Sentiment Analysis before and after an event: Oscars 2019

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IV.7 Semester Long Innovation Project

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Abstract

While machine learning approaches and natural language processing have made sentiment analysis what it is in today's tech derived and fed world, one should not forget the very origin of these sentiments. Our project takes into account the analysis of sentiments/opinions in and around timelines of a specific event viz a viz the eight heavily involved movies in The Oscars of 2019. We derive these opinions from Twitter and compute them to quantify the impact before and after these eight feature films got released, nominated and awarded. Once we have the numbered results from the model, we link them to what we understand of our target audiences as psychologically influenced models.

Certificate

Acknowledgement

We would like to express our special thanks of gratitude to our mentor Mr. Sachin Kumar, who gave us the opportunity to work on this Semester Long project. He provided us with the much needed direction, clarity of thought and help in the technical areas of the work. We are also thankful to our seniors, who have been helpful constantly and have been extremely knowledgeable about our subject of work. The project was a learning experience for the both of us as it helped us grow individuals as well as professionals. Also, we are thankful to all our references from the web, especially some of the data sets. This project would not have been possible without them. Thanks to everyone, once again.

Adit Negi
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1. Introduction

Sentiment analysis is identified as the process of computationally identifying, categorizing, or quantifying opinions, facts, or simply texts so as to derive a thematically general numerical value which enables us to compare such texts. But the story of sentiment analysis doesn't just limit itself to raw comparison or understanding.[1] Due to its ability to bend into the mind of who wrote it as the much obvious point of understanding here is the intention of the writer viz a viz the one whose sentiment is expressed, we can link this very technical feature into a psychological study.

L Festinger in his paper 'Behavioural support for opinion change' stated that "It is my present contention that, in order to produce a stable behavior change following opinion change, an environmental change must also be produced which, representing reality, will support the new opinion and the new behavior. Otherwise, the same factors that produced the initial opinion and the behavior will continue to operate to nullify the effect of the opinion change." [2]

So to get through the process, we tried to evaluate people's perceptions before and after events. We picked the eight Best Film nominees for Oscars 2019 and computed the tweets of three target audiences through three timelines.

1.1. Why only Oscars?

The Oscars are a global event, so much so that they have become a metaphor for the highest honour in any field. It is greatly talked about, especially on Twitter. However, the greatest argument in the favour of this subject is its subjectivity. Opinion on art has been a thing from ages, especially movies. Twitter has given it a boost and almost everyone keeps out their opinion regarding every movie they watch on the platform. Hashtags further help our cause in differentiating and extracting our tweets of interest.

1.2. Subjects of study

We picked the eight Best Film nominees for Oscars 2019 - A Star is Born, Blackkklansman, Black Panther, Bohemian Rhapsody, Green Book, Roma, The Favourite and Vice.

We picked three timelines -

Table 1

Timeline Number	Event	Start Date	End Date
1	Release	Release date	Release date plus seven days
2	Before Oscars	15th February 2019	24th February 2019
3	After Oscars	24th February 2019	5th March 2019

We also picked three target groups -

1. General Audience - This category talks about the public notion and any shift in opinion in any timeline reflects a major thought change. Due to no particular restrictions, this is the largest data set.
2. Repeated Audience/Enthusiasts - This crucial section takes into account the Twitter handles that tweeted about the same film before and after the event in the same timeline. It is of particular interest because this section identifies individual notions and personal interests.
3. Critics - Though only a handful in number, tweets by selected critics help us to identify the gap between those who have necessarily seen all of these movies as compared to those who may not have.

2. Problem Statement

To computationally quantify the opinions and sentiment (derived via Twitter) around five timelines, from three target audiences with eight movies as the subjects. Once done, compare the change and if possible link it to psychological reasons.

