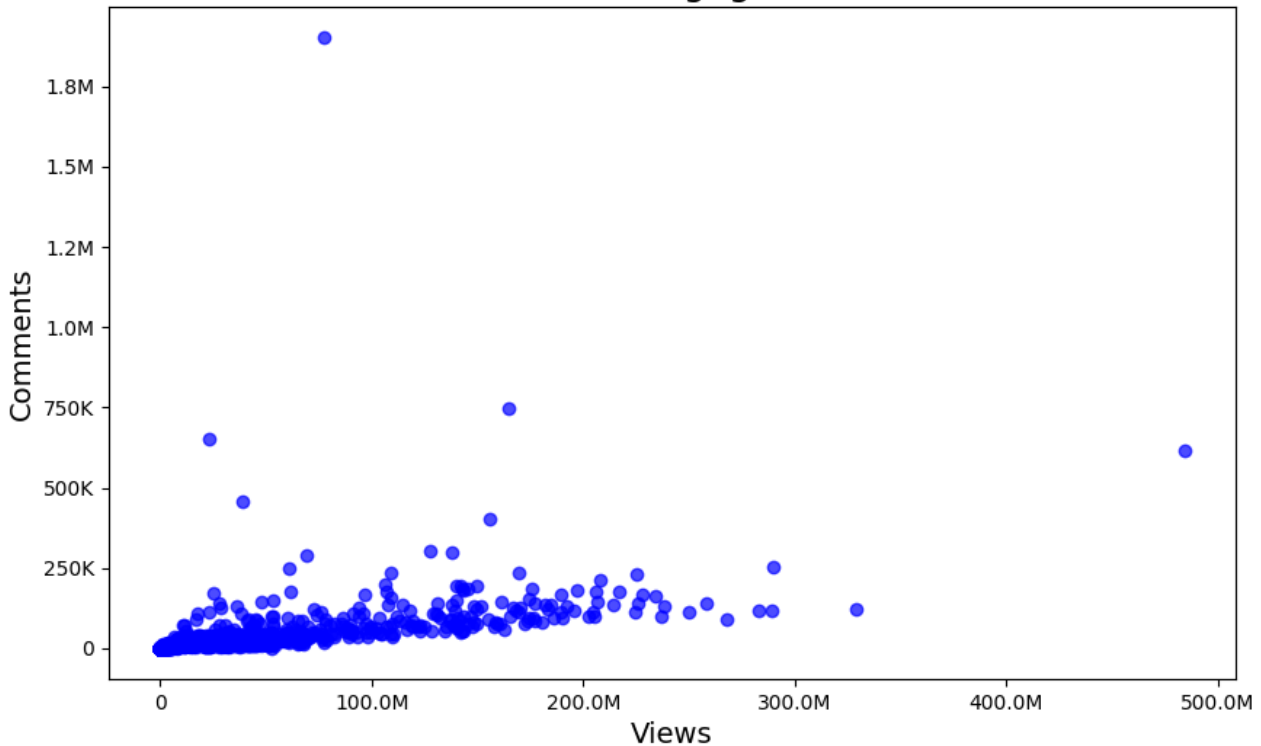
Do videos with lots of views render more likes and comments, or do audience interaction patterns not correlate with one another? Understanding the relationship between engagement metrics provides valuable insights into audience behavior and preferences. By investigating potential correlations, patterns can start to uncover on audience responses to MrBeast’s content. These scatter plots can illustrate the correlation between each engagement metric. Each point represents a video, and its position on the graph shares the relationship between different engagement metrics in terms of likes, comments, and views.



Likes to Comments Engagement Correlation



Views to Comments Engagement Correlation

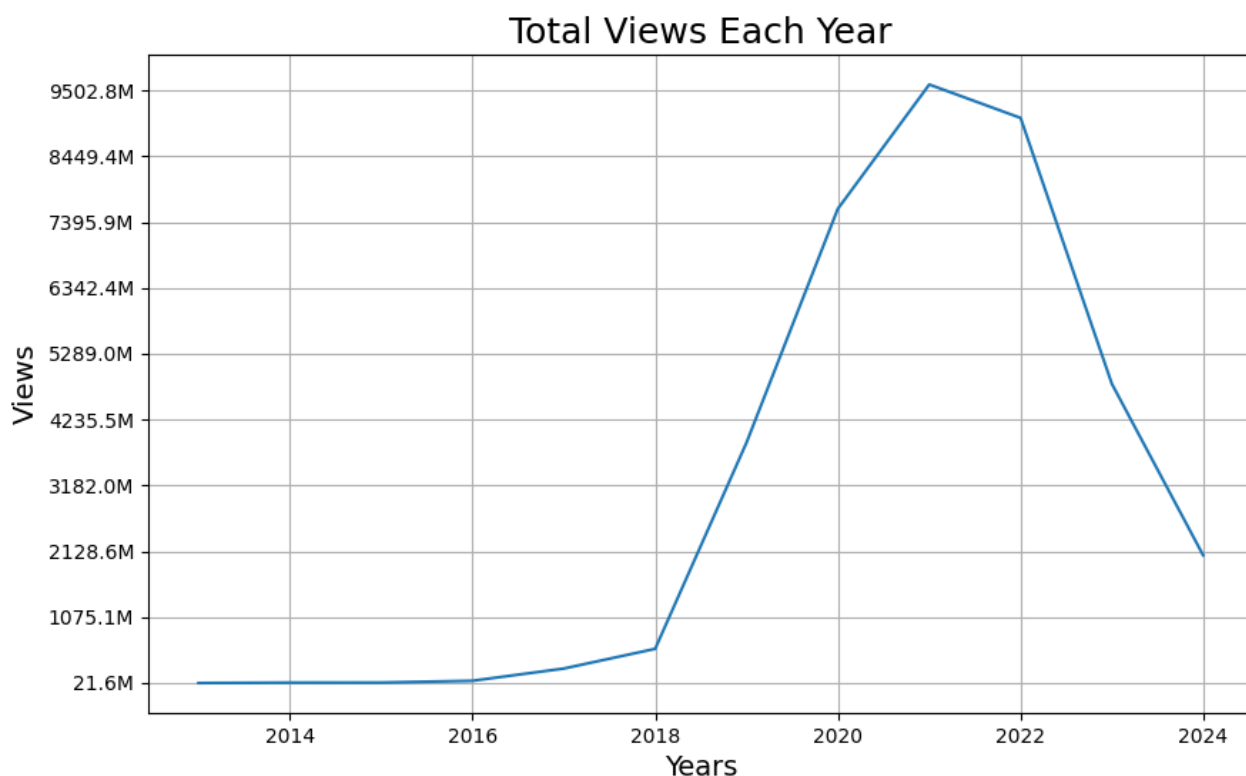


Analyzing these graphs, patterns in engagement correlation start to unfold. As videos receive more views, both comment and like count start to increase. The positive trend for both likes and comments to views aren't as similar to one another as you think. When views on a video receive 100 million, comments are averaging an estimate of 150 thousand, but likes get an average

