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DO I HAVE YOUR ATTENTION?

AN ANALYSIS OF THE DIFFERENT MARKETING STRATEGIES USED BY ORGANISATIONS ON SOCIAL MEDIA

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Abstract

A research project conducted, exploring the different marketing strategies employed by groups such as companies and political parties, to gain the attention of social media users. Using multiple methods to obtain data from Twitter and YouTube, performing sentiment analysis and analysing survey data to analyse these methods and their overall effectiveness

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1. Introduction

Social media and social networking sites continue to be at the forefront of modern life. It would be easier to say what could not be found, than the ever-growing list of what their users post, interact with, and share to countless others on these platforms. Additionally, the number of people accessing these sites and applications are increasing too, with a reported "3.8 billion active social media users" this year, an increase of 9% from 2019 [1].

As such, it has become paramount for organisations and large bodies to understand how to navigate and appeal to this large landmass of untapped, potential clientele. As a result of this, social media marketing and advertising has transformed into a lucrative business, with large budgets being assigned to attracting users on these platforms. Numerous different marketing strategies are employed daily by companies, political parties, and others, attempting to maximise their online presence and add to their consumer base/following.

However, not all advertisement and promotional media are successful in their endeavours; companies have sunk millions into ambitious projects and failed, whereas some companies succeeded with relatively little spending needed. Some implementations of methods end up being tone-deaf and miss completely, whereas others are straightforwardly offensive – *Dove's* Facebook advertisement of 2017 being an example [2].

Images from Dove's Facebook online advertising campaign in 2017 [2]

1.1 Aims of Project & Motivation

With this project, I aim to explore different strategies employed by groups such as companies and political parties, and determine their effectiveness using different methods. This will mainly be gauged by user reaction, as the overall goal of these strategies are to be welcomed by people in the current consumer base or following, as well as connect to potential new customers.

As a frequent social media user, it has become easy to recognise and be aware of different strategies being used. It has also become infinitely easier to express my opinion on the aforementioned sites. Any Twitter user can post how they feel about anything with a simple tweet, as well as liking and/or retweeting a post. YouTube users can leave a like, dislike, and a comment (if a video allows), clearly indicating their views on the matter. Online surveys also exist, which aim to compartmentalise answers so that they can be easily analysed.

With these reactions available readily on these mediums, I aim to explore the different marketing strategies used by these groups and analyse it, seeing which of those are effective, and offer reasons as to why some work, and others may not. These conclusions will be supplemented with the data collected from the aforementioned platforms.

This was a topic that interested me greatly. The importance of social networking sites in modern society, and the shift from traditional television advertising to mainly social media marketing, has been very interesting to observe over the past decade. With world processions now being heavily influenced by social media (Trump's presidential campaign and the Cambridge Analytica Scandal being a large example of this), I want to learn the approaches of groups such as companies on social media platforms, and dissect them to see whether they were truly effective.

Furthermore, this project combines the multiple modules I have undergone this year: *Social Media, Crowdsourcing and Citizen Sensing*, *Data Visualisation and the Web*, as well as *Data Mining* and *Machine Learning*.

1.2 Report Overview

The report is structured as follows:

- Section 2 will outline the Research Objectives, and what the project aims to work towards.
- Section 3 looks at the methodology of the project, and how I will go about achieving the research objectives.
- Section 4 will contain a detailed background research, where I will be indicating the different strategies used by companies (and groups alike) that will be analysed, as well as research on the methods that I will use and their relevance.
- Section 5 looks at the implementation of the practical methods applied to obtain data for analysis, based on the strategies discovered in the background research.
- Section 6 will have the findings of the practical methods displayed.
- Section 7 will be a detailed analysis of the findings of the practical method, drawing conclusions and offering reasonings as to why the data has turned out how it did.

- Section 8 will be a concluding chapter on this report, where I will evaluate the project as a whole. I will look at the limitations of the research undergone, reviewing the restrictions of the research imposed by the methods. Furthermore, I will look at how the research could be furthered by the possibility of different methods, improvements on current methods etc.
- Section 9 is the bibliography and Section 10 is the appendix

2. Research Objectives

As mentioned before, this project aims to analyse the different strategies used by companies, political parties, and groups alike to attract the attention of social media users. In order to accomplish this goal, this project has 3 main research objectives:

1) Explore and identify various common strategies used by organisations such as companies, political parties etc.

This is the first objective that needs to be completed. There are a multitude of advertisement and promotional media used daily by a mass of organisations on social media platforms. However, to keep a reasonable scope for this project, I will be looking at methods that are applied frequently, and are recognisable by the public. This is so that reactions and opinions to these can be found easily, and those reactions are clearly about the discovered strategies

2) Observe people's reactions to these strategies by using practical methods to attain data on different platforms

The ultimate goal of these strategies is to interest new people and turn them into potential new customers/consumers, in turn increasing the following of the company. Furthermore, maintaining the current consumer base is paramount too. Therefore, many people will be exposed to these strategies constantly (especially those used by large organisations with a substantial budget towards social media marketing). Although companies will be quick to announce positive spikes in following counts and statistics of that nature, they will also be tight-lipped at those times where they did not gain as many engagements as first predicted. Also, this data is not readily available. A good measure of whether a strategy employed worked is by simply seeing the reaction of those who have been exposed to said strategy.

The second research objective is to gauge people's reactions to these methods. As people post on social media constantly, and social media marketing methods are used continually, there will be a large amount of responses and reactions to these strategies on these platforms. These social networking sites are designed so that it is easy for people to post their opinions and engage in conversations with others about this. Practical methods will be applied to gain data across these platforms for analysis, as well as looking at particular instances of these strategies. These examples will then allow for stronger conclusions to be drawn.

These include (but are not limited to) scraping tweets from Twitter, as well as conducting a survey, asking questions about whether the respondents have actively interacted with these strategies.

3) Analyse data gathered to draw relevant conclusions (which strategies are effective/are received well, and which ones are received negatively/fail to attract attention)

The final research objective will be to look at the data gathered about these strategies and analyse them. From this, we can see which strategies have been received well by social media users, and give reasons as to why, using the data gathered as evidence. Additionally, we can also see which ones have been received poorly and offer reasons as to why this is the case. Furthermore, analysing the instances of those strategies being used can allow for more answers to be drawn. Although these marketing strategies are quite universal and available to most, they can be implemented differently. Looking at these different instances of those strategies can allow one to go more in-depth in the analysis.

3. Methodology

In this section, I will go over how I plan to achieve the research objectives listed above.

3.1 Identifying the strategies that will be analysed

I will be conducting background research to identify the strategies that will be analysed in this project. As many strategies are used constantly, it will be hard to analyse a large amount of them and also draw strong, relevant conclusions from them all. Therefore, in keeping with the project's scope, I will identify 5 strategies that are used by companies, political parties etc., and justify why each one has been picked. Further information can be found in the 'Background Research' section, which follows this section.

3.2 Practical methods to gain data

To achieve the second research objective, I will be utilising practical methods to gain data, primarily feedback by users on social networking platforms about the discovered strategies. The data will be gathered using multiple tools, and I will go through what I have used here:

3.2.1 Twitter Scrape

The social networking platform giant Twitter has become a place for users to easily post their opinions, as well as follow accounts which they like, and directly communicate with companies and members of political parties easily. With "330 million monthly active users" recorded in early 2019 [3], to say its reach is enormous is an understatement. It has even become the place where the President of the United States easily voices his opinion without having to host a press conference or hold an interview. The platform has become a lucrative ground, holding many untapped customers for companies to advertise their services to. Therefore, it is a good place to scrape data from.

However, the Twitter API does come with limitations. Firstly, you have to gain access to the API by contacting Twitter themselves, and that is not something that is guaranteed. Furthermore, the number of tweets that can be scraped is limited too [4]. Therefore, it is important to work around these restrictions and use alternative methods to scrape tweets.

3.2.2.1 Twint

Twint is a Twitter scraping tool written in Python [5]. This tool allows for multiple pieces of information to be collected from the Twitter website without the use of Twitter's API. Twint allows for relevant tweets to be found from search terms. It also bypasses the API's limits, meaning a large sum of tweets can be collected without access to the API required. The tool allows for great

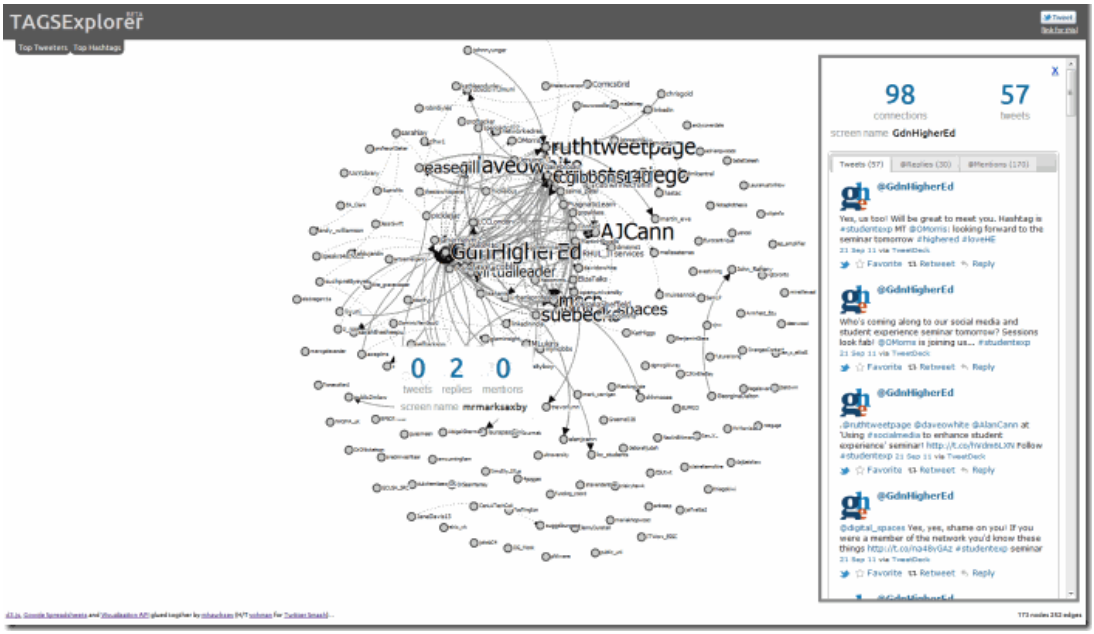
customisation when it comes to searching for tweets, including date of tweet, and how to store the information collected.

The tweets can be stored as a .csv file, containing multiple pieces of data about the tweet. These include the tweet string itself, the account it was posted by, media included in the tweet, as well as any links or URLs in the tweet as well. Saving it into a .csv file allows for the tweets to be saved somewhere and then used elsewhere, and all the columns of the .csv can be used for data analysis.

3.2.2.2 TAGS

TAGS, or Twitter Archiving Google Sheet, is a Google Sheet template which runs a script which collates tweets related to the parameters inputted [6]. Like Twint, TAGS allows for a large amount of tweets to be collected, however it does come with an imposition that it can only collect tweets up to 7 days old. TAGS returns these tweets as a Google Sheet, with multiple columns including information such as the tweet string itself, and the location the tweet was posted.

The reason I used TAGS as opposed to only using Twint for tweet scraping is that the tweets scraped with TAGS can then be passed into the TAGSExplorer. The TAGSExplorer utilises the Google Visualisation API, allowing for the information collected to be visualised in a graph, with each node representing a user, and each edge or connection between nodes is an interaction between the two users [7]. This can be something like a reply to a tweet the individual posted.



An example of a visualisation by TAGSExplorer, taken from the website [7]

Furthermore, the tweets can be reformatted "returning Twitter functionality like reply/retweet" [7]. This data can be carried forward and saved into something like a .csv file, which can then be used

later for visualisation using other tools. The information about engagements between users can be analysed in other visualisation tools to observe their reach and influence.

3.2.2 YouTube API

Another social networking site that is utilised by companies and political parties is the video-sharing platform YouTube. Although at its inception it was just a website for people to post videos, it has grown into a cornerstone of social media, available on many devices and mediums, with many people making livelihoods off of posting videos on there. It is considered a type of social media by many, with people able to leave likes/dislikes on videos, as well as posting comments. Moreover, a community tab allows for content creators to communicate directly with their subscribers without having to post a video, alongside the recent addition of YouTube Stories (similar to Snapchat & Instagram), solidifying it as a type of social media.

By utilising the YouTube API, data can be gathered about certain strategies utilised by companies and political parties used on the platform. Information that can be gathered from videos, such as likes/dislikes and comments, can be used to gauge how users have responded to that strategy [8]. An example can be looking at in-video advertisements; before a YouTube video plays, there is a chance that an advertisement will play. Analysing data on these advertisement videos can be done using the API. Furthermore, looking at related videos, and seeing the network of these videos can be useful in analysing the reach and effect of how a company uses YouTube to attract social media users.

3.2.3 Public Survey

A survey is a good way to get concentrated answers from a group of people. It can also be used to prove a hypothesis, or to identify trends from groups by asking specific questions and collecting and comparing the results of multiple questions against each other. Regression analysis can be used to observe the relationship between two variables, or in this instance two types of questions and their answers.