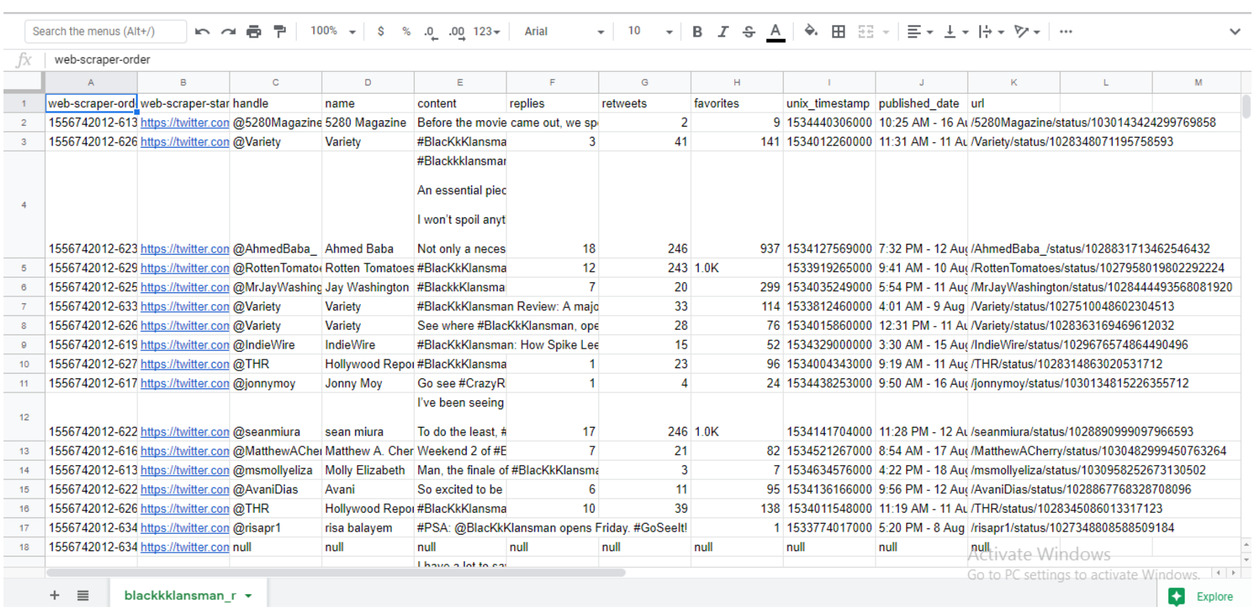
3. Methodology

3.1. Extracting Tweets

3.1.1. General Audience

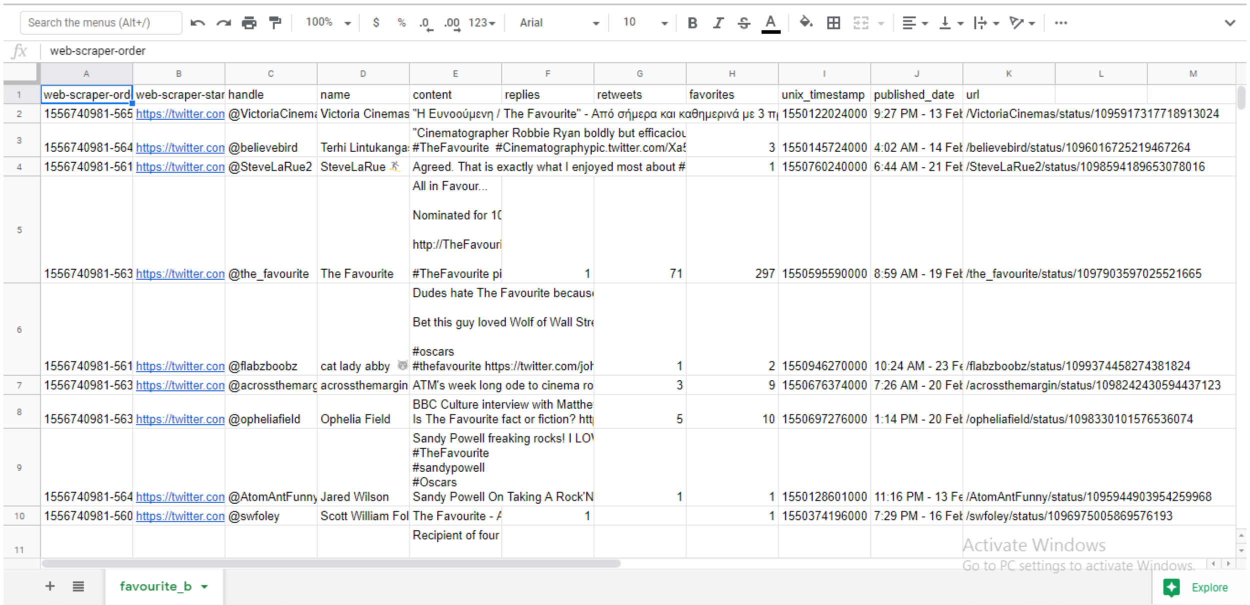
A Twitter API as well as web scraping techniques were used to extract the tweets into a .csv file.
The key here was to get our dates right as our timelines provided us with windows of 7-10 days each. Using the advanced search option in twitter we defined the hashtags and the timeline from which the tweets were to be displayed, then standard python libraries such as Beautiful Soup and requests were used to scrape the page along with chrome's web scraping tool. Hashtags differentiated movies and it was vital to make sure that a single tweet does not talk about multiple of these films. Our data set made up to around thousand tweets for each timeline, movie and target audience.The text was extracted from the tweets the images and gifs were ignored.

For example, here are a few of the .csv files across different timelines and films, and here is how they look. The important thing to notice is the second column from right showcasing that our extracted tweets validates the timelines.



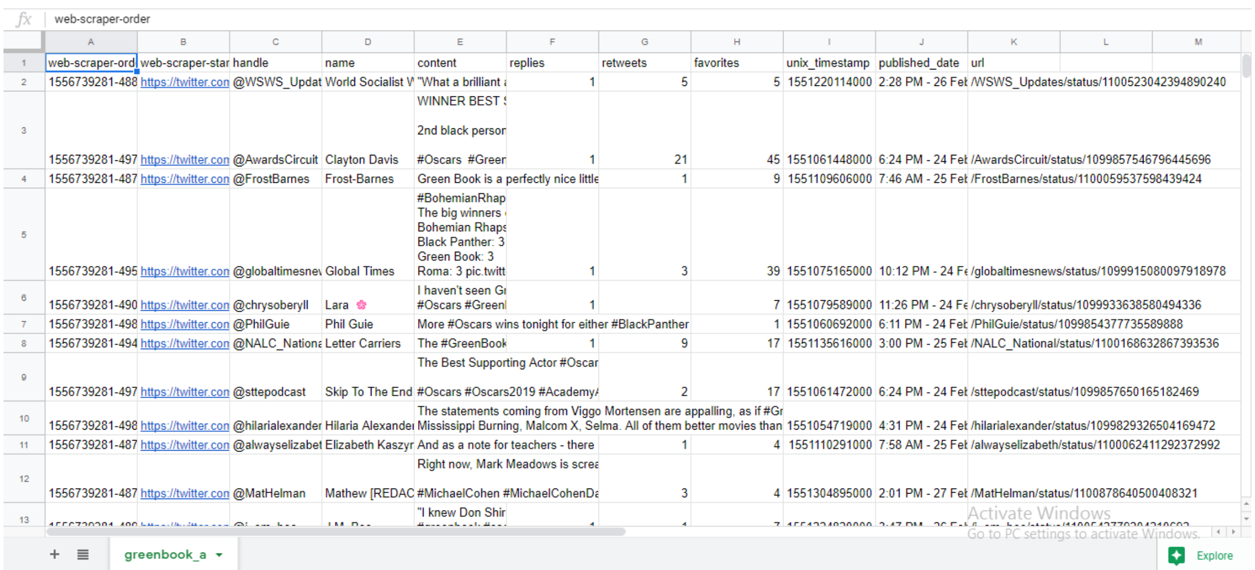
web-scraper-ord	web-scraper-star	handle	name	content	replies	retweets	favorites	unix_timestamp	published_date	url
1556742012-613	https://twitter.con	@5280Magazine	5280 Magazine	Before the movie came out, we sp		2	9	1534440306000	10:25 AM - 16 Au	/5280Magazine/status/1030143424299769858
1556742012-626	https://twitter.con	@Variety	Variety	#BlacKkKlansma	3	41	141	1534012260000	11:31 AM - 11 Au	/Variety/status/1028348071195758593
1556742012-623	https://twitter.con	@AhmedBaba_	Ahmed Baba	#Blackkklansmar An essential piec I won't spoil anyt Not only a neces	18	246	937	1534127569000	7:32 PM - 12 Aug	/AhmedBaba_/status/1028831713462546432
1556742012-629	https://twitter.con	@RottenTomatoe	Rotten Tomatoes	#BlacKkKlansma	12	243	1.0K	1533919265000	9:41 AM - 10 Aug	/RottenTomatoes/status/1027958019802292224
1556742012-625	https://twitter.con	@MrJayWashing	Jay Washington	#BlackkKlansma	7	20	299	1534035249000	5:54 PM - 11 Aug	/MrJayWashington/status/1028444493568081920
1556742012-633	https://twitter.con	@Variety	Variety	#BlacKkKlansman Review: A majo		33	114	1533812460000	4:01 AM - 9 Aug	/Variety/status/1027510048602304513
1556742012-626	https://twitter.con	@Variety	Variety	See where #BlacKkKlansman, ope		28	76	1534015860000	12:31 PM - 11 Au	/Variety/status/1028363169469612032
1556742012-619	https://twitter.con	@IndieWire	IndieWire	#BlacKkKlansman: How Spike Lee		15	52	1534329000000	3:30 AM - 15 Aug	/IndieWire/status/1029676574864490496
1556742012-627	https://twitter.con	@THR	Hollywood Repor	#BlacKkKlansma	1	23	96	1534004343000	9:19 AM - 11 Aug	/THR/status/1028314863020531712
1556742012-617	https://twitter.con	@jonnymoy	Jonny Moy	Go see #CrazyR	1	4	24	1534438253000	9:50 AM - 16 Aug	/jonnymoy/status/1030134815226355712
1556742012-622	https://twitter.con	@seanmiura	sean miura	I've been seeing To do the least, #	17	246	1.0K	1534141704000	11:28 PM - 12 Au	/seanmiura/status/1028890999097966593
1556742012-616	https://twitter.con	@MatthewAChe	Matthew A. Cher	Weekend 2 of #E	7	21	82	1534521267000	8:54 AM - 17 Aug	/MatthewACherry/status/1030482999450763264
1556742012-613	https://twitter.con	@msmollyeliza	Molly Elizabeth	Man, the finale of #BlacKkKlansma		3	7	1534634576000	4:22 PM - 18 Aug	/msmollyeliza/status/1030958252673130502
1556742012-622	https://twitter.con	@AvaniDias	Avani	So excited to be	6	11	95	1534136166000	9:56 PM - 12 Aug	/AvaniDias/status/1028867768328708096
1556742012-626	https://twitter.con	@THR	Hollywood Repor	#BlacKkKlansma	10	39	138	1534011548000	11:19 AM - 11 Au	/THR/status/1028345086013317123
1556742012-634	https://twitter.con	@risapr1	risa balayem	#PSA: @BlacKkKlansman opens Friday. #GoSeeIt!			1	1533774017000	5:20 PM - 8 Aug	/risapr1/status/1027348808588509184
1556742012-634	https://twitter.con	null	null	null	null	null	null	null	null	null