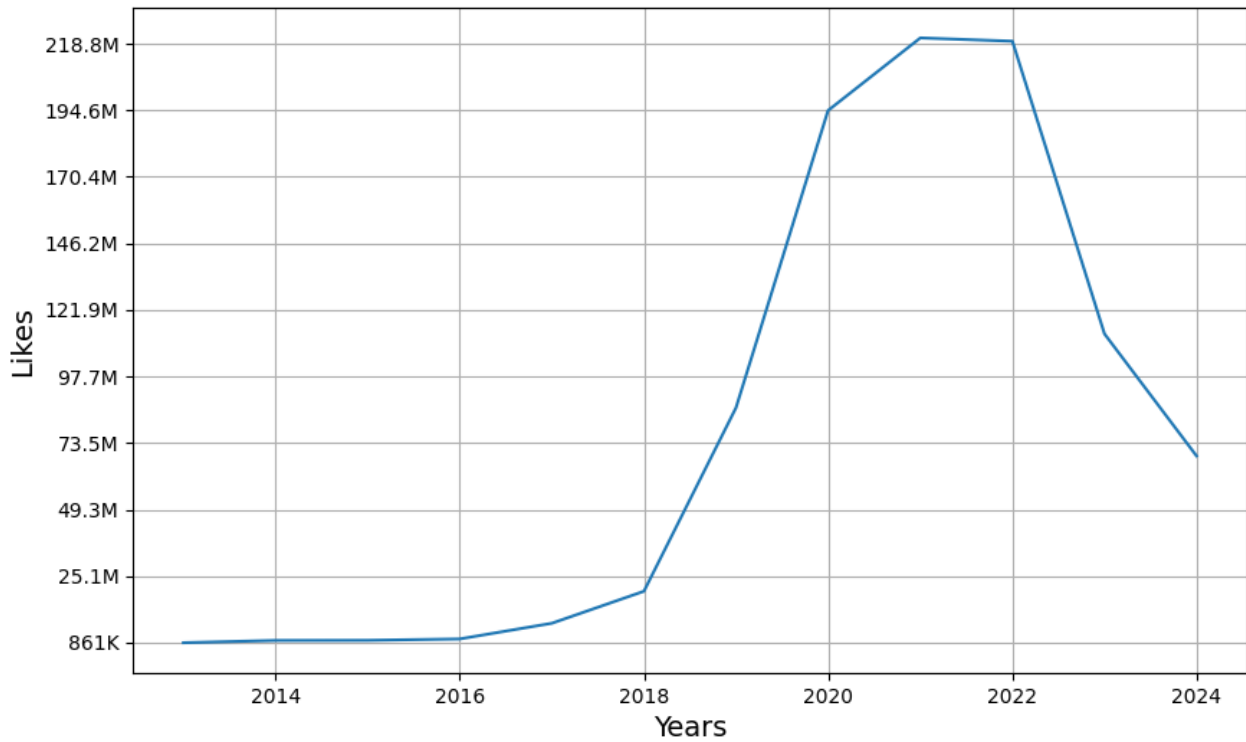
estimate of 2.5 million. When views on videos pass 200 million, comments are averaging above the estimate of 150 thousand, but likes average over 5 million nearly doubling. The relationship between likes and comments also results in a positive trend. Where the more likes a video has the increase in comments it will receive. Comment interaction for both views and likes are similar as the average of comments trend under 250 thousand. Each graph has multiple outliers for all cases. One video with less views has excelled in video comments with the same happening for a video with likes to views. Also, a video excelling in views has received low comments and like count but still above the average trend. After identifying the patterns, videos that receive more views will have an increase in likes. These videos will also receive an increase in comments but only a small increase.

Engagement Over Time:

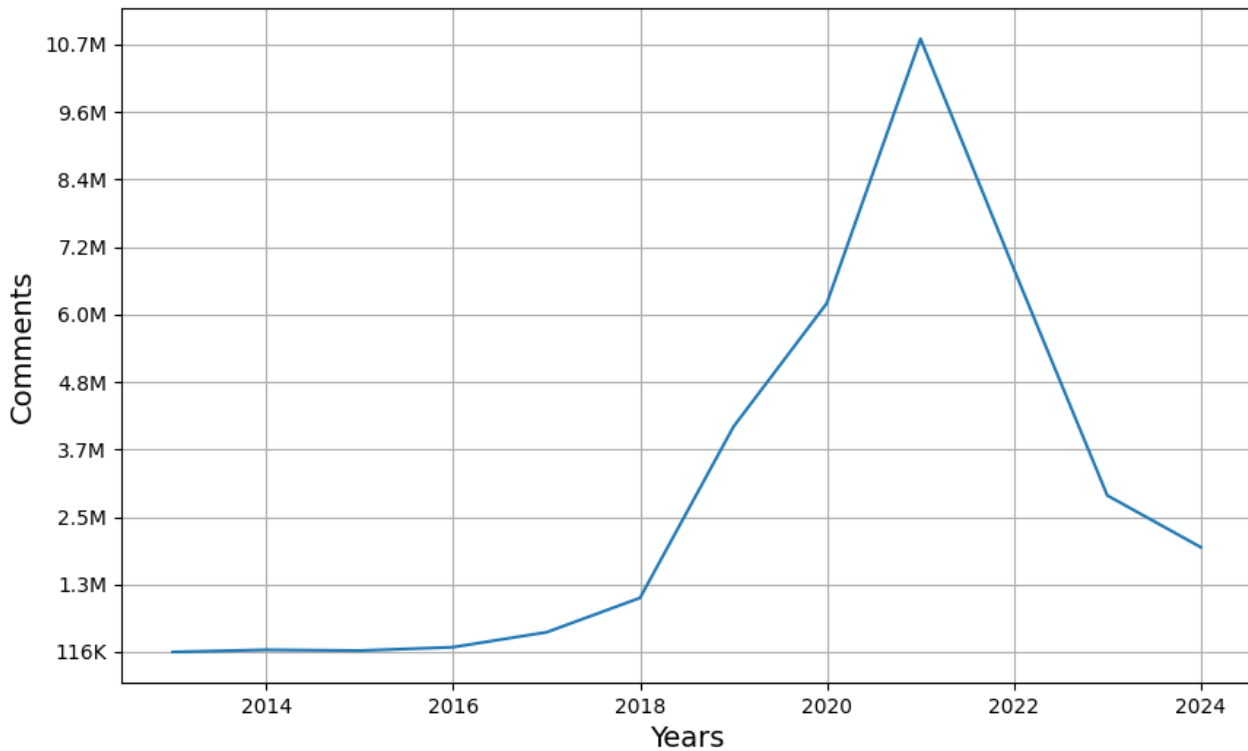
Is each year more successful than the last? Investigating engagement metrics over time offers an insight into viewer interaction trends throughout a channel's lifecycle. Observing engagement patterns over the years, a pattern of trajectory for engagement can be seen. The following line graphs illustrate trends in engagement metrics over the years in terms of likes, comments, and views. The x-axis represents the years, while the y-axis indicates the total amount of each engagement during that time period. Note 2024 is on the graph, but this is due to the newest video in the dataset's upload date, August 12th, 2023, being close to the new year.



