

**OPIM 5671**

**Data Mining and Business Intelligence**

**Group 1: Text Mining: Oscar movie trailer reviews on YouTube**

*(Team members: Ekaterina Burkhanova, Neehar Namjoshi, Pooja Shah)*

## **Table of Contents**

### **1. Executive Summary**

### **2. Data Overview**

2.1 Explaining YouTube comments on Oscar Movie Trailer dataset

2.2 Column summary

2.3 Data cleansing

### **3. Data Exploration**

3.1 Exploring all movies together

3.2 Exploring each movie independently

3.2.1 Dunkirk

3.2.1.1. Sentiment Analysis

3.2.1.2. Topic Analysis

3.2.2. The Shape of Water

3.2.2.1. Sentiment Analysis

3.2.2.2. Topic Analysis

3.2.3. Phantom Thread

3.2.3.1. Sentiment Analysis

3.2.3.2. Topic Analysis

3.2.4. Get Out

3.2.4.1. Sentiment Analysis

3.2.4.2. Topic Analysis

### **4. Key Trends and Insight**

### **5. Business Recommendations & Conclusion**

## **1. Executive Summary:**

The dataset contains YouTube comments on Oscar-nominated movie trailers for 4 select few movies: “Dunkirk”, “The Shape of Water”, “Phantom Thread”, and "Get Out". Text-mining can be explored to understand the kind of sentiment that flows amongst the audience for a particular movie, the kind of comments, frequently used words, reactions (likes / dislikes), etc. for these movies.

### **Business context:**

By understanding the sentiments and trend patterns around movie trailers, social media platforms like YouTube, Instagram, Facebook, Twitter, etc. can help movie industry prioritize content building and sequencing of the most trending to least trending movies generating high CTR (Click through rates), converting more users to watch the content, etc. and hence generating revenue sources through advertisements, renting, and buying movies, etc.

### **Model overview:**

The study showcases a text mining learning exercise to understand trends and patterns through movie trailer reviews. The dataset originally contained 5 columns. To extract information from the dataset, we have added one more column “Movie name” to create separate clusters for each of the 4 movies.

The analysis was split into 2 parts:

1. Analyzing how the reviews trend and what are the key topics for all the movies together
2. Individually understand the key topics discussed and sentiments that follow watching the movie trailers

We found out that people gravitate towards war and action movies, such as movie named “Dunkirk”. Secondly, people tend to reflect negatively on topics which are sensitive and attract a lot of flak amongst viewers if not portrayed well, for example the topic of racism. Lastly, actors and actresses can overpower the fame a movie receives, and influences viewership driven by crazy fan-base to a very large extent. For instance, in the movie “Phantom Thread”, the famous actor Daniel Day Lewis portrayed the role of Reynolds Woodcock and was very well received by the audience as will be seen in the analysis.

In conclusion, people like war and history genres. YouTube and other media platforms can look at creating content along those lines. Also, a huge part of viewership depends on the actors / actresses casted. This effectively drives revenue generation. Highly acclaimed actors earn higher viewership and hence increase revenue generation. And lastly, the degree of viewership tends to increase as there are events like nomination announcements, trailer launches, etc. Doing events around those time frames can help drive revenue generation due to higher CTR and viewership.

## 2. Data Overview

### 2.1 Explaining YouTube comments on Oscar Movie Trailer datasets:

The datasets contain YouTube comments on Oscar-nominated movie trailers for 4 select few movies:

Movie Name	Genres
Dunkirk	History/War
The Shape of Water	Romance/Fantasy
Phantom Thread	Romance/Drama
Get Out	Psychological Thriller/Horror

It does not contain a target variable and therefore the text-mining exercise would be unsupervised learning.

By understanding the sentiments and trend patterns around movie trailers, social media platforms like YouTube, Instagram, Facebook, Twitter, etc. can prioritize content building and sequencing of the most trending to least trending movies generating high CTR (Click through rates), converting more users to watch the content, etc. and hence generating revenue sources through advertisements, renting, and buying movies, etc.

YouTube Comments on Oscar-nominated movie trailers dataset:

<https://data.world/promptcloud/youtube-comments-on-oscar-nominated-movie-trailers>

### 2.2 Column summary

The dataset consists of 32070 rows x 8 columns in size. The rows represent individual viewer and columns represent the comments received along with the time stamp. The detailed overview of columns is as below:

Column Name	Description
Timestamp	Indicates the time and date when user has posted a comment or reacted
Viewer comments	Comments from the content viewer
Likes	No. of users who have liked the comment posted on the movie trailer
Has replies or not	Categorical variable containing “True” or “False” details based on replies to the comment.

No. of replies	Shows the total count of the no. of replies made to the user comment
Movie name (New column)	Contains name of the movie for which viewer reaction has been received
Time (New column)	Converted from Timestamp to Time
Date (New column)	Converted from Timestamp to Date

## 2.3 Data cleansing

To extract usability out of the dataset, we cleansed and manipulated the data in Excel by adding three more columns “Movie name”, “Time”, and “Date”. The “Timestamp” column was converted to two columns “Time” and “Date”. One new dataset was created to combine all 4 movie trailers into one dataset for the 1<sup>st</sup> part of the analysis. Also, all 4 movie trailers datasets were used individually in the 2nd part of the analysis to understand how the sentiments are trending across these clusters. So, in total, we had 5 different datasets.

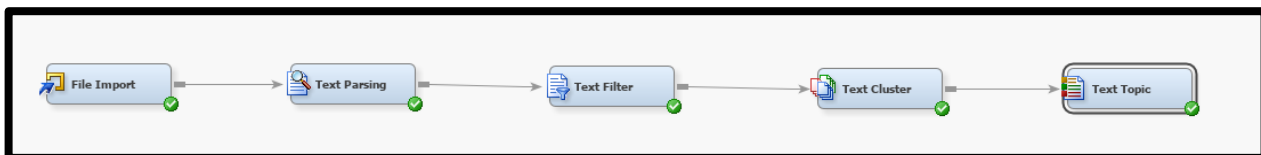
## 3. Data Exploration

Having introduced the dataset, the next portion will be to explore the data and find any patterns and trends. Firstly, as described previously, there is no target variable in this dataset, therefore unsupervised learning will be used to decipher trends and patterns.

### 3.1 Exploring all movies together:

Firstly, the data was explored by combining all 4 movies together in a separate excel sheet and the same was passed through the enterprise miner software with the below model:

SAS diagram for all movies together:



The data was imported through the file import node. Then, text parsing, text filtering, and clustering nodes were joined and run. Finally, the text topic node was connected to the text cluster node and ran. The below were the node setting for the above model:

- 1) **Text Parsing:** The default stop list was used.
- 2) **Text Filter:** For the text filtering node, the most common term and frequency weights were used: Log for frequency and IDF for term weight.
- 3) **Text Cluster:** Clustering was run with high SVD resolution and 15 dimensions. Initially, the clusters had a setting of exact and 4 for number of clusters. It is known that there are 4 movies here, so this is what was used to explore further.
- 4) **Text Topic:** Lastly, the text topic node had 12 as the number of topics to be created.

## Text Cluster Results:

Clusters		
Cluster ID	Descriptive Terms	Frequency
1	harry nolan +style styles christopher +fan tom hardy war +amaze +excite murphy +girl cillian +history	6670
2	+good +love good +time +great +story +song +god music +feel +day +play hell peelee +comedy	8624
3	+white +people +black +white people' +fuck +shit +race +want racist lol +black people' +racist horror racism peopl...	4534
4	dunkirk british french +war +soldier hitler +german churchill +fight german +beach +army ww2 +nazi britain	2463
5	sabe hellboy sapien bioshock toro guillermo +shape +story +water +origin hell +creature abraham +egg water	1017

Next, the text cluster results were examined. Generally, the terms in each cluster are extremely noisy. It is mostly dominated by Dunkirk's cast in most clusters. This is because of the huge number of reviews received for Dunkirk (at 45% of the total dataset). So, this was not very useful to see patterns or trends. To reaffirm, exploration of the text topic node was done followed by individual movie analysis.

## Text Topic Node Viewer:

Topics					
Topic	Category	Term Cutoff	Document Cutoff	Number of Terms	# Docs
Racism	User	0.011	0.094	154	1820
junk	User	0.01	0.147	11	0
War + History	User	0.017	0.07	245	2542
Raw excitement emotions	User	0.014	0.061	52	461
Harry Styles Fanbase	User	0.014	0.093	33	1154
Christopher Nolan Movie Reviews	User	0.015	0.084	44	1233
People's Choice of Oscar Accolades	User	0.015	0.079	52	1342
Marine + Related Movies to SOW	User	0.014	0.072	48	542
Mixed Emotions	User	0.015	0.067	62	753
Disgust + Fear	User	0.015	0.069	95	1441
Movie Soundtrack	User	0.014	0.061	28	449
Dunkirk Actors Fanbase	User	0.015	0.066	58	520

Similar to the cluster node results, text topic node results were also quite noisy. After looking through the different terms, certain themes were deciphered. These were then updated individually for each movie as user topics. Looking at the topics above, again a similar trend or pattern can be seen. Dunkirk dominates almost all the topics, either with the actors or directors. Secondly, all movies got a mixed set of responses. Therefore, to deal with this issue in the exploration of the dataset, the analysis was next done at the movie level. The analysis will begin with Dunkirk.

