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Joseph Asamoah

University of Salford, j.s.o.asamaoh@edu.salford.ac.uk

Adam Galpin

University of Salford, A.J.Galpin@salford.ac.uk

Aleksej Heinze

University of Salford, A.Heinze@salford.ac.uk

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What is video virality? An introduction to virality metrics.

Joseph Asamoah

The University of Salford, Salford UK.
Email: j.s.o.asamaoh@edu.salford.ac.uk

Abstract:

Video virality is acknowledged by many marketing professionals as an integral aspect of digital marketing. It is being mentioned a lot as a buzz word but there has not been any definitive terminology ascribed to what exactly it is. It is common to hear a phrase such as, “this video has gone viral”. However, this raises fundamental or philosophical questions such as, “what exactly is virality – Is it a video with large views or shares, or both”? If it is “How many views or shares must a video have to be considered a “viral” video? “How quickly must a video be passed on from person to person to achieve “virality” and how long must a video stay viral? Is there a relationship between a videos views and shares, likes and “share through rate” and dislikes and “share through rate”? These questions pose a conundrum and hence to piece the missing puzzle an amalgamation of literature needs to be synthesised to answer these questions adequately.

The current study reviews the extant literature on viral marketing, explores the differences of opinions presented and associated challenges each of the definitions has in order to develop a working definition for video virality and how it can be measured. It also brings to light a much less focused construct identified as popularity whose emphasis is on the staying power of viral videos. The virality growth model was developed to predict the level virality and compared with other models in literature.

In order to derive the working definition for virality, data from a pre-selected range of viral YouTube videos were collated. New formulae such as the STR (Share Through Rate), Relative Likes and Relative Dislikes was created to assess the extent of virality. Based on the STR formula, a threshold for virality was established and then categorized to give a greater insight on the different levels of virality. Next, the Spearman’s rank correlation coefficient was used to measure the relationship strengths among the set of video viral drivers i.e. between views, shares, share through rate, likes and dislikes. The Spearman’s rank correlation was preferred for the analysis as the data is monotonic (nonlinear).

This paper offers a conceptual and practical understanding of video virality. The concept of viral video marketing is advanced by introducing a “Share Through Rate” and “Relative Likes Rate” to the definition of viral video marketing as well as the distinctive categorizations. Finally, and most significantly, the study provides an exhaustive answer to the key fundamental questions such as what is used as a basis for virality and what it takes for a video to go viral.

Keywords: Virality, Popularity, Share Through Rate, Relative Likes, Relative Dislikes, Propagation Rate.

1.0 Introduction

The UK Internet Advertising Bureau 2015 reported that the growth in digital marketing is partly due to the two trends – mobile and video advertising, with video in particular worth £442 million in 2014, a rise of 43% YoY (Year on Year) (Iabuk.net, 2016). This is supported by international trends where for example in the US, brands and their advertising agencies are increasingly adding viral videos to their strategies. For example, in a survey of 40 executives at top US agencies and media buying firms, the majority (72.1%) reported that their clients were interested or very interested in using a viral video as part of their marketing campaigns and 86% had created at least one video in the first eight months (Eckler and Bolls, 2011). But in layman's terms, what exactly are viral videos? (Broxton et al 2013; Feruz Khan and Vong 2014) defines viral videos as *videos that are distributed from persons to persons across social networking sites, blogs, email and instant messaging resulting in the videos becoming popular*, though this can also occur through paid promotion and through the amplified effect of TV broadcasting (Dafonte-Gomez, 2014). A more detailed definition can be found from Southgate, Westoby and Page (2010:350) who described viral videos as *'unpaid peer-to-peer communication of "provocative" content originating from an identified sponsor using the internet to persuade or influence an audience to pass along the content to other'*.

The benefits of going viral are immense and of great potential value to digital marketers, especially with the growth of online video which has seen a huge rise over the years, enhanced by the use of online sharing platforms such as YouTube, which is expected to account for 69% of all consumer traffic worldwide by 2017 (Cisco, 2015). With online videos rapidly becoming a means for users to satisfy their information and entertainment needs, businesses that fail to include it in their internet marketing strategies would lag behind as it is the future of content marketing (Trimble, 2015). The potential reach of video is massive; YouTube, which is the online video host to be used in the study, receives more than 1 billion unique visitors each month (YouTube.com, 2015). This can be attributed to producing different video content for various

customer engagement touch points, linking it with different social media channels, and using targeted advertising (Clampa and Goeldi, 2013).

The need to obtain viral views from online sharing platforms such as YouTube is important as *Viral views* provide free advertising and beyond it can represent deeper brand engagement which allows for further interaction such as replaying the video, rating it (liking or disliking), adding a comment and most significantly *forwarding it to a friend to continue the viral cycle* (Southgate, Westoby and Page,2010). Viral videos have had a profound social impact of many aspects of society such as politics and online marketing. For example during the 2012 US presidential election , Obama style and Mitt Romney style , the parodies of the famous Gangnam style , both peaked on election day and received approximately 30 million views within a month before election day (Jiang et al.,2014).

In understanding the phenomenon relating to the nature of virality, Mashable a digital marketing and technology website developed an algorithm based on predictive analytics to show how quickly people are sharing articles which they produce on the social web. The algorithm known as *Mashable velocity* scours the social web collecting data and how people engage with *published articles*.

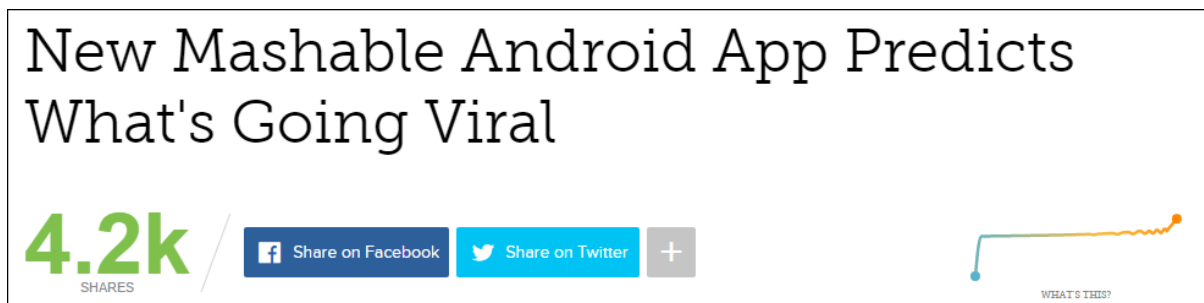


Figure 1.0

Though this technology does not focus on videos which is the subject of this study it does indicate that there have been strides to understand virality and how it affects consumers. In terms of videos, Broxton et al (2013) developed a model to rank viral video blogs and advanced the construct on video “socialness” whilst Jiang et al. (2014) proposed a model to forecast the future peak day of viral videos.

1.1 How quickly must a video be passed on from person to person to achieve “virality”?

(Broxton et al.,2013) in the study on virality identified its core characteristics. It was found that videos that gain traction in social media (*Secondary/Social sharing*), do so rapidly, often within hours of initial reports and fade quickly. The stats are backed by the data which indicates that 25% of the daily views on YouTube come from person to person sharing, with the first day averaging at 34% then dropping gradually to around 16% in the third month. This fact can be supported by studies done by cha et al (2007) who studied the *popularity cycle* of YouTube videos finding out that the most popular videos are ones that have been recently uploaded. (Broxton et al.,2013) also found out that blog posting is a driving force in a video going viral, with 47% of all viral videos on YouTube having links from external sites.

1.1 Viral Video Example



Figure 2.0

Classification: viral video

The figure above depicts an example of a YouTube video that can be deemed to have gone viral based on a *subjective* fact that it has obtained over 2 million views, has over 1000 shares and 5000 likes. However, in this loose notion, will the same video be considered to be more of a *viral* video if it had the same number of views, shares and other engagement data within *3 weeks as opposed to a year before it steadily began to rise, what triggered it?* The underlying graph above

brings up the phenomenon of how a viral video grows which varies from one viral video to another viral video. Watts and Paretti (2007) observed that both the *propagation rate* (the degree to which people are willing to pass a video to another) and *the scale of initial seeding* determine the size of the viral video audience, the model is based on the analogy of an infectious disease. The hypothesis is that a viral video starts with a seed of individuals who spread a message by infecting their friends, where the expected number of new infectious people is called the Propagation Rate or PR. When PR is greater than 1, each person who gets the message will, on average, spread it to more than one additional person, who does the same thing leading to an exponential growth as seen below.

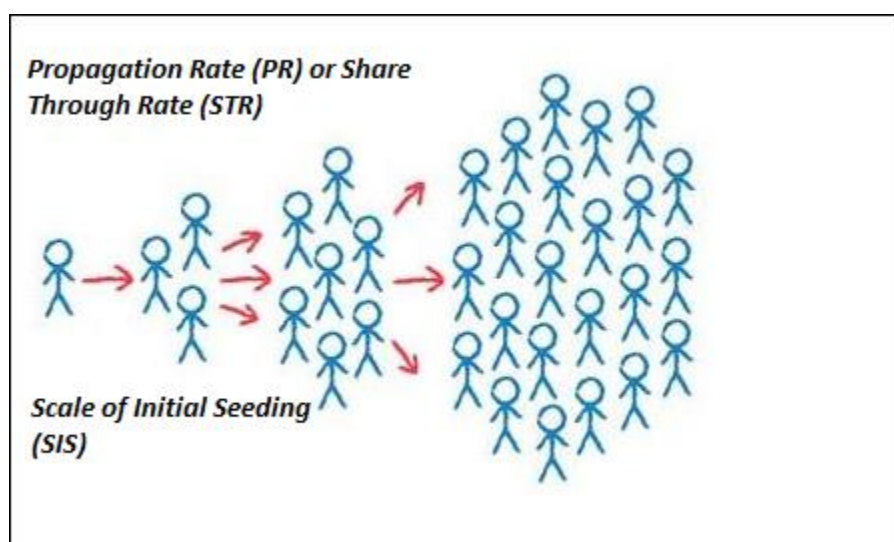


Figure 3.0

For the initial seeding to be most effective it needs to be backed by the *social media influencer* who in most cases are well connected people, celebrities, media vehicles, or anyone who has a huge following though their greater reach (Mohr,2014). (Mohr,2014) further explained that the construct has its basis from the *two-step flow model* which was first introduced by (Gosnell,1946) which hypothesized that ideas flow from mass media to opinion leaders then from them to the wider population. The model was later elaborated by Katz and Lazarsfeld (1955) to become the *extended multi-flow model* which concluded that most people based their opinions on opinion leaders that influence the media. A real life example of the model can be exemplified when Susan Boyle the 2009 Britains Got Talent Sensation performance went *viral* when she sang a rendition of the Les Miserables musical 'I dreamed a dream'. The video took an

instant hit on YouTube when Ashton Kutcher and Demi Moore tweets were retweeted repeatedly, Susan Boyle became a twitter trend, instigating the YouTube counts to rise (Mohr,2014).