Total Likes Each Year



Total Comments Each Year



Analyzing these graphs, you can notice a positive trend for each engagement metric from 2018 to 2021, then a negative trend from 2021 to 2024. The initial uprise during 2018 can come from MrBeast's success in hitting popular trends with the unique video uploads. The boom from 2020 to 2021 can be a result of covid-19 where more YouTube received an increase in activity during

quarantine. The decrease trend after 2021 can result from majority of viewership returning to a normal schedule of school and work after the covid-19 quarantine. Both views and likes are almost identical with a slight decrease from 2021 to 2022. Viewer interaction with comments has a significant drop-in activity from 2021 to 2022 going well below the total of 2019 and almost below the boom of 2018.

Implications and Considerations:

The insights obtained from exploring engagement patterns and time-based analysis offer awareness into optimizing strategies for viewer engagement. Understanding how audience engagement has evolved throughout the years allows content creators to curate approaches for enhancing their audience interactions.

Understanding audience behavior can lead to understanding a negative incline in engagement. The result of a channel's hard work in 2022 and 2023 might not perform as well with engagements during 2020 and 2021. The leading cause of this can come from audience members returning back to a normal work and school schedule, not spending as much time on YouTube. Even with a decline in engagement, videos that perform well in views still receive a positive incline in likes and comments. The more views a video receives, the more likes and comments it will acquire.

Understanding the importance of sustaining engagement through learning audience behavior can help keep engagement numbers positive. Knowing how to maintain viewer interaction over time will keep channel content relevant and fresh. Monitoring engagement trends for the current year will help the channel adapt new strategies to keep engagement levels consistent.

Duration Exploration Analysis

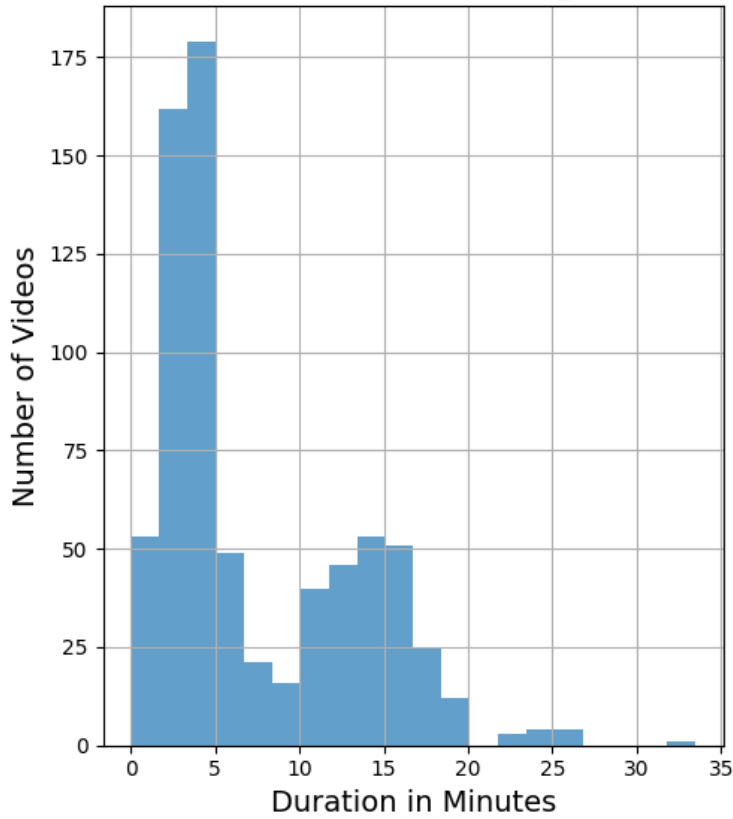
Overview of Section:

This section explores the relationship between video duration and engagement levels. Also, it investigates how video duration influences viewer interactions. By analyzing the relationship between video duration and engagement, insights are gathered to form patterns for audience preferences and optimal duration for maximizing video engagement.

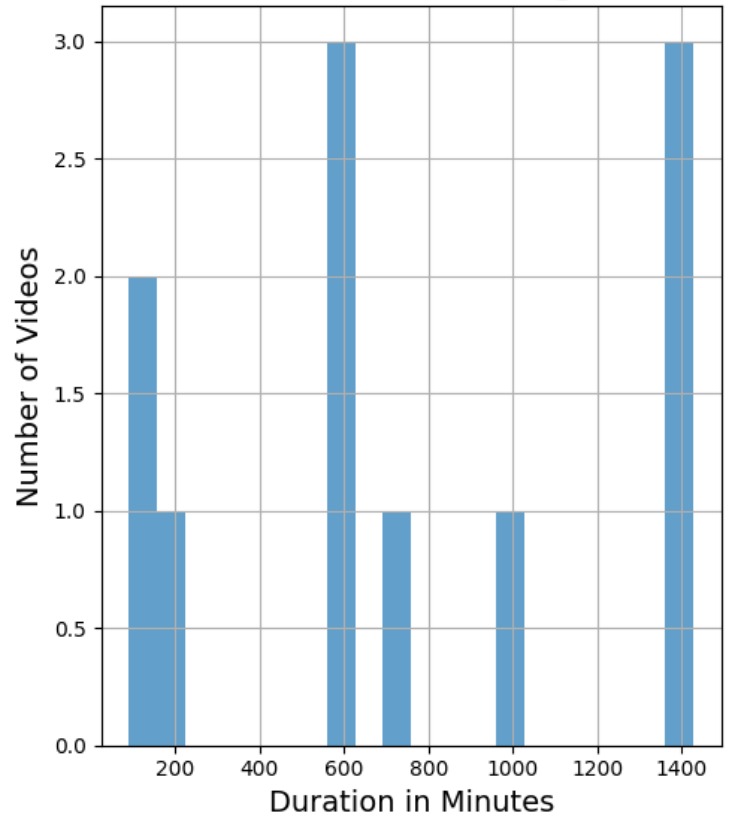
Video Duration Distribution:

Analyzing the amount of video uploaded for each duration length provides insights into the variety of lengths in MrBeast's channels. Understanding how video duration is distributed across videos will help illustrate any engagement patterns. The following histograms display the distribution of video durations for each channel. The x-axis represents video duration, and the y-axis indicates the number of videos with that duration. Note the @MrBeast channel is the only channel with uploads longer than 60 minutes.