3.2 Exploring each movie independently:

Sentiment Analysis Start List:

First, let us look at the curated start list that we used for sentiment analysis. This list contains well over 500 words related to emotions and was used to filter out other words. A sample of this list is seen below. This unsupervised learning yielded much better results, as will be seen below.

Start List-EMWS2.TextParsing\_startList

Term	Role
abandoned	
absolved	
absorbed	
abused	
accepted	
accused	
aching	
acquitted	
acrimonious	
addicted	
adequate	
admired	
adorable	
adored	
affected	
affectionate	
afflicted	
affronted	
afraid	
aghast	
agog	
agonized	
airy	
alarmed	
alone	
ambivalent	

Replace Table

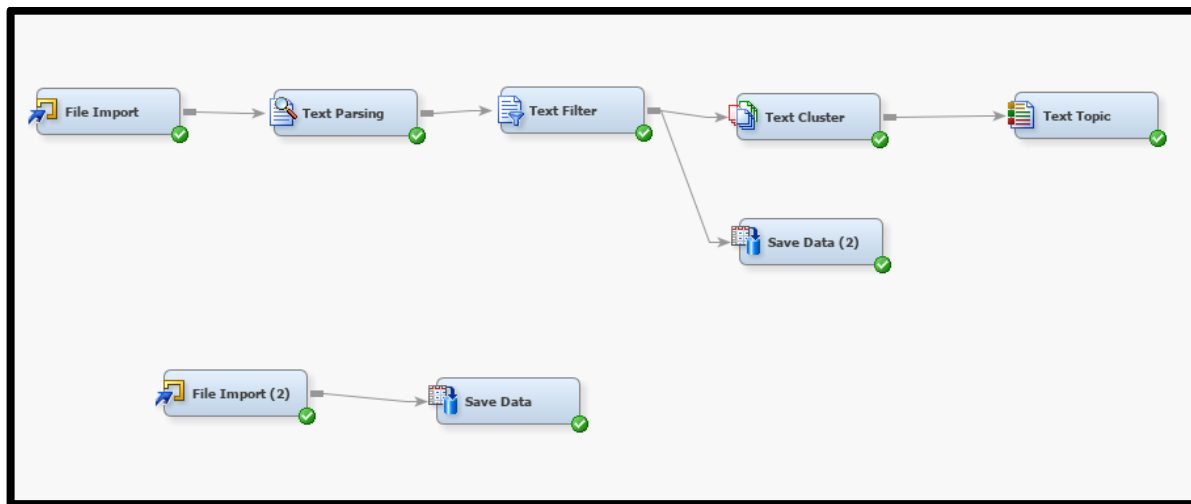
Add Table

OK

Cancel

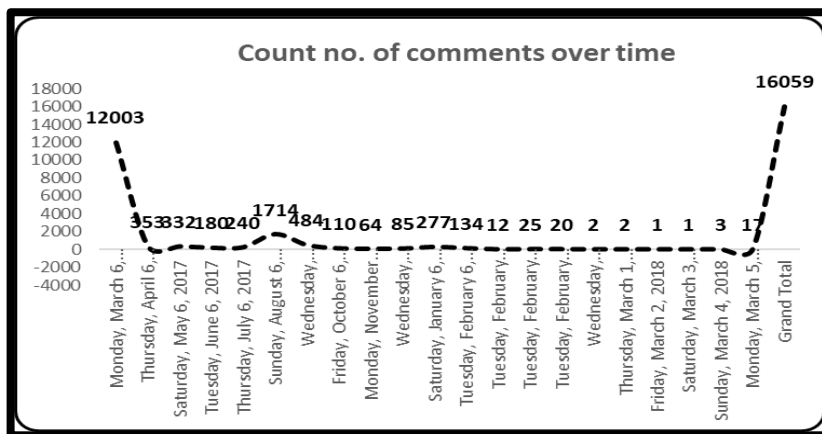
### 3.2.1 Dunkirk

#### SAS diagram for Dunkirk:



Similar to the diagram for all movies combined, this diagram follows the same general flow chain. The main difference or hyperparameter that was changed is in the text parsing node. Instead of using the default stop list, for sentiment analysis, a curated start list was used. This will be further explored below as well.

#### Count of Comments over time for Dunkirk:



Before jumping into the sentiment analysis, first a general trend was explored regarding when the comments were made on the Dunkirk trailer on YouTube. It can be seen from the plot above that there is a spike seen on March 6, 2017. This is right about the time that YouTube released the trailer for Dunkirk on its platform. When an event or external variable is added, the trend of comments sees a surge. In this case, the event was adding the movie trailer to the YouTube platform. Overall, after the event, the trend is stable.



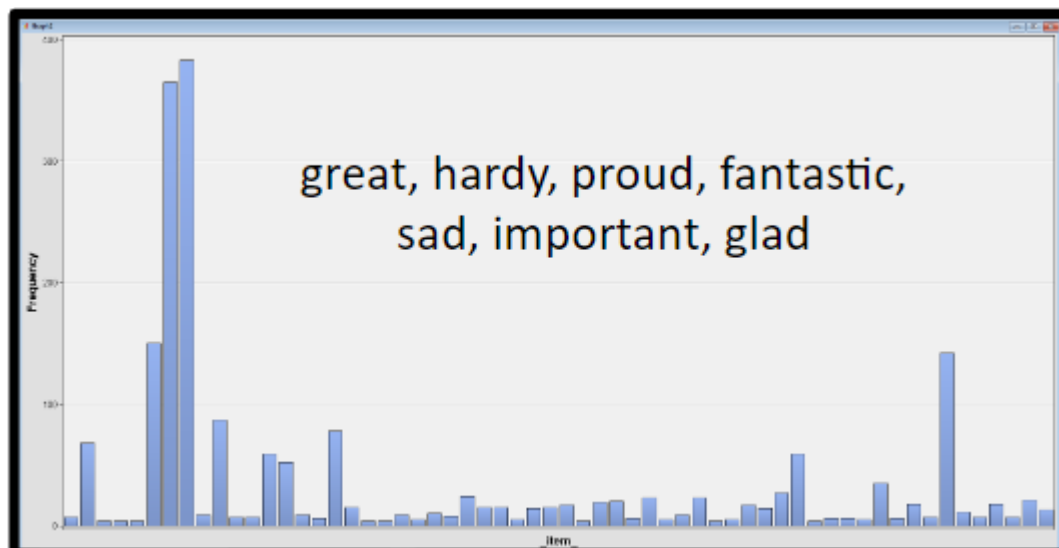
### 3.2.1.1 Sentiment Analysis

#### Text Topic Node Viewer for Dunkirk:

Topic	Category
hardy,+sad,+happy,+dark,+great	Multiple
+great,+happy,+dark,important,significant	Multiple
+great,+great,hardy,great,important	Multiple
hardy,hardy,+great,+dark,+great	Multiple
+proud,+great,+great,important,+lucky	Multiple
great,+great,hardy,important,+proud	Multiple
+sad,+proud,+dark,important,+great	Multiple
excited,great,+proud,+happy,hardy	Multiple
+happy,+dark,+sad,+proud,glad	Multiple
hardy,mad,+great,important,+great	Multiple