Figure 1: .csv file with the Release timeline tweets of Blackkklansman



	A	B	C	D	E	F	G	H	I	J	K	L	M
1	web-scraper-ord	web-scraper-star	handle	name	content	replies	retweets	favorites	unix_timestamp	published_date	url		
2	1556740981-565	https://twitter.con	@VictoriaCinem	Victoria Cinemas	"Η Ευνοούμενη / The Favourite" - Από σήμερα και καθημερινά με 3 π				1550122024000	9:27 PM - 13 Fel	/VictoriaCinemas/status/1095917317718913024		
3	1556740981-564	https://twitter.con	@believebird	Terhi Lintukanga	"Cinematographer Robbie Ryan boldly but efficaciou #TheFavourite #Cinematographypic.twitter.com/Xa5			3	1550145724000	4:02 AM - 14 Fel	/believebird/status/1096016725219467264		
4	1556740981-561	https://twitter.con	@SteveLaRue2	SteveLaRue	Agreed. That is exactly what I enjoyed most about #			1	1550760240000	6:44 AM - 21 Fel	/SteveLaRue2/status/1098594189653078016		
5	1556740981-563	https://twitter.con	@the_favourite	The Favourite	All in Favour... Nominated for 1(http://TheFavouri #TheFavourite pi	1	71	297	1550595590000	8:59 AM - 19 Fel	/the_favourite/status/1097903597025521665		
6	1556740981-561	https://twitter.con	@flabzboobz	cat lady abby	Dudes hate The Favourite becaus Bet this guy loved Wolf of Wall Stre #oscars #thefavourite https://twitter.com/joh		1	2	1550946270000	10:24 AM - 23 Fe	/flabzboobz/status/1099374458274381824		
7	1556740981-563	https://twitter.con	@acrossthemarg	acrossthemargin	ATM's week long ode to cinema ro		3	9	1550676374000	7:26 AM - 20 Fel	/acrossthemargin/status/1098242430594437123		
8	1556740981-563	https://twitter.con	@opheliafield	Ophelia Field	BBC Culture interview with Matthe Is The Favourite fact or fiction? htt		5	10	1550697276000	1:14 PM - 20 Fel	/opheliafield/status/1098330101576536074		
9	1556740981-564	https://twitter.con	@AtomAntFunny	Jared Wilson	Sandy Powell freaking rocks! I LO\ #TheFavourite #sandypowell #Oscars Sandy Powell On Taking A Rock'N		1	1	1550128601000	11:16 PM - 13 Fe	/AtomAntFunny/status/1095944903954259968		
10	1556740981-560	https://twitter.con	@swfoley	Scott William Fol	The Favourite - A	1		1	1550374196000	7:29 PM - 16 Fel	/swfoley/status/1096975005869576193		
11					Recipient of four								

Figure 2: .csv file with the Before Oscars timeline tweets of The Favourite



	A	B	C	D	E	F	G	H	I	J	K	L	M
1	web-scraper-ord	web-scraper-star	handle	name	content	replies	retweets	favorites	unix_timestamp	published_date	url		
2	1556739281-488	https://twitter.con	@WSWS_Updat	World Socialist V	"What a brilliant a	1	5	5	1551220114000	2:28 PM - 26 Fel	/WSWS_Updates/status/1100523042394890240		
3	1556739281-497	https://twitter.con	@AwardsCircuit	Clayton Davis	WINNER BEST S 2nd black persor #Oscars #Greer	1	21	45	1551061448000	6:24 PM - 24 Fel	/AwardsCircuit/status/1099857546796445696		
4	1556739281-487	https://twitter.con	@FrostBarnes	Frost-Barnes	Green Book is a perfectly nice little		1	9	1551109606000	7:46 AM - 25 Fel	/FrostBarnes/status/1100059537598439424		
5	1556739281-495	https://twitter.con	@globaltimesnev	Global Times	#BohemianRhap The big winners Bohemian Rhaps Black Panther: 3 Green Book: 3 Roma: 3 pic.twitt	1	3	39	1551075165000	10:12 PM - 24 Fe	/globaltimesnews/status/1099915080097918978		
6	1556739281-490	https://twitter.con	@chrysoberyll	Lara	I haven't seen Gr #Oscars #Greenl	1		7	1551079589000	11:26 PM - 24 Fe	/chrysoberyll/status/1099933638580494336		
7	1556739281-498	https://twitter.con	@PhilGuie	Phil Guie	More #Oscars wins tonight for either #BlackPanther			1	1551060692000	6:11 PM - 24 Fel	/PhilGuie/status/1099854377735589888		
8	1556739281-494	https://twitter.con	@NALC_Nationa	Letter Carriers	The #GreenBook	1	9	17	1551135616000	3:00 PM - 25 Fel	/NALC_National/status/1100168632867393536		
9	1556739281-497	https://twitter.con	@sttepodcast	Skip To The End	The Best Supporting Actor #Oscar #Oscars #Oscars2019 #AcademyA		2	17	1551061472000	6:24 PM - 24 Fel	/sttepodcast/status/1099857650165182469		
10	1556739281-498	https://twitter.con	@hilarialexander	Hilaria Alexande	The statements coming from Viggo Mortensen are appalling, as if #Gr Mississippi Burning, Malcom X, Selma. All of them better movies than				1551054719000	4:31 PM - 24 Fel	/hilarialexander/status/1099829326504169472		
11	1556739281-487	https://twitter.con	@alwayselizabet	Elizabeth Kaszyr	And as a note for teachers - there		1	4	1551110291000	7:58 AM - 25 Fel	/alwayselizabeth/status/1100062411292372992		
12	1556739281-487	https://twitter.con	@MatHelman	Mathew [REDAC	Right now, Mark Meadows is screa #MichaelCohen #MichaelCohenDa		3	4	1551304895000	2:01 PM - 27 Fel	/MatHelman/status/1100878640500408321		
13					"I knew Don Shir								

Figure 3: .csv file with the After Oscar timeline tweets of Green Book

3.1.2. Enthusiasts

Of the thousands of tweets we extracted through Python, we manually looked around to find the ones with most engagement, hence increasing the chance of regular posting by that account. The data set here was smaller than the one above, but it is important to remember how significant changes in one's own opinion here is to the act of sentiment analysis.