For video marketers interested in such trends it is possible to predict the *level of views* which arguably can be one concrete metric for measuring virality using a *continuous* or *exponential* growth (Ciese.org ,2016). Based on the formula the *virality growth model* can be depicted where:

$$V(t) = Pe^{rt}$$

V(t) = amount of views after t days

P = Initial views

e = exponential constant

r = STR (Share Through Rate) or PR (Propagation Rate), where STR = shares/views.

t = time in days.

The virality growth model can be used to predict a videos views during the period where the *growth of a video is continuous*, as seen in the example below the model predicts the number of views the video is likely to get within 4 days based on the existing STR or PR.



Figure 4.0

$$V(t) = Pe^{rt}$$

$$V(t) = 24,585,211e^{(185,108/24,585,211)t}$$

$$V(t) = 24,585,211e^{(0.0075)t}$$

$$V(t) = 24,585,211e^{(0.0075)t}$$

$$V(t) = 24,592,587$$

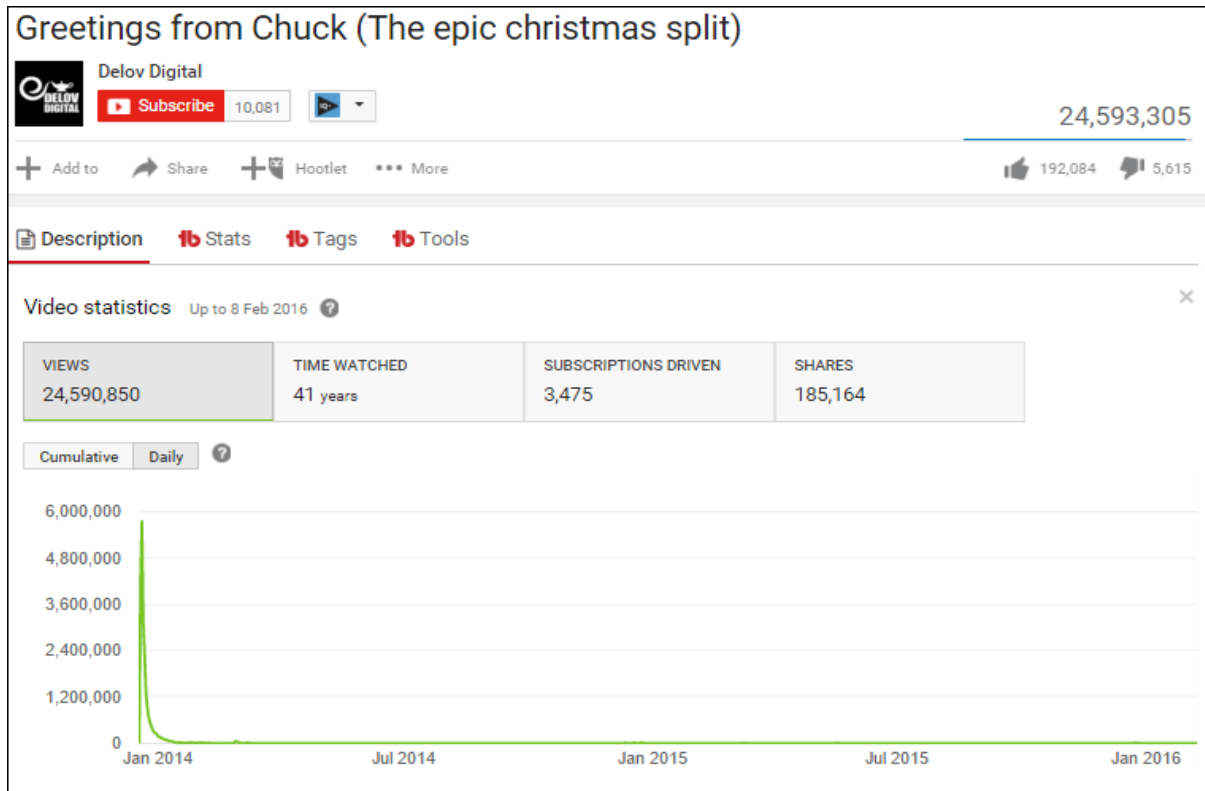


Figure 5.0

Actual result is > 1,737 expected views.

Classification: Memoryless

Video

There are other advanced or more complex models for predicting a videos popularity prominent among these is the *Szabo-Huberman* model that predicts the total number of views (i.e the popularity) of a piece of content at target date t_t based on a linear function of its total number of views at an earlier reference date $t_r(t_r < t_t)$ (Scazo and Huberman,2010).

Pinto et al. (2013) acknowledged that though the model is reasonably accurate it does have some shortcomings. In particular, where two similar pieces of content may have very similar popularity at the same reference date and yet exhibit different popularity behaviours thereafter. They therefore came up with the MBRF model that leads to an accuracy gain of 71% over the S-H model.

1.2 How long must a video stay viral?

A video's *popularity* can be categorized into four main classes (Pinto et al.,2013). The first class of video can be classed as *memoryless*. *Memoryless videos* attract little attention or experience

some popularity fluctuation through a simple stochastic process. *Viral videos* experience a popularity peak that emerges through a word of mouth epidemic – internal like propagation process as seen in **figure 2.0**. Their popularity increases slowly up to a peak decreasing slowly afterwards. *Quality videos* experience a very sudden peak in popularity possibly due to some external events. (Such as being featured on the first page of YouTube or due to a tweet from a high profile celebrity) and a slow decay afterwards as users propagate the videos among themselves. The last but not least are *junk videos* which also experience a burst of popularity but in contrast they do not *spread through the social network* and thus their popularity drops afterwards.

In further understanding the nature of virality, Harvard Business Review (2015) found out that nearly 18% of internet users share at least once a week and at least 9% share daily. Thus, companies should find ways to reach these *supersharers* who are responsible for more than 4/5 of all total shares. It was also observed that timing counts as the more shares a video generates during the first two days after launch, the higher the viral peak and the greater the overall volume of shares. It is important to emphasize that view sources are crucial factors for video popularity as already indicated however, they are quite a few such as the keyword – based search engine, related video recommendation, video highlight on YouTube homepage, channel subscription (Which have been excluded in the literature) and *embedding capabilities on webpages, blogs and social networks* (Zhou et al, 2015)– which within this literature suggests is the main way a video gains popularity or attains virality.

2.0 Literature Review

Alhabash et al. (2015) highlighted that virality can be construed as a *social norm* as stemmed from prior research which are integral to the theories of planned behaviour. Alhabash et al. (2015) explained that it is possible to observe an effect of social norms by algorithmic measures of *popularity* and *virality*, where virality of online content (high likes, shares and comments) reflects acceptance of the advocated behaviour. These metrics of virality are often correlated where a video with a high number of likes, also has high shares and views – as supported in this research in **section 4.0**.

2.1 What is a “viral” video?

Feder (2014) explored the construct of virality theoretically in some detail whereby he assessed that virality was dissected into 4 notions: *propagation, reach, network and speed*. The notion of reach stems from the fact that a video shared by an influencer or a celebrity on a social media platform such as twitter with over a million followers is expected to do better than if its shared by common people, the practicality here is filtering out a video with over 2,000 shares to determine who is an influencer and ordinary viewer. Alhabash et al. (2015) expressed reach simply in terms of viewership and the sharing of content. Then comes the notion of speed and propagation thereby how long does it take for a video to go viral? Hence, the question is whether a video getting only 100,000 views on YouTube network in 3 days and suddenly coming to a halt would be more viral than a video that obtained 500,000 in two months? *The fundamental questions arise such as at what point does a video become viral and how can it be determined? Is the key to answering this question formulating a formula that encompasses the rudiments of a specific video engagement?*

Alhabash et al.(2015) also identified the problem and argued that there is inconsistency in the industry with regards to specifying a single metric for assessing whether a piece of content is viral or not. For example, Adweek *regards the number of shares* as the metric to assess the virality of an online advertisement (Nudd, 2014) whilst AdAge.com (2015) *highlights the number of views*. To solve the ambiguity, this research (*i.e. answering the main key research question – what is virality*) will first bring to light a common error among industry experts where *views* and *shares* are used interchangeably to denote virality which is not the case and much more complex as explained by Broxton et al. (2013) where evidence indicates that not all highly shared videos generate a large number of views, however, highly shared videos tend to generate more views over a shorter period of time than less shared videos. For e.g. which of the following will one consider to be a more viral video?

YouTube Video A	YouTube Video B
Views: 100,000	Views: 200,000
Shares: 10,000	Shares: 25,000
Time since upload: 6 months	Time Since upload: 2 years

Table 1.0

The basic formula for virality in this assessment will be the shared through rate of the video (Which is the number of times a video is shared when viewed)

Share through rate (STR) => shares/views

YouTube Video A

⇒ $10,000/100,000 * 100$

⇒ 10%

YouTube Video B

⇒ 12.5%

Hence Video B, has a higher virality variation by 2.5%. It is worth noting that the independent analysis of views and shares can give a significant outlook on the scope of virality though it does not depict the whole picture where *popularity* also needs to be considered.

As explained, prior studies suggests that viral videos do not continue to generate social views across longer periods of time. To understand this phenomenon, a Popularity Ratio can be culled from (Broxton et al ,2013) where:

$PR(\text{Video}) = \text{Views in the second month} / \text{views in the first 10 days}.$

Since we have already established that uniquely using views is not best metric to identify virality the formula can be advanced to:

$PR (\text{Video}) = \text{Share Through Rate in the second month} / \text{Share Through Rate in the first 10 days}.$

Relative likes: Atkinson (2013) noted that likes and dislikes are significant in order to perceive users interests and are a good indicator if a message is being conveyed across appropriately. The concept of relative likes is interesting as when measured with views it can show a significant level of virality or “negative virality”. For example a study done by (Sen and Lerman, 2007; Wojnicki and Godes, 2008) found that a strong correlation exists among the likes and dislikes received by video and the views count suggesting that content virality on YouTube may take either a positive (i.e. a video goes viral mainly because it is liked and appreciated) or a negative form (i.e. a video goes viral mainly because it is disliked and not appreciated). This finding has very important implications for video marketers, for example, strategies should be in place to

encounter negative virality (the phenomenon that content over YouTube is viral in a negative sense); failing to do so may hurt a brand name (Feruz Khan and Vong,2014). A good example of negative virality is “Rebecca Black”, YouTube video which went “viral” with *a share through rate of 0.19%* as at the time of writing. The Video had a relative like percentage of 357.5% which computes as dislikes/likes.