A survey targeted towards social media users, asking about how they feel about the strategies will provide strong backup towards conclusions drawn in the analysis of the data gathered. It would be difficult to search on social media how many times a user actually engages with the advertisement and promotional content presented to them. This is how the survey can be an advantage; frequency based questions can be used to gauge the effectiveness of strategies employed. Furthermore, regression analysis can be performed on the different strategies used and statement questions, for example a question like “I believe social media marketing strategies are effective”. If someone

strongly agrees with this question and indicates that they regularly engage with a certain strategy, the data from the survey would suggest that for the particular individual the strategy is effective in gaining their attention.

Comparisons can be drawn towards the data gathered from social media platforms and the responses from the survey. If data gathered from the social media platforms illustrates that users of the platform speak positively about that certain strategy, and the survey answers can be used to offer an explanation as to why. Contrarily, the two types of data could also disagree with each other. In this occurrence, analysis of the data could bring conclusions as to why this is the case. Factors such as time of the data gathered, sample size etc. could offer reasons as to why the data gathered from social media platforms and the survey would disagree with each other.

3.2.4 Sentiment Analysis of Tweets & YouTube Comments

Upon gathering tweets from Twitter and comments from YouTube videos, sentiment analysis will be performed to see whether the posts are in a positive, neutral, or negative attitude or view. Sentiment analysis is a powerful tool as it allows for us to gain an overview of how people feel about certain topics and discussions.

As discussed earlier, platforms such as Twitter is home to many users posting their opinions about things, which also quite regularly extends to their opinions about businesses and their practices. Utilising search terms relevant to strategies employed by these corporations, we can uncover the multiple different opinions people have about said strategy and/or company. Then, by performing sentiment analysis on these tweets, we can see whether these posts are talking about these methods positively, indicating that they have been received well. Additionally, if a post is judged to have been in negative sentiment, then analysis can be performed to see reasons as to why this is the case. (One could also say that negative attention or feedback is still good attention regardless, so maybe it is can be seen as a positive that a discussion is sparked regarding the company, by the methods they use to gain the attention of social media users)

Furthermore, the comments section of YouTube videos is another area where people post their opinions about what they have watched. This can be used alongside information such as likes/dislikes on the videos, will indicate whether the videos posted have been received well, or negatively.

However, sentiment analysis is not definite, and each person's opinion can be viewed differently if viewed at a different perspective. There are limitations of how much one should rely on sentiment analysis (discussed further in "Limitations of Research" section). At the end of the day, it is an

estimate of the sentiment of what people have posted. Therefore, only using one sentiment analysis model can reduce the reliability and accuracy of the conclusions drawn from the data gathered only from that model.

I intend to use two different sentiment analysis models in this project. The results of each can be used similarly to how I intend to use the survey data with the data gathered from social media platforms. The use of two models can increase the reliability of the data, therefore leading to accurate conclusions to be made. If only one model was used, then there will be no measure of relative accuracy. Comparing the data found between the two models can strengthen the results found and improve their reliability. Additionally, I intend for the models used to be distinctive, so that the research methods are more varied. This in turn boosts the credibility of the research conducted.

3.2.5 Gephi

Gephi is an open-source graph visualisation platform, used in exploring graphs and networks, and manipulating these to discover information [9]. The application can be used to "reveal underlying structures of associations between objects", and can the graphs created by the numerous algorithms provided by the application can be traversed to analyse the reach of nodes in the graph, and the range of the connections.

An example of a graph created by Gephi, from the Gephi website [10]

Gephi was used to analyse the connections between tweets found in Twitter, mainly those scraped via TAGS. Although TAGS has its own visualisation software in the TAGSExplorer, Gephi allows for more customisation with the graphs generated with the tweets scraped. The use of the engagement between users on Twitter discovered with TAGS alongside Gephi will allow for more information to be uncovered. For example, I analyse a giveaway held by a company on Twitter. By using Gephi, I could uncover different accounts posting about the giveaway, seemingly unrelated to the company. Which Twitter accounts are engaging with who? Why is an account seemingly unrelated to this strategy engaging with users about this topic? The answers to these questions can be used to further

understand the reach/influence these companies obtain via the strategies used, and in turn observe the overall effectiveness of gaining user attention.

Furthermore, I will be looking at the network of related videos found using the YouTube API. In the same fashion as with the TAGS data, I will be looking at the reach of these videos and attempt to uncover any additional information. Which types of videos are being recommended? Are they really related to the original content?

In the Implementation section of the report, I will go into further detail about these practical methods, showcasing how I used each one (alongside screenshots of code, application usages and survey questions) to gain relevant data about the marketing strategies used.

4. Background Research

In this section, I will go over the background research performed, looking at the different strategies identified, as well as further research about aspects of the project, such as the reliability of sentiment analysis.

4.1 Identifying the strategies

As mentioned, there are a multitude of strategies employed by organisations on social media platforms constantly. Therefore, in keeping within the scope of the project, I will be analysing those that are utilised frequently. These will in turn garner a lot of responses on social media platforms and elicit responses in the survey questions without making the respondent think too long.

To summarise, these are the strategies that I will look at:

- Video Advertisements
- Personalised/Targeted Advertisements
- Discounts, Competitions & Giveaways
- Sponsored Posts
- Consumer-based interaction

4.1.1 Video advertisements

YouTube, the popular video sharing platform, seemingly grows in popularity every year. With a reported "2 billion users worldwide in 2019", the platform has risen to the "2nd most popular social media platform", with a reported "79% of internet users saying they have a YouTube account" [11]. This obviously means that the platform commands a titanic number of users.

YouTube allows for advertisements to be presented before, during, or after viewing a video. These advertisements can range from short 5 second adverts, to 30 seconds, or even longer. The process of posting a YouTube advertisement is very accessible, which makes sense. It is one of the biggest sources of income for the platform.

The shift from traditional television advertising to YouTube advertisement is a profound one. A prominent example of this was the 2008 Presidential Election Campaign, between Barack Obama and John McCain, dubbed the 'YouTube Election' [12]. This election had both candidates take to YouTube as another medium to gain votes and appeal to the population of the US.

Before this, the site's potential for political campaigning had been understood but not necessarily appreciated (the viral video was still rare back then). Television advertising had been the main place

for campaigners to get their message across, with $300 million spent on broadcasting in the 1992 presidential election, and $400 million spent in 1996 [13]. YouTube was more so viewed as an area for politicians to be caught out, and have a slip-up recorded and posted for millions to view – an example being a video recorded of Senator George Allen used a derogatory term to refer "to his opponent's campaign aide". This incident picked up a lot of traction from major news networks, and soon "within weeks the Virginia Republican's career was effectively over" [12].

Obama's campaign utilised the platform to attempt to gain the vote of the younger age demographic. Divinity Metrics discovered that Obama received 500 million views on the videos that his campaigning group posted on the website, with the largest viewing demographic being those between the ages of 18 and 24 years old, making up 37% of the total views, and the 2nd largest age group being between 25 and 34 years old [14]. It would then make sense that more of the younger population would be influenced to have more of an interest in Obama. A study performed by the Pew Research Center showed that 66% of 18 to 29 year olds voted Obama over McCain [14] [15]. From then on, YouTube grew into a platform for many companies and political campaigners to post their content and attempt to bolster their following.

There are many advantages to posting video advertisements on sites like YouTube. An advantage it has over traditional television advertising is that the content can be more readily accessed by people. Television advertisements actively require one to be watching TV, and specifically at the time that the ad is being played. Furthermore, getting access to desired air-times comes with harsh competition, nevertheless the steep price they command. For example, the Super Bowl notoriously has some of the most coveted advertisement air-time in broadcasting. This year a "30 second Super Bowl ad … cost companies $5.6 million" [16].

YouTube advertisements can easily be shared by viewers, with the YouTube mobile application integrating a share feature to post video links to other social media platforms such as Twitter and WhatsApp. Furthermore, YouTube offers advanced analytical tools, meaning even small companies can directly see which advertisements are doing well by looking at things such as how much of the advert is actually being viewed (leading them to maybe shift their most appealing information toward the beginning of the advert). Viewers also do not need to pay to watch these videos, with YouTube primarily being a free platform (with subscriptions that also allow people to get rid of advertisements), whereas people require certain television packages to view live sports such as the Super Bowl. These adverts also help the content creators on YouTube whose videos are contain these adverts. This financial ecosystem that YouTube and Google have created insures it is one of

the foremost areas for organisations to gain to post their commercials and gain the attention of social media users.

4.1.2 Personalised/Targeted Advertisements

With promotional media bountiful on social media platforms, users can often feel as if the advertisements posted have nothing to do with them and do not relate to them. A powerful tool used by companies on social media platforms is personalised or targeted advertising.

Social media platforms track your activity and can use the data to mould the adverts you receive. For example, Twitter states that "When you use Twitter to follow, tweet … we may use these actions to customise Twitter Ads for you. For example, if you search for a specific term, … show you promoted content related to that topic" [17]. Many other social media platforms follow this model, tuning the content you see by using your activity on the platform.

Furthermore, companies can specify the target audience they want to be receiving their content. This increases the overall effectiveness of the advertisement; a children's toy company would not necessarily aim their promotional material towards elderly people.

This can be seen in political campaigning as well. A study conducted by Applied Data Science looked at how the different political parties in the UK targeted specific Facebook users based on things such as their age and gender. It looked at the spend of each party on these groups. As you can see from the data gathered, it shows how different parties focused on groups to convey their messages. For example, the right-wing Brexit Party led all parties in adverts targeted towards people aged over 45 [18]. Furthermore, during the European Elections in May 2019, the Labour Party increased their female demographic targeting to 60% [18].

However, sometimes advertisement material may be shown to those who may not be suitable for it on purpose. A study by AdWatch looked at how minors (people under the legal age to vote) received adverts targeted for them by political parties on Facebook. Although people under the age of 18 cannot vote, Facebook allows users from age 13 and older to create an account. Therefore, these political parties can then target the younger users of the site, conveying their agendas to them at a young age, potentially adding new followers of their party in the near future. From the data gathered by AdWatch, you can see that the Independent Group for Change spent roughly £25,000 on adverts targeted at minors between over a duration lasting over a year. These adverts went on to gain over 1 million impressions [19].

It is important to understand that the data gathered for personal advertising needs to be collected in an ethical and un-invasive manner. The Cambridge Analytica scandal led to a massive reform in data

collection, as personal information about Facebook users was illegally acquired without their consent [20]. Data gathered about the user and user's friends were used in advertisement targeting and was used in Donald Trump's presidential campaign [21]. Now users are advised make sure they understand the privacy policies of different social media platforms, as well as acknowledging their right to have personalised adverts turned off.

A study done on personalised targeting conducted on a group of students and a group of consumers and observed their engagement with personalised & standard adverts on a website. The study tested the hypothesis "personalised adverts were more often clicked on than a standard one". It was shown to be validated at different levels between the student and consumer group [22]. This shows that at the base level, personalised adverts attract more attention than standard ones.

Overall, personalised targeting is a powerful tool and in the right way can be used to gain a boost in following and user attention.

4.1.3 Competitions, Discounts & Giveaways

Sometimes the price is simply too high to attract people to your business. Offering products at a discounted price is sure to interest more people into the services you offer. When done over social media, it allows for the new slashed prices to be relayed very quickly (i.e. retweets and sharing on Twitter). Competitions and giveaways give further opportunities for social media users to engage with the company hosting them, and potentially acquire a product that they like for a lower price, or even for free.

A study done, interviewing "14 different marketing managers responsible for the social media activity of their company" showed that one of "two most common and important activities" held on their respective company's social media account was "making competitions with prizes such as coupons, discounts…". It also states that "special discounts, offers, competitions… can increase sales" [23]. At the cost of reducing revenue gained, interaction and engagements with customers on social media spikes, as the sentiment of receiving something for a lower price naturally draws people.

An example of a company that uses social media platforms in this fashion is Uber, the ride-sharing company. Uber, and its food-delivering subsidiary Uber Eats, regularly uses social media platforms to communicate with customers, and inform them of discounts and offers currently available. Uber "relay its deals, discounts… through its Facebook account to the large base of followers". On Twitter, "followers can be informed of the new deals and discounts using pictures and videos" [24]. Furthermore, Uber uses Instagram to "unveil new features, and offers exclusive deals and discounts"

[25]. This approach to social media marketing has led Uber to become one of the dominant companies in its field, with "6.4 million US installs [of the application] in Q1 2019" [26].

4.1.4 Sponsored Posts

A sponsored post can be defined as a "post … explicitly sponsored as an advertisement by a particular company in order to draw a large amount of popularity" [27]. Through sponsored posts, organisations can reach a specific audience, boosting the effectiveness of their advertisement. Above I discussed targeted advertisement, something that sponsored posts is similar to. However, I am more so looking at using 'influencers' and accounts on social media to promote products.

A social media 'influencer' is an individual that has amassed a following on social media platforms, and "can affect purchasing decisions of others because of (their) authority, knowledge, position or relationship with their audience" [28].

A study by TapInfluence & Nielsen Catalina Solutions showed that influencer marketing "spurs 11 times the (return on investment)" than other types of advertising, raising incremental sales of a certain product by 10% [29]. A reason for this is because the followers of large social media accounts resonate and can relate with whom they follow. If the influencer promotes a product, the followers can feel that product is used by someone who they relate to, and in turn can be of use to them as well.