Notice how most of the account handles appear twice in this screenshot.

fx @AlezM132

	A	B	C	D	E	F	G	H	I	J	K	L	M
10	1556636117-41	https://twitter.con	@brwc	brwc	Callum Forbes lo https://battleroya	1			1550148929000	4:55 AM - 14 Fet	/brwc/status/1096030166864793602		
11	1556636117-17	https://twitter.con	@MajBenTallma	Major Benjamin	I'm trying but I ar	1		1	1553560487000	5:34 PM - 25 Ma	/MajBenTallmadge/status/1110339278008012800		
12	1556636117-13	https://twitter.con	@kydizzel	Dizzel	Gary Oldman is	1	1	2	1553058867000	10:14 PM - 19 M	/kydizzel/status/1108235332468695040		
13	1556636117-12	https://twitter.con	@KatieSilverSpri	KatieSilverSpring	If everyone could watch #DarkestHour again and ag			2	1555198830000	4:40 PM - 13 Apr	/KatieSilverSpri/status/1117210984119242752		
14	1556636117-27	https://twitter.con	@aresluoga	Andres Quiroga	Born on this day #SidAndNancy (#Dracula (1992) #DarkestHour (2	1	3	3	1553166717000	4:11 AM - 21 Mar	/aresluoga/status/1108687687165329408		
15	1556636117-31	https://twitter.con	@SonyPIX	Sony PIX	This amazing tra Don't miss this st	1	4	22	1552638244000	1:24 AM - 15 Ma	/SonyPIX/status/1106471111791968256		
16	1556636117-36	https://twitter.con	@GaryOldmanW	Gary Oldman We	1 year ago - Mar #GaryOldman #D	4	39	177	1551739134000	2:38 PM - 4 Mar	/GaryOldmanWeb/status/1102699969184710656		
17	1556636117-28	https://twitter.con	@filmser	filmser	The one and only! Born this day, b		3	12	1553157827000	1:43 AM - 21 Ma	/filmser/status/1108650399135866880		
18	1556636117-34	https://twitter.con	@marksims94	linkinparkmark	Gary Oldman is phenomenal as W		2	25	1552401535000	7:38 AM - 12 Ma	/marksims94/status/1105478279610404864		
19	1556636117-9	https://twitter.con	@Mindlessnat77	Natalia Ortiz Me	Lately I've been watching films from last year that I c			2	1553566964000	7:22 PM - 25 Ma	/Mindlessnat77/status/1110366445106532358		
20	1556636117-7	https://twitter.con	@OnlyRedNow	OnlyRedNow	Another misty m	1		1	1553567372000	7:29 PM - 25 Ma	/OnlyRedNow/status/1110368154759225344		
21	1556636117-5	https://twitter.con	@AlezM132	alex	I'm entered to win #DarkestHour Hearts of Iron Game on #Steam PC				1551304290000	1:51 PM - 27 Fet	/AlezM132/status/1100876100467593231		
22	1556636117-30	https://twitter.con	@SonyPIX	Sony PIX	Amazing casting Today at 1 pm, w	1	3	28	1552802270000	10:57 PM - 16 M	/SonyPIX/status/1107159083486830595		
23	1556636117-10	https://twitter.con	@OnlyRedNow	OnlyRedNow	@nml423 Thank	1		1	1553567648000	7:34 PM - 25 Ma	/OnlyRedNow/status/1110369314656247808		
24	1556636117-8	https://twitter.con	@MajBenTallma	Major Benjamin	Just got off the p	1		1	1553569004000	7:56 PM - 25 Ma	/MajBenTallmadge/status/1110375000282820608		
25	1556636117-29	https://twitter.con	@Working_Title	Working Title	Happy Birthday (	3	21	80	1553154639000	12:50 AM - 21 M	/Working_Title/status/1108637027447255040		
26					It's the Academy								

tweets

Figure 4: .csv file with the tweets of Repeated Audience/Enthusiasts

3.1.3. Critics

We handpicked 60 of the most reputed critics and placed their tweets into our .csv file. We also combined results with websites like Rotten Tomatoes and Metacritic which link their reviews to Twitter as well. Despite the smallest data set, this one was crucial to establish the gap between the general audience and the knowledgeable critics.

3.2. Pipeline

Once the tweets are extracted, we can begin to compute them. They will need to be run through a pipeline of natural language processing approaches which includes sentence segmentation, word tokenization, text lemmatization and dependency parsing among others. We used Textblob here - a Python library used for processing texts and implementing basic natural language processing. We also used Panda - a Python library used generally for data analytics. The key here was to measure the polarity and not just the ‘good review’ percentage, hence opening up to the chance that a movie maybe negatively reviewed. Every section of each timeline, each movie and each target audience was marked between -1 and 1, with 0 being the perfectly neutral score.

movie	release(general)	beforeOscar(g)	afterOscar(g)	release(critic)	BO(critic)	AO(critic)	release(enthusi	BO(enthusiast)	AO(enthusiast)
bohemian rhapsody	0.212	0.3	0.249	0.196	0.24	0.241	0.296	0.329	0.301
Black panther	0.2	0.271	0.302	0.256	0.238	0.291	0.256	0.277	0.233
roma	0.123	0.23	0.358	0.439	0.392	0.401	0.439	0.324	0.287
green book	-0.019	0.218	0.259	0.328	0.297	0.3	0.328	0.25	0.231
vice	0.101	0.185	0.196	0.201	0.256	0.271	0.201	0.172	0.196
a star is born	0.17	0.143	0.172	0.211	0.157	0.198	0.211	0.322	0.258
the favourite	0.17	0.31	0.335	0.342	0.311	0.221	0.342	0.299	0.223
blackkklansman	0.124	0.291	0.265	0.301	0.231	0.327	0.301	0.281	0.299

Figure 5: .csv file with the ratings across all timelines, movies and target audiences

Realize how in the above ratings, only one section (that of Release(general) for Green Book) edges below 0 i.e at -0.019 to showcase presence of a case where the general consensus was more negative than positive. Which is expected as only the best movies get nominated for oscars so the sentiment is going to be positive.

3.3. Plotting

All the data we got was put in a dataframe and then basic properties of the data such as mean, variance, mode etc. were found to analyze the results.

We had 9 columns in our data frame along with 8 rows, the rows are divided into two parts for the analysis popular movies and movies which were not as mainstream-

1. Popular movies- A star is born, Black Panther, Bohemian Rhapsody
2. Less known movies- Roma, The Favourite, Green Book, Blackklansman, Vice

To plot the data a lot of combinations of columns and rows were taken each combination was then analysed to check for significant result and as expected the popular movies all exhibited similar trends.

Starting out with a general plot of all the movies with all the parameters, different combinations were tried and tested.

4. Results

With such amounts of cross sectional data, a lot could be derived and was. We now get to play with our ratings and highlight potential reasons for dips and raises.

Firstly, the consensus around the general audience shows us a very **united and surprising result**. One which sums up the need to do this study. As below from the graph below, public opinion of all the movies increased significantly from the time it got released. An event i.e nominations brought the fame upon the eight said films and because it got regarded by The Academy, people started finding reasons to like it. That can be said especially in the case of Green Book, whose negative rating peaked to above 0.2 just across the nominations.