Through an empirical study Yin et al. (2012) noted that users can display positive or negative opinions about items (such as the like/dislike) on YouTube. As they are either *conformers*, voting due to opinion of the majority or mavericks who vote in disagreement with the majority. They argued that an individual user exhibits both of these personalities to some degrees, and that when a user votes on a specific item, one of these personalities prevails. Though understanding the determinants of virality is beyond the scope of the paper, its worth mentioning *that consumers are drawn to videos that make a deep emotional connection* (Berger 2011; Harvard Business Review 2015; Russel 2014). The use of animals especially puppies has been a popular success. Budweiser’s puppy love super bowl commercial as at the time of writing has harnessed close to 50 million views. The secret was simple; it drove mass viewership and sharing online. The Harvard Business Review (2015) also found out that *social motivation* was a factor for people sharing videos, elicited motivations such as opinion seeking, social utility, self-expression, social good etc.

To support this construct in theoretical terms Rodriguez et al. (2015) exemplified the SSE (Social Sharing of Emotion) theory to indicate a phenomenon where a person (Conformer or Maverick) will share an emotional experience with another when it is considered potentially beneficial, be it **positive**, **negative** or **bivalent**. Rime (2009) explains that positive valence occurs when positive affect is expressed (“happiness or contentment”), negative valence occurs when negative affect is expressed such as (“Sadness, anger or fear”), whilst a bivalent affect occurs when there are conflicting feelings. In practical terms a YouTube video whose likes is more than its dislikes can be seen as positive, where dislikes are more than the likes it is negative and when it is at par it can be considered as bivalent. *The table below shows the relative likes data for all videos which are positive.*

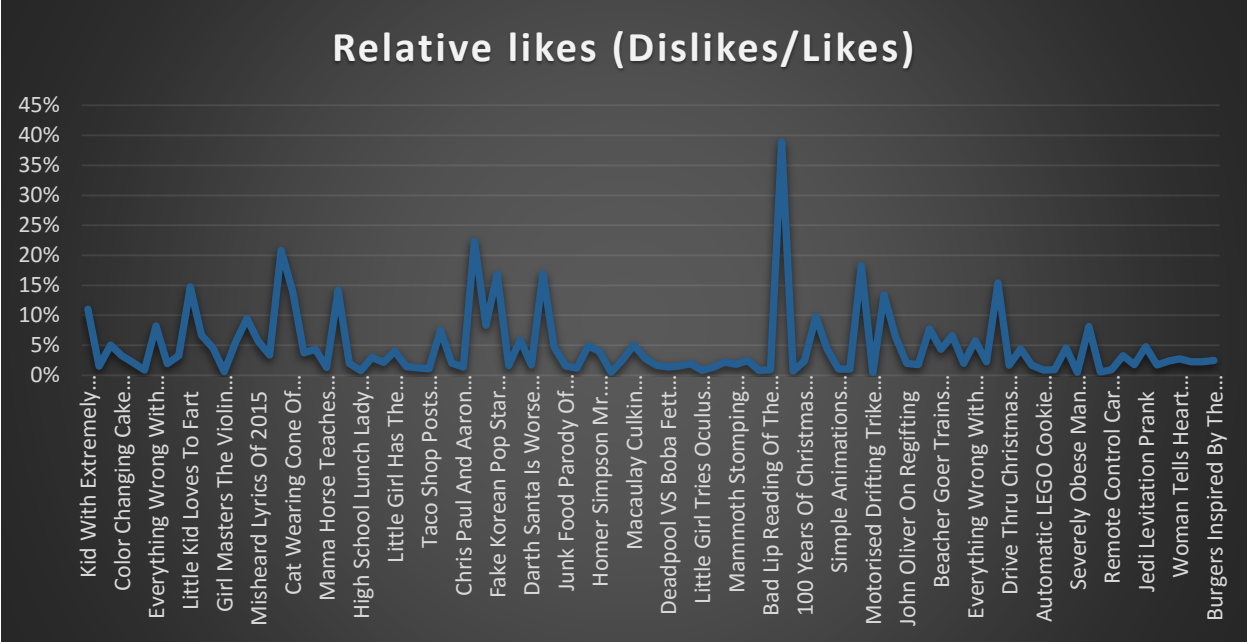


Figure 6.0

The video with the highest relative likes (positive) is the Google – Year in search 2015 as seen below.

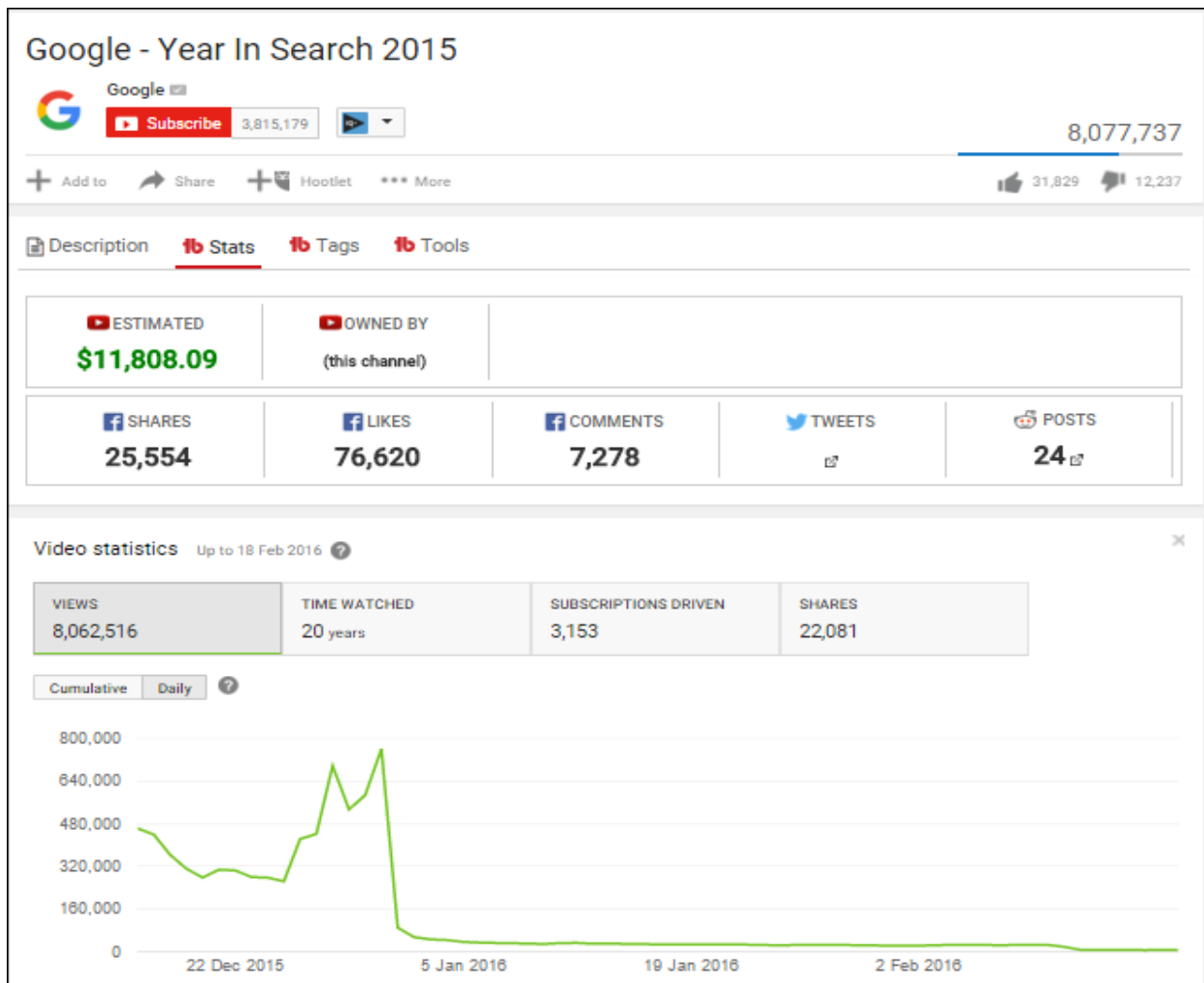


Figure 7.0

Classification: Quality Video

The positive emotion rated video had high relative likes rate signalling that it had some mixed emotions from users, as expected its popularity waned in January indicating a loss of interest or *buzz*. On the other hand, the positive emotion rated video that had the least relative likes rate also showed a *similar trend* despite the fact that it did not incite mixed feelings as seen below.