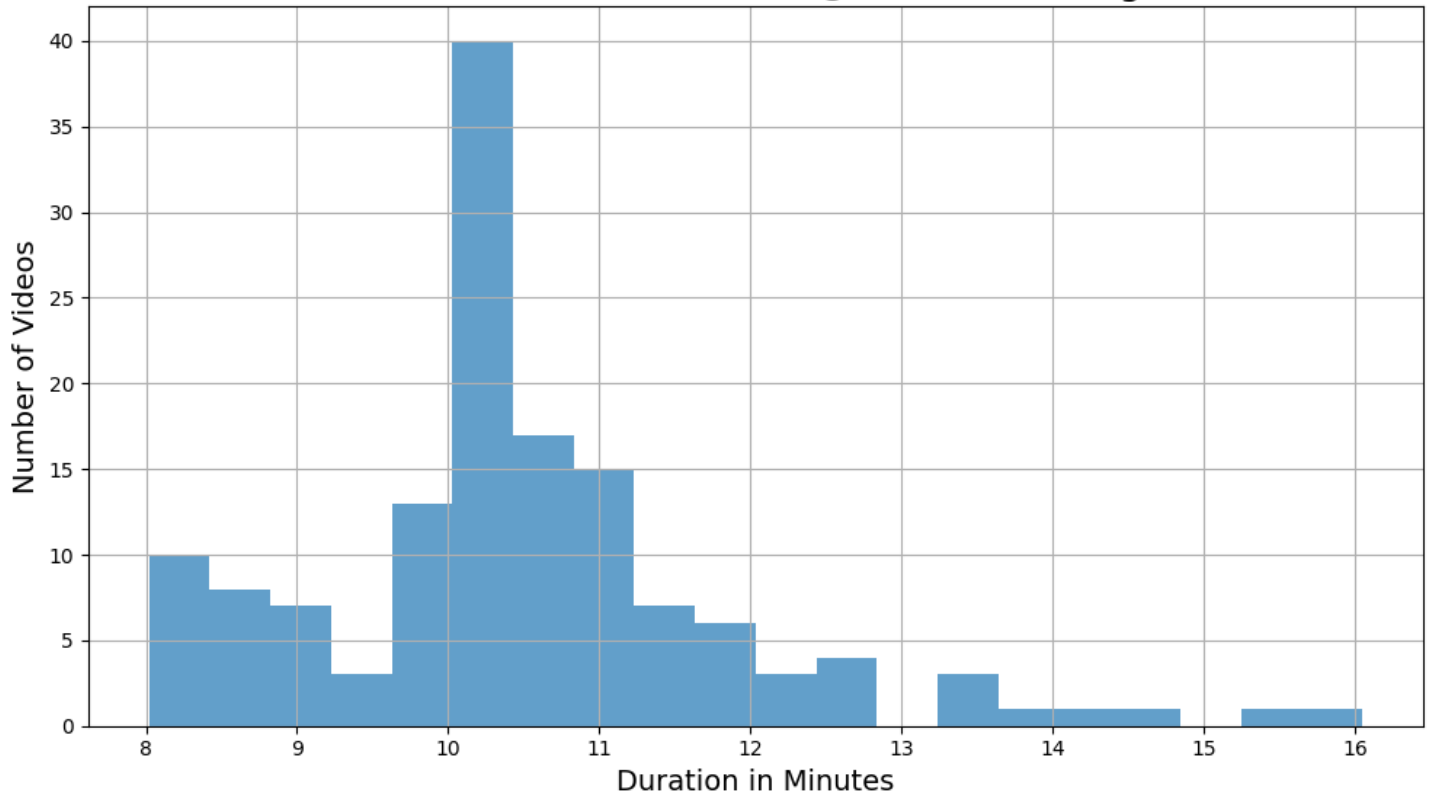
Video Duration < 60 for @MrBeast



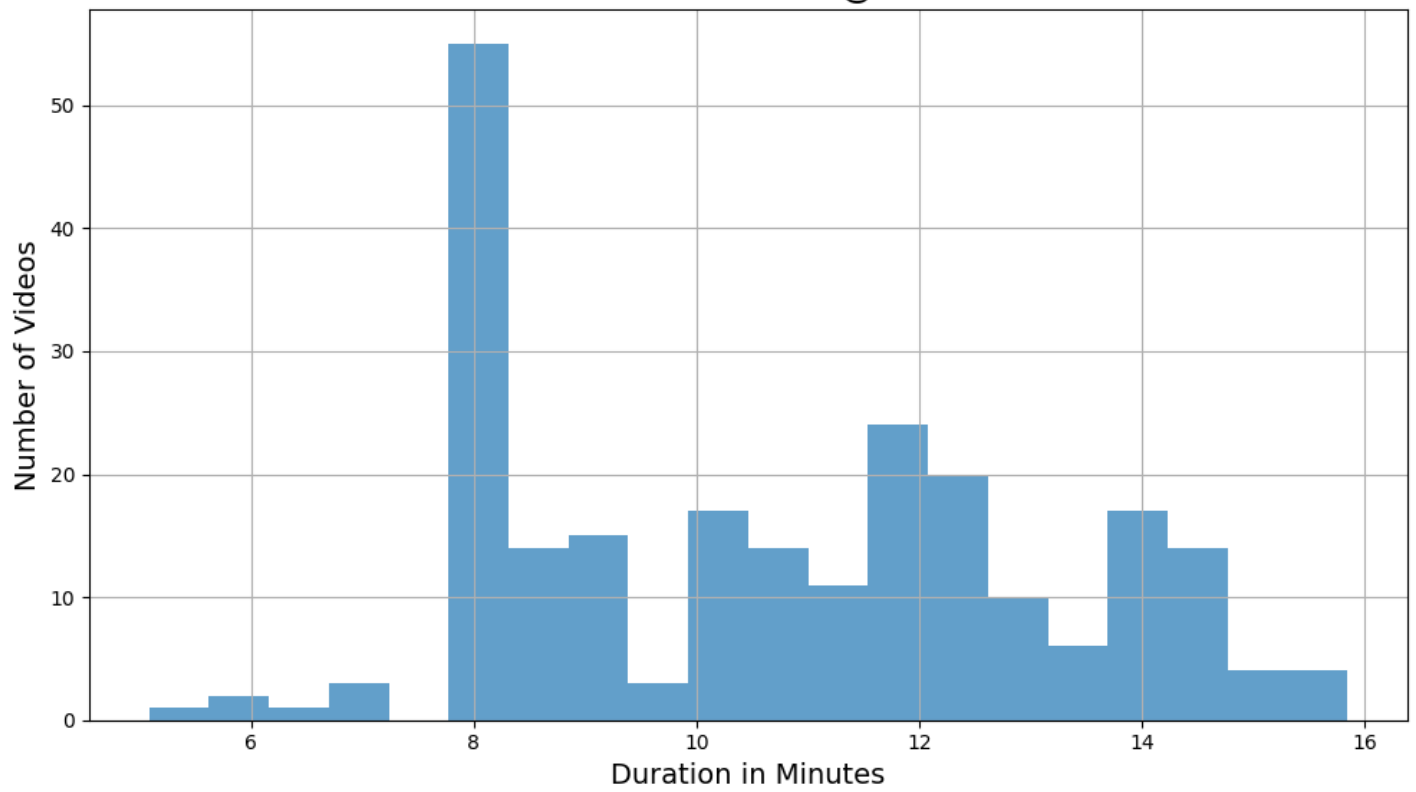
Video Duration > 60 for @MrBeast



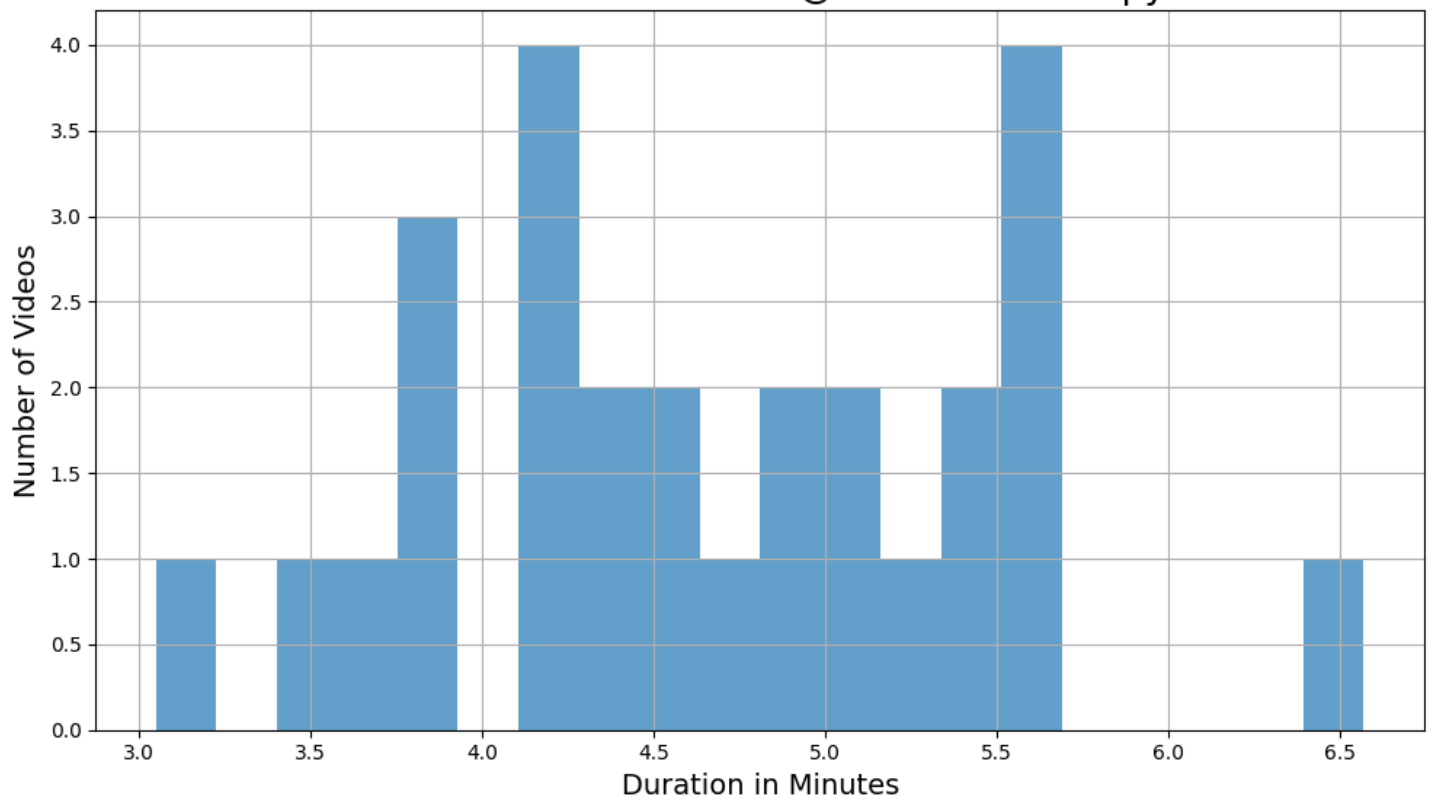