Secondly, the public opinion for all the movies except two went up after the awards ceremony. The **public tends to sympathise with those who failed to win** and it shows heavily. The two which received a negative growth were - Green Book and Blackkklansman. Green Book won and so the opposite happened - **people tried to acknowledge how it wasn't even that good.** Blackkklansman though, had a different case as an incident around its director at that time lowered the ratings.

4.1 General Public

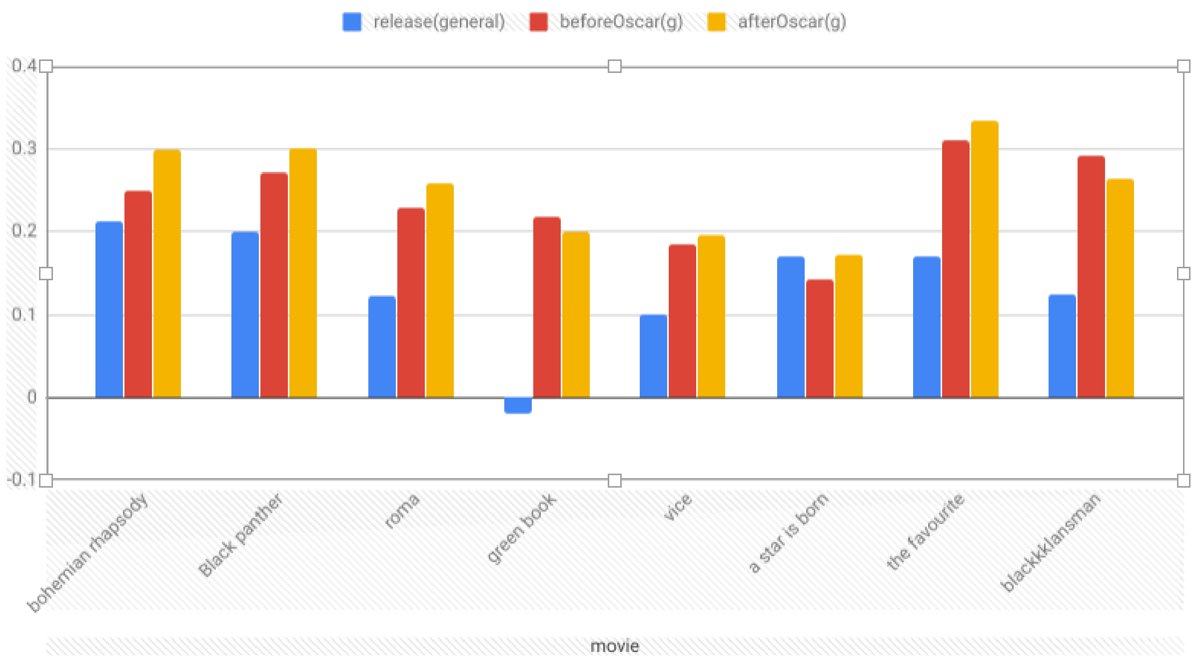


Figure 6: Graph for general audience across movies and timelines

There general folks show a huge disparity from when the movie was released and when it was nominated, which tells us that when an institution as big as the Academy nominates certain movies calling them the best the public tends to believe that and hence the sentiment is far more positive, as we can see from the graph the polarity of each and every movie increases from release to after the nominations, a movie like Green Book even goes from having a slightly negative review to a positive one.

4.2 Critics

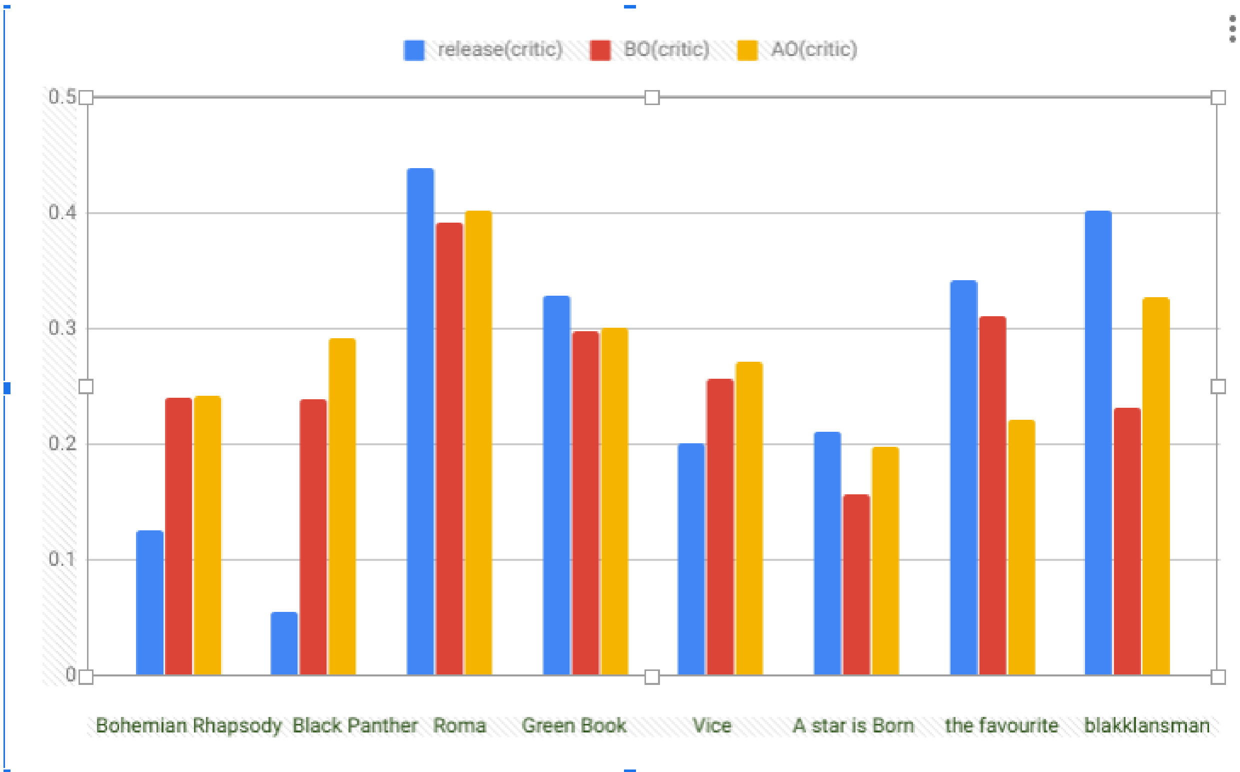


Figure 7: Graph for critics across movies and timelines

Thirdly, the critics almost always got it right. For seven out of the eight movies, critics opinion at the time of release, ten days before the Oscars and ten days after it were all generally high. Goes on to show the difference between them and the general audience.The critics review are similar throughout the timeline barring some anomalies about which we'll talk about in a later section, this also shows that a person who has to judge the movies unbiasedly isn't affected by a sudden major event because ideally he cannot take that into consideration. Also the dataset for critics wasn't large so the results aren't concrete.