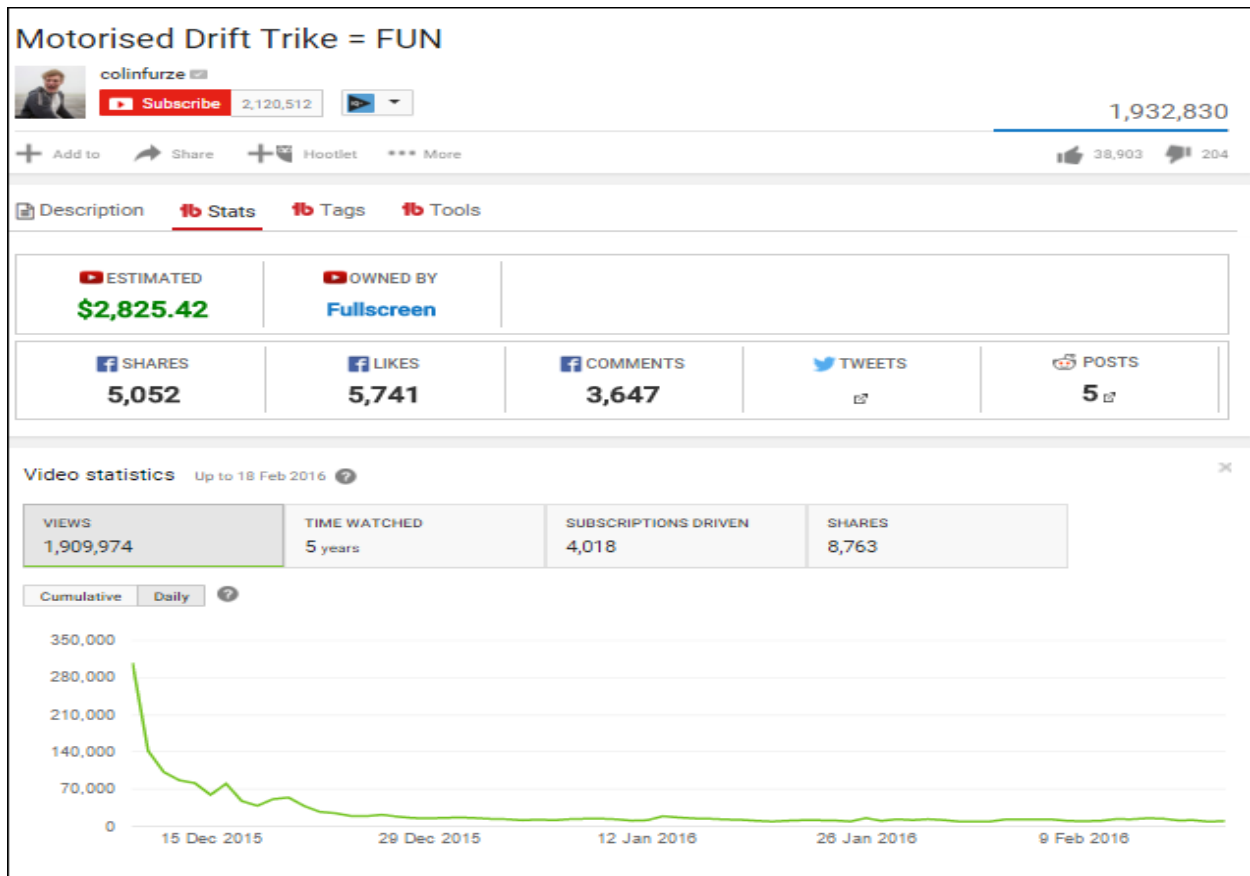


Figure 8.0
Video

Classification: Memoryless

It can be hypothesized from the two video stats that the popularity or the staying power of a video is not highly correlated to the positive emotions of a video. A more interesting outlook will be to assess the nature of a negative emotion type video of which are very few. Nevertheless, a good example will be the “Rebecca Black – Friday video” as seen below.

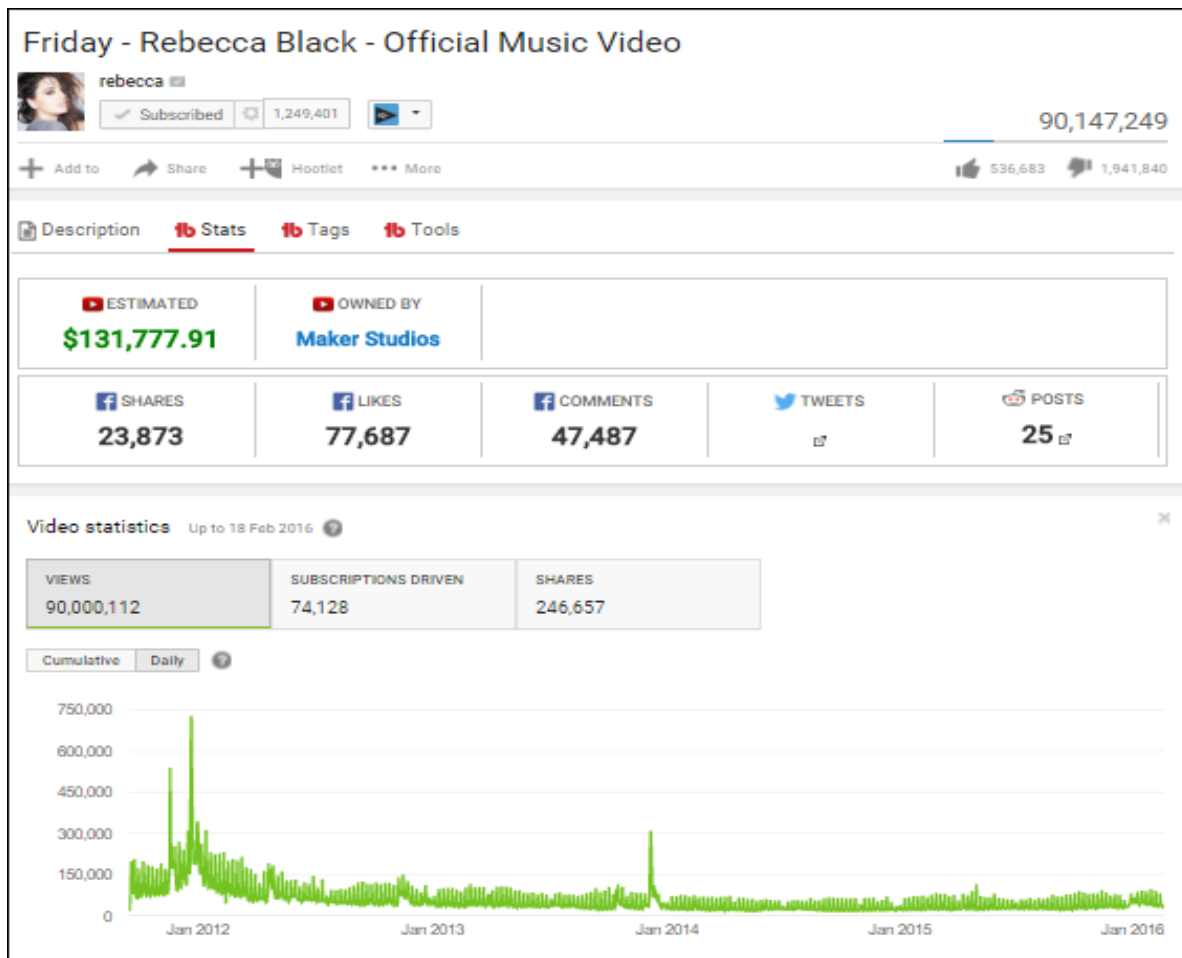


Figure 9.0

Classification: Viral Video

Negative emotion type videos are usually characterized by having the relative likes rate $>1\%$. In this particular example the *relative likes rate* is 3.62% with a Share Though Rate (STR) of 0.27% . Though this video currently is not trending within the *certifications* (See **Table 2.0**), it had moments with high viewing peaks, as it continues to receive views and shares momentarily. These kind of viral videos in its true sense can lay dormant and erupt in terms of engagement as it did in January 2014 perhaps due to a trigger. This video went on record to be the worst video ever uploaded on YouTube for disliked videos (Gornstein, 2011) - and still is.

(Berger, 2011) who supports the same view not only theorised that certain content evokes emotions but also went further to state that emotions characterised by high arousals such as anxiety or amusement will boost sharing more than emotions characterized by low arousals such as sadness. The (Harvard Business Review, 2015) from its study of emotions on YouTube videos noted the top 4 most positive emotional responsive that will make users share as warmth (58%),

Happiness (56%), Hilarity (31%) and surprise (10%) whilst the top 4 negative emotions include confusion (8%), Contempt (8%), Disgust (4%) and anger(1%). Tucker (2015) went a step further in a different study to understand persuasion in viral videos instead of looking at the drivers of virality as done by Berger and Milkman (2012), Eckler and Bolls (2011) and Peter and Golan (2006). The results which used survey respondents for two distinct videos were interesting as it indicated that there is a *significant negative relationship between total ad views and ad persuasiveness. In simple terms, the ads that receive the most views are less able to persuade consumers to purchase the product.* However, it was noted that video ads that are successful at not just provoking consumers to share the videos but also take time to respond to the videos through comments appear more successful. Tucker (2015) noted that video ads that receive high views because they are outrageous are also less persuasive as a result of the same outrageousness. In contrast ads that are humorous can achieve high views and simultaneously be persuasive.

3.0 Methodology

From a positivist standpoint, a quantitative analysis was used for the study. Oates (2006) describes data generation as the means in which empirical data is produced. Where quantitative data is numeric data which may comprise website hits, number of employees, annual turnover etc, in this case the quantitative aspect will comprise YouTube Video hits which will be collated and analysed statistically. In the first phase, data is collated and sorted based on the STR (Share Through Rate) from highest to the lowest in order to establish the range and the mean of the viral videos. The videos are then categorized on the music certification threshold (Gold, Platinum and Diamond) using the STR as the indicator. To appraise the relationship between video virality and a videos likeability this study will make use of the Spearmans Correlation coefficient instead of the Pearson correlation since the data collated is not linear in nature but monotonic (Hauke and Kossowski, 2011). The Spearmans correlation assesses how well an arbitrary monotonic function can describe the relationship between two variables, without making any assumptions about the frequency distribution of the variables. Unlike Pearson's product-moment correlation coefficient, it does not require the assumption that the relationship between the variables is

linear, nor does it require the variables to be measured on interval scales; it can be used for variables measured at the ordinal level (Hauke and Kossowski, 2011).

METHOD: 100 viral videos were selected from the online viral video database (<http://www.viralviralvideos.com/>). The selected videos were picked on the basis of obtaining the following front end YouTube Analytics Data: number of views, number of shares, subscriptions driven from views and total opinions (Likes + Dislikes) as seen from **figure 10.0** below.

- Viral YouTube videos which had opted not to show their YouTube analytics data were rejected
- YouTube analytics data was culled between the 29th – 31st of Dec, 2015 and put on the spreadsheet as seen in **figure 11.0** below.