Video Duration < 60 for @MrBeastGaming



Video Duration < 60 for @BeastReacts



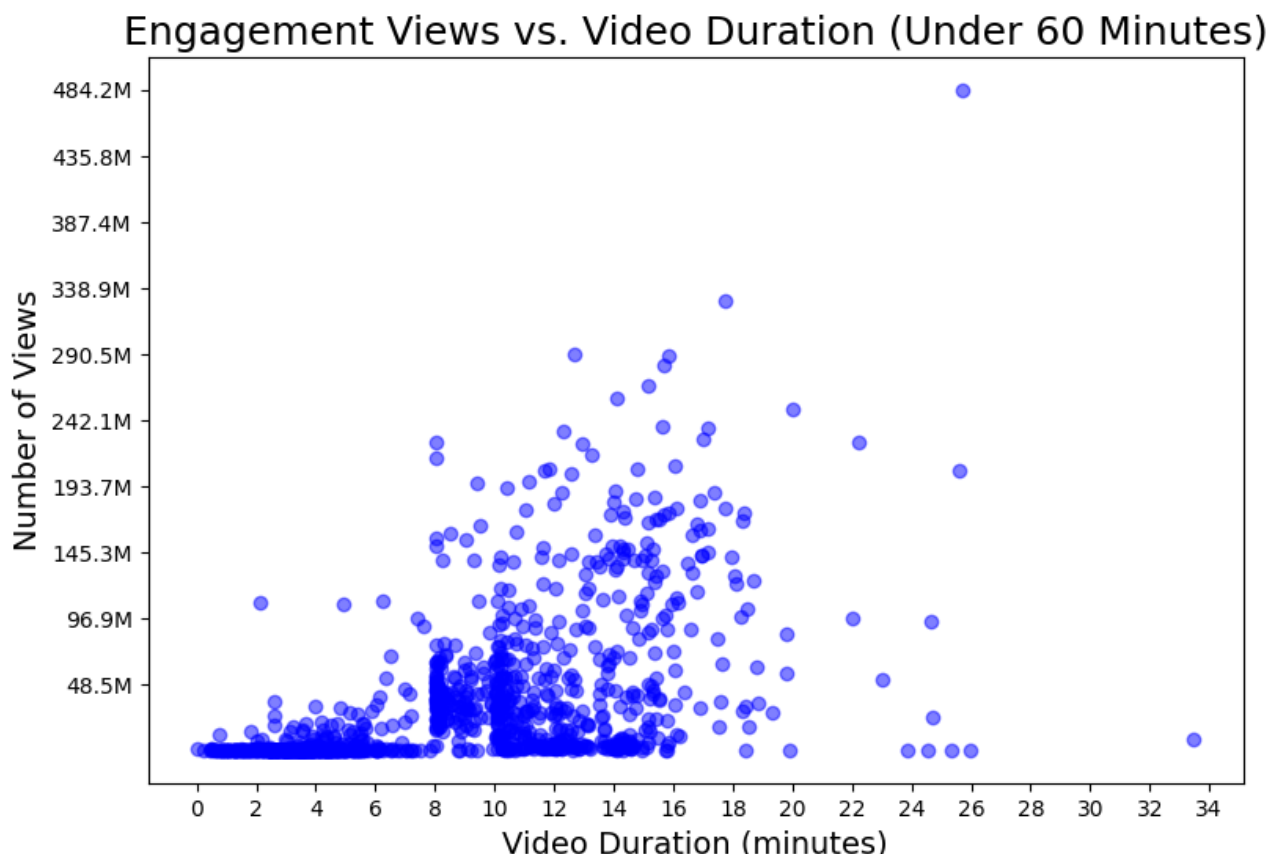
Video Duration < 60 for @BeastPhilanthropy