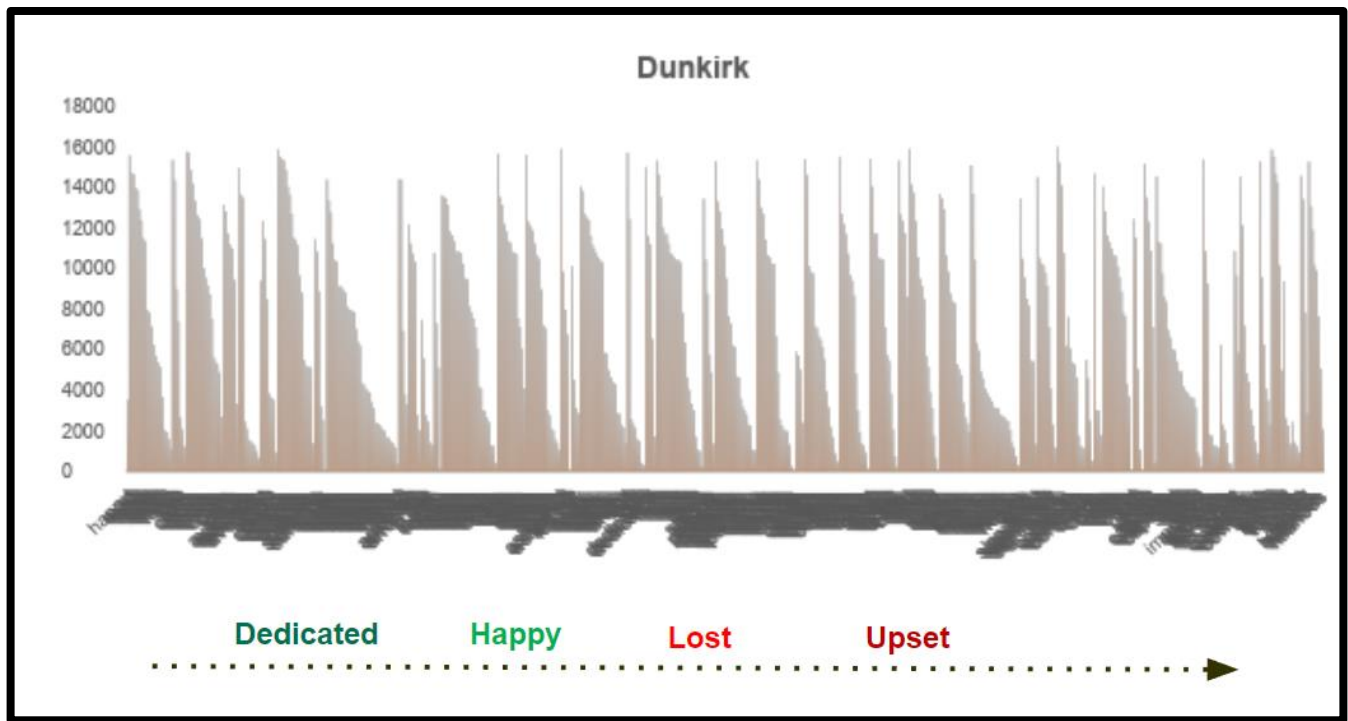
After adding the curated start list in the text parsing node, the above text topic viewer results were generated. The words contain a mix of emotions. But certain words that come to the forefront can be further explored with the frequency graph below.

#### Word frequency plot for Dunkirk:



From the transactions of the exported data from the text topic node, the above plot was created. There are many spikes seen here for various words. But certain words that come to the forefront are the following: great, hardy, proud, fantastic, sad, important, glad. Generally, a mixed bag of emotions ranging from positive to negative can be seen. Another visualization is created, as seen below to further illustrate the sentiments that people felt after watching the trailer.

### Sentiment Analysis Plot for Dunkirk:



Generally, words showcase positive and negative emotions. This makes sense, as the movie is about WW2 with several plots that are going on simultaneously. Maybe some people found Tom Hardy's or Harry Styles' acting dedicated and felt connected. On the other hand, when the plot seemed happier, people felt happy. However, again with war comes darker themes, such as the feeling of being lost and upset. There is a mixed bag of emotions present here that we can decipher but they align with what is expected from a movie that is in the war/action genre.

#### **3.2.1.2 Topic Analysis**

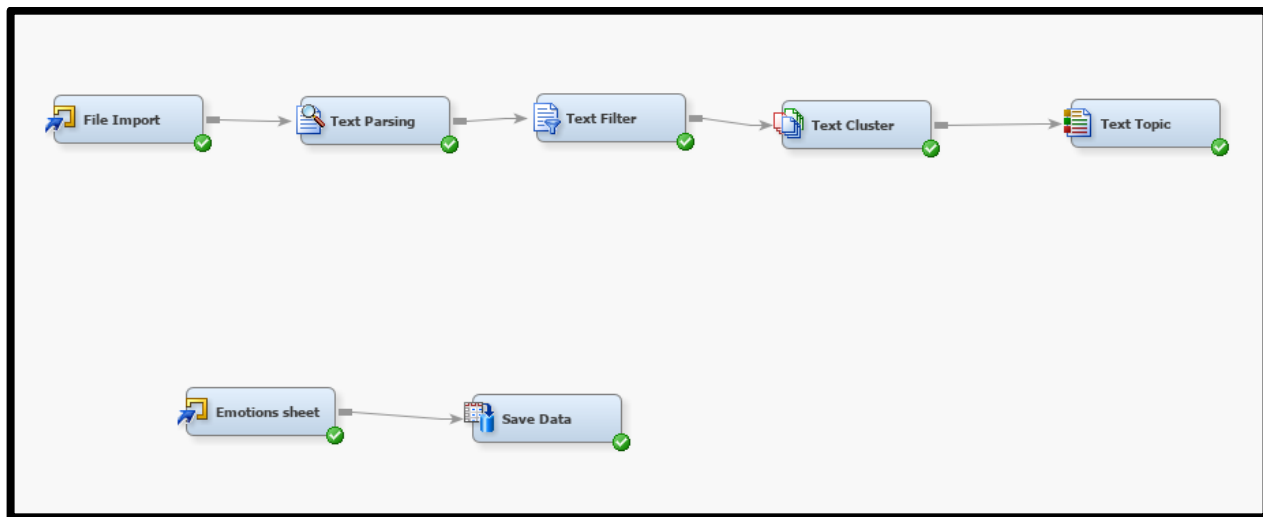
Next, we removed the start list and simply looked at all the words and their associated counts or frequency to see what more information can be extracted.

[illegible]

Putting everything together, the movie trailer got well over 15059 comments. This is the most number of comments received in comparison to the rest of the movies. It is filled with a star-studded cast and an Academy award director, which in itself seems to promote the movie more. War/Action movies tend to be better nowadays, and people really enjoy this genre. Many of the comments are from the actor's fanbase and emotions are varied but this does not mean that they will not watch the movie, rather it is causing engagement between the audience.

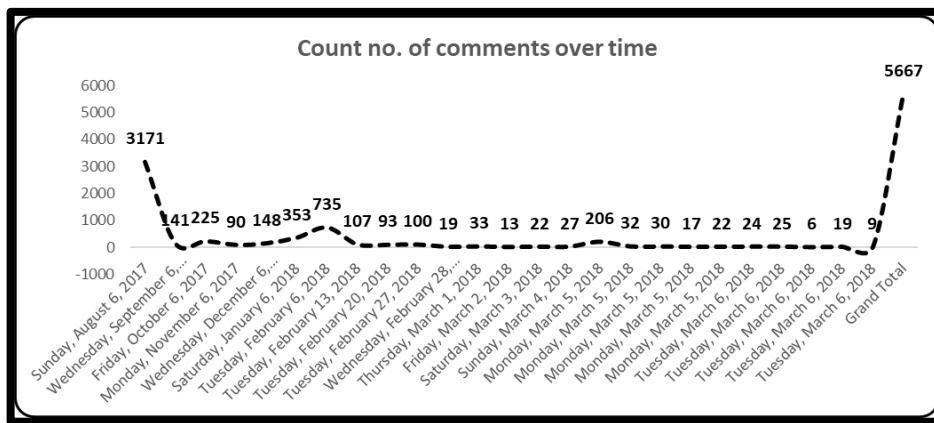
### 3.2.2 The Shape of Water

SAS diagram for The Shape of Water:



Similar to the diagram made for Dunkirk, this diagram follows the same general flow chain. The main difference or hyperparameter that was changed is in the text parsing node. Instead of using the default stop list, for sentiment analysis, a curated start list was used. This will be further explored below as well.

Count of Comments over time for The Shape of Water:



A general trend was explored regarding when the comments were made on The Shape of Water trailer on YouTube. It can be seen from the plot above that there is a spike on August 6, 2017. This is right about the time that YouTube released the trailer for The Shape of Water on its platform. When an event or external variable is added, the trend of comments sees a surge. In this case, the event was adding the movie trailer to the YouTube platform. Overall, after the launch, the trend is stable as compared to the initial spike.