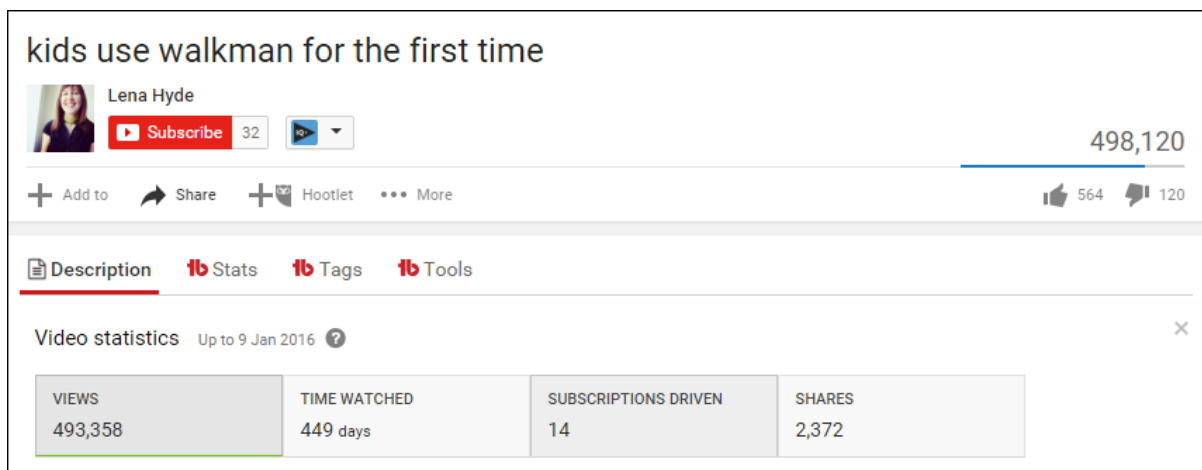


Figure 10.0 YouTube Analytics video example

	Views	No of shares	No of subscription Driven	Likes	Dislikes	Total Opinions	Relative likes (Dislikes/Likes)	Share Through Rate
Viral Videos								
Kid With Extremely Flexible Neck Will Shock You	2,421,182	5,465	31	7,851	865	8,716	11.02%	0.23%
Woman Tells Powerful Story About Giving A Piece Of Chocolate During The Holocaust	977,364	11,810	1,147	6,562	99	6,661	1.51%	1.21%
Dog Hides Entire Sandwich In His Mouth	128,905	403	7	2,641	133	2,774	5.04%	0.31%
Color Changing Cake Will Mesmerize You	534,482	716	17	793	26	819	3.28%	0.13%
Modern Trailer Of Star Wars: The Empire Strikes Back	1,264,398	5,166	134	16,466	349	16,815	2.12%	0.41%
Who Owns Really Antarctica	292,302	423	200	22,373	195	22,568	0.87%	0.14%
Everything Wrong With The Lion King	2,556,907	2,393	880	44,538	3,662	48,200	8.22%	0.09%
Budget Remake Of Star Wars: The Force Awakens Trailer	92,298	798	101	7,523	147	7,670	1.95%	0.86%
Chunk Of Ice Flies Off Of Car On Highway And Smashes The Windshield Another Car	398,673	454	6	523	17	540	3.25%	0.11%
Little Kid Loves To Fart	893,129	1,822	15	3,705	547	4,252	14.76%	0.20%
Giant Squid Found In Japan	2,172,740	2,450	205	7,670	514	8,184	6.70%	0.11%
Woman Freaks Out In The Best Way After Being Surprised She's A Grandmother	5,840,159	1,042	29	7,706	351	8,057	4.55%	0.02%
Girl Masters The Violin In Two Years Compilation	1,065,079	2,338	4,050	21,319	131	21,450	0.61%	0.22%
Space Debris Over The Past 60 Years	1,254,748	2,676	65	1,547	86	1,633	5.56%	0.21%
Terrifying Footage Of Family Driving Passed Solimar Fire	108,994	173	4	391	37	428	9.46%	0.16%
Misheard Lyrics Of 2015	2,782,568	5,301	484	82,416	4,622	87,038	5.61%	0.19%
The Gym As A Wildlife TV Show	7,387,575	63,202	5,004	124,052	4,164	128,216	3.36%	0.86%
Chopping Machine TV Shop commercial	646,443	690	141	7,363	1,534	8,897	20.83%	0.11%
Cat Wearing Cone Of Shame Figures Out Drinking Hack	338,571	486	4	1,315	184	1,499	13.99%	0.14%
Parrot Sick Of The Holidays Takes Down Toy Santa Claus	3,744,874	10,001	2,660	70,533	2,627	73,160	3.72%	0.27%
What A World Champion Whistler Sounds Like	603,571	1,004	329	3,927	171	4,098	4.35%	0.17%
Mama Horse Teaches Baby Horse How To Jump	2,832,254	549	9	395	5	400	1.27%	0.02%
Giant Tornado In Holly Springs, Mississippi	566,703	572	20	1,541	218	1,759	14.15%	0.10%
Marv From Home Alone Is Still Terrified Of Kevin MacCallister	2,297,178	4,837	1,761	19,467	391	19,858	2.01%	0.21%
High School Lunch Lady Stuns Cafeteria With Christmas Singing	2,297,355	250	6	654	5	659	0.76%	0.09%
Orangutan Builds Hammock In Zoo Enclosure	742,256	4,390	138	2,449	73	2,522	2.98%	0.59%
Gorgeous Bruno Mars A Cappella Medley	452,867	1,128	667	17,875	381	18,256	2.13%	0.25%
Little Girl Has The Cutest And Most Excited Reaction To Star Wars Trailer Ever	479,940	3,286	27	3,794	153	3,947	4.03%	0.68%
Kitten Trapped In Storm Drain Is Rescued	858,542	2,949	118	21,190	305	21,495	1.44%	0.34%
Curb Your Enthusiasm Parody Of Steve Harvey's Miss Universe Mishap	641,097	4,024	12	4,212	52	4,264	1.23%	0.63%
Taco Shop Posts Security Video Of Two Late Night Burglars 'Looking For Tacos'	738,692	14,535	281	27,399	296	27,695	1.08%	0.38%
Robotic 'Dogs' Pull Santa's Sleigh	3,070,807	21,852	1,754	18,586	1,403	19,989	7.55%	0.71%
Space X Falcon 9 Rocket Vertically For First Time	2,062,328	12,190	618	15,757	320	16,077	2.03%	0.59%
Chris Paul And Aaron Rodgers Perform Trick Shots	6,463,027	9,982	3,651	115,632	1,568	117,200	1.36%	0.15%
Lexus Makes Wheels Out Of Pure Ice	747,295	1,671	146	1,414	316	1,730	22.35%	0.22%
Cat Demonstrates What Happens When He Climbs Christmas Tree	860,564	1,677	33	1,174	98	1,272	8.35%	0.19%
Fake Korean Pop Star Prank	3,402,003	6,279	1,976	10,731	1,813	12,544	16.89%	0.18%
Funerals Are A Total Ripoff	1,101,163	1,945	291	33,074	539	33,613	1.63%	0.18%
Kid Has Perfect Pitch	481,251	949	36	1,594	94	1,688	5.90%	0.20%
Darth Santa Is Worse Than The Grinch	2,287,888	38,297	3,054	72,513	1,249	73,762	1.72%	1.67%
Guy Flies On \$32,000 Flight To Abu Dhabi	871,280	1,256	457	1,582	268	1,850	16.94%	0.14%
Devils Fingers Or Octopus Fungus Emerging Is The Creepiest Thing Ever	2,750,533	918	25	489	23	512	4.70%	0.03%
Junk Food Parody Of 'Hello' Is Perfect For Your New Year's Resolution	2,278,554	78,815	1,052	26,573	421	26,994	1.58%	3.46%
Doing A Backflip While Breathing Fire Under A Giant Water Balloon	2,465,117	3,816	2,176	96,500	1,136	97,636	1.18%	0.15%
Donald Trump With A Sophisticated British Accent	843,085	3,657	445	7,128	352	7,480	4.94%	0.43%
Homer Simpson Mr. Plow YouTube Commercial	3,473,937	1,009	209	4,106	163	4,269	3.97%	0.03%
Pop Stars Sing 'Joy To The World' With James Corden In The Car	2,398,745	6,371	1,216	71,646	338	71,984	0.47%	0.27%
Sheriff's Deputy Jumps Onto Moving Semi-Truck To Save Unconscious Driver	157,309	77	1	40	1	41	2.50%	0.05%
Macaulay Culkin Returns As A Much Older And Very Neurotic Kevin McCallister	21,798,683	99,336	17,998	122,370	6,156	128,526	5.03%	0.46%
Nerd Makes Real Life Light Saber	4,711,654	12,165	2,130	30,476	848	31,324	2.78%	0.26%
Lady Gaga Performs New York, New York	997,684	7,431	568	34,648	579	35,227	1.67%	0.74%
Deadpool VS Boba Fett Epic Rap Battle	10,028,221	67,818	9,412	286,185	4,041	290,226	1.41%	0.68%
British Weather Report With Star Wars Puns	3,749,961	16,189	153	40,845	638	41,483	1.56%	0.43%
Hacker Who Built A Self-Driving Car In His Garage	781,936	4,040	661	4,956	97	5,053	1.96%	0.52%
Little Girl Tries Oculus Rift For First Time	161,997	127	7	3,460	29	3,489	0.84%	0.08%
Pouring Molten Aluminum Into A Tank Of Water Balls	3,407,861	2,523	8,363	20,567	279	20,846	1.36%	0.07%
Three Year Old Adorably Explains Why She Cut Her Hair	1,823,880	1,475	227	964	21	985	2.18%	0.08%
Mammoth Stomping Stuff In Slow Motion	1,723,641	972	1,031	62,700	1,136	63,836	1.81%	0.06%
Bad Lip Reading Of The Original Star Wars : A New Hope	5,233,976	46,852	9,357	82,008	2,024	84,032	2.47%	0.90%
Bad Lip Reading Of The Original Star Wars : The Empire Strikes Back	2,171,386	23,510	3,363	44,670	361	45,031	0.81%	1.08%
Bad Lip Reading Of The Original Star Wars : Return of the Jedi	1,659,042	15,028	2,174	35,473	324	35,797	0.91%	0.91%
Google Year In Search 2015	6,709,406	17,787	2,562	27,553	10,719	38,272	38.90%	0.27%
One Direction Carpools With James Corden	17,501,977	87,110	24,349	548,587	3,952	552,539	0.72%	0.50%
100 Years Of Christmas Toys	497,072	1,165	258	3,820	91	3,911	2.38%	0.23%
Japanese Girl Eats 100 Pieces Of Bread In One Sitting	1,123,438	2,688	2,638	11,469	1,124	12,593	9.80%	0.24%
The Reason We Think Vitamins Are Good For Us	1,267,366	4,459	561	32,686	1,430	34,116	4.73%	0.35%
Simple Animations Battle In Minecraft	11,318,923	29,581	57,963	324,843	3,346	328,189	1.03%	0.26%
Fan Made Johnnie Walker Commercial About Brotherly Love Will Give You Chills	3,381,081	22,436	1,771	39,340	405	39,745	1.03%	0.66%
Vanish In A Robe Like Obi Wan Prank	839,123	1,360	108	25,282	4,615	29,897	18.25%	0.16%
Motorised Drifting Trike Is Awesome	1,292,447	6,109	2,434	33,694	141	33,835	0.42%	0.47%
Commercial A350 Flight Leaving USA Aborts At Last Minute Of Takeoff	1,108,764	800	47	596	80	676	13.42%	0.07%
How To Learn Calculus In 20 Seconds	256,431	763	696	2,197	141	2,338	6.42%	0.30%
John Oliver On Regifting	2,093,069	4,192	1,437	33,291	661	33,952	1.99%	0.20%
Why Orange Juice Is Totally Unnatural	683,182	1,209	653	9,250	165	9,415	1.78%	0.18%
Japanese Police Drone Captures Nearby Drones Using Net	750,183	1,916	38	762	59	821	7.74%	0.26%
Beacher Goer Trains Pelicans To Dance	230,159	260	4	487	21	508	4.31%	0.11%
Aussie Road Train Driver Demonstrates How To Drive Through Gate	157,132	39	1	151	10	161	6.62%	0.02%
Downton Abbey With American Accents Is Bizarre	2,235,940	5,048	432	8,161	162	8,323	1.99%	0.23%
Everything Wrong With Star Wars Episode I: The Phantom Menace	2,528,115	2,642	1,055	37,347	2,158	39,505	5.78%	0.10%
Kitchen Drawer Blocked By Oven Door Is Fixed In Unexpected Way	284,232	103	0	537	12	549	2.23%	0.04%
Michelle Obama Stars In Rap Music Video Encouraging College Enrollment	4,208,551	33,772	1,352	65,472	10,064	75,536	15.37%	0.80%
Drive Thru Christmas Caroling	323,727	944	87	14,625	241	14,866	1.65%	0.29%
Alton Brown Reviews Dumbest Kitchen Gadgets	3,700,699	18,233	2,421	39,888	1,760	41,648	4.41%	0.49%
Condom Challenge In Super Slow Motion	5,055,248	7,509	12,392	118,453	1,986	120,439	1.68%	0.15%
Automatic LEGO Cookie Icing Machine	90,773	307	71	1,284	11	1,295	0.86%	0.34%
Elders React To Star Wars The Force Awakens	2,231,528	1,553	1,119	57,817	517	58,334	0.89%	0.07%
Historical Myths Many Still Believe	1,718,204	2,326	2,266	54,359	2,481	56,840	4.56%	0.14%
Severely Obese Man Loses Hundreds Of Pounds With Yoga	1,043,877	2,339	483	9,695	48	9,743	0.50%	0.22%
YouTube Rewind Best Of 2015 Compilation	73,065,696	224,064	134,343	1,751,119	142,104	1,893,223	8.12%	0.31%
Quantum Computers Explained	1,398,381	10,796	10,835	62,614	340	62,954	0.54%	0.77%
Remote Control Car Tricks	5,497,909	7,933	5,664	119,596	1,117	120,713	0.93%	0.14%
Crystal Pepsi Is Returning Commercial	2,247,404	4,595	399	8,381	272	8,653	3.25%	0.20%
What It Would Be Like To Visit A Roller Coaster Tycoon Park	2,198,688	7,469	6,027	41,122	724	41,846	1.76%	0.34%
Jedi Levitation Prank	818,304	441	738	18,867	900	19,767	4.77%	0.05%
Instagram Husband	4,709,003	50,205	1,187	41,060	715	41,775	1.74%	1.07%
The USAF Band Holiday Flash Mob	1,892,972	8,828	935	5,926	141	6,067	2.38%	0.47%
Woman Tells Heart Breaking Story About Walmart Cashier Having Worst Day Ever	144,225	763	216	6,132	167	6,299	2.72%	0.53%
Carrie Fisher Is Hilarious In ABC Interview About Star Wars	1,463,965	5,086	101	8,222	185	8,407	2.25%	0.35%
Things Get Really Creepy At Christmas Party When Guests Demand To See Santa	1,428,271	8,472	619	9,696	220	9,916	2.27%	0.59%
Burgers Inspired By The Holidays Will Make You Drool	54,571	371	257	325	8	333	2.46%	0.68%