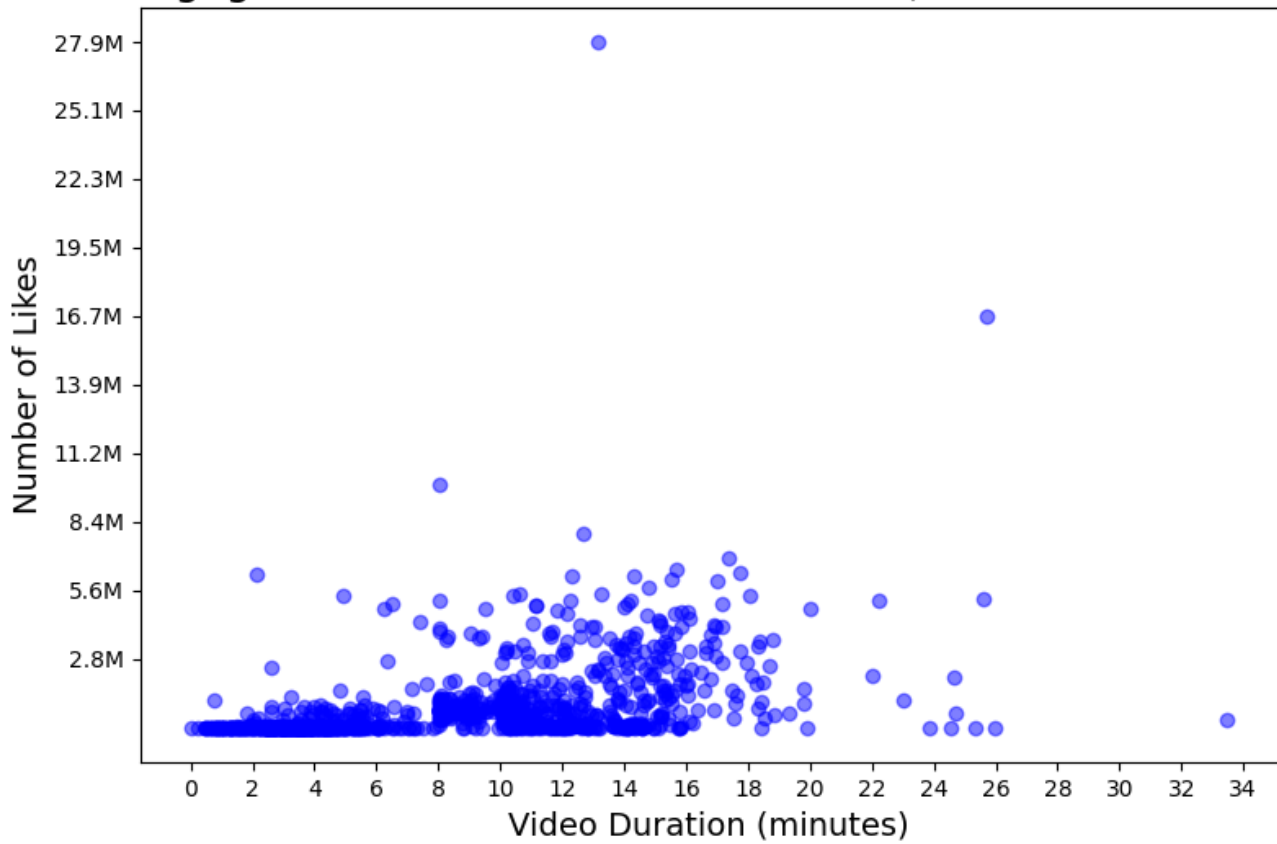
Analyzing these graphs, each channel has a range of videos from zero minutes to twenty minutes. The @MrBeast channel has multiple videos with a duration of over twenty minutes, but the other three channels stay below sixteen minutes. For the @MrBeast channel, the duration with the most uploads is around four to five minutes. For the @MrBeastGaming channel, the duration with the most uploads is ten minutes. For the @BeastReacts channel, the duration with the most uploads is eight minutes. For the @BeastPhilanthropy channel, the duration with the most uploads is tied between four minutes and five minutes. The @MrBeast channel durations are scattered but this could result in videos uploaded years ago not being formed around audience preferences. For both the @MrBeastGaming and @BeastReacts channels the average duration is between eight to fourteen minutes. This could be a result of MrBeast editing each video's duration to match each channel viewer's preference. One outlier in this case is the @BeastPhilanthropy channel not having a single video past the seven-minute mark. This could be a result of MrBeast wanting to retain viewer attention while sharing MrBeast's philanthropy work so MrBeast opts for a shorter duration compared to the other channels.

Engagement by Video Duration:

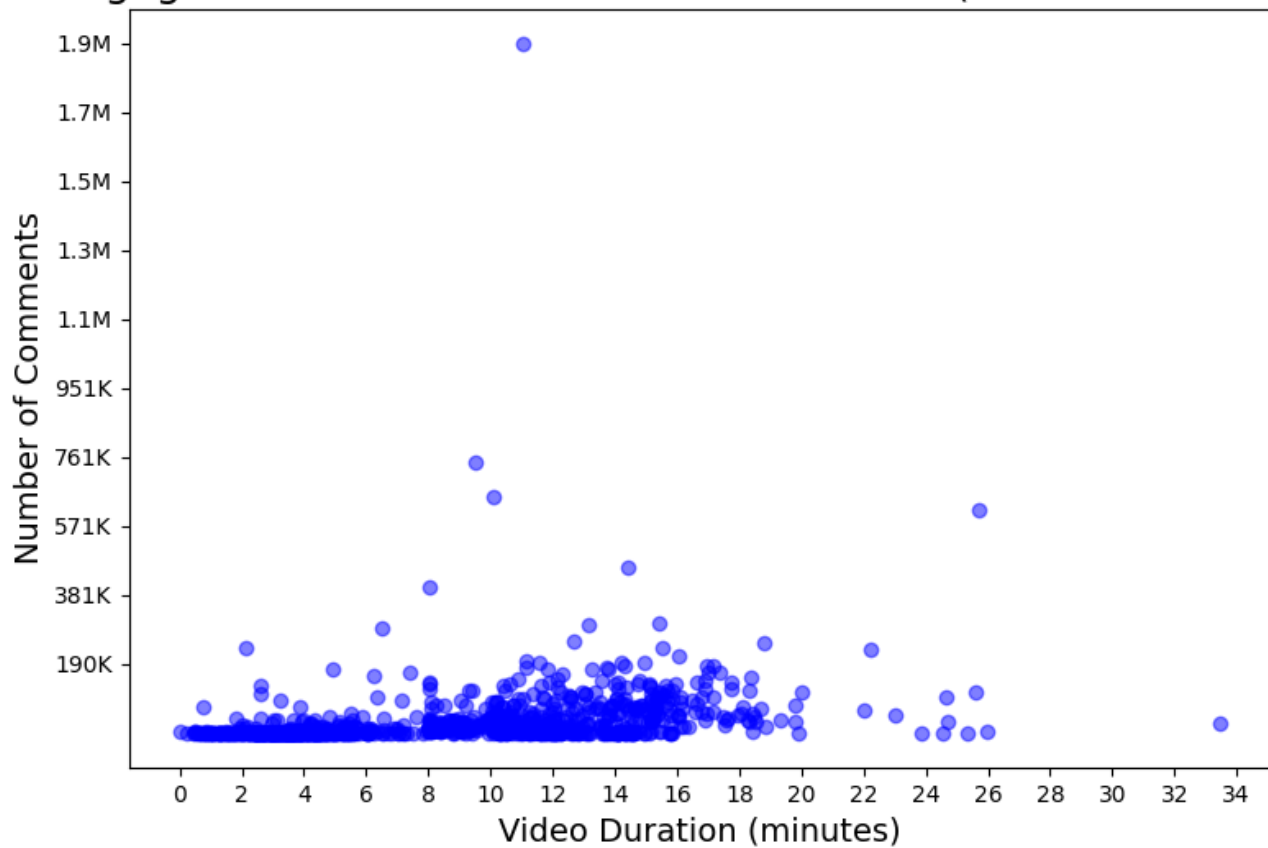
Does curating a video's duration to an audience's preference render in more engagement? Analyzing how engagement metrics such as likes, comments, and views vary across different video durations offer valuable insight. This can lead to patterns arising from viewer preferences for content length and the impact on audience interaction. The following scatter plots depict engagement metrics based on video duration. Each point represents a video, and its position indicates the level of engagement for that duration.