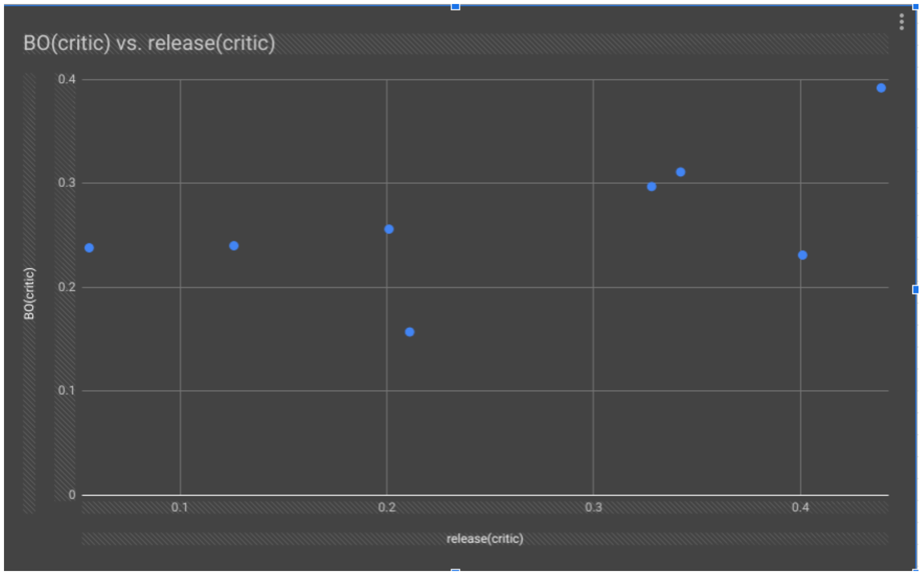


Figure 8: The critics form a linear almost unchanged opinion

4.3 Enthusiasts

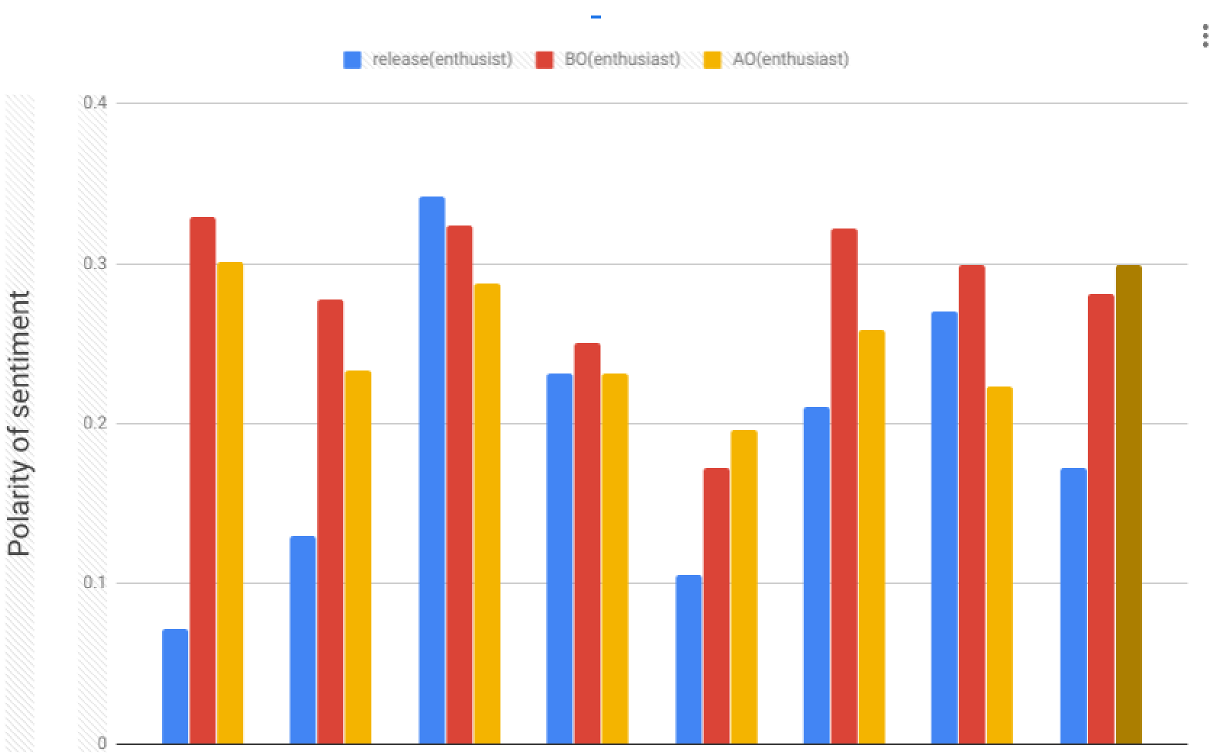
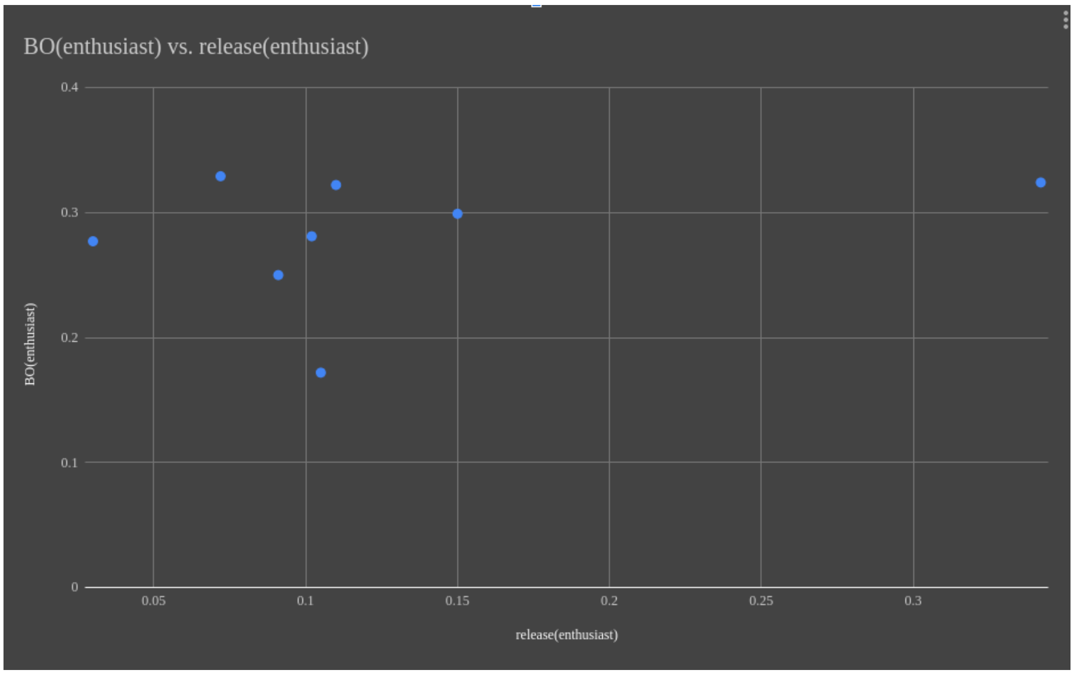


Figure 9: Graph for Enthusiasts across movies and timelines

The enthusiasts are much like the general although the disparity is not that extreme, the clear effect can been seen from the graph.