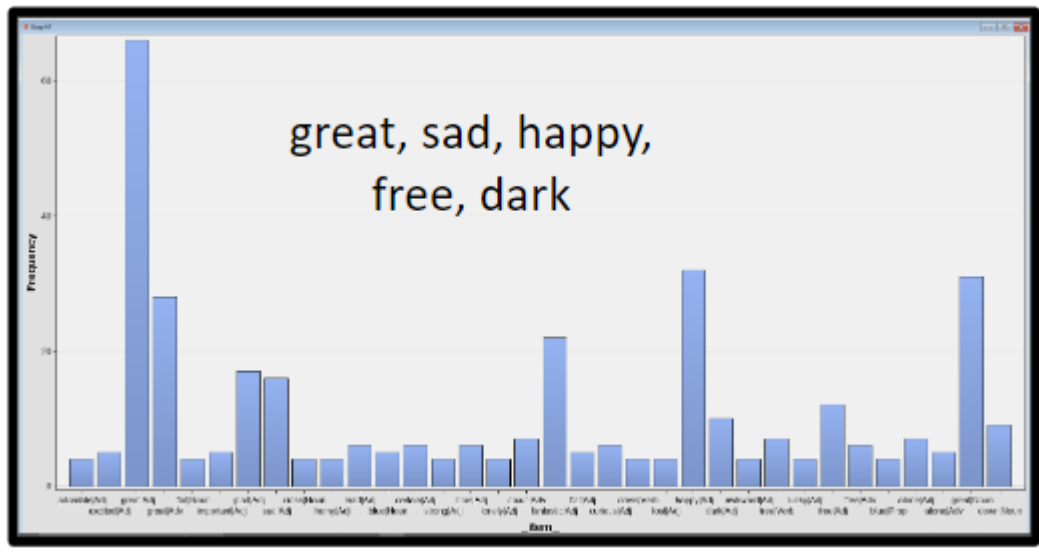
3.2.2.1 Sentiment Analysis:

Text Topic Node Viewer for The Shape of Water:

Topic	Category
+great,cross,happy,+free,important	Multiple
+great,mad,great,+great,happy	Multiple
happy,sad,lucky,adorable,excited	Multiple
great,+great,happy,awkward,adorable	Multiple
fantastic,horny,+great,great,adorable	Multiple
glad,happy,great,adorable,+great	Multiple

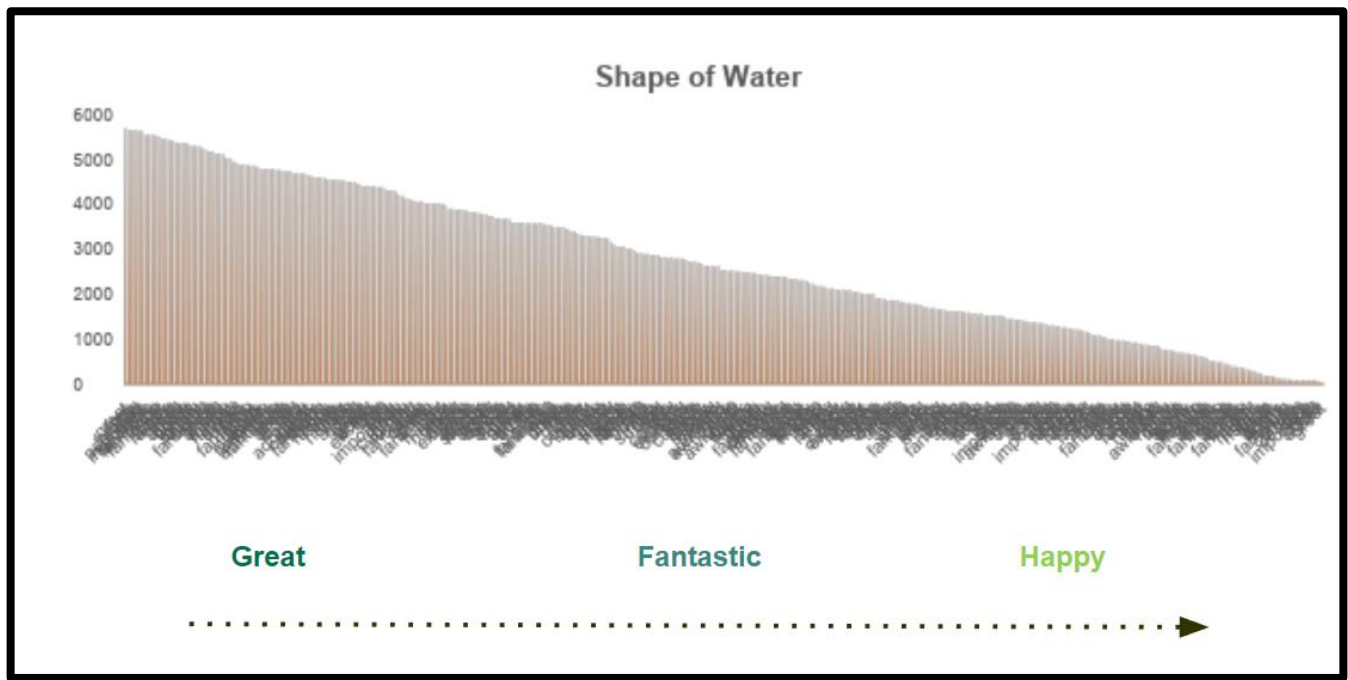
It can be seen from the table above that the words contain mostly positive or happy emotions. But certain words that come to the forefront can be further explored with the frequency graph below.

Word frequency for The Shape of Water:



From the transactions of the exported data from the text topic node, the above plot was created. There are many spikes seen here for various words. But certain words that come to the forefront are the following: great, sad, happy, free, and dark. Generally, more on the positive side as compared to Dunkirk and moreover, just 2 words that seem a bit darker, which are sad and dark. This probably shows insight into the fantasy romantic genre of this movie. While it is a romantic movie, it contains some difficulties or issues the characters need to overcome, which is probably why these words show up. Another visualization is created, as seen below to further illustrate the sentiments that people felt after watching the trailer for the movie.

### Sentiment Analysis Plot for The Shape of Water:



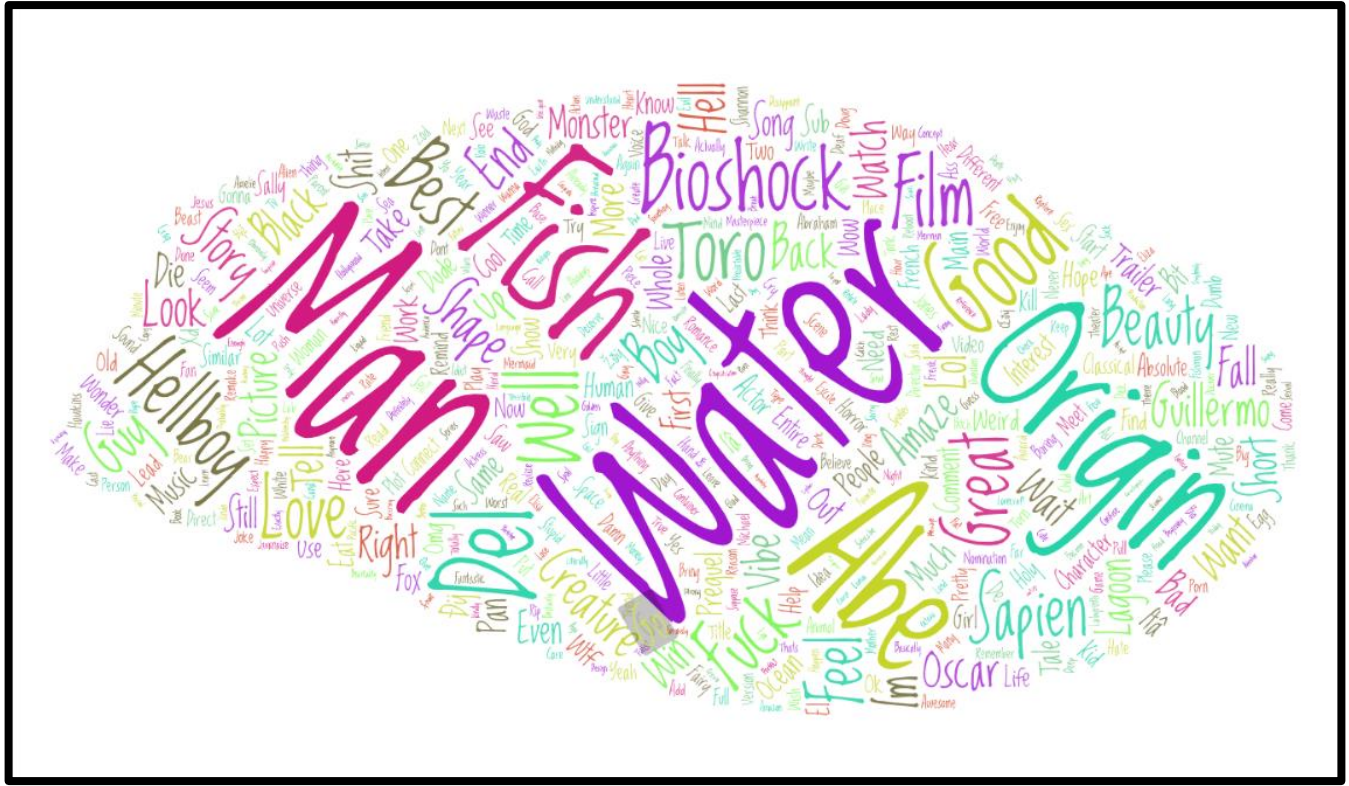
As stated previously, the words seem to be more on the positive spectrum. This makes sense, as the movie is a fantasy/romantic genre movie. Maybe some people found the plot as well as the cast to be great and were overall happy about the movie being released.