Engagement Likes vs. Video Duration (Under 60 Minutes)



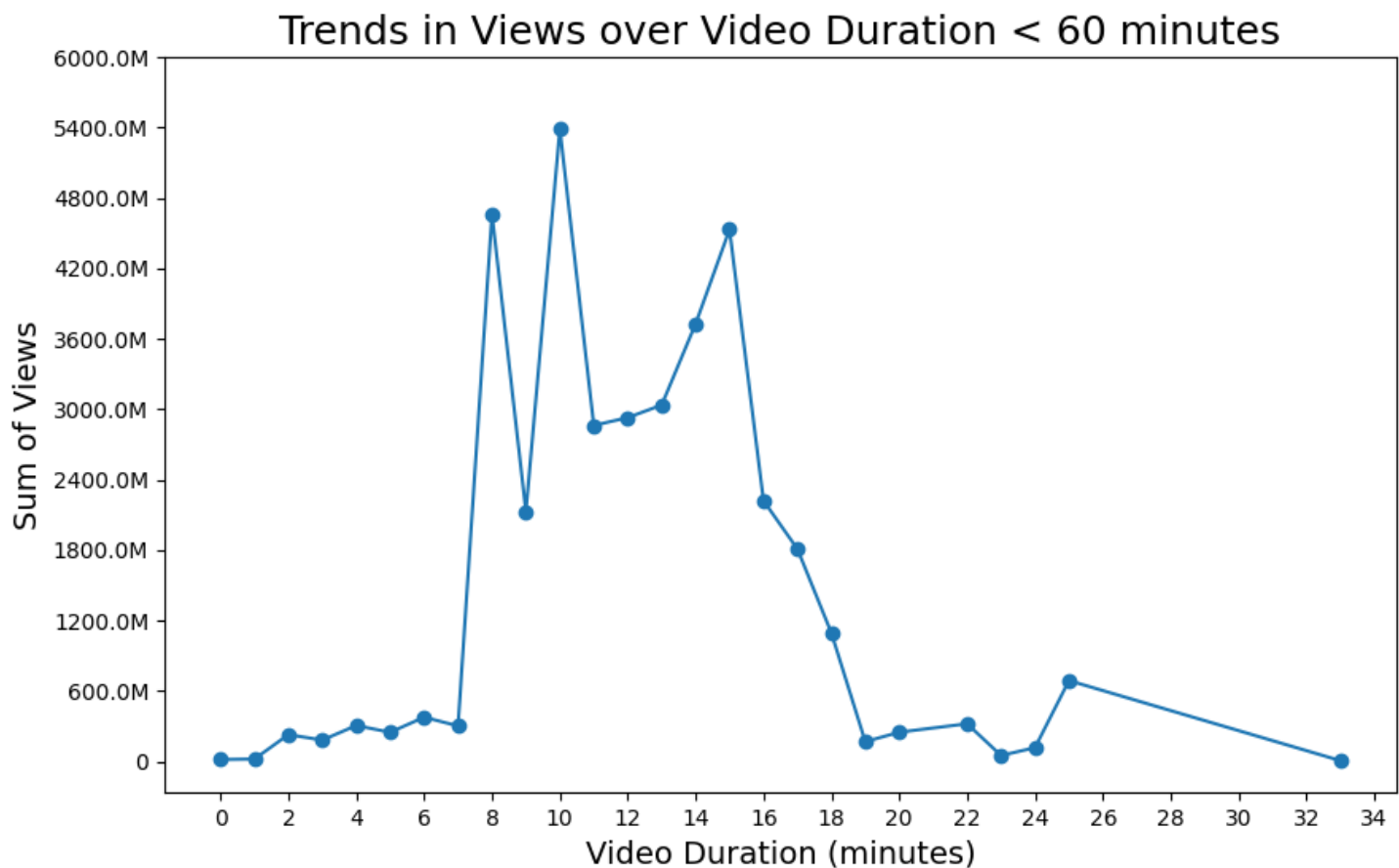
Engagement Comments vs. Video Duration (Under 60 Minutes)



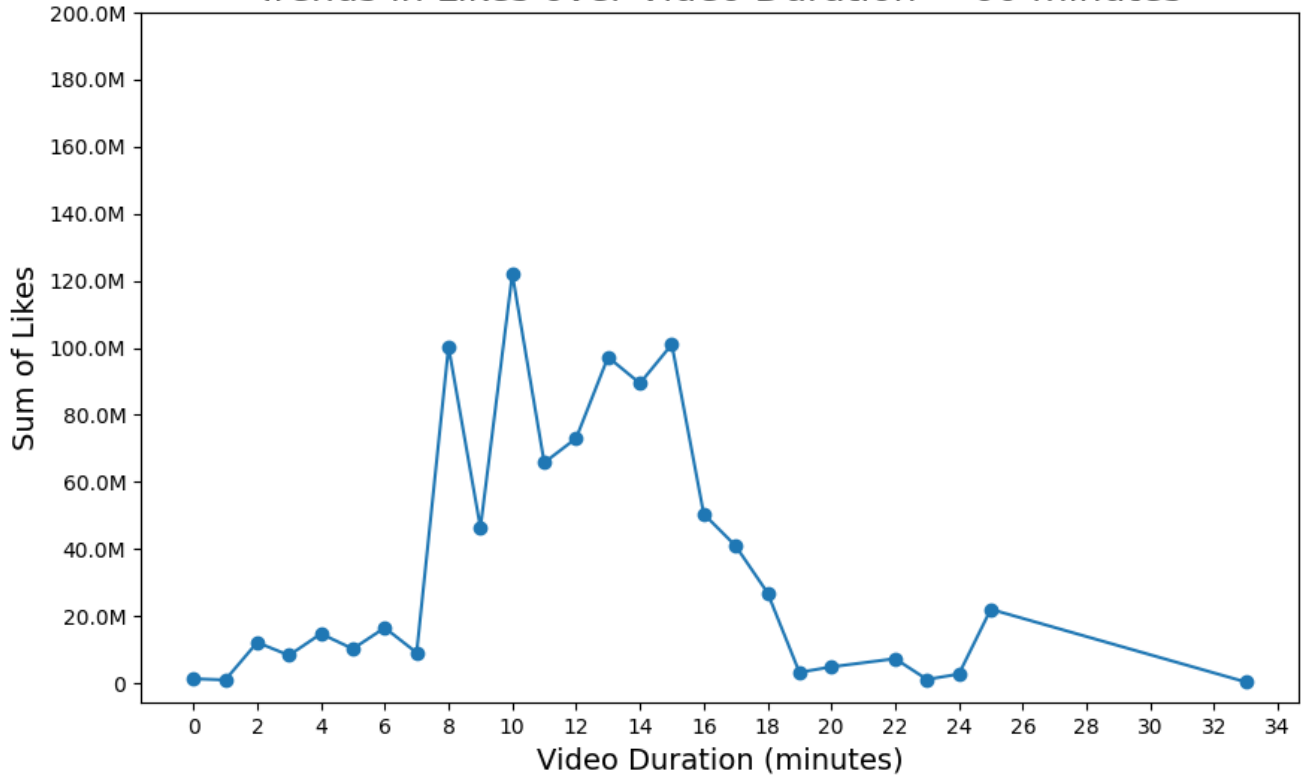
Analyzing these graphs, a majority of the points are between zero and eighteen minutes. The video durations with the most engagements are between eight and fourteen minutes. For each graph the majority of the population is dense under the first y-axis tick. This is a result of each graph having multiple outliers. Outliers on these graphs are points past twenty minutes and videos that gained lots of engagement. One can say that commenter preferences for duration do not comment on videos longer than eighteen minutes. Liker preferences tend to like videos shorter than sixteen minutes. Viewer preferences tend to like videos less than ten minutes.