The enthusiasts polarity changes a lot as we can see.

4.4 Comparisons

4.4.1 General public after Oscars vs Critics before Oscars

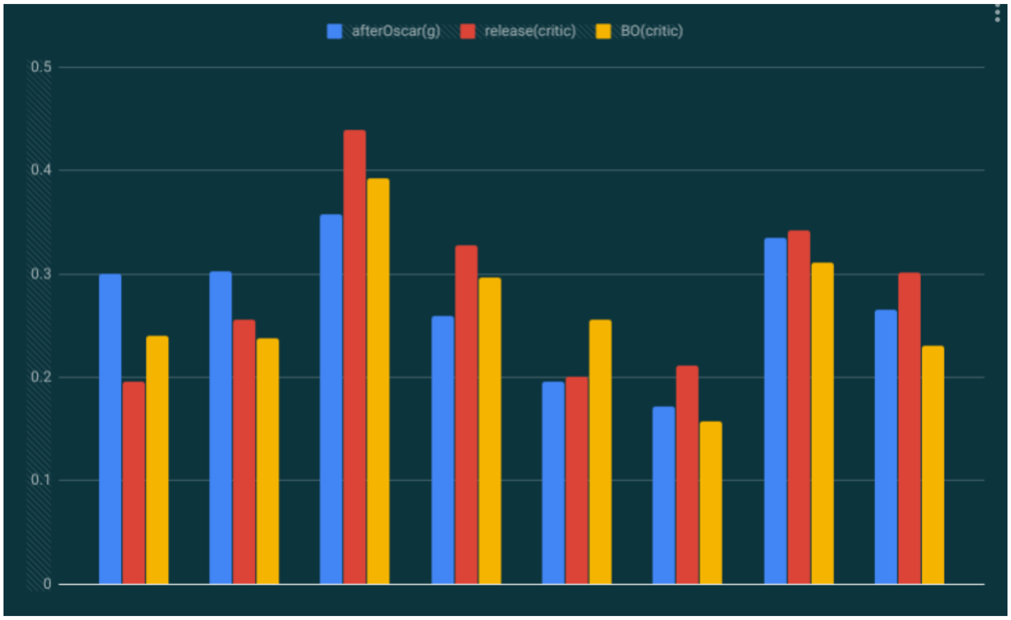


Figure 10: Graph comparing Critics and General Audience

The gap between critics and the general audience has to be expressed. Here it shows that not only are critics most likely to find a movie better after the Oscars, the public opinion too tries to shift. The public opinion shows a disparity if we compare it with the critics around the release while the critic is more likely to give an unbiased opinion the Oscars are drastically changing the views of the public.

Thirdly, the critics almost always got it right. For seven out of the eight movies, critics opinion at the time of release, ten days before the Oscars and ten days after it were all generally high. Goes on to show the difference between them and the general audience.

4.4.2 After Oscars

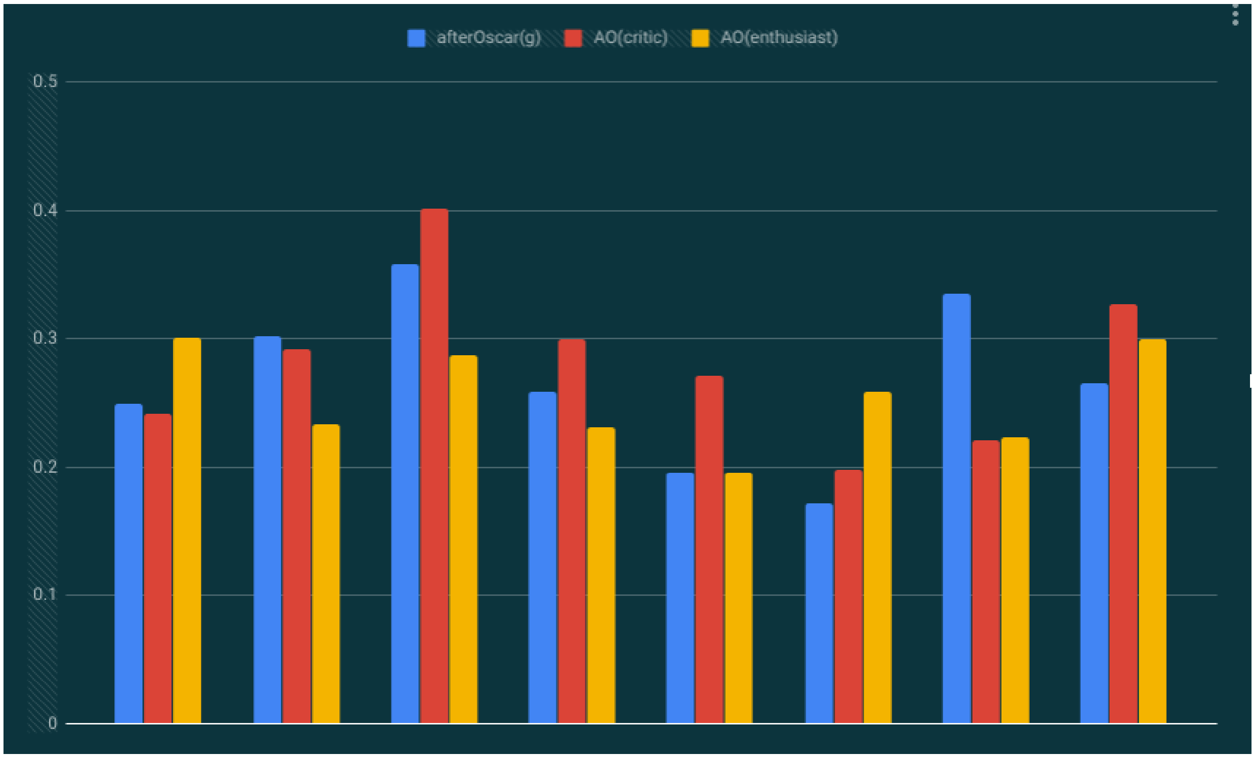
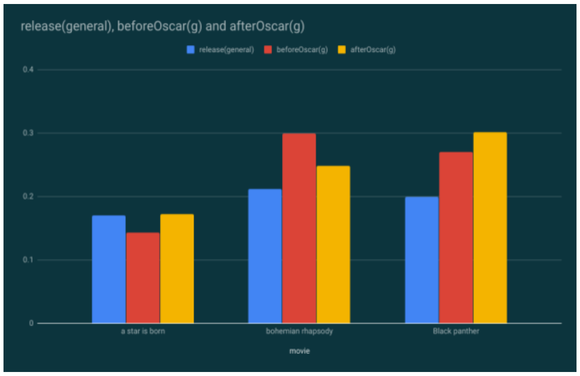