### 3.2.2.2 Topic Analysis:

Next, we looked at all the words and their associated counts or frequency as below:

### Word Jumble Plot for The Shape of Water:

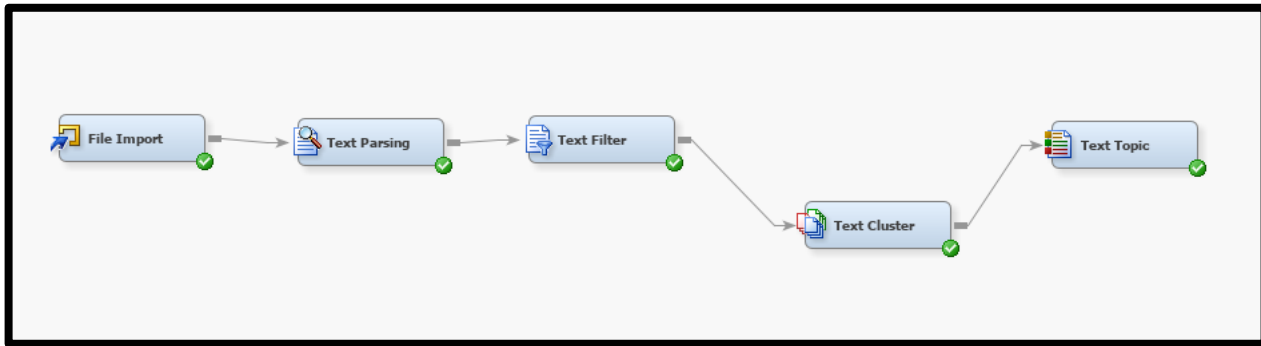


The above plot was generated. It can be seen that certain words come to the forefront right away. Water, Fish, Man, Origin, Abe, Bioshock, Del, Toro, and Monster seem to pop out right away. This is generally what people are writing about in their comments for The Shape of Water movie. The fantasy aspect of it is what ties it to Fish and Water. Del Toro is an acclaimed director, which is being highlighted here as well. As well as some of his other movies such as Hellboy. Again, we see that people tend to talk about the director and other cast in the movie or directors rather than specifically about just the movie.

Putting everything together, the movie trailer got 5667 comments. It is directed by an acclaimed director, which in itself seems to promote the movie more. Romance/Fantasy movies tend to be not as prevalent these days but given the sentiment analysis, people really seem to still enjoy this genre and have a positive response to it. Many of the comments are from the director's fan base and emotions are mostly positive. This movie won the Oscars, which may be a byproduct of the majorly positive response it received.

### 3.2.3 Phantom Thread

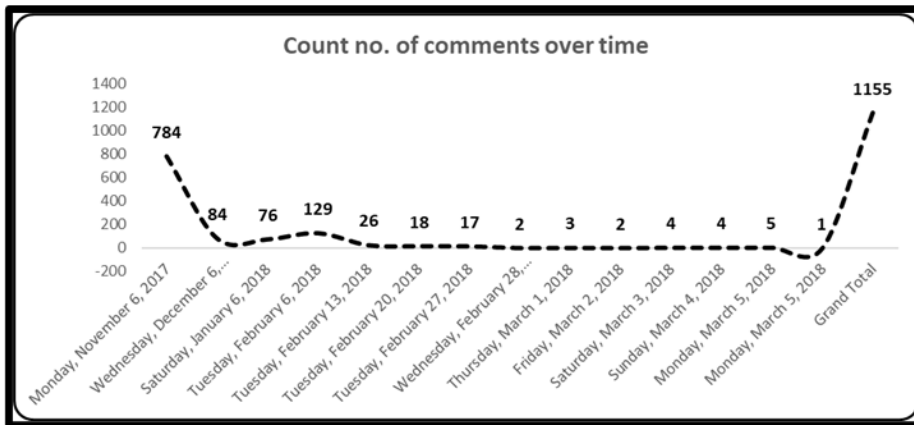
SAS diagram for Phantom Thread:



The diagram shown above follows the regular pattern on determining the key topics. The text was parsed with the start list containing the sentiments and emotions key words and was also separately parsed using the default stop list to do the sentiment analysis and the topic discovery. Post that, the text filter node was used followed by cluster node to identify key clusters or patterns in the data. This was followed by the topic node to find key topics or subjects being discussed in the reviews.

To understand the effect of any promotional event like a trailer launch, movie announcement, etc. we plotted the movement of no. of reviews received over a period. Same has been plotted below.

Count of Comments over time for Phantom Thread:



Here as well, before jumping into the sentiment analysis, a general trend was explored regarding when the comments were made on the Phantom Thread trailer on YouTube. It can be seen from the plot above that comments where a spike is seen is on November 6, 2017. YouTube had released the trailer for Phantom Thread on its platform just a week prior to this. This is worth noting, as the general trend of comments being made when an event or external variable is added is quite different from the one where we do not see any activity. In this case, it was adding this trailer to the YouTube platform that created a huge surge in viewership which then declined as that period did not see any promotional event or activity. Hence, the trend is pretty stable in the later part as compared to the initial spike.



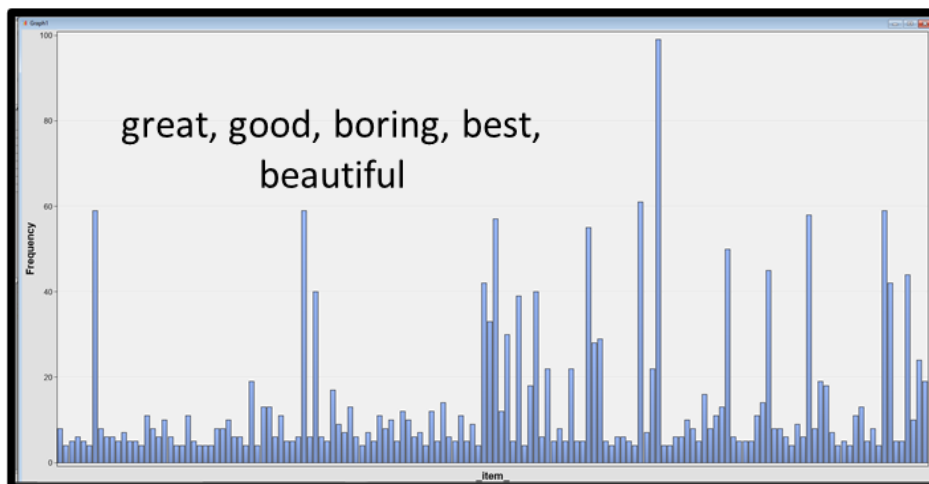
### 3.2.3.1 Sentiment Analysis:

#### Text Topic Node Viewer for Phantom Thread:

Topic	Category
not,+do,+wait,+film,+have	Multiple
daniel,+day,lewis,daniel day,+retire	Multiple
anderson,paul,thomas,+be,+make	Multiple
+oscar,+go,+get,4th,bait	Multiple
ðy,â,thread,+movie,phantom	Multiple
+be,+movie,+think,blood,i	Multiple
+look,boring,+good,+movie,+be	Multiple
+movie,+see,i,+make,+want	Multiple
pta,ddl,+film,+see,+year	Multiple
+good,+actor,day-lewis,+film,+year	Multiple