Interviews held with different advertisers from different agencies of varying sizes about influencer marketing showed that they value influencers as they hold "engaged audience but also a captive one". Additionally, a participant said "(influencers) are used a lot, because that's who the consumers are looking at" [30]. Looking at the influencer and who their audience is allows companies to reach a target audience quite easily. This allows for consumers on social media who may not know about the company to be exposed to it directly via the influencers they follow.

4.1.5 Consumer-based Interaction

Consumer-based interaction is one desired end result of all these strategies. This means that it is very prevalent. Once promotional material has been posted on to a social media platform, is it then interactions between users that causes it to spread forward and reach potential new consumers. This includes (and is not limited to) liking, sharing the post (i.e. retweet), commenting, and directly forwarding posts to people. Once someone sees a friend of theirs like a post by a company, influencer etc., they may take an interest in it. This one post about a certain product, can then be forwarded to others– "it is like a snowball effect" [30].

Furthermore, people value word of mouth highly in modern society, as they trust what their friends and family would say than organisations. Nielsen states that 92% of people believe "recommendations from friends and family, above all other forms of advertising" [31]. Seeing a friend like a post about a product can incite interest, potentially adding a new consumer for that company.

Instead of necessarily searching for tweets directly related to this strategy, I will be analysing the spread of tweets using Gephi and asking questions about this in the survey.

4.2 Sentiment Analysis in Marketing

Sentiment analysis returns whether mentions of something is in a positive, negative, or neutral sentiment or attitude. It is therefore used by organisations to gauge how people feel about them, their products, and their proceedings (i.e. strategies employed, public standing etc.). From this, companies can use this information to make changes to areas that are not being received well – "if… latest marketing campaign is gaining too much negative responses, (the company is) in a position to notice this and make necessary changes" [32].

Sentiment analysis offers organisations ways to measure the effect of their strategies, as well as identifying new trends which they can adopt themselves, and keep the relationship with their consumer base strong.

5. Implementation

In this section, I will go over how I had implemented my practical methods to produce results on the different marketing strategies. The code was written in Python unless stated otherwise, using Jupyter Notebook. The code can be found in the GitLab repository linked in the appendix.

5.1 Twitter Search Using Twint

This code is located in *TwitterScrape.ipynb*. This file uses the Twint library [5] and collects tweets relevant to the search terms. Twint has multiple methods which allow you to collect tweets relevant to your parameters.

```
import twint
import nest_asyncio
nest_asyncio.apply()
#importing twint for twitter scraping and nest_asyncio for notebook
#compatibility
```

```
import csv
import pandas as pd
```

Code 5.1 – Importing relevant libraries at the beginning of the file

At the beginning of the file, 4 libraries are imported. *Twint* allows access to the Twint methods. *Nest_asyncio* is necessary for Twint to be used in Jupyter notebook. It allows for concurrent actions within the notebook [33]. *Csv* allows for operations related to .csv files to be performed. Finally, *Pandas* is used so that the tweets saved are compatible with Pandas operations.

I will show an example of how I used Twint to search for tweets related to YouTube ads.

```
c = twint.Config()
c.Search = "youtube ads"
c.Format = "Tweet: {tweet} | Date: {date}"
c.Since = "2020-03-01"
c.Until = "2020-04-27"
c.Limit = 1500
c.Lang = "en"
c.Count = True
c.Pandas = True
c.Store_csv = True
c.Output = "youtubeadstweets.csv"
#configures twint to search twitter for the term 'youtube ads'
#with the following parameters, and saves it to a csv file named 'youtubeadstweets.csv'

twint.run.Search(c)
#executes search
```

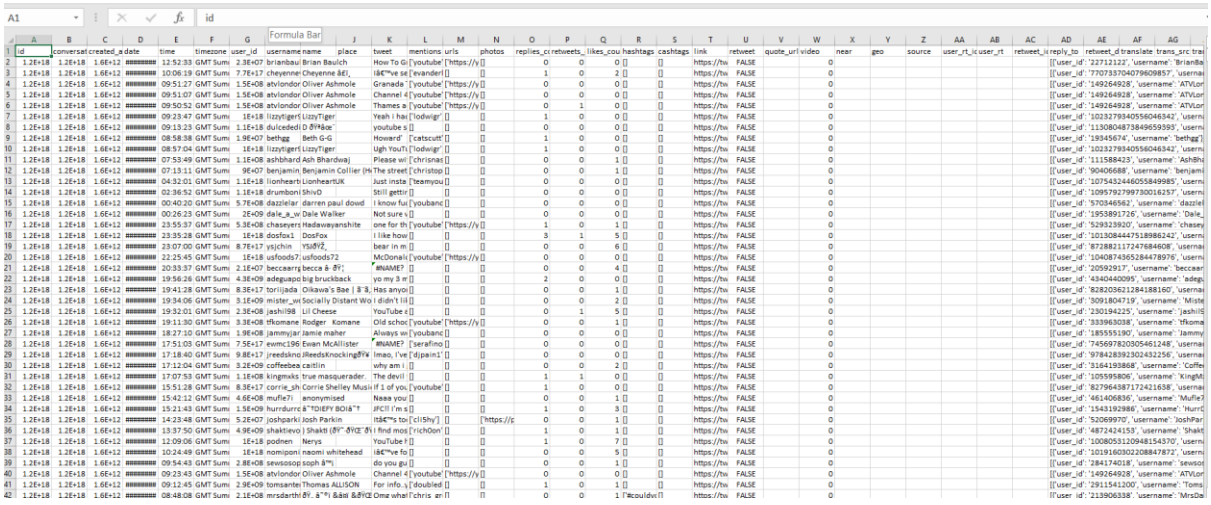
Code 5.2 – Performing a Twitter search using Twint for "youtube ads"

The first line assigns twint.Config() to *c*. This then allows us to configure this search with parameters. using *c*. The following lines then have the different parameters. *c.Search* is the specific search term. In this example, I am looking for tweets related to "youtube ads" (it is not case sensitive). *Format*

allows for output setting in the notebook. Here, I wanted to see only the tweet and the date it was posted. *Since* & *Until* defines the selected time period the tweets will be found from. *Lang* is the language of the tweets. *Count* returns the total amount of tweets searched for, which I specified for using *Limit* at 1500 (meaning roughly 1500 tweets should be returned. For some unforeseen reasons, the number of tweets returned exceeded this limit by a bit). *Pandas* allows for Pandas integration. *Store_csv* and *Output* saves the information about the tweets into a .csv file, which I named 'youtubeadstweets.csv'. The final line executes the search with the parameters defined in *c* [34].

```
Tweet: please @guardian I report a British person in Spain bombing us with adverts about funerals on youtube . I am not e
ven an expat. I don't know how to report them. 100 times a day they sell death to me. Please find out who they are and do
something  https://expat-funeral-plans.co.uk/  | Date: 2020-03-29
Tweet: Every time I spit on #riseofkingdoms advert in YouTube videos, I will mention it here , and I will continue tellin
g about my frequent spits until the adverts stop appearing to me in YouTube 😁 @riseofkingdoms | Date: 2020-03-29
Tweet: Till June ...  I've already started watching youtube adverts 😭😭 | Date: 2020-03-29
Tweet: @YouTube why do you think adverts in the middle of a YouTube video is going to entice people to buy that product?
SO ANNOYING | Date: 2020-03-29
Tweet: every person that stars in those Honey adverts on youtube deserves to be in the bad place | Date: 2020-03-29
Tweet: Yes I agree but the adverts are getting way to often now... | Date: 2020-03-29
Tweet: It's going to cost 5.8 million pounds to send this letter out. Money that could be diverted towards the NHS. Broad
cast it on the news, radio, TV adverts, YouTube, Facebook etc | Date: 2020-03-29
Tweet: Hi can you kindly please subscribe to our Youtube channel and share the link with all your friends to subscribe an
d watch all our TV adverts  https://youtu.be/W_Yi9N8jZwA  https://www.instagram.com/p/B-UQhPUFyFh/?igshid=1qhv326kdvjy
3 … | Date: 2020-03-29
```

Code 5.3 – Part of the notebook output of the code snippet above



The .csv file 'youtubeadstweets.csv'

As people may use the word 'adverts' as well, I then searched for tweets with the term "youtube adverts".

```
c = twint.Config()
c.Search = "youtube adverts"
c.Format = "Tweet: {tweet} | Date: {date}"
c.Since = "2020-03-01"
c.Until = "2020-04-27"
c.Limit = 1500
c.Lang = "en"
c.Count = True
c.Pandas = True
c.Store_csv = True
c.Output = "youtubeadstweets.csv"
#tweaked search term to 'adverts', writes tweets to same csv file as above

twint.run.Search(c)
```

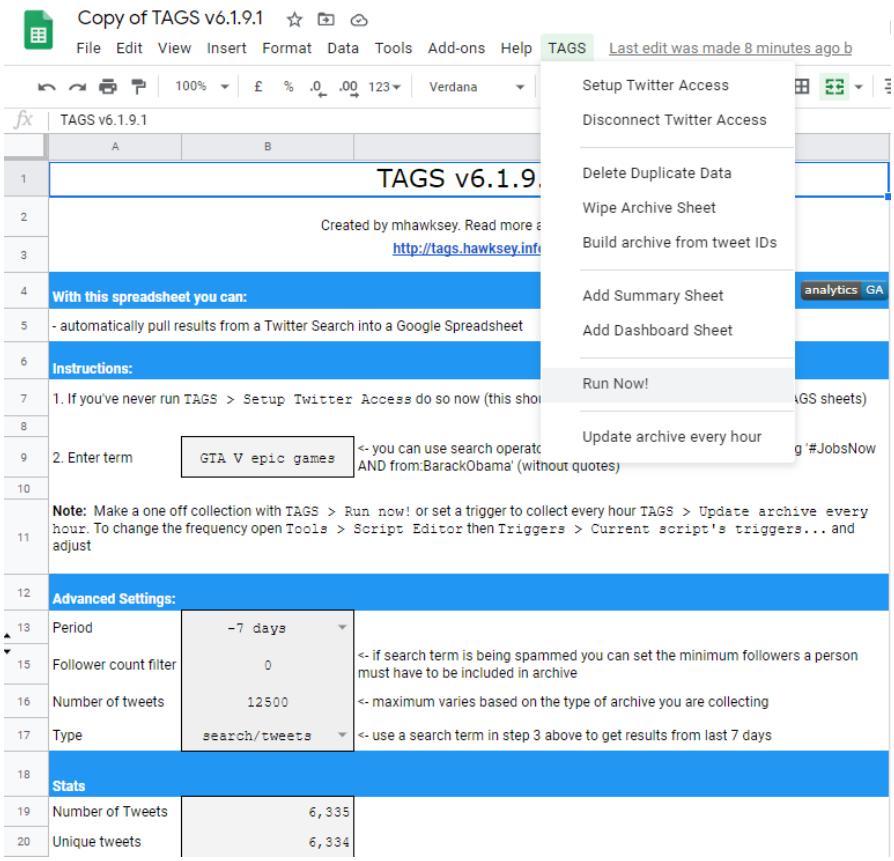
Code 5.4 – performing a Twitter search using Twint for the term "youtube adverts"

Here, the tweets related to "youtube adverts" will be added to the same .csv file that the previous search was as well. This is so that all the tweets are in one place so that they can be passed through the sentiment analysis model, and some of the links in the tweets can be passed through the YouTube API. I used Twint to search for things relevant to the different marketing strategies.

- Video Advertisements – I searched for "youtube ads", "youtube adverts", as well as tweets related to YouTube adverts about Raid Shadow Legends, looking at tweets close to the adverts' release & now (will be explained more in the next section)
- Personalised/Targeted Ads – searched for "personalised ads", "personalised adverts", "targeted adverts" ("targeted ads" had a large number of tweets unrelated to the strategy, so this was omitted)
- Discounts, Giveaways & Competitions – using Twint, I searched for examples of discounts, using the terms "uber discounts", "lyft discounts" and "ola discounts"
- Sponsored Posts – searched for "sponsored vids", "sponsored videos", "sponsored insta" and "sponsored Instagram"

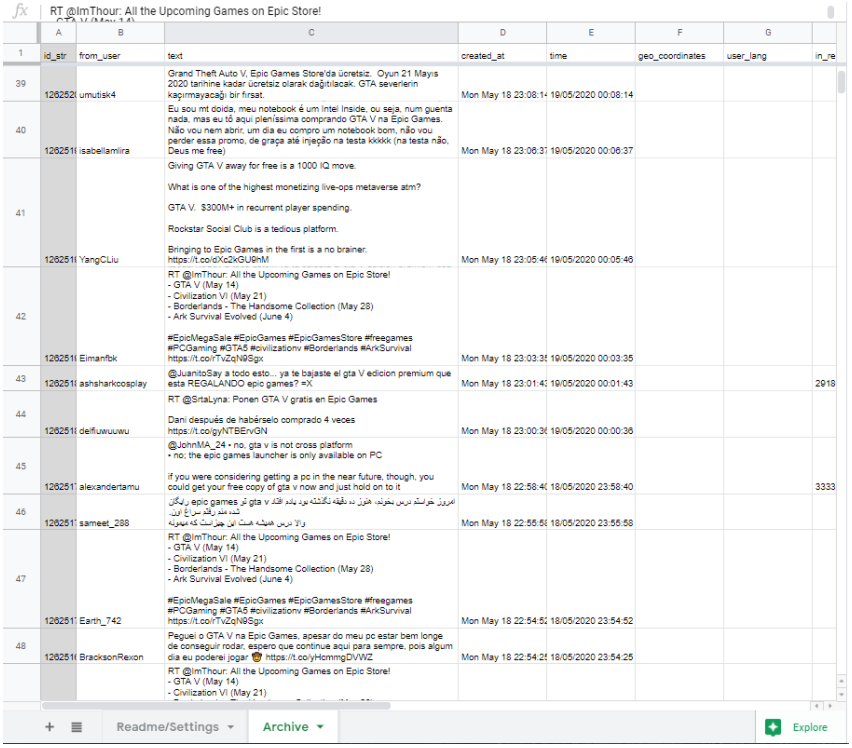
5.2 Twitter Search Using Tags

Alongside Twint, I used TAGS to search for tweets. As TAGS operates inside a Google Sheet, you need to link your Google account with it (a copy of the Google Sheet can be found on the TAGS website [8]). Furthermore, you need to link a Twitter account with to make it work. Below is an example of using TAGS to search for tweets related to the Epic Games Store releasing the game GTA V for free on their store. I used the search term 'GTA V epic games' to see tweets related to this giveaway.