Figure 11.0

Collated YouTube data

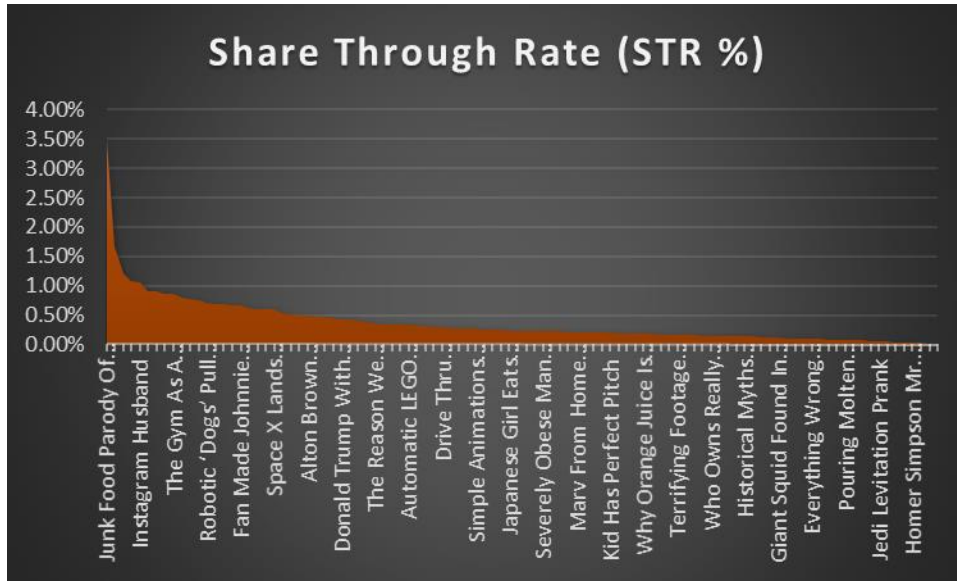


Figure 12.0 Relative Share Through Rate Data

3.1 How many views or shares must a video have to be considered a “viral” video?

A virality threshold can be established based on the STR just as in the music industry where music single can go either Gold, Platinum or Diamond (US). A video that has a Share Through Rate (STR) of less than 1% is NOT considered a trending viral video.

YouTube	Gold	Platinum	Diamond
Share Through Rate (STR)	1% > (25% percentile)	2% > (50% percentile)	3% > (75% percentile)

Table 2.0

From the sample of 100 videos only 1 video went **Diamond**.

Viral Videos	Views	No of		Likes	Dislikes	Total Opinions	Relative likes (Dislikes/Likes)	Share Through Rate
		shares	No of subscription Driven					
Junk Food Parody Of 'Hello' Is Perfect For Your New Year's Resolution	2,278,554	78,815	1,052	26,573	421	26,994	1.58%	3.46%

Figure 14.0 Video Data (Used in Analysis)

The latest data as of 9th January 2016 is depicted below.

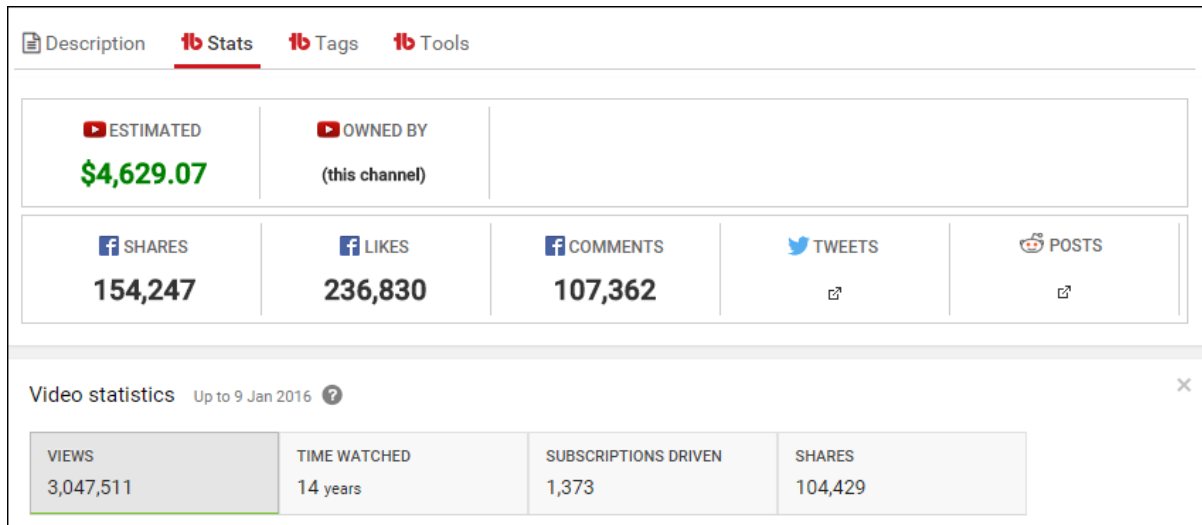


Figure 15.0 Current video data (Not used in analysis)

Do note that the Facebook shares (154,247) is more than the shares data on YouTube (104,429), this suggest the occurrence of *secondary sharing (social sharing)* where a user on Facebook shares the video to another person on Facebook. *Primary sharing* occurs when a user shares a video directly from YouTube to another social platform such as Facebook. The Share Through Rate data was based solely on *primary shares*.