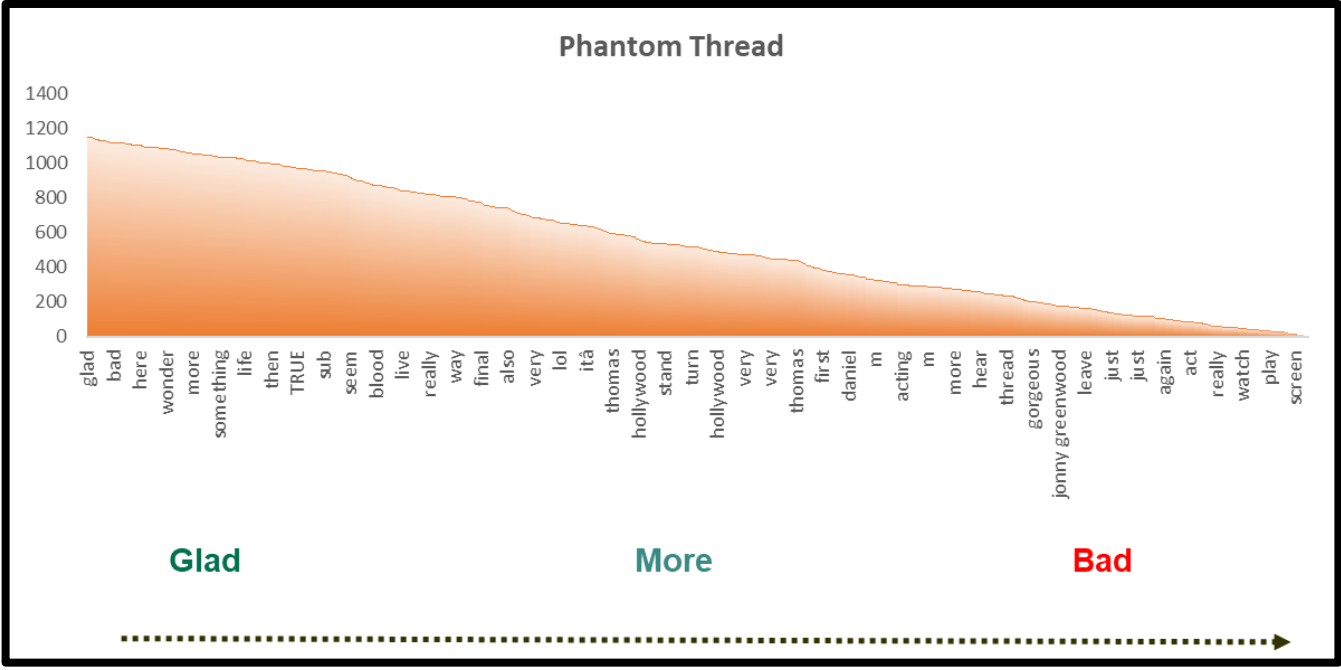
Firstly, after adding the curated start list in the text parsing node, containing over 500 words related to emotions, the text topic viewer results were generated. The same is shown in the above table. It can be seen that the words contain a mix of emotions. But certain words that come to the forefront can be further explored with the frequency graph below.

#### Word frequency for Phantom Thread:



This plot was created from the transactions of the exported data from the text topic node. There are many spikes seen here for various words. The words which have occurred the most and shown heavy spikes are: great, good, boring, best, beautiful. In contrast to the other movie reviews, this list shows a general sentiment which is positive. There are few words with negative connotations and hence shows that viewers have liked the movie or the stars or the story line and have shared their reviews accordingly. Another visualization is created, as seen below to further illustrate the sentiments that people felt after watching the trailer for the movie.

Sentiment Analysis Plot for Phantom Thread:

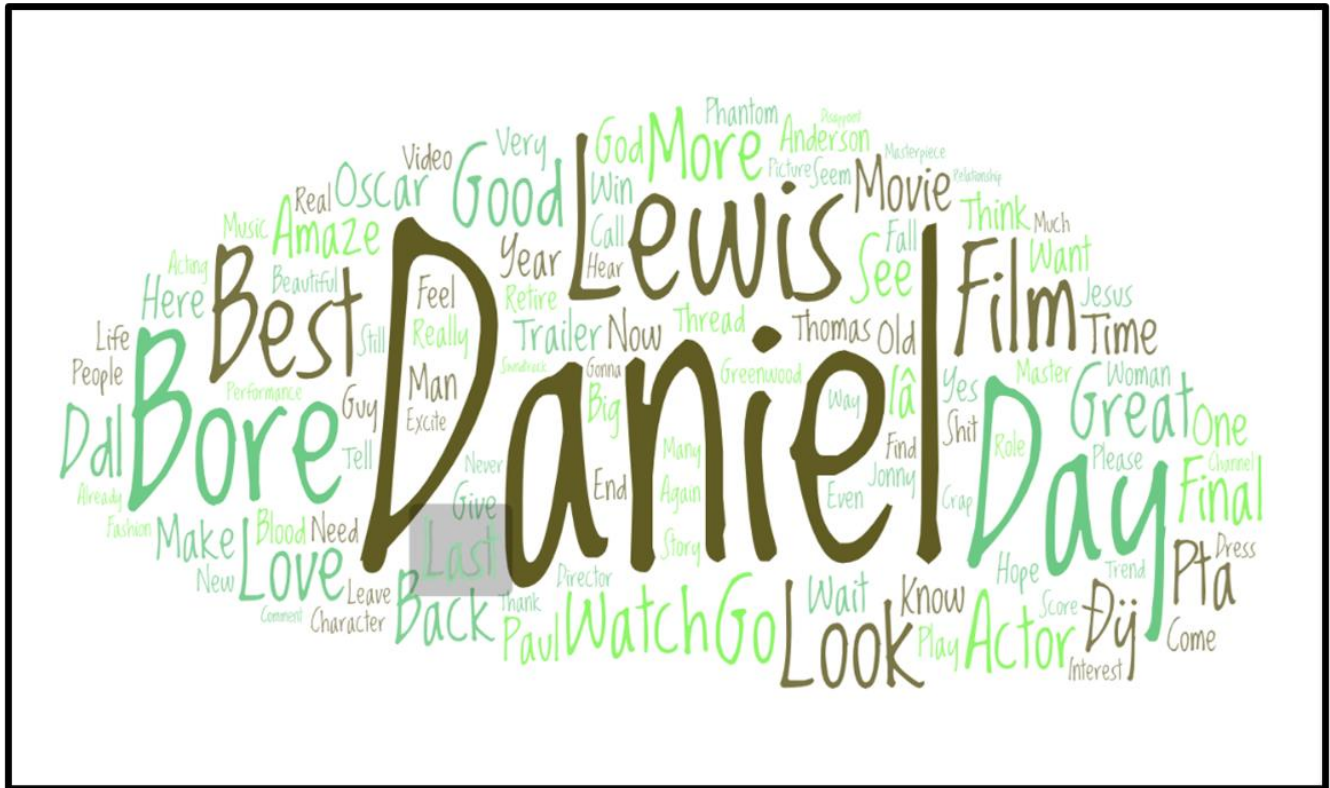


The words stating the emotions range from “Glad” to “Bad” but show a major inclination towards positive sentiment. Here, the movie is an American historical drama film and stars Daniel Day along with other actors. The love and affection people have for the actor is quite evident in their reviews and also is reflected in the topics being discussed which will be quite clear through the topic analysis being showcased next. Also, the same makes sense as the affinity towards historical drama films here in America reaffirms the analysis done here.

### 3.2.3.2 Topic Analysis

Next, we looked at all the words and their associated counts or frequency to see what more information could be extracted.

### Word Jumble Plot for Phantom Thread:

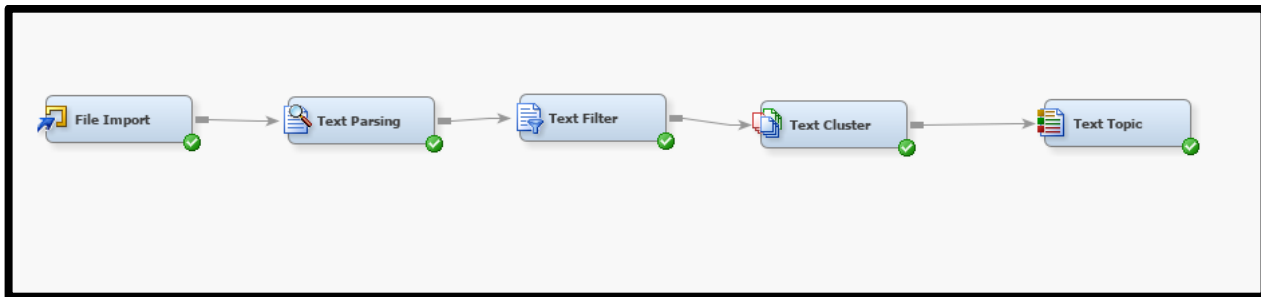


The above plot was generated by creating a word jumble of the most widely talked about topics in the reviews . It can be seen that certain words come to the forefront right away. Daniel, Bore, Best, Lewis, More, etc. seem to pop out right away. This is generally what people are writing about in their comments for the Phantom Thread movie trailer.

Putting everything together, it can be seen that the movie trailer got well over 1155 comments. Many of the comments are from the actor's fanbase and emotions are varied. In general, people have talked about the movie being one of the best they have watched, their interests in getting "MORE" of such content, and the request to "Go Watch" this movie. Hence, overall, the feedback for the movie has been quite good and has been well received by the audience.