Using TAGS to search for tweets related to a giveaway

After running the script, tweets are returned in the next sheet:

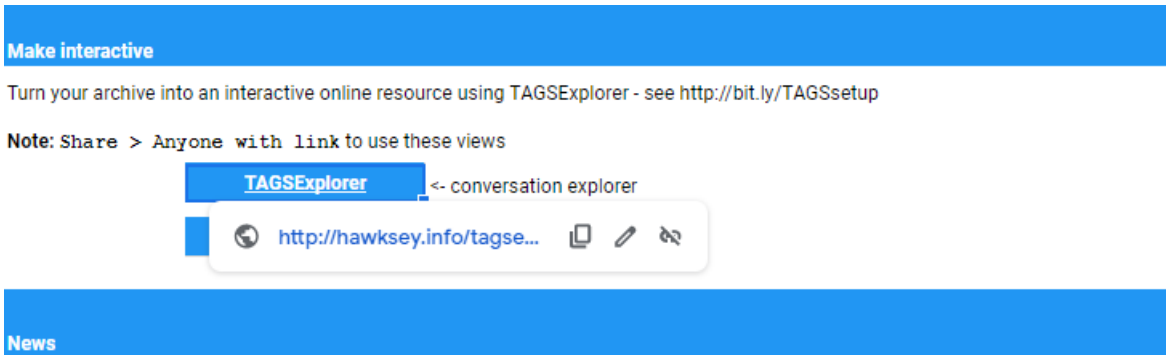


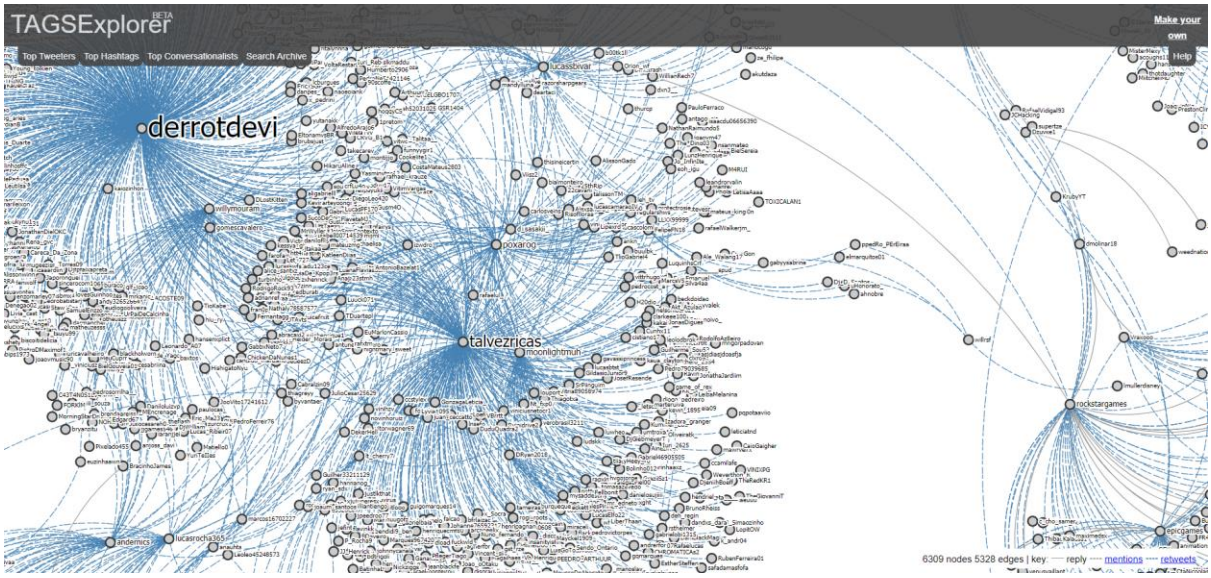
	A	B	C	D	E	F	G	
1	id_str	from_user	text	created_at	time	geo_coordinates	user_lang	in_re
39	126252	umutisk4	Grand Theft Auto V, Epic Games Store'da ücretsiz, Oyun 21 Mayıs 2020 tarihine kadar ücretsiz olarak dağıtılacak. GTA severlerin kaçırmayacağı bir fırsat.	Mon May 18 23:08:14	19/05/2020 00:08:14			
40	126251	isabellamlira	Eu sou mt doida, meu notebook é um Intel Inside, ou seja, num guenta nada, mas eu tô aqui pleníssima comprando GTA V na Epic Games. Não vou nem abrir, um dia eu compro um notebook bom, não vou perder essa promo, de graça até injeção na testa kkkkk (na testa não, Deus me free)	Mon May 18 23:06:37	19/05/2020 00:06:37			
41	126251	YangCLiu	Giving GTA V away for free is a 1000 IQ move. What is one of the highest monetizing live-ops metaverse atm? GTA V. $300M+ in recurrent player spending. Rockstar Social Club is a tedious platform. Bringing to Epic Games in the first is a no brainer. https://t.co/dXo2kGU9hM	Mon May 18 23:05:46	19/05/2020 00:05:46			
42	126251	Eimanfbk	RT @ImThour: All the Upcoming Games on Epic Store! - GTA V (May 14) - Civilization VI (May 21) - Borderlands - The Handsome Collection (May 28) - Ark Survival Evolved (June 4) #EpicMegaSale #EpicGames #EpicGamesStore #freegames #PCGaming #GTA5 #civilizationv #Borderlands #ArkSurvival https://t.co/rTvZqN9Sgx	Mon May 18 23:03:35	19/05/2020 00:03:35			
43	126251	ashsharkcosplay	@JuanitoSay a todo esto... ya te bajaste el gta V edicion premium que esta REGALANDO epic games? =X	Mon May 18 23:01:43	19/05/2020 00:01:43			2918
44	126251	delfiuwuuwu	RT @SrtaLyna: Ponen GTA V gratis en Epic Games Dani después de habérselo comprado 4 veces https://t.co/gyNTBErvGN	Mon May 18 23:00:36	19/05/2020 00:00:36			
45	126251	alexandertamu	@JohnMA_24 • no, gta v is not cross platform • no; the epic games launcher is only available on PC if you were considering getting a pc in the near future, though, you could get your free copy of gta v now and just hold on to it	Mon May 18 22:58:40	18/05/2020 23:58:40			3333
46	126251	sameet_288	امروز خواستم درس بخونم، هنوز ده دقیقه نگذشته بود، یادم افتاد v gta تو epic games رایگان شده، فقط واقعا سراغ اون. والا درس همیشه هست این چیزاست که مهمونه	Mon May 18 22:55:58	18/05/2020 23:55:58			
47	126251	Earth_742	RT @ImThour: All the Upcoming Games on Epic Store! - GTA V (May 14) - Civilization VI (May 21) - Borderlands - The Handsome Collection (May 28) - Ark Survival Evolved (June 4) #EpicMegaSale #EpicGames #EpicGamesStore #freegames #PCGaming #GTA5 #civilizationv #Borderlands #ArkSurvival https://t.co/rTvZqN9Sgx	Mon May 18 22:54:52	18/05/2020 23:54:52			
48	126251	BracksonRexon	Peguei o GTA V na Epic Games, apesar do meu pc estar bem longe de conseguir rodar, espero que continue aqui para sempre, pois algum dia eu poderei jogar 😎 https://t.co/yHomrgDVWZ	Mon May 18 22:54:25	18/05/2020 23:54:25			
			RT @ImThour: All the Upcoming Games on Epic Store! - GTA V (May 14) - Civilization VI (May 21)					

Readme/Settings | Archive | Explore

Result of running TAGS script

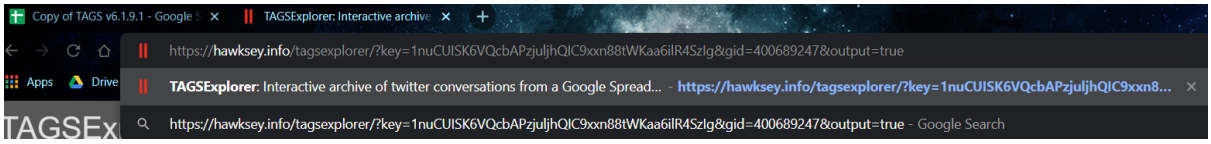
From there, you can pass on the tweets into the TAGSExplorer by pressing the link that is generated for you at the bottom of the first sheet.





Part of the graph generated by TAGSExplorer

Above is a snippet of the graph created by the TAGSExplorer. Each node is an account, and each connection/edge is a retweet (this graph has the argument 'retweet = true'). If you at the end of the link you add 'output=true', then it returns a new window showing the source (account), target (who the tweet is directed at) and tweet type. This can then be saved to a .csv file.



Adding to the URL to get the tweet data

```
Source,Target,Tweet Type
silvadigao0,derrotdevi,retweet
ktechxd,_fivem,retweet
alex_notturner,g1,retweet
vasanor_,i_am_wildcat,retweet
zeinacio7,snopey_,retweet
qamarhakimi,myaksiz,retweet
mdfariz185,matheusdaring_,retweet
cmol75,theorus_,retweet
rafaelajborgs,derrotdevi,retweet
arriqariq,vraxooo,retweet
ethansm23767443,hypex,retweet
viisz2,talvezricas,retweet
therealfyyre,i_am_wildcat,retweet
hiisyamm,tech_lagi,retweet
manorahz,hypex,retweet
lucascharmoso_,derrotdevi,retweet
joaosouuza13,lucassbivar,retweet
mishvin60,derrotdevi,retweet
cabralzin09,talvezricas,retweet
distantvicinity,news18tech,retweet
distantvicinity,distantvicinity,retweet
tchetchenencore,theorus_,retweet
arifnaufal_,tech_lagi,retweet
thierrymaccel3,derrotdevi,retweet
cewek_berponi,gamesmenfess,retweet
simaobichinho,eusouosena,retweet
gonzaboquete,porquetendencia,retweet
mkieromorir,porquetendencia,retweet
juandie55178426,sayorijoestar,retweet
```

	A	B	C	D
1	Source	Target	Tweet Type	
2	silvadigao0	derrotdevi	retweet	
3	ktechxd	_fivem	retweet	
4	alex_nottu	g1	retweet	
5	vasanor_	i_am_wild	retweet	
6	zeinacio7	snopey_	retweet	
7	qamarhaki	myaksiz	retweet	
8	mdfariz18	matheusda	retweet	
9	cmol75	theorus_	retweet	
10	rafaelajbo	derrotdevi	retweet	
11	arriqariq	vraxooo	retweet	
12	ethansm23	hypex	retweet	
13	viisz2	talvezricas	retweet	
14	therealfyy	i_am_wild	retweet	
15	hiisyamm	tech_lagi	retweet	
16	manorahz	hypex	retweet	
17	lucascharm	derrotdevi	retweet	
18	joaosouuz	lucassbiva	retweet	
19	mishvin60	derrotdevi	retweet	
20	cabralzin0	talvezricas	retweet	
21	distantvici	news18tec	retweet	
22	distantvici	distantvici	retweet	
23	tchetchen	theorus_	retweet	
24	arifnaufal_	tech_lagi	retweet	

Snippet of the data that is returned, and snippet of subsequent GTAVTweetsVisualisation.csv

This data can then be added loaded into Gephi, allowing for custom graphs to be generated.

5.3 YouTube API

Here I will go through how I used the YouTube API to gain data. The code used here can be found in the *RSLYouTubeScrape.ipynb* file.