4.0 Correlation Analysis (views and shares)

Viral Videos	Views	No of shares	Views Ranking	No of Shares Rank	Diff	Diff^2
YouTube Rewind Best Of 2015 Compilation	73,065,696	224,064	1	1	0	0
Macaulay Culkin Returns As A Much Older And Very Neurotic Kevin Mc	21,798,683	99,336	28	2	26	676
One Direction Carpools With James Corden	17,501,977	87,110	24	3	21	441
Junk Food Parody Of 'Hello' Is Perfect For Your New Year's Resolution	2,278,554	78,815	53	4	49	2401
British Weather Report With Star Wars Puns	3,749,961	16,189	30	17	13	169
Bad Lip Reading Of The Original Star Wars : Return of the Jedi	1,659,042	15,028	63	18	45	2025
Taco Shop Posts Security Video Of Two Late Night Burglars 'Looking For	3,788,692	14,535	32	19	13	169
Space X Lands Falcon 9 Rocket Vertically For First Time	2,062,328	12,190	21	20	1	1
Nerd Makes Real Life Light Saber	4,711,654	12,165	10	21	-11	121
Woman Tells Powerful Story About Giving A Piece Of Chocolate During	977,364	11,810	72	22	50	2500
Quantum Computers Explained	1,398,381	10,796	64	23	41	1681
Parrot Sick Of The Holidays Takes Down Toy Santa Claus	3,744,874	10,001	39	24	15	225
Chris Paul And Aaron Rodgers Perform Trick Shots	6,463,027	9,982	5	25	-20	400
The USAF Band Holiday Flash Mob	1,892,972	8,828	27	26	1	1
Things Get Really Creepy At Christmas Party When Guests Demand To	1,428,271	8,472	19	27	-8	64
Remote Control Car Tricks	5,497,909	7,933	7	28	-21	441
Condom Challenge In Super Slow Motion	5,055,248	7,509	9	29	-20	400
What It Would Be Like To Visit A Roller Coaster Tycoon Park	2,198,688	7,469	36	30	6	36
Lady Gaga Performs New York, New York	997,684	7,431	71	31	40	1600
Pop Stars Sing 'Joy To The World' With James Corden In The Car	2,398,745	6,371	50	32	18	324
Fake Korean Pop Star Prank	3,402,003	6,279	42	33	9	81
Motorised Drifting Trike Is Awesome	1,292,447	6,109	26	34	-8	64
Kid With Extremely Flexible Neck Will Shock You	2,421,182	5,465	49	35	14	196
Misheard Lyrics Of 2015	2,782,568	5,301	44	36	8	64
Modern Trailer Of Star Wars: The Empire Strikes Back	1,264,398	5,166	31	37	-6	36
Carrie Fisher Is Hilarious In ABC Interview About Star Wars	1,463,965	5,086	34	38	-4	16
Commercial A350 Flight Leaving USA Aborts At Last Minute Of Takeoff	1,108,764	800	67	79	-12	144
Budget Remake Of Star Wars: The Force Awakens Trailer	92,298	798	100	80	20	400
Woman Tells Heart Breaking Story About Walmart Cashier Having Wor	144,225	763	22	81	-59	3481
How To Learn Calculus In 20 Seconds	256,431	763	94	82	12	144
Color Changing Cake Will Mesmerize You	534,482	716	84	83	1	1
Chopping Machine TV Shop commercial	646,443	690	81	84	-3	9
Giant Tornado In Holly Springs, Mississippi	566,703	572	83	85	-2	4
Mama Horse Teaches Baby Horse How To Jump	2,832,254	549	43	86	-43	1849
Cat Wearing Cone Of Shame Figures Out Drinking Hack	338,571	486	89	87	2	4
Chunk Of Ice Flies Off Of Car On Highway And Smashes The Windshield	398,673	454	88	88	0	0
Jedi Levitation Prank	818,304	441	77	89	-12	144
Who Owns Really Antarctica	292,302	423	91	90	1	1
Dog Hides Entire Sandwich In His Mouth	128,905	403	38	91	-53	2809
Burgers Inspired By The Holidays Will Make You Drool	54,571	371	15	92	-77	5929
Automatic LEGO Cookie Icing Machine	90,773	307	37	93	-56	3136
Beacher Goer Trains Pelicans To Dance	230,159	260	95	94	1	1
High School Lunch Lady Stuns Cafeteria With Christmas Singing	279,355	250	93	95	-2	4
Terrifying Footage Of Family Driving Passed Solimar Fire	108,994	173	99	96	3	9
Little Girl Tries Oculus Rift For First Time	161,997	127	96	97	-1	1
Kitchen Drawer Blocked By Oven Door Is Fixed In Unexpected Way	284,232	103	92	98	-6	36
Sheriff's Deputy Jumps Onto Moving Semi-Truck To Save Unconscious I	157,309	77	97	99	-2	4
Aussie Road Train Driver Demonstrates How To Drive Through Gate	157,132	39	98	100	-2	4
			101	Summation	Sum	50908
Average			102		6*Sum	305448
			103	Count	n	100
			104		n(n^2-1)	999900

Spearman's Rank	
Range	1 to -1
	0 is no correlation
	Positive 1 is strong correlation
	Negative 1 is a strong negative correlation
rho	0.30548
	0.69452
This indicates a positive correlation between views and shares	

A correlation *figure of 0.69* suggests that there is a high correlation between views and the number of shares. This is significant as it indicates that for a video to be viral it must have a significant number of views for there to be a tendency to share. Further probing can be done to understand what factors lead people to view a video (i.e. YouTube thumbnail, title, video length, etc.), and if the videos was shared due to user experience goals such as being satisfying, enjoyable, pleasurable, etc (Rime,2009). It can be hypothesised that a video with a lot of views but low shares could be a 'deceptive video' that entices users to watch (i.e. using deceptive thumbnails or titles, wrong video, or a video with poor picture or audio quality or buffering experience).

5.0 Correlation Analysis (Likes and Share Through Rate)

Viral Videos	Likes	Share Through Rate	Likes Ranking	Share Through Rate Rank	Diff	Diff^2
Junk Food Parody Of 'Hello' Is Perfect For Your New Year's Resolution	9,695	3.46%	54	1	53	2809
Darth Santa Is Worse Than The Grinch	7,851	1.67%	59	2	57	3249
Woman Tells Powerful Story About Giving A Piece Of Chocolate During	118,453	1.21%	8	3	5	25
Bad Lip Reading Of The Original Star Wars : The Empire Strikes Back	8,381	1.08%	56	4	52	2704
Instagram Husband	62,614	1.07%	18	5	13	169
Bad Lip Reading Of The Original Star Wars : Return of the Jedi	82,416	0.91%	11	6	5	25
Bad Lip Reading Of The Original Star Wars : A New Hope	7,523	0.90%	62	7	55	3025
Budget Remake Of Star Wars: The Force Awakens Trailer	7,706	0.86%	60	8	52	2704
The Gym As A Wildlife TV Show	6,562	0.86%	65	9	56	3136
Michelle Obama Stars In Rap Music Video Encouraging College Enrollm	34,648	0.80%	30	10	20	400
Quantum Computers Explained	10,731	0.77%	52	11	41	1681
Lady Gaga Performs New York, New York	115,632	0.74%	9	12	-3	9
Robotic 'Dogs' Pull Santa's Sleigh	18,586	0.71%	46	13	33	1089
Little Girl Has The Cutest And Most Excited Reaction To Star Wars Traile	3,794	0.68%	73	14	59	3481
Burgers Inspired By The Holidays Will Make You Drool	325	0.68%	98	15	83	6889
How To Learn Calculus In 20 Seconds	40	0.30%	100	40	60	3600
Drive Thru Christmas Caroling	596	0.29%	91	41	50	2500
Parrot Sick Of The Holidays Takes Down Toy Santa Claus	1,751,119	0.27%	1	42	-41	1681
Pop Stars Sing 'Joy To The World' With James Corden In The Car	3,820	0.27%	72	43	29	841
Google Year In Search 2015	44,670	0.27%	21	44	-23	529
Simple Animations Battle In Minecraft	72,513	0.26%	13	45	-32	1024
Nerd Makes Real Life Light Saber	65,472	0.26%	16	46	-30	900
Japanese Police Drone Captures Nearby Drones Using Net	793	0.26%	88	47	41	1681
Gorgeous Bruno Mars A Cappella Medley	964	0.25%	87	48	39	1521
Japanese Girl Eats 100 Pieces Of Bread In One Sitting	33,074	0.24%	33	49	-16	256
100 Years Of Christmas Toys	44,538	0.23%	22	50	-28	784
Downton Abbey With American Accents Is Bizarre	21,319	0.23%	41	51	-10	100
Kid With Extremely Flexible Neck Will Shock You	11,469	0.23%	51	52	-1	1
Severely Obese Man Loses Hundreds Of Pounds With Yoga	96,500	0.22%	10	53	-43	1849
Lexus Makes Wheels Out Of Pure Ice	523	0.22%	93	54	39	1521
Girl Masters The Violin In Two Years Compilation	391	0.22%	97	55	42	1764
Space Debris Over The Past 60 Years	9,250	0.21%	55	56	-1	1
Marv From Home Alone Is Still Terrified Of Kevin MacCallister	8,161	0.21%	58	57	1	1
Crystal Pepsi Is Returning Commercial	1,414	0.20%	83	58	25	625
Little Kid Loves To Fart	22,373	0.20%	40	59	-19	361
John Oliver On Giftgiving	3,705	0.20%	74	60	14	196
Kid Has Perfect Pitch	654	0.20%	90	61	29	841
Giant Squid Found In Japan	19,467	0.11%	44	81	-37	1369
Chopping Machine TV Shop commercial	7,670	0.11%	61	82	-21	441
Everything Wrong With Star Wars Episode I: The Phantom Menace	762	0.10%	89	83	6	36
Giant Tornado In Holly Springs, Mississippi	37,347	0.10%	28	84	-56	3136
Everything Wrong With The Lion King	30,476	0.09%	35	85	-50	2500
High School Lunch Lady Stuns Cafeteria With Christmas Singing	18,867	0.09%	45	86	-41	1681
Three Year Old Adorably Explains Why She Cut Her Hair	33,291	0.08%	32	87	-55	3025
Little Girl Tries Oculus Rift For First Time	489	0.08%	94	88	6	36
Pouring Molten Aluminum Into A Tank Of Water Balls	14,625	0.07%	50	89	-39	1521
Commercial A350 Flight Leaving USA Aborts At Last Minute Of Takeoff	3,927	0.07%	71	90	-19	361
Elders React To Star Wars The Force Awakens	1,547	0.07%	81	91	-10	100
Mammoth Stomping Stuff In Slow Motion	1,594	0.06%	79	92	-13	169
Jedi Levitation Prank	54,359	0.05%	20	93	-73	5329
Sheriff's Deputy Jumps Onto Moving Semi-Truck To Save Unconscious t	4,106	0.05%	70	94	-24	576
Kitchen Drawer Blocked By Oven Door Is Fixed In Unexpected Way	62,700	0.04%	17	95	-78	6084
Devils Fingers Or Octopus Fungus Emerging Is The Creepiest Thing Ever	324,843	0.03%	3	96	-93	8649
Homer Simpson Mr. Plow YouTube Commercial	2,197	0.03%	78	97	-19	361
Aussie Road Train Driver Demonstrates How To Drive Through Gate	151	0.02%	99	98	1	1
Mama Horse Teaches Baby Horse How To Jump	71,646	0.02%	14	99	-85	7225
Woman Freaks Out In The Best Way After Being Surprised She's A Gran	35,473	0.02%	29	100	-71	5041
			101	Summation	Sum	148304
Average		0.37%	102		6*Sum	889824
			103	Count	n	100
			104		n(n^2-1)	999900

Spearman's Rank						
Range	1 to -1	0 is no correlation				
		Positive 1 is strong correlation				
		Negative 1 is a strong negative correlation				
	0.88991					
rho	0.11009					
This indicates a somewhat positive correlation between likes and share though rate						

Studies undertaken by (Sen and Lerman 2007; Wojnicki and Godes, 2008) showed that a strong correlation exists among the likes and dislikes received by videos and the views, however since views as indicated prior is not a very concrete measure of virality, the hypothetical question then is whether there exists a correlation between the STR (Share Through Rate) and likes or dislikes? The data above and the interpretation depicts that there exist a strong correlation between the Share Through Rate and likes, which supports the Berger theory (Berger and Milkman, 2012), as well as the SSE (Social Sharing of Emotion) theory (Rodriguez Hidalgo, Tan, and Veleigh, 2015), that underlines that positive valence (“happiness” or “contentment”) leads to sharing. From the study, it is worth noting that the video that went *diamond* had 26,573 likes and a *relative dislike of 1.58%* as seen in **figure 16.0** below. That data collated also showed that the video with the most likes only had a Share Through Rate of 0.31% as seen below, not even making the status quo of a viral video in its true sense.