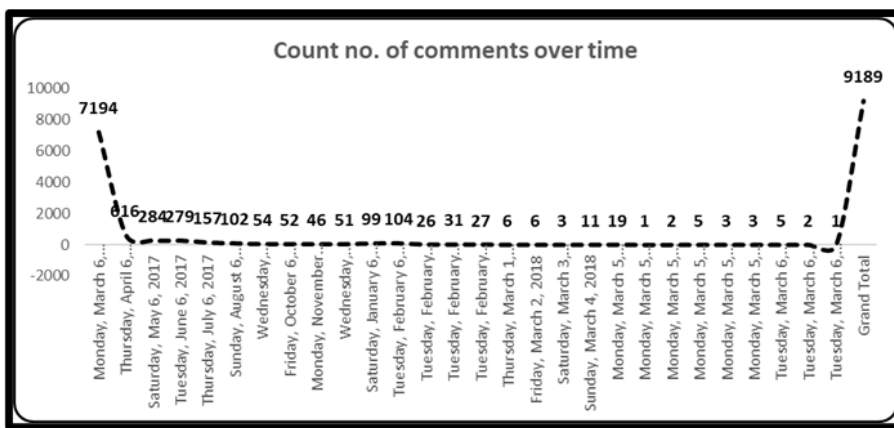
### 3.2.4 Get Out

SAS diagram for Get Out:



Similar to the diagram made for Get Out, this diagram follows the same general flow chain. The main difference or hyperparameter that was changed is in the text parsing node. Instead of using the default stop list, for sentiment analysis, a curated start list was used. This will be further explored below as well.

Count of Comments over time for Get Out:



Here, a general trend was explored regarding when the comments were made on Get Out trailer on YouTube. It can be seen from the plot above that there is a spike seen on March 6, 2017. This is right about the time that YouTube released the trailer for Get Out on its platform. This is worth noting, as the general trend of comments being made are when an event or external variable is added. In this case, it was adding this trailer to the YouTube platform. Overall, after, the trend is stable as compared to the initial spike.

### 3.2.4.1 Sentiment Analysis

Text Topic Node Viewer for Get Out:

Topic	Category
+great,glad,important,alone,uncomfortable	Multiple
glad,great,mad,nervous,fantastic	Multiple
hilarious,glad,uncomfortable,curious,afraid	Multiple
great,+great,common,+sad,angry	Multiple
mad,hilarious,angry,+down,+upset	Multiple
nervous,uncomfortable,angry,afraid,+upset	Multiple
+happy,+sad,nervous,+hurt,excited	Multiple
great,alone,free,+great,+sad	Multiple
+sad,guilt,+down,+dark,+upset	Multiple
down,calm,+down,calm,+dark	Multiple

Firstly, after adding the curated start list in the text parsing node, containing over 500 words related to emotions, the text topic viewer results were generated. It can be seen from the above table that the words contain mostly positive or happy emotions. People have gone hysterical watching the trailer. But certain words that come to the forefront can be further explored with the frequency graph below.

Word frequency for Get Out:



From the transactions of the exported data from the text topic node, this plot was created. There are many spikes seen here for various words. But certain words that come to the forefront are the following: great, hilarious, glad, sad, mad. Generally, the remarks have been quite stark. People have made comments about the movie being maddening. That essentially is because the movie talks about a certain race and people have not liked the portrayal of the same in the movie.

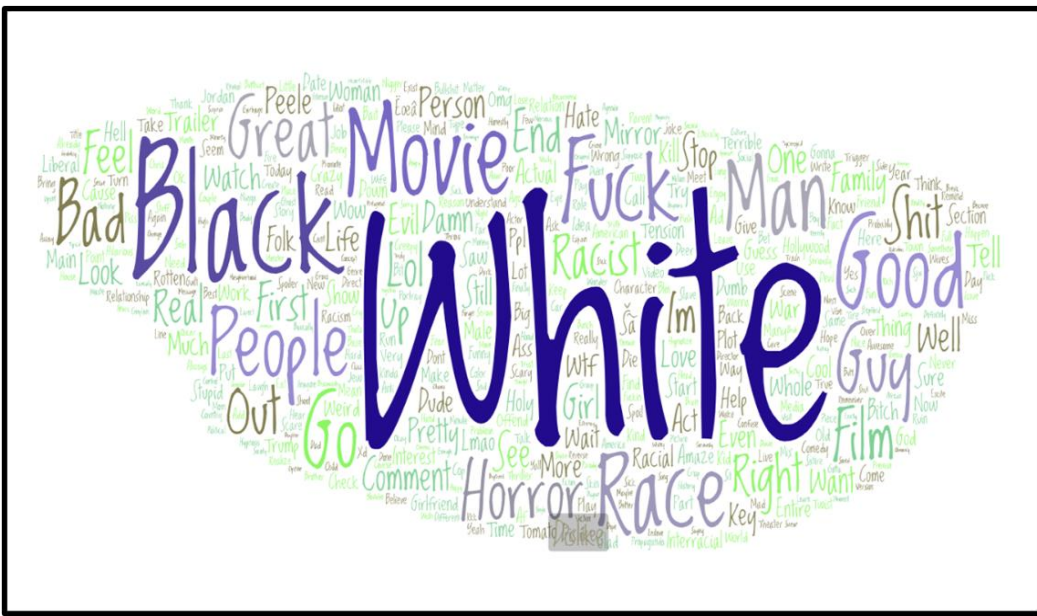
**Get Out**

Word	Frequency (approx.)	Category
dark	9000	Loving
loving	8500	Loving
uncomfortable	8000	Uncomfortable
down	7500	Uncomfortable
dark	7000	Loving
sad	6500	Uncomfortable
weak	6000	Uncomfortable
dark	5500	Loving
insecure	5000	Uncomfortable
curious	4500	Uncomfortable
strong	4000	Uncomfortable
insecure	3500	Uncomfortable
certain	3000	Uncomfortable
upset	2500	Uncomfortable
nervous	2000	Uncomfortable
uncomfortable	1800	Uncomfortable
down	1600	Uncomfortable
sad	1400	Uncomfortable
guilt	1200	Uncomfortable
responsible	1000	Uncomfortable
privileged	900	Uncomfortable
calm	800	Uncomfortable
calm	750	Uncomfortable
calm	700	Uncomfortable
down	650	Uncomfortable
proud	600	Uncomfortable
guilt	550	Uncomfortable
free	500	Uncomfortable
down	450	Uncomfortable
down	400	Uncomfortable
curious	350	Uncomfortable
angry	300	Uncomfortable
down	250	Uncomfortable
dark	200	Loving
strong	180	Uncomfortable
upset	160	Uncomfortable
lucky	140	Uncomfortable
angry	120	Uncomfortable
uncomfortable	100	Uncomfortable
comfortable	80	Dark
alone	60	Dark
lucky	40	Dark
weak	20	Dark

**Loving** **Uncomfortable** **Dark**

### 3.2.4.2 Topic Analysis

Word Jumble Plot for Get Out:



The above plot was generated through the word jumble of the key topics discussed. It can be seen that certain words come to the forefront right away. White, Black, race, people, bad etc. seem to pop out right away. This is generally what people are writing about in their comments for the Get Out movie. Here, the movie talks about the relationship between a White and a Black character and the portrayal is what people have disliked.

Putting everything together, it can be seen that the movie trailer got 9189 comments, which is one of the highest comments received amongst the 4 movies in the analysis. It is an American psychological horror movie and fails to get the viewers' appreciation. However, given that the plot was great, the movie was nominated for Oscars but failed to win.

## **4. Key Trends and Insights**

### **4.1. People gravitate towards war and action movies**

People gravitate towards Oscar-nominated war and action movie trailers due to several key trends and insights:

- **4.1.1. Thrill and Excitement:** War and action movie trailers often showcase intense action sequences, explosive visuals, and adrenaline-pumping moments. Viewers are drawn to the excitement and thrill that these movies offer, as the trailers provide a glimpse of the thrilling experiences they can expect from the film.
- **4.1.2. Cinematic Spectacle:** War and action movies are known for their visually stunning scenes, elaborate set pieces, and impressive special effects. The trailers highlight the cinematic spectacle, capturing the attention of viewers who appreciate the visual artistry and immersive experience that these movies provide.
- **4.1.3. Emotional Engagement:** War and action movie trailers often evoke a range of emotions, including tension, suspense, and patriotism. They present compelling narratives and characters that viewers can emotionally connect with. The trailers may highlight themes of heroism, sacrifice, and resilience, resonating with audiences and drawing them into the story.
- **4.1.4. Star Power:** Oscar-nominated war and action movies often feature renowned actors and actresses who have established fan bases. The trailers prominently showcase the presence of these talented performers, generating excitement among their fans and attracting audiences who are interested in their performances.
- **4.1.5. Awards Recognition:** The association of war and action movies with Oscar nominations adds prestige and credibility. The trailers highlight the critical acclaim and recognition these films have received, generating curiosity and interest among viewers who value high-quality cinema.