To use the YouTube API, you first need to create an API key. This is done by following the instructions on the YouTube Data API Overview page [35].

```
In [1]:
import csv
import numpy as np
import matplotlib.pyplot as plt
```

```
In [2]:
from apiclient.discovery import build

api_key = "AIzaSyC4wU8gLZPxsmzk-9F5TW6DA7tazqn-xxo"

youtube = build('youtube', 'v3', developerKey=api_key)
```

Code 5.5 – Importing relevant libraries

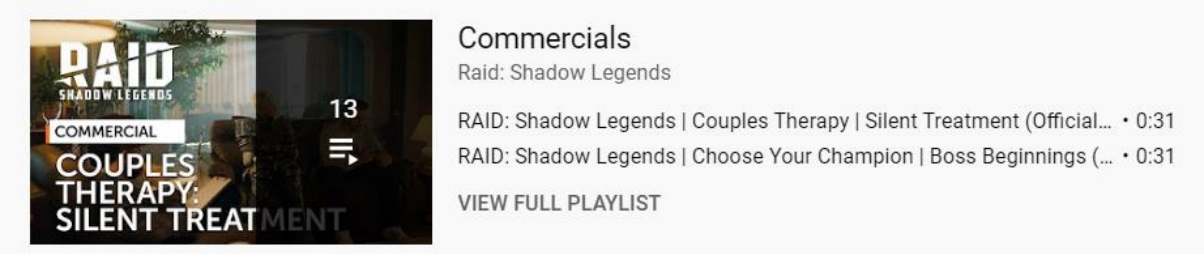
The *build* function from the *apiclient.discovery* library constructs a resource for interacting with the YouTube API [36]. By passing through the '*youtube*', relevant version and API key parameters through the function, I can directly interact with the methods of the YouTube API.

The first section of the file is me learning how to use the API. I will go over the second portion where I look at actually scraping relevant data whilst also making references to the first part.

```
RSLPlaylist = youtube.playlistItems().list(part="snippet", maxResults=20, playlistId="PLKsMVIY2OJRPVWbWjH05cxG1CB0cbP_uv")
#collects all the videos in the Raid Shadow Legends 'Commercials' playlist
RSLPlaylist_ = RSLPlaylist.execute()
```

Code 5.6 – executing a playlist search with parameters

Here I am looking at the YouTube videos in the Raid Shadow Legends 'Commercials' playlist. These videos have been used as advertisements on the platform to promote the mobile game.



The 'Commercials' playlist

In the first line in Code 5.6, I am using the method *playlistItems* with the ID of the playlist. *RSLPlaylist* is a HTTP request, and in the following line I execute the request. This then returns a resource in JSON structure in a Python dictionary, holding the different details of the playlist, assigned to *RSLPlaylist_*.

```
RSLPlaylist_
```


```
]: {'kind': 'youtube#playlistItemListResponse',
    'etag': 'bT_J2WE4zsx7uiJ2xPDK2FVqeQE',
    'items': [{'kind': 'youtube#playlistItem',
      'etag': 'ImcdjB89ILf3cdJ3vGX3HEhaOMU',
      'id': 'UExLc01WSVkyT0pSUFZXYldqSDA1Y3hHMUNCMGNiUF91di4wOTA3OTZBNzVEMTUzOTMy',
      'snippet': {'publishedAt': '2019-09-27T12:45:21Z',
       'channelId': 'UCVME1RlhWxfoZ2ZcGWlz_KA',
       'title': 'RAID: Shadow Legends | Couples Therapy | Silent Treatment (Official Commercial)',
       'description': 'As your roster grows and the challenges you face become ever more dangerous, you'll have to choose th
e best Champion for every task. Sometimes, it means leaving weaker Champions behind.\n\nThey've got some opinions on tha
t. It's that buzzing in your ear.\n\nDon't take it too hard; you've got dozens of bosses and dungeon battles to fight. Ta
ctics and strategies don't develop themselves. So get out there, gather your forces, and bring the fight to Siroth!\n\nAn
d maybe get some earplugs.\n\nPlay RAID: Shadow Legends for free on all devices:\n\nPlay on iOS → https://itunes.apple.co
m/ua/app/raid-shadow-legends/id1371565796?mt=8\n\nPlay on Android → https://play.google.com/store/apps/details?id=com.pla
rium.raidlegends&hl=en\n\nPlay on PC →  https://plrm.me/RaidShadowLegends\n\n\nJoin our Facebook Community → \nhttps://ww
w.facebook.com/RaidShadowLegends/\n\nAnswer the call of the Arbiter now!',
       'thumbnails': {'default': {'url': 'https://i.ytimg.com/vi/QjDi9tWDGcg/default.jpg',
        'width': 120,
        'height': 90},
```


*Code 5.7 – Notebook output of RSLPlaylist_*

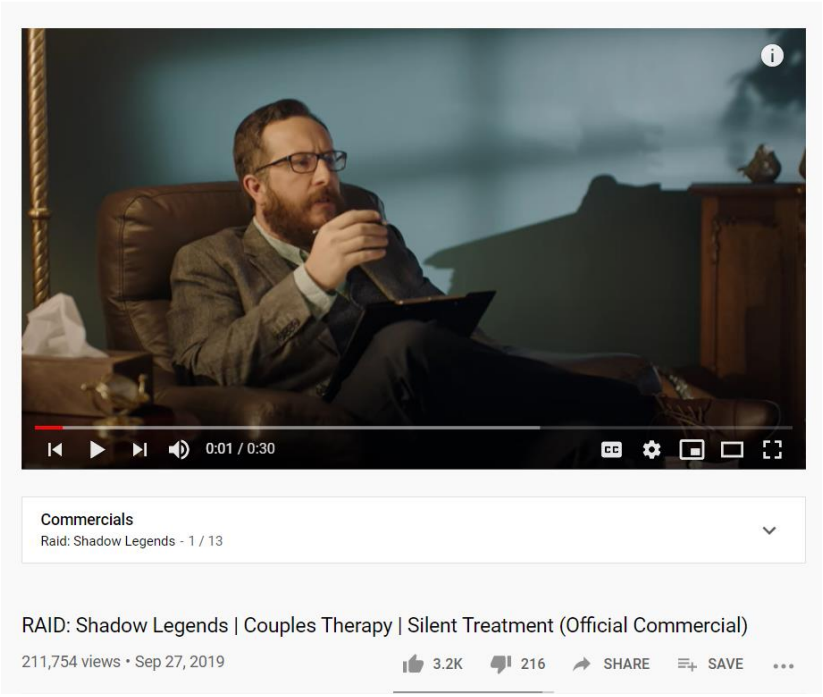
The 'kind' and 'etag' keys describe what *RSLPlaylist_* is. The 'items' heading contains the information about the contents of the playlist. As there are 13 videos in the playlist, there will then be 13 different resources being described in 'items'.

```
RSLPlaylist_['items'][0]
```


```
{'kind': 'youtube#playlistItem',
 'etag': 'ImcdjB89ILf3cdJ3vGX3HEhaOMU',
 'id': 'UExLc01WSVkyT0pSUFZXYldqSDA1Y3hHMUNCMGNiUF91di4wOTA3OTZBNzVEMTUzOTMy',
 'snippet': {'publishedAt': '2019-09-27T12:45:21Z',
  'channelId': 'UCVME1RlhWxfoZ2ZcGWlz_KA',
  'title': 'RAID: Shadow Legends | Couples Therapy | Silent Treatment (Official Commercial)',
  'description': 'As your roster grows and the challenges you face become ever more dangerous, you'll have to choose the bes
t Champion for every task. Sometimes, it means leaving weaker Champions behind.\n\nThey've got some opinions on that. It's t
hat buzzing in your ear.\n\nDon't take it too hard; you've got dozens of bosses and dungeon battles to fight. Tactics and st
rategies don't develop themselves. So get out there, gather your forces, and bring the fight to Siroth!\n\nAnd maybe get som
e earplugs.\n\nPlay RAID: Shadow Legends for free on all devices:\n\nPlay on iOS → https://itunes.apple.com/ua/app/raid-shad
ow-legends/id1371565796?mt=8\n\nPlay on Android → https://play.google.com/store/apps/details?id=com.plarium.raidlegends&hl=e
n\n\nPlay on PC →  https://plrm.me/RaidShadowLegends\n\n\nJoin our Facebook Community → \nhttps://www.facebook.com/RaidShado
wLegends/\n\nAnswer the call of the Arbiter now!',
  'thumbnails': {'default': {'url': 'https://i.ytimg.com/vi/QjDi9tWDGcg/default.jpg',
    'width': 120,
    'height': 90},
   'medium': {'url': 'https://i.ytimg.com/vi/QjDi9tWDGcg/mqdefault.jpg',
    'width': 320,
    'height': 180},
   'high': {'url': 'https://i.ytimg.com/vi/QjDi9tWDGcg/hqdefault.jpg',
    'width': 480,
    'height': 360},
   'standard': {'url': 'https://i.ytimg.com/vi/QjDi9tWDGcg/sddefault.jpg',
    'width': 640,
    'height': 480},
   'maxres': {'url': 'https://i.ytimg.com/vi/QjDi9tWDGcg/maxresdefault.jpg',
    'width': 1280,
    'height': 720}},
  'channelTitle': 'Raid: Shadow Legends',
  'playlistId': 'PLKsMVIY2OJRPVWbWjH05cxG1CB0cbP_uv',
  'position': 0,
  'resourceId': {'kind': 'youtube#video', 'videoId': 'QjDi9tWDGcg'}}}
```


*Code 5.8 – Notebook output of first item in 'items' key of RSLPlaylist_*

The information here is from the first video in the playlist.



The first video in the playlist

```
RSLVideoId = []
RSLVideoName = []

for i in range(0, len(RSLPlaylist_['items'])):
    RSLVideoId.append(RSLPlaylist_['items'][i]['snippet']['resourceId']['videoId'])
    RSLVideoName.append(RSLPlaylist_['items'][i]['snippet']['title'])
#adds ID of videos in playlist to the RSLVideoId list, and names of videos in playlist to the RSLVideoName
```

Code 5.9 – Extracting video title & ID

RSLVideoID and *RSLVideoName* are two lists used to hold the ID and titles of the videos, respectively. These are extracted from *RSLPlaylist_*, for each video contained in the 'items' key using a loop.

```
VideosRelatedToRSL = []
#list to hold videos related to RSL adverts

for RSLVideoID_ in RSLVideoId:
    RSLRelated = youtube.search().list(relatedToVideoId=RSLVideoID_, type="video", part="snippet", maxResults=20)
    RSLRelated_ = RSLRelated.execute()
    #for each video, return 20 videos that are related to it

    for item in RSLRelated_['items']:
        VideosRelatedToRSL.append((RSLVideoID_, item['id']['videoId']))
        #adds seed video and related videos to list
```

```
VideosRelatedToRSL_Names = []

for RSLVideoName_ in RSLVideoName:
    for item in RSLRelated_['items']:
        VideosRelatedToRSL_Names.append((RSLVideoName_, item['snippet']['title']))

VideosRelatedToRSL_Names
```

Code 5.10 – Using the IDs to find videos related to the advertisement videos

Using the *relatedToVideoId*, we can find videos related to the video in question. Here, we find 20 videos related to each video in the playlist using a loop. *RSLRelated_* will hold the information of each of these related videos. The video ID and subsequently the titles are added to relevant lists. With each item in the list, the ID/title of the 'seed' video (video from playlist) and the related video are added. This relevant information can be saved into a .csv file, which can then be used in Gephi for visualisations.

```
[('QjDi9tWDGcg', 'oCymApjq6uw'),
 ('QjDi9tWDGcg', '-Aiw3wk-3ik'),
 ('QjDi9tWDGcg', 'TkPGJARlXdw'),
 ('QjDi9tWDGcg', '2xZY2RkrRMQ'),
 ('QjDi9tWDGcg', 'nw01uuIBROQ'),
 ('QjDi9tWDGcg', 'qE1qLlUQEx4'),
 ('QjDi9tWDGcg', 'fA2az38oT2k'),
 ('QjDi9tWDGcg', '9pcW8nesY-o'),
 ('QjDi9tWDGcg', 'TVf1ejk_vZw'),
 ('QjDi9tWDGcg', 'j6XRbwii8WM'),
 ('QjDi9tWDGcg', 'In2PKh47PsI'),
 ('QjDi9tWDGcg', 'gqG6HQEQr88'),
 ('QjDi9tWDGcg', 'qo5mZwA1sJo'),
 ('QjDi9tWDGcg', 'ihMy6xndCe4'),
 ('QjDi9tWDGcg', 'bS5vCDDNqrk'),
 ('QjDi9tWDGcg', 'daCGyZkG_38'),
 ('QjDi9tWDGcg', 'fG126TVfTUw'),
 ('QjDi9tWDGcg', 'vTdv_d2lF7s'),
 ('9pcW8nesY-o', 'QjDi9tWDGcg')]
```

Code 5.11 – Notebook output of last 20 elements of VideosRelatedToRSL

```
RSLComments = []
#list to hold all comments

for RSLVideoId_ in RSLVideoId:
    RSLComms = youtube.commentThreads().list(part="snippet", maxResults=100, videoId=RSLVideoId_)
    RSLComms_ = RSLComms.execute()
    #for each video, return 100 comments

    for comment in RSLComms_['items']:
        RSLComments.append(comment['snippet']['topLevelComment']['snippet']['textOriginal'])
        #add each comment to the list
```

Code 5.12 – Extracting comments from each video

Using *commentThreads*, you can extract comments from YouTube videos. This is limited to 100 only. Executing the request, *RSLComms_* will hold 100 comments from video with the ID that the loop is using. We extract the string of each comment and add it to the list *RSLComments* (this code was re-used in the files containing the sentiment analysis models, as there was an issue writing the comments to a .csv file).

```
likesNumber = []
dislikesNumber = []
#lists to hold likes and dislikes numbers

for AdID in RSLVideoId:
    ratingsFromAd = youtube.videos().list(part="statistics", id=AdID)
    ratings_ = ratingsFromAd.execute()
    likesNumber.append(int(ratings_['items'][0]['statistics']['likeCount']))
    dislikesNumber.append(int(ratings_['items'][0]['statistics']['dislikeCount']))
    #for each video, add the number of likes/dislikes to relevant list
```

Code 5.13 – Getting likes/dislikes numbers from videos

Using the *videos* method and assigning the 'part' parameter to 'statistics', you can get information about the statistics of each video. Using a loop, we execute the request with the ID of each video in the playlist. We then add the likes/dislikes number of each video into the relevant list. We can then visualise this information in a graph

```
y_pos = np.arange(len(RSLVideoId))


likesBar = plt.barh(y_pos, likesNumber, alpha=0.4, color='g', label='Likes')
dislikesBar = plt.barh(y_pos, dislikesNumber, alpha=0.7, color='b', label='Dislikes')

plt.yticks(y_pos, RSLVideoName)
plt.title("Number of Likes/Dislikes for Each RSL Commercial")
plt.legend()
plt.show()
#plots the like/dislike splits into a graph for each video
```

Code 5.14 – Visualising the likes/dislikes number

I also used the YouTube API to get information regarding advertisements on the Labour Party YouTube channel. This can be found in the *LabourPartyYoutubeScrape.ipynb* file. Furthermore, I looked at the tweets gathered about YouTube adverts, and used the API to gather information about these links. This can be found in the *YouTubeLinksFromTweets.ipynb*.