Viral Videos	Likes	Dislikes	Total Opinions	Relative likes (Dislikes/Like)	Share Through Rate
YouTube Rewind Best Of 2015 Compilation	1,751,119	142,104	1,893,223	8.12%	0.31%

Figure 16.0 Most liked video

The signifying factor is that it also had 142,104 dislikes with a *relative dislike as high as 8.12%*. Based on this evidence the study had to probe further to understand the effect of dislikes on sharing which is shown in the data below.

6.0 Correlation Analysis (Dislikes and Share Through Rate)

Viral Videos	Share Through		Dislikes Ranking	Share Through Rate rank	Diff	Diff^2
	Dislikes	Rate				
Junk Food Parody Of 'Hello' Is Perfect For Your New Year's Resolution	421	3.46%	38	1	37	1369
Darth Santa Is Worse Than The Grinch	1,249	1.67%	22	2	20	400
Woman Tells Powerful Story About Giving A Piece Of Chocolate During The Holocaust	99	1.21%	72	3	69	4761
Bad Lip Reading Of The Original Star Wars : The Empire Strikes Back	361	1.08%	42	4	38	1444
Instagram Husband	715	1.07%	31	5	26	676
Bad Lip Reading Of The Original Star Wars : Return of the Jedi	324	0.91%	48	6	42	1764
Bad Lip Reading Of The Original Star Wars : A New Hope	2,024	0.90%	14	7	7	49
Budget Remake Of Star Wars: The Force Awakens Trailer	147	0.86%	66	8	58	3364
The Gym As A Wildlife TV Show	4,164	0.86%	7	9	-2	4
Michelle Obama Stars In Rap Music Video Encouraging College Enrollment	10,064	0.80%	3	10	-7	49
Quantum Computers Explained	340	0.77%	46	11	35	1225
Lady Gaga Performs New York, New York	579	0.74%	34	12	22	484
YouTube Rewind Best Of 2015 Compilation	142,104	0.31%	1	39	-38	1444
How To Learn Calculus In 20 Seconds	141	0.30%	69	40	29	841
Drive Thru Christmas Caroling	241	0.29%	55	41	14	196
Parrot Sick Of The Holidays Takes Down Toy Santa Claus	2,627	0.27%	11	42	-31	961
Pop Stars Sing 'Joy To The World' With James Corden In The Car	338	0.27%	47	43	4	16
Google Year In Search 2015	10,719	0.27%	2	44	-42	1764
Simple Animations Battle In Minecraft	3,346	0.26%	10	45	-35	1225
Nerd Makes Real Life Light Saber	848	0.26%	29	46	-17	289
Japanese Police Drone Captures Nearby Drones Using Net	59	0.26%	79	47	32	1024
Gorgeous Bruno Mars A Cappella Medley	381	0.25%	41	48	-7	49
Japanese Girl Eats 100 Pieces Of Bread In One Sitting	1,124	0.24%	25	49	-24	576
100 Years Of Christmas Toys	91	0.23%	76	50	26	676
Downton Abbey With American Accents Is Bizarre	162	0.23%	64	51	13	169
Kid With Extremely Flexible Neck Will Shock You	865	0.23%	28	52	-24	576
Severely Obese Man Loses Hundreds Of Pounds With Yoga	48	0.22%	81	53	28	784
Lexus Makes Wheels Out Of Pure Ice	316	0.22%	50	54	-4	16
Girl Masters The Violin In Two Years Compilation	131	0.22%	71	55	16	256
Space Debris Over The Past 60 Years	86	0.21%	77	56	21	441
Marv From Home Alone Is Still Terrified Of Kevin MacCallister	391	0.21%	40	57	-17	289
Crystal Pepsi Is Returning Commercial	272	0.20%	53	58	-5	25
Little Kid Loves To Fart	547	0.20%	35	59	-24	576
John Oliver On Regifting	661	0.20%	32	60	-28	784
Kid Has Perfect Pitch	94	0.20%	75	61	14	196
Cat Demonstrates What Happens When He Climbs Christmas Tree	98	0.19%	73	62	11	121
Misheard Lyrics Of 2015	4,622	0.19%	5	63	-58	3364
Fake Korean Pop Star Prank	1,813	0.18%	16	64	-48	2304
Why Orange Juice Is Totally Unnatural	165	0.18%	62	65	-3	9
Funerals Are a Total Ripoff	539	0.18%	36	66	-30	900
What A World Champion Whistler Sounds Like	171	0.17%	60	67	-7	49
Vanish In A Robe Like Obi Wan Prank	4,615	0.16%	6	68	-62	3844
Terrifying Footage Of Family Driving Passed Solimar Fire	37	0.16%	82	69	13	169
Doing A Backflip While Breathing Fire Under A Giant Water Balloon	1,136	0.15%	23	70	-47	2209
Chris Paul And Aaron Rodgers Perform Trick Shots	1,568	0.15%	18	71	-53	2809
Condom Challenge In Super Slow Motion	1,986	0.15%	15	72	-57	3249
Who Owns Really Antarctica	195	0.14%	57	73	-16	256
Remote Control Car Tricks	1,117	0.14%	26	74	-48	2304
Guy Flies On \$32,000 Flight To Abu Dhabi	268	0.14%	54	75	-21	441
Cat Wearing Cone Of Shame Figures Out Drinking Hack	184	0.14%	59	76	-17	289
Historical Myths Many Still Believe	2,481	0.14%	12	77	-65	4225
Color Changing Cake Will Mesmerize You	26	0.13%	83	78	5	25
Chunk Of Ice Flies Off Of Car On Highway And Smashes The Windshield Another Car	17	0.11%	94	79	15	225
Beacher Goer Trains Pelicans To Dance	21	0.11%	93	80	13	169
Giant Squid Found In Japan	514	0.11%	37	81	-44	1936
Chopping Machine TV Shop commercial	1,534	0.11%	19	82	-63	3969
Everything Wrong With Star Wars Episode I: The Phantom Menace	2,158	0.10%	13	83	-70	4900
Mammoth Stomping Stuff In Slow Motion	1,136	0.06%	24	92	-68	4624
Jedi Levitation Prank	900	0.05%	27	93	-66	4356
Sheriff's Deputy Jumps Onto Moving Semi-Truck To Save Unconscious Driver	1	0.05%	100	94	6	36
Kitchen Drawer Blocked By Oven Door Is Fixed In Unexpected Way	12	0.04%	95	95	0	0
Devils Fingers Or Octopus Fungus Emerging Is The Creepiest Thing Ever	23	0.03%	92	96	-4	16
Homer Simpson Mr. Plow YouTube Commercial	163	0.03%	63	97	-34	1156
Aussie Road Train Driver Demonstrates How To Drive Through Gate	10	0.02%	97	98	-1	1
Mama Horse Teaches Baby Horse How To Jump	5	0.02%	99	99	0	0
Woman Freaks Out In The Best Way After Being Surprised She's A Grandmother	351	0.02%	44	100	-56	3136
Average		0.37%		101 Summation	Sum	114008
				102	6*Sum	684048
				103 Count	n	100
				104	n(n^2-1)	999900

*Some data hidden to fit page

Spearman's Rank							
Range	1 to -1	0 is no correlation					
		Positive 1 is strong correlation					
		Negative 1 is a strong negative correlation					
	0.68412						
rho	0.31588						
This indicates a positive correlation between share through rate and dislikes							

The interpretation of the data is that there exists a strong correlation between the Share Through Rate and dislikes, which also supports the Berger theory (Berger and Milkman, 2012), as well as the SSE (Social Sharing of Emotion) theory (Rodriguez et al., 2015), which underlines that negative valence (“Sadness”, “anger”, and “fear”) can also lead to sharing. However, in contrast the correlation for sharing in positive valence (0.45%) is stronger to negative valence (0.32%) when compared with both sets of data above.

7.0 MULTIPLE REGRESSION

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.861164496							
R Square	0.741604289							
Adjusted R Square	0.736276542							
Standard Error	14607.28484							
Observations	100							
ANOVA								
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>			
Regression	2	59401534229	2.97E+10	139.19661	3.13211E-29			
Residual	97	20697158717	2.13E+08					
Total	99	80098692946						
	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	4832.715986	1576.214186	3.066027	0.0028103	1704.367146	7961.064826	1704.367146	7961.064826
Likes	0.152189505	0.022385151	6.798681	8.634E-10	0.107761176	0.196617834	0.107761176	0.196617834
Dislikes	-0.2897367	0.292712932	-0.98983	0.3247188	-0.870690842	0.291217444	-0.870690842	0.291217444

Figure 17.0 Regression Analysis

It is also judicious to see how both likes and dislikes have an effect on shares simultaneously instead of independently (i.e. a correlation) hence to do so a multiple regression is needed. The above model for example based on the collated viral video data explains up to 74% of the variation of the dependent variable (shares). The model is significant as its P value is below 0.05 in relation to its 95% confidence level. *It is important to note that likes has a positive co-efficient hence a single like for a video would increase its number of shares by 15%.*

Conversely, a single dislike would decrease the likelihood of it being shared by 29% since it has a negative co-efficient.

8.0 LIMITATIONS

The study used a sample of 100 videos that were deemed to have gone viral (Subjective) due to the fact that there wasn't a clear established construct on what exactly qualifies a video to be deemed as a viral one. Though 100 videos are significant, a larger population sample would be a more representative distribution which will have an impact on the categorization of virality, the nature of popularity and relative dislikes, and distort earlier results and analysis.

Secondly, the study in understanding the Share Through Rate (STR) did not include *social shares* or *secondary shares* as it would be very cumbersome to collate analytics data from third parties' platforms i.e. users who may have shared a video from Facebook to another friend on Facebook and hence, this area of the research was omitted with more focus on the seeders (Those who initially shared directly from YouTube), though there is the opportunity to focus alone on that front in a future study.

9.0 CONCLUSION & FURTHER WORK

The study was able to expand upon the concepts to derive a formula for measuring virality and a much less focused construct – popularity. A measure on how to predict popular videos was also developed and compared with other existing methods already established in literature. Through the collection of data from viral videos this study was able to establish a threshold and categorization for virality which can be used in any setting and placed in a context where a viral video can be defined as any video which has a Share Through Rate of more than 1% (Though it may not necessarily qualify as a popular video). Statistically, the study went further to establish that there exists a strong correlation between shares and views, relative likes and Share Through Rate and relative dislikes and Share Through Rate.

Further work will seek to take the same approaches in the study however *popular videos* will be categorized into different themes as seen within YouTube (Film and Animation, cars and vehicles, people and blogs, music, Sports, Travel etc.). Further analysis will assess if the categories have a distinct Share Through Rates (STR) or PR (Propagation Rates) and also analyse if its metrics are correlated under the different categories.

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