Duration Trend:

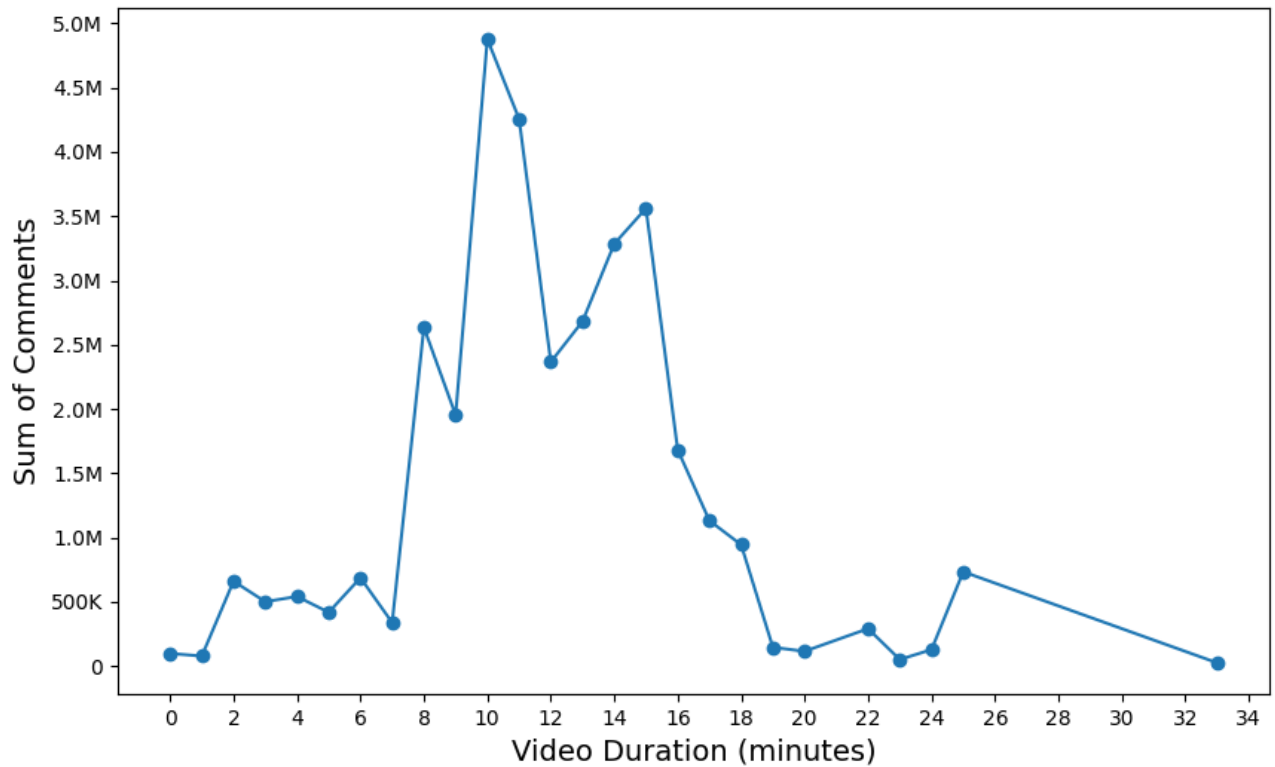
Investigating how engagement fluctuates for each video duration provides insight into the trajectory of viewer interaction. Whether its each minute's engagement sustains or diminishes as a video progress, a picture should be painted as to what the best duration is for an upload. The following line graphs illustrate the trends in engagement metrics such as likes, comments, and views over video duration. The x-axis represents video duration, and the y-axis indicates the total amount of each engagement metric for videos within each duration.



Trends in Likes over Video Duration < 60 minutes



Trends in Comments over Video Duration < 60 minutes



Analyzing these graphs, for each engagement metric, the video duration of ten minutes outperforms every other duration. The best duration for a video duration is between eight to sixteen minutes. The same trend for each metric occurs between eighteen to thirty-three minutes. Each metric has a sudden drop from ten minutes to twelve minutes, but a trending rise follows after until dropping after sixteen minutes. The shorter a video is the more viewer attention this holds, dwindling the longer it goes on for.

Implications and Considerations:

The analysis of video duration and its impact on engagement metrics offers significant evidence as to why content creators need to optimize viewer interaction and align content length with audience preferences. Knowledge and benefits for identifying a channel's video duration range can consistently generate higher engagement metrics.

After investigating MrBeast's channel duration range, the optimal duration for an upload is ten minutes. Aiming for a duration range of eight to sixteen minutes can yield a significant amount of viewer engagement and audience interactions compared to videos outside that range. Adapting to this content length can not only retain viewers' attention but keep viewers commenting on videos.

The duration exploration expresses the relationship between video duration and viewer engagement. Following this analysis, content creators can optimize content length to around ten minutes for maximum interaction. By aligning content duration with audience preferences, content creators can sustain viewer attention and enhance the overall impact of their videos.

Analysis Conclusion

Unveiling Insights:

The analysis of MrBeast's YouTube video engagement has shined insight into viewer behavior, content strategies, and temporal dynamics. By examining a range of factors, including video categories, tags, timing, and duration, garner a comprehensive understanding of factors that contribute to audience interaction and engagement.

Key Takeaways:

Here is my list of success that I have gathered from each analysis that content creators can follow to reach levels of engagement like MrBeast:

- Upload videos on Saturday with a time range of 4pm to 9pm EST.
- Use the Entertainment and Gaming categories for videos.
- Tags are not needed for videos.
- The more views and likes a video receives does not mean more comment engagement.

- The best duration of a video is ten minutes, but still to a range of between eight to sixteen minutes.

Final Remarks:

In conclusion, the insights from the descriptive analysis, temporal analysis, engagement pattern analysis, and duration exploration analysis have helped shine light on multiple factors that contribute to successful YouTube video engagement. These findings serve as guidance for content creators and marketers seeking to optimize content distribution, enhance audience interactions, and build a lasting community.

As the digital landscape continues to grow, diving further into these areas of research provides an even deeper understanding of the dynamics that go into YouTube engagement. By continuously refining content around a channel's audience, content creators can create content that resonates with their audience.

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The dataset as well as all graphs can be recreated for any channel on YouTube using my code at the following GitHub repository: <https://github.com/EthanStanks/YouTubeChannelDataAnalysis>