5.4 Sentiment Analysis Models

5.4.1 Model A

As discussed earlier, I used two sentiment analysis models. The code being discussed here can be found in *SentimentAnalysisModelA.ipynb*. This sentiment analysis model is adapted from a tutorial by Medium [37].

```
from nltk.corpus import twitter_samples
#twitter samples used to train model
from nltk.tokenize import word_tokenize
#used to tokenize tweets
from nltk.tag import pos_tag
#classifies each token with a POS, outputting specific tag for words
#e.g. tags given to verbs start with 'V'
from nltk.stem.wordnet import WordNetLemmatizer
#used to lemmatize words i.e. sort variants of words into one
#e.g. talking -> talk
from nltk.corpus import stopwords
#used to remove noise from tweets
from nltk import classify
from nltk import NaiveBayesClassifier
#trains model in predicting whether tweet is positive or negative
```

Code 5.15 – Importing relevant libraries [37]

This model uses the Natural Language Toolkit to train a Naïve-Bayes classifier to perform sentiment analysis on piece of string. The training data for this model is provided by the NLTK library.

```
positive_tweets = twitter_samples.strings('positive_tweets.json')
#collection of tweets with a positive sentiment, will be used to train model
negative_tweets = twitter_samples.strings('negative_tweets.json')
#collection of tweets with a negative sentiment, will be used to train model
```

```
positive_tweets_tokenized = twitter_samples.tokenized('positive_tweets.json')
negative_tweets_tokenized = twitter_samples.tokenized('negative_tweets.json')
#tokenises string, splits sentences into words and punctuation
stop_words = stopwords.words('english')
#stop words for the English langauge. Used to remove noise from tweets
```

Code 5.16 – Loading in training data and preparing it [37]

positive_tweets and *negative_tweets* both hold the training data, which is a .json file containing tweets that are classified as positive or negative. We then tokenize each tweet, which splits each word and punctuation into its own separate token.

```python
def reformat_tweet(tokenized_tweet, stop_words = ()):
    #function used to format the tweets in the training data from the nltk library

    formatted_tweet = []
    #list to hold formatted tweet

    for tweet_token, POStag in pos_tag(tokenized_tweet):
        #for each token, and the POS tag that it is given
        tweet_token = re.sub('http[s]?://(?:[a-zA-Z]|[0-9]|[$-_@.&+#]|[!*\(\),]|'\
                        '(?:%[0-9a-fA-F][0-9a-fA-F]))+','', tweet_token)
        tweet_token = re.sub("(@[A-Za-z0-9_]+)","", tweet_token)
        #cleans string, getting rid of special characters, hyperlinks etc.

        if POStag.startswith("NN"):
            pos = 'n'
        elif POStag.startswith('VB'):
            pos = 'v'
        else:
            pos = 'a'
        #adds relative POS tag depending on what the word is e.g. verb -> 'v'

        lem_tweet = WordNetLemmatizer()
        tweet_token = lem_tweet.lemmatize(tweet_token, pos)
        #lemmatizes word (e.g. talking -> talk)

        if len(tweet_token) > 0 and tweet_token not in string.punctuation and tweet_token.lower() not in stop_words:
            #if there is a string, and it is not inlcuded in the stop words
            formatted_tweet.append(tweet_token.lower())
            #add to formatted tweet list
    return formatted_tweet
```

Code 5.17 – function to reformat string [37]

The function *reformat_tweet* is used to reformat a string. It removes things such as hyperlinks and special characters, as well as unnecessary words (or stop words), such as 'my', replacing them with an empty string. The token is also lemmatized based on its 'part of speech' tag e.g. if a token is a word that is a verb, then it is assigned the tag 'v'. If the token is neither empty nor a stop word, then it will be added to a list which holds the reformatted string.

```python
print(positive_tweets_tokenized[0])
print("**")
print(reformat_tweet(positive_tweets_tokenized[0], stop_words))
```

```
['#FollowFriday', '@France_Inte', '@PKuchly57', '@Milipol_Paris', 'for', 'being', 'top', 'engaged', 'members', 'in', 'my',
'community', 'this', 'week', ':)']
**
['#followfriday', 'top', 'engage', 'member', 'community', 'week', ':)']
```

Code 5.18 – Notebook output of function of a string and the function output

```python
positive_formatted_tweets = []
negative_formatted_tweets = []
#list to hold positive/negative formatted tweets

for tokenized_tweets in positive_tweets_tokenized:
    positive_formatted_tweets.append(reformat_tweet(tokenized_tweets, stop_words))


for tokenized_tweets in negative_tweets_tokenized:
    negative_formatted_tweets.append(reformat_tweet(tokenized_tweets, stop_words))

#format each tweet and add them to list
```

Code 5.19 – reformatting the training data tweets, and adding them to a list [37]

```python
def prepare_NLP_model(formatted_tweets_list):
    for tweets in formatted_tweets_list:
        yield dict([tokens, True] for tokens in tweets)
#function used to collect tokens for training the model. Adds tokens from
#positive/negative tweets into a dictionary with value "True"

positive_tokens_for_NLP = prepare_NLP_model(positive_formatted_tweets)
negative_tokens_for_NLP = prepare_NLP_model(negative_formatted_tweets)
#collects all the tokens from the positive tweets data, and from the negative
#tweets data and passes them through function

positive_words_dataset = [(tweet_dict, "Positive") for tweet_dict in positive_tokens_for_NLP]
#for each token taken from the positive tweets data, assigns value "Positive"

negative_words_dataset = [(tweet_dict, "Negative") for tweet_dict in negative_tokens_for_NLP]
#for each token taken from negative tweets data, assigns value "Negative"

random.shuffle(positive_words_dataset)

random.shuffle(negative_words_dataset)

totalDataset = positive_words_dataset + negative_words_dataset
#shuffles and adds data to a total dataset

training_data = totalDataset[:7000]
test_data = totalDataset[7000:]
#70% training data, 30% testing data

NLPclassifier = NaiveBayesClassifier.train(training_data)
#trains a Naive-Bayes classifier using data
```

Code 5.20 – building the model [37]

Here, we build a Naïve-Bayes classifier using the training data. The function *prepare_NLP_model* adds each tweet into a Python dictionary. All the tokens from the positive tweets are added together, with the value “positive”. The same is done for the negative tweets. Adding all this to a dataset, we can build the classifier to classify a string based on the data.

```python
RSLComments_formatted = []
#list used to hold formatted comments
RSL_sentiment_type_comments = ["Positive", "Negative"]
#graph heading
RSL_sentiment_analysis_of_comments = []
#used to hold the sentiment of comments
RSL_sentiment_count_comments = [0, 0]
#used to count how many comments are positive or negative i.e. if there are 100 positive comments and 50 negative
#will look like [100, 50]

for i in range(0, len(RSLComments)):
    #loops through each comment
    RSLComments_formatted.append(reformat_tweet(word_tokenize(RSLComments[i])))
    #formats comment and adds to list

    RSL_sentiment_analysis_of_comments.append(NLPclassifier.classify(dict([token, True] for token in RSLComments_formatted[i]
    #returns sentiment of comment and adds to list

    if RSL_sentiment_analysis_of_comments[i] == "Positive":
        RSL_sentiment_count_comments[0] = RSL_sentiment_count_comments[0] + 1
        #if sentiment is positive, add 1 to first element
    else:
        RSL_sentiment_count_comments[1] = RSL_sentiment_count_comments[1] + 1
        #if sentiment is negative, add 1 to second element

y_pos = np.arange(len(RSL_sentiment_type_comments))
#used for graph

plt.bar(y_pos, RSL_sentiment_count_comments, align='center')
plt.xticks(y_pos, RSL_sentiment_type_comments)
plt.title("Amount of Positive and Negative Comments in RSL's Commercials")
plt.show()
#plots graph with data shown
```

Code 5.21 – Using the model to perform sentiment analysis on comments from the Raid Shadow Legends commercial videos

Here, sentiment analysis is performed on the comments scraped from the RSL commercials. Lists are used to hold the formatted strings, the determined sentiment of the string, and a count of how many positive and negative comments there are.

With each comment, its sentiment is determined by the model. This is then added to a list. If the sentiment of the string is either positive or negative, then the relevant element in count list has its tally increased. We can then plot a graph using the data. Sentiment analysis was performed on all the tweets & comments gathered.

5.4.2 Model B

Another model was used so that the results could be compared for accuracy. Furthermore, the first model could only define whether a tweet was positive or negative. With this second model, I wanted to a model which could define whether a string is in positive, neutral, or negative sentiment. The code used can be found in *SentimentAnalysisModelB.ipynb*.

```
import re
from textblob import TextBlob
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
#imports relevant libraries
```

Code 5.22

This model utilises the TextBlob library [38]. The library can return lots of information about strings/sentences, including the sentiment.

```
def clean_string(sentence):
    return ' '.join(re.sub("(@[A-Za-z0-9]+)|([^0-9A-Za-z \t])|(\w+:\/\/\S+)", " ", sentence).split())
#removes hyperlinks, special characters etc. from a string
```

Code 5.23 – function to clean string

Once again, we need a function to clean the string.

```
def get_sentiment(sentence):
    sentiment_analysis = TextBlob(clean_string(sentence))
    if sentiment_analysis.sentiment.polarity > 0.4:
        return sentiment_analysis.sentiment.polarity, 'Strong Positive'
    if sentiment_analysis.sentiment.polarity > 0:
        return sentiment_analysis.sentiment.polarity, 'Slight Positive'
    elif sentiment_analysis.sentiment.polarity == 0:
        return sentiment_analysis.sentiment.polarity, 'Neutral'
    elif sentiment_analysis.sentiment.polarity > -0.4:
        return sentiment_analysis.sentiment.polarity, 'Slight Negative'
    else:
        return sentiment_analysis.sentiment.polarity, 'Negative'
#performs sentiment analysis using TextBlob library
#finds the polarity (i.e. how much a sentence is positive or negative [or neutral])
#and from there can identify whether it is positive, neutral, or negative
```

Code 5.24 – function to perform sentiment analysis

The function *get_sentiment* obtains the sentiment of the string passed through. *sentiment_analysis* is assigned to the TextBlob object of the string passed through, after it has been formatted/cleaned. The *sentiment.polarity* property returns a polarity value between -1 and 1, with -1 being deemed very negative, and 1 being very positive. 0 is therefore neutral. As you can see, I set up different

values to determine whether the sentiment is either strong or slight positive, neutral, or slight or strong negative. The function then returns the polarity of the string, and the sentiment label it was given.

```
def sentiment_number(sent_list, sent_count):
    #function used to update list which holds number of tweets based on their
    #sentiment
    #takes in the list holding the actual sentiment of the tweets, as well
    #as the list which will be used for the graph
    #for example, if there are 5 Strong +ve, 1 Slight +ve, 2 Neutral
    #2 Slight -ve, and 3 Strong -ve tweets,
    #the list will look like [5, 1, 2, 2, 3]
    for i in range(len(sent_list)):
        if sent_list[i][1] == sentiment_type[0]:
            sent_count[0] += 1
        #if the sentiment of the tweet is "Strong Positive", update
        #relative element of sent_count list
        elif sent_list[i][1] == sentiment_type[1]:
            sent_count[1] += 1
        #"Slight Positive" tweets
        elif sent_list[i][1] == sentiment_type[2]:
            sent_count[2] += 1
        #"Neutral" tweets
        elif sent_list[i][1] == sentiment_type[3]:
            sent_count[3] += 1
        #"Slight Negative" tweets
        else:
            sent_count[4] += 1
        #"Strong Negative" tweets
    return sent_count
    #returns list
```

Code 5.25 – function to return the count of the sentiment of a list of strings

The function *sentiment_number* has the arguments *sent_list* and *sent_count*. The *sent_list* is a list holding the sentiment analysis of the string. This is passed through into the function, alongside a list used to hold the tally, similar to the previous model. Depending on the label, that specific element in the list is increased.

```
ytCSV = pd.read_csv('YouTubeAPIandTwint/youtubeadstweets.csv', header = 'infer')

ytTweets = ytCSV['tweet']
#reads csv file containing tweets related to YouTube ads

yt_sent_count = [0,0,0,0,0]
#list used to hold how many tweets are Strong +ve, Slight +ve, Neutral
#Slight -ve, Strong -ve. Used in graph

yt_pol_sent = []
#list used to hold polarity and sentiment

for tweet in ytTweets:
    yt_pol_sent.append(get_sentiment(tweet))
    #for every tweet, get polarity & sentiment, add to list

sentiment_number(yt_pol_sent, yt_sent_count)
#passes list through function sentiment_number

fig, ax = plt.subplots()
ax.barh(y_pos, yt_sent_count, align ='center')
ax.set_yticks(y_pos)
ax.set_yticklabels(sentiment_type)
ax.invert_yaxis()
ax.set_title("Sentiment Analysis of Tweets Related to YouTube Adverts")
plt.show()
#plots a bar graph with data retrieved
```

Code 5.26 – Example of sentiment analysis performed using model B

Here is an example of sentiment analysis performed on the tweets related to YouTube adverts. Sentiment analysis is performed on each tweet, being held in the *yt_pol_sent* list, which is then passed into the *sentiment_number* function alongside the tally list *yt_sent_count*. The list will then have the counts for the sentiment analysis conducted on those tweets. This data can then be used to a plot a graph.