- **4.1.6. Cultural Fascination:** War and action movies explore historical events, military conflicts, and the complexities of combat. They tap into a cultural fascination with war narratives and attract viewers who are interested in exploring these themes. The trailers offer glimpses into significant historical periods or provide insights into the experiences of soldiers and veterans.
- **4.1.7. Shared Experience and Social Influence:** Oscar-nominated war and action movies often become cultural phenomena, generating buzz and anticipation. Viewers are drawn to these films as a way to be part of a shared experience, engaging in discussions with friends, colleagues, or online communities. The influence of social media and word-of-mouth recommendations can further drive the gravitation towards these movie trailers.

It's important to note that individual preferences may vary, and not everyone is drawn to war and action movies or their trailers. However, the combination of thrilling action, visual spectacle, emotional engagement, star power, awards recognition, cultural fascination, and social influence contribute to the gravitation towards Oscar-nominated war and action movie trailers.

## **4.2. People tend to reflect negatively on topics which are sensitive and attracts a lot of flak amongst viewers if not portrayed well**

When people reflect negatively on Oscar-nominated movie trailers that mishandle sensitive topics, it can be attributed to several key trends and insights:

- **4.2.1. High Expectations:** Oscar-nominated movies are often associated with quality and critical acclaim. Viewers expect a thoughtful and nuanced approach to sensitive topics, and if the movie trailer fails to deliver, it can lead to disappointment and negative reflections.
- **4.2.2. Sensitivity and Authenticity:** Sensitive topics require a careful and authentic portrayal to resonate with audiences. If a movie trailer mishandles the subject matter, lacks sensitivity, or comes across as exploitative or superficial, viewers are more likely to respond negatively. They may perceive the trailer as disrespectful or dismissive of the lived experiences associated with the topic.
- **4.2.3. Social and Cultural Impact:** Movies have the power to shape perceptions and influence societal attitudes. When sensitive topics are mishandled in Oscar-nominated movie trailers, it can contribute to the perpetuation of harmful stereotypes, misinformation, or the erasure of marginalized voices. Viewers who recognize these flaws may react negatively due to concerns about the social and cultural impact of such portrayals.
- **4.2.4. Representation and Inclusivity:** In an era that values diverse representation and inclusivity, viewers have heightened expectations for responsible and authentic portrayals. If a movie trailer fails to include authentic representation of marginalized communities or misrepresents their experiences, it can generate criticism and negative reflections. Viewers who value representation and inclusivity may express their discontent and hold the filmmakers accountable.



- **4.2.5. Offense and Discomfort:** Movie trailers that mishandle sensitive topics can offend or make viewers uncomfortable. Insensitive or exploitative portrayals may be seen as crossing ethical boundaries or capitalizing on the suffering of others. Such trailers can evoke strong negative emotions and lead to backlash from viewers who feel offended or disturbed by the content.
- **4.2.6. Amplification through Social Media:** Negative reactions to movie trailers spread rapidly through social media platforms. Viewers who are critical of the mishandling of sensitive topics express their concerns on platforms like Twitter, Facebook, or YouTube. Social media amplification can significantly impact the perception and reception of the movie, contributing to negative reflections.
- **4.2.7. Advocacy and Activism:** Advocacy groups and organizations dedicated to the issues portrayed in sensitive topics often voice their concerns when movie trailers mishandle the subject matter. Their activism and criticism can contribute to negative reflections, as they highlight the importance of responsible and accurate portrayals and hold filmmakers accountable for their representations.

It is crucial for filmmakers to approach sensitive topics with care, research, and a willingness to listen to feedback. Engaging in consultations, diverse perspectives, and employing sensitivity training can contribute to responsible portrayals in movie trailers and help avoid negative reflections from viewers.

### **4.3. Actors and Actresses can overpower the fame a movie can get and influence viewership driven by crazy fan-base to a very large extent**

The influence of Oscar-nominated movie trailer actors and actresses on the fame and viewership of a film, driven by a passionate fan base, can be attributed to several key trends and insights:

- **4.3.1. Star Power and Celebrity Culture:** Actors and actresses who have achieved recognition and acclaim through Oscar nominations or wins often have a strong following of dedicated fans. These fans are drawn to their favorite performers' charisma, talent, and on-screen presence. The mere involvement of these actors and actresses in a movie can generate excitement and anticipation, leading to increased viewership.
- **4.3.2. Fan Engagement and Social Media:** In the era of social media, fans have direct access to their favorite actors and actresses. Celebrities engage with their fan bases through platforms like Twitter, Instagram, and YouTube, building personal connections and fostering loyalty. When these actors and actresses are associated with Oscar-nominated movies, they use their social media presence to promote and generate buzz, further influencing their fan base to watch the film.
- **4.3.3. Award-Winning Reputation:** Actors and actresses who have received Oscar nominations or wins have established a reputation for delivering exceptional performances. Their presence in a movie, particularly in an Oscar-nominated film, reinforces the perception of quality and

excellence. Fans are often eager to see their favorite actors and actresses deliver memorable performances, which can drive viewership and contribute to the film's fame.

- **4.3.4. Media Coverage and Publicity:** Oscar nominations and awards generate significant media coverage and publicity. The media often focuses on the actors and actresses involved, highlighting their performances, interviews, and red carpet appearances. This heightened visibility keeps the film in the public consciousness and amplifies the influence of the actors and actresses on the viewership.
- **4.3.5. Influence of Film Communities and Fandoms:** Film communities and fandoms devoted to specific actors and actresses are highly engaged and vocal. They actively promote their favorites' projects, creating anticipation and word-of-mouth recommendations among their fellow fans. The passion and enthusiasm of these communities can greatly impact viewership and contribute to the film's overall fame.
- **4.3.6. Fan Loyalty and Repeat Viewership:** Fans of actors and actresses often have a deep sense of loyalty and admiration for their favorite stars. They are more likely to watch movies featuring their favorite performers multiple times, contributing to higher viewership numbers. This loyalty extends to Oscar-nominated films, as fans want to support and celebrate the achievements of their favorite actors and actresses.
- **4.3.7. Personal Identification and Emotional Connection:** Fans often develop a personal identification and emotional connection with actors and actresses who resonate with them. They feel a sense of pride and ownership in their favorites' success and eagerly support their projects, including Oscar-nominated films. This emotional connection drives viewership and can amplify the film's fame through the dedication of the fan base.

It's important to note that while the involvement of Oscar-nominated actors and actresses can significantly influence viewership and contribute to a film's fame, other factors such as the quality of the movie, critical acclaim, marketing efforts, and word-of-mouth recommendations also play crucial roles in shaping the film's success.

## **5. Business Recommendations & Conclusion:**

**5.1. Content Creation and Promotion:** YouTube and other media platforms can capitalize on the interest in war and history topics by creating and promoting content related to these themes. This could include historical documentaries, analysis of war films, interviews with historians, or behind-the-scenes features that delve into the historical context of Oscar-nominated movies. By providing engaging and informative content in line with viewer interests, these platforms can attract a wider audience and increase engagement and viewership.

**5.2. Leveraging Acclaimed Actors and Actresses:** Recognizing the influence of highly acclaimed actors and actresses on viewership, media platforms can prioritize featuring content related to films that involve these talented performers. This could involve creating dedicated sections or playlists that highlight the work of these actors and actresses, promoting their performances, and curating content that

showcases their talent and success. By leveraging the star power of these individuals, platforms can attract viewers and increase revenue generation through higher viewership.

**5.3. Event-driven Promotions:** Events such as nomination announcements and trailer launches create significant buzz and anticipation among movie enthusiasts. Media platforms can leverage these events by hosting live streams, interviews, panel discussions, or special content releases around these time frames. By capitalizing on the increased interest and engagement during these events, platforms can drive higher click-through rates (CTR) and viewership, ultimately leading to increased revenue generation through ad impressions, sponsored content, or partnerships.

**5.4. Collaborations and Partnerships:** Media platforms can explore collaborations and partnerships with movie studios, production companies, or even individual actors and actresses to create exclusive content or behind-the-scenes features tied to Oscar-nominated movies. This could involve conducting interviews with the cast and crew, providing exclusive access to film sets or events, or offering unique promotional opportunities. Such collaborations can generate excitement, attract viewership, and drive revenue through increased engagement and ad revenue.

**5.5. Targeted Advertising:** Based on the interest in war and history topics, media platforms can optimize their advertised return on investment for advertisers.

**5.6. User-generated Content and Engagement:** Encouraging users to create and share their own content related to Oscar-nominated movies, war, and history can foster community engagement and increase viewership. Media platforms can organize contests, challenges, or discussions around these topics, incentivizing users to actively participate and share their thoughts, reviews, and creative interpretations. This user-generated content can generate buzz, increase viewership, and contribute to revenue generation through increased engagement and ad impressions.

By implementing these recommendations, media platforms can tap into the interest in war and history, leverage the star power of acclaimed actors and actresses, capitalize on event-driven promotions, and optimize advertising strategies. These efforts can help drive revenue generation through increased viewership, higher CTR, and enhanced engagement among users.