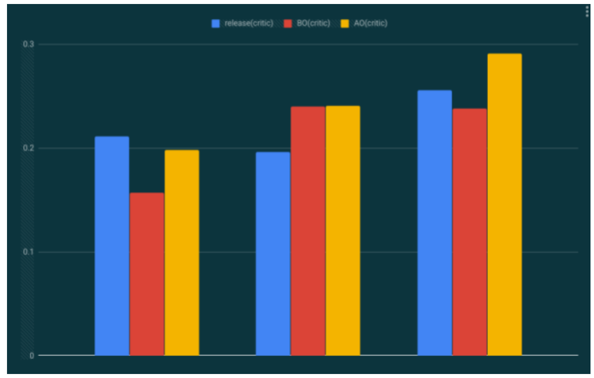
Figure 11: Graph for the three target audiences compared

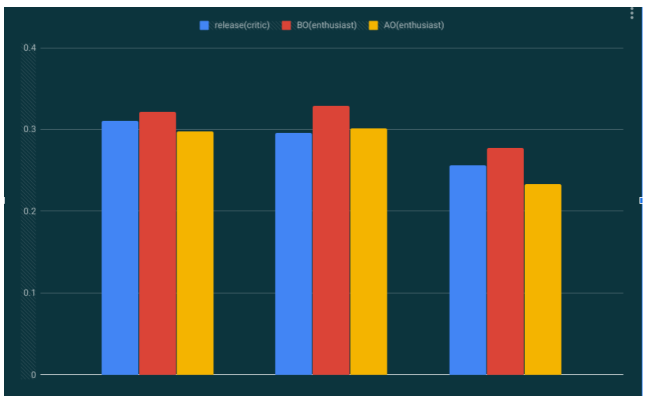
After Oscars all categories form a similar positive opinion on the movies, showing the power of an event on the human mind.

Also the sentiment is also similar throughout the 3 categories which were so far apart before oscars.

4.4.3 Popular vs Unpopular movies







Figures 12,13,14: Popular and unpopular movies compared

The above charts represent the sentiment of popular movies for all 3 categories and as we can see the opinions for popular movies with big name stars doesn't change nearly much as they do for the smaller films.

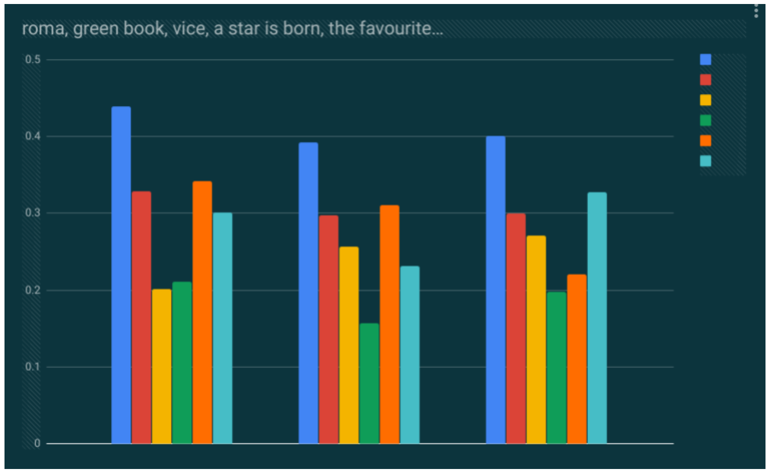


Figure 15: Unpopular movies

As we can see the sentiment of smaller films varies a lot more than there popular counterpart, which shows us the influence of stars in Hollywood.

4.4.4 Before and After Oscars

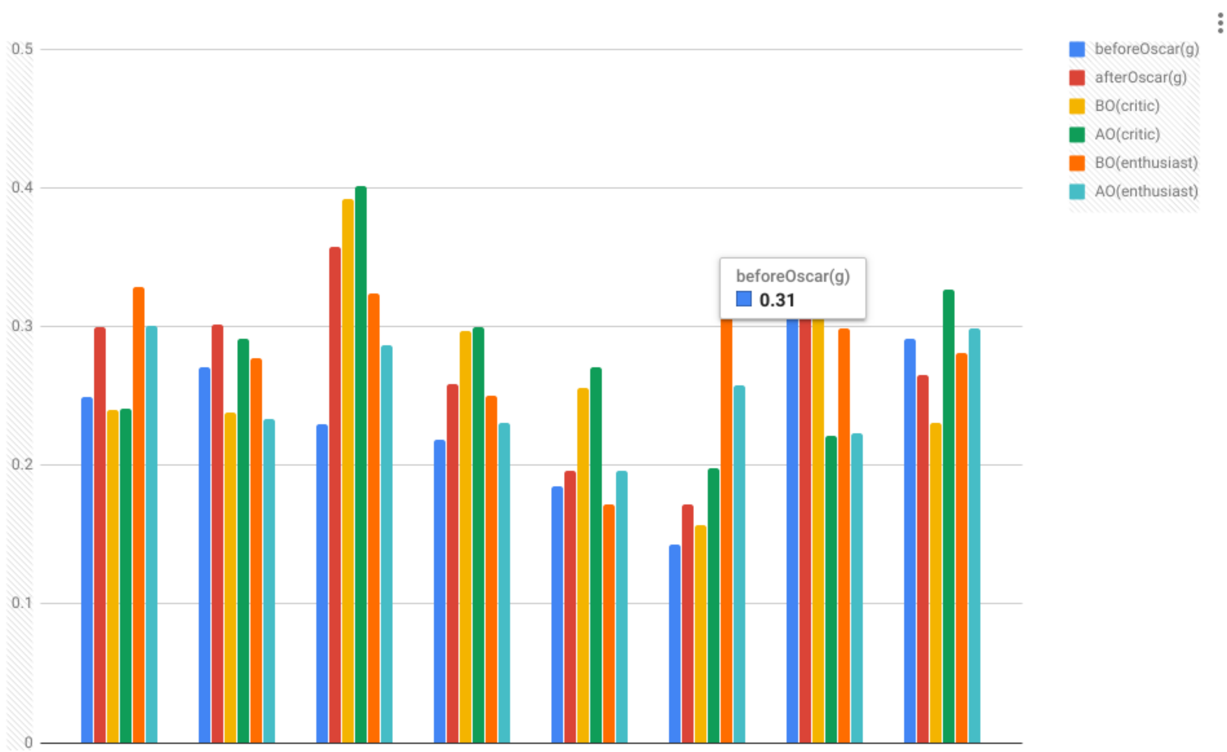


Figure 16: Before and after the Oscars

The chart above represents the sentiment before and After the Oscar remain similar for each category, which shows the academy nomination is far more significant in peoples eye than the actual winner .

5. Conclusion

The results derived above pave way to the bigger conclusion that the change in opinion is in fact a result of a change in the environment around us. We have computationally calculated and shown the same. The specific results mentioned further talk about the smaller details.

6. Future Scope

The quantification of the tweets down to their emotional aspects can be used to further research the impact events have on opinions. Such a model can go a long way in understanding the society we live in and can have ethical and commercial implications. Research papers have gone in depth about analysing the impact of well structured big data on advertising and marketing. [4] Public awareness around knowledge that there are sourced factors which influence decisions and opinions can open them up to what is propaganda and intentional, and what is not.

Finally, what we have done with specific target audiences, target timelines and target subjects can further use geo-tagging and Twitter handles' data to analyse what are the factors that can contribute to a change in opinion.[5] We talk about demographics, race, past and even genes contributing to likes and dislikes, a model of our kind only enhanced to work on more factors can quantify those aspects as well.

7. References

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