5.5 Public Survey

A public survey was released via Google Forms. The survey asked questions about social media usage and also asked for the opinions on the different types of strategies. Furthermore, concluding questions were asked about whether the respondents thought marketing strategies on social media were effective, whether they felt like they gained more information that others may not have access to, and whether they have a relationship with the organisations who utilise these strategies.

I used Likert scale for questions, allowing users to assess how much they agreed with a particular statement. Additionally, I used frequency based questions, and made sure to ask questions within a recent time frame where applicable – an example being asking how many times someone shared a link in the past week. Instead of directly asking how frequently they send a link, specifying a recent time frame means that it will yield more reliable data, as it is in the respondent's memory. Also, using a time frame allows us to get numerical data which we can use in analysis [39]. However, for a question like how many YouTube adverts did you skip, I gathered ordinal data, due to the sheer amount of video adverts played on the platform.

I used Microsoft Excel to perform regression analysis on the data. I wanted to see if there was a relationship with the engagements with a certain strategy and the answers of the concluding questions. These were:

- "I feel like I have a relationship with the companies/political parties I interact with on social media sites"
- "Interacting with companies/political parties online allows me to gain information that others might not be able to"
- "The strategies that companies/political parties employ on social media sites to attract people are effective"

The answer to these questions was in Likert-scale format, with 1 being strongly disagree and 5 being strongly agree.

Using Microsoft Excel's Analysis ToolPak add-in, you can perform regression analysis on the data. I made the dependent variable the answers to these concluding questions, and the independent

variable the frequency questions asking how much one engaged with a certain strategy over a time period. I changed the answers for the frequency questions to integers so that they could be used in regression analysis (e.g. None → 0, 1 to 2 → 1 etc.).

All of the survey questions and answers can be found in the Appendix.

6. Results

I will present the data gathered about each strategy in this section.

6.1 Video Advertisement

Sentiment analysis on tweets gathered about “YouTube Adverts”:

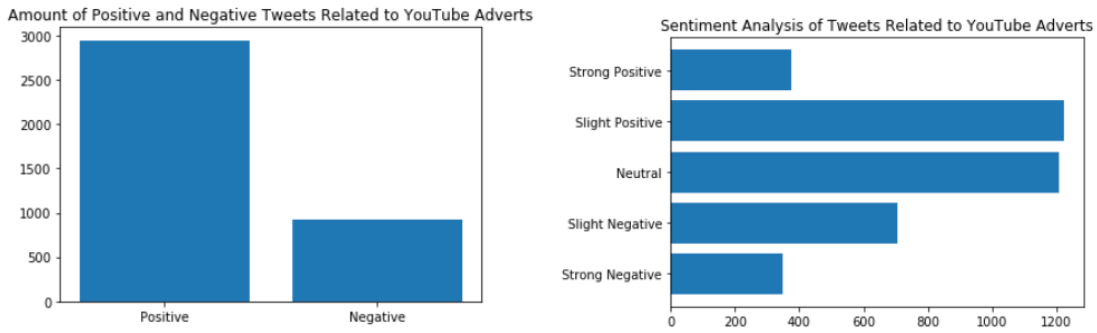


Fig 6.1

I then looked at specific YouTube advertisements, one with the aforementioned Raid Shadow Legends commercials and the other looking at videos posted by the Labour Party.

6.1.1 Raid Shadow Legends

I looked at tweets about the RSL commercials close to their release, and tweets closer to now.

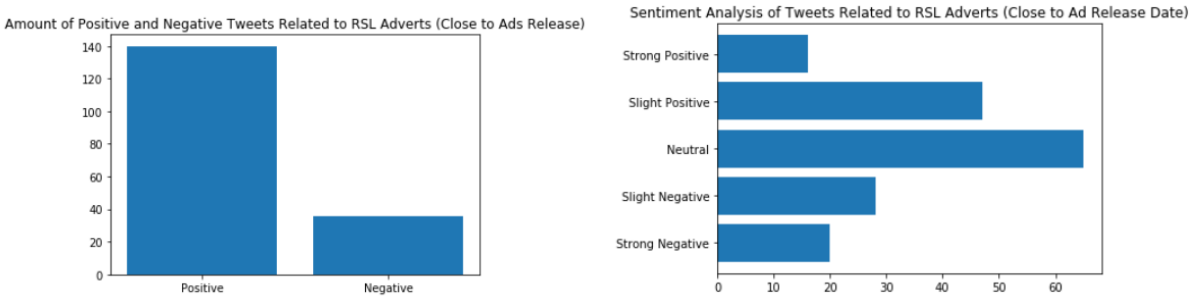


Fig 6.2

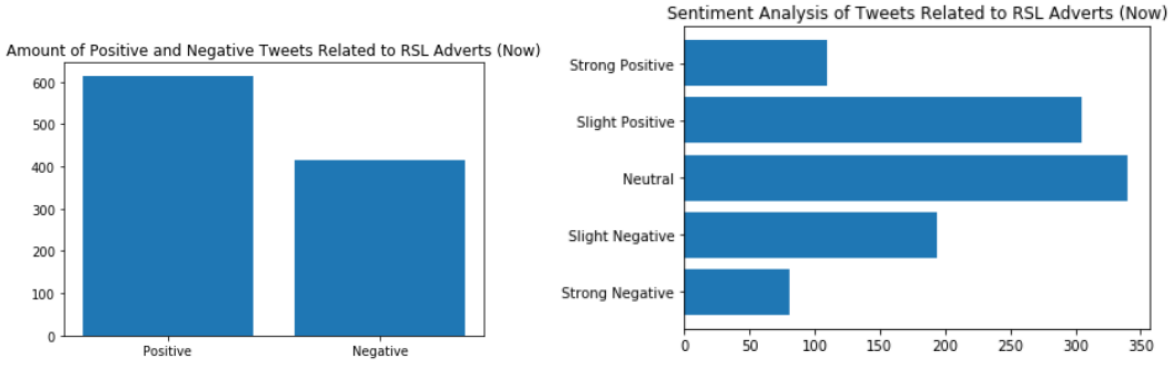


Fig 6.3

Sentiment analysis on the YouTube comments:

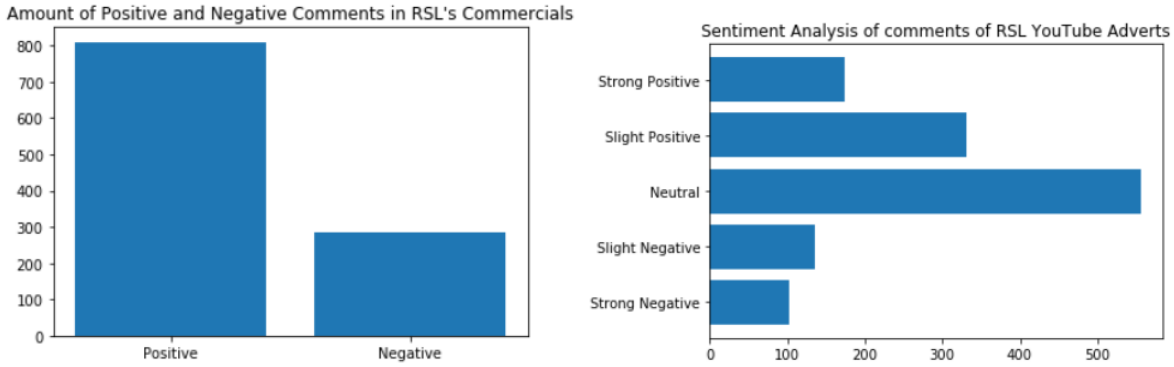


Fig 6.4

Likes & dislikes numbers of the YouTube videos:

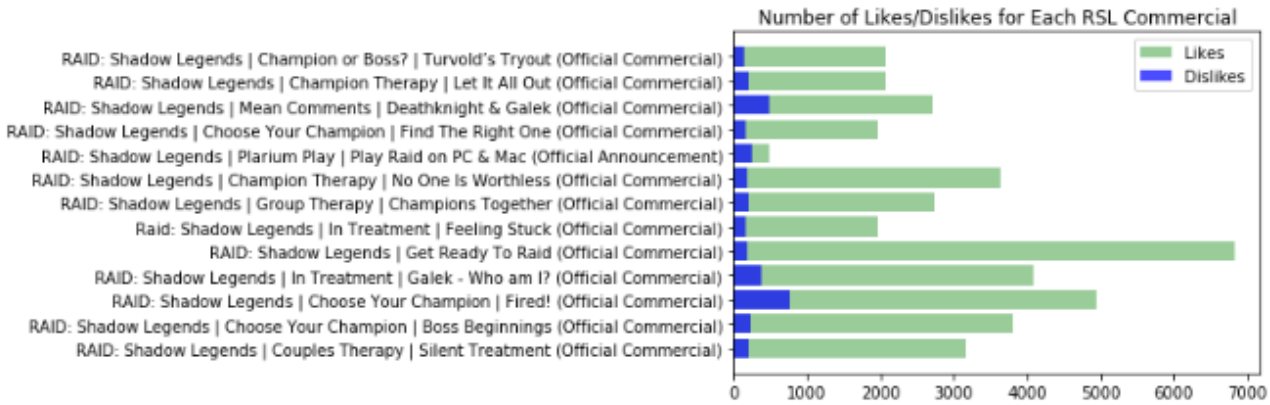


Fig 6.5

6.1.2 Labour Party Videos

Sentiment analysis on video comments:

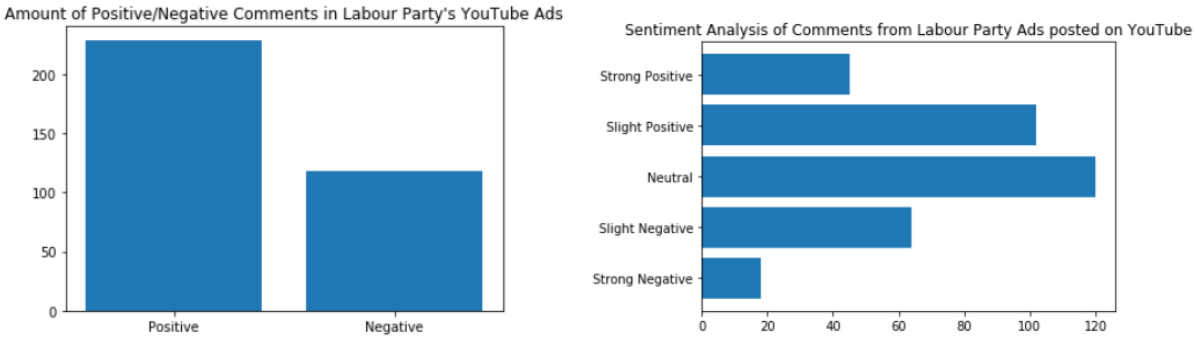


Fig 6.6

Likes & dislikes of the videos:

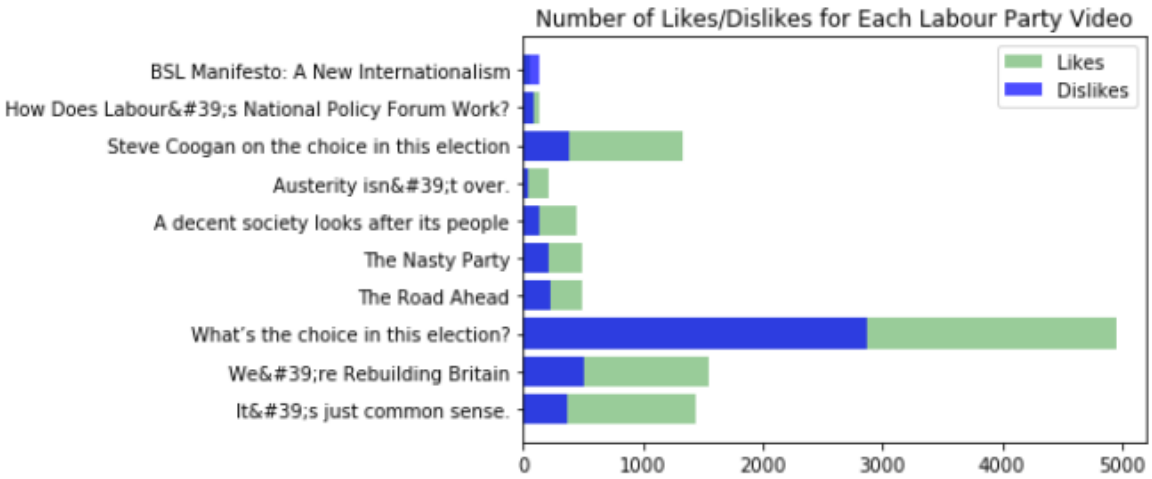


Fig 6.7

6.1.3 YouTube Links shared on Twitter

From the twitter search about "YouTube adverts", I looked at the 4 most common YouTube links shared. This can be found in the *YouTubeLinksFromTweets.ipynb*.

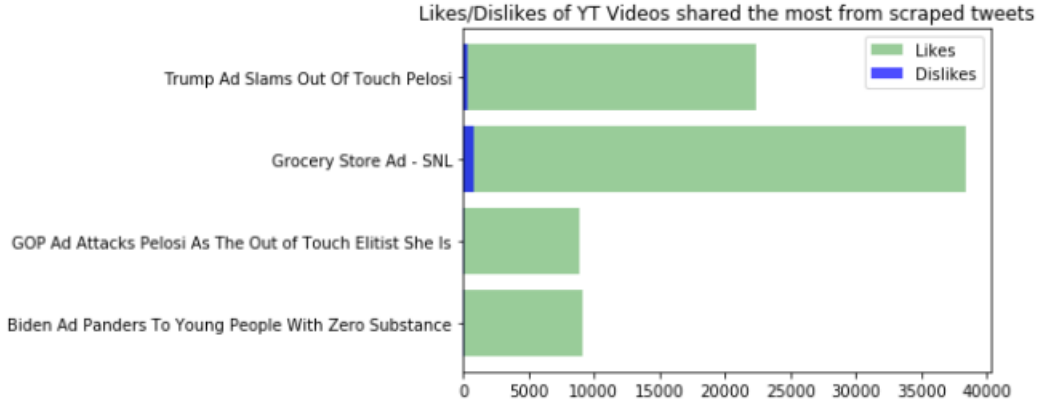


Fig 6.8

From these links, I discovered 3 of the 4 links were related political videos, whereas the 4th was a comedy skit. I then looked at the comments from these 3 political videos:

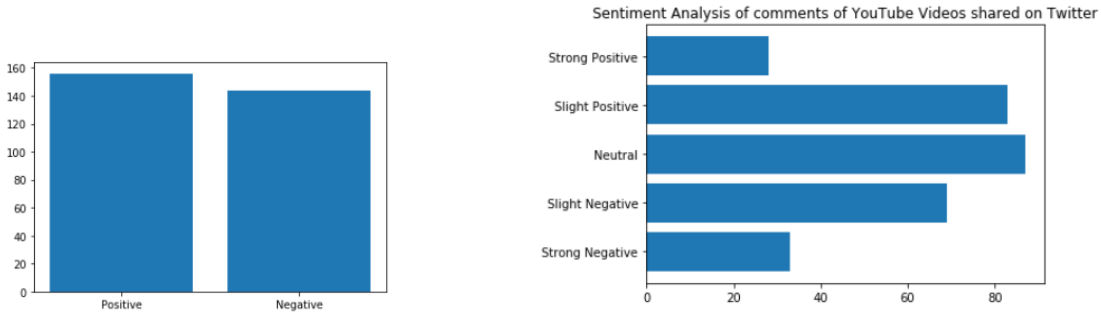


Fig 6.9

6.2 Personalised/Targeted Adverts

Sentiment analysis on tweets related to personalised/targeted adverts:

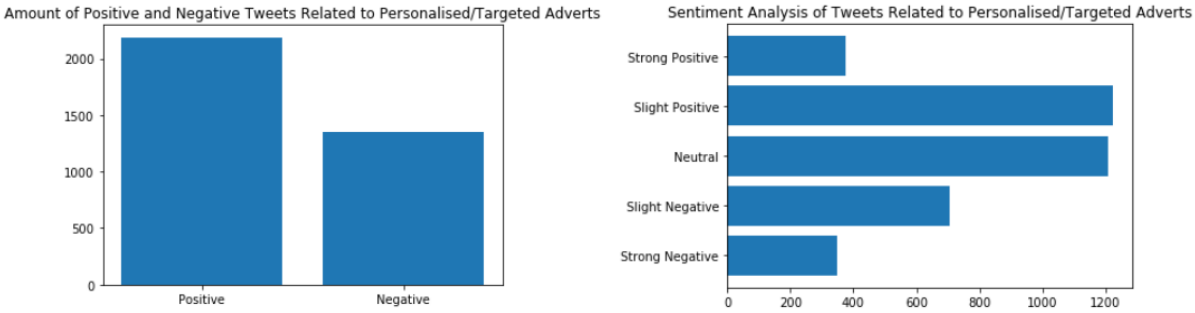


Fig 6.10

6.3 Competitions, Discounts & Giveaways

6.3.1 Uber, Lyft & Ola Discounts

Sentiment analysis on tweets related to the Uber, Lyft & Ola discounts:

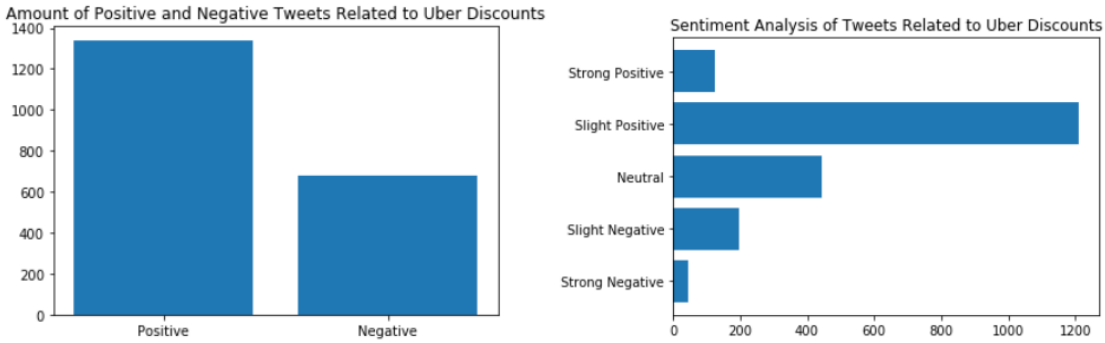


Fig 6.11

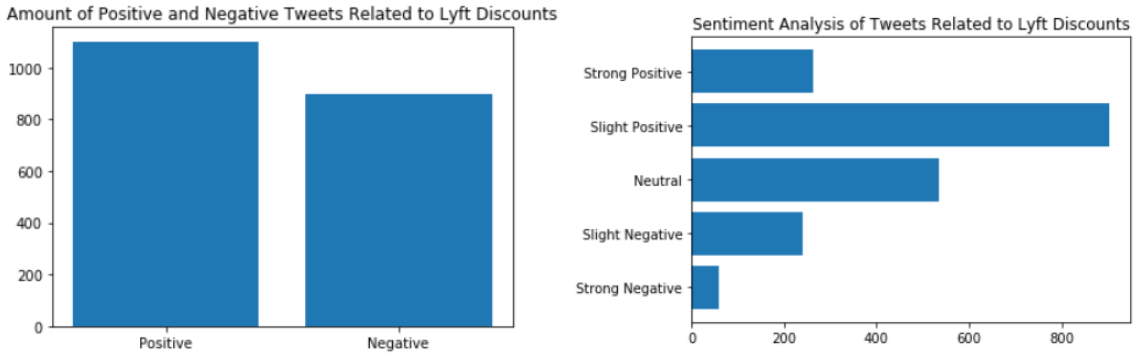


Fig 6.12

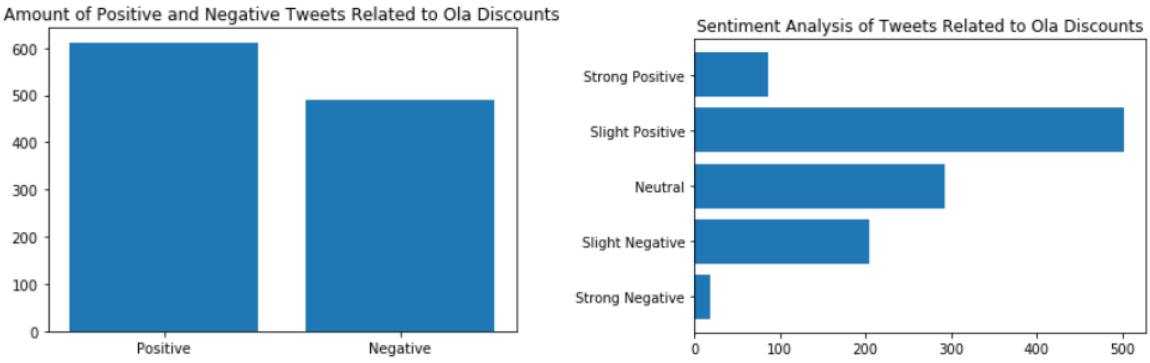


Fig 6.13

6.3.2 Call of Duty

Tweets related to the Call of Duty giveaway competition:

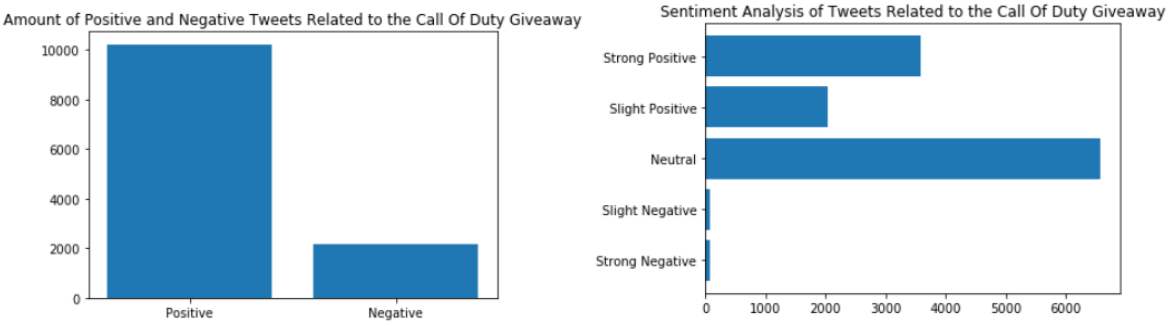


Fig 6.14

6.3.3 GTA V

Tweets related to Grand Theft Auto V being released for free on the Epic Games Store:

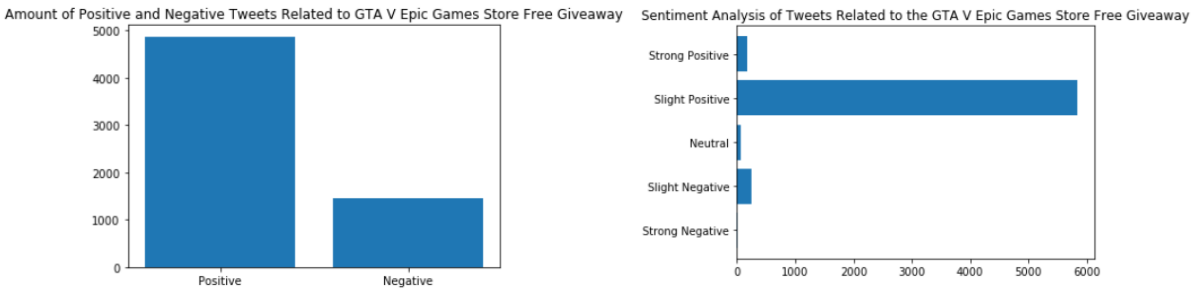


Fig 6.15

6.4 Sponsored Posts

Tweets related to sponsored videos:

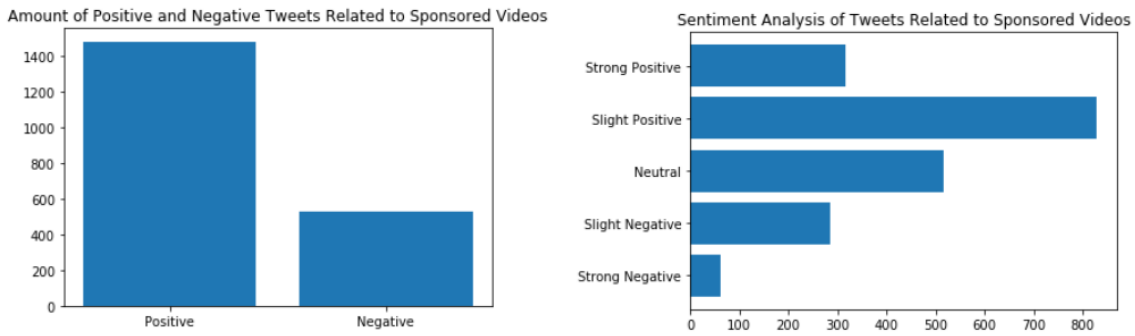


Fig 6.16

Tweets related to sponsored Instagram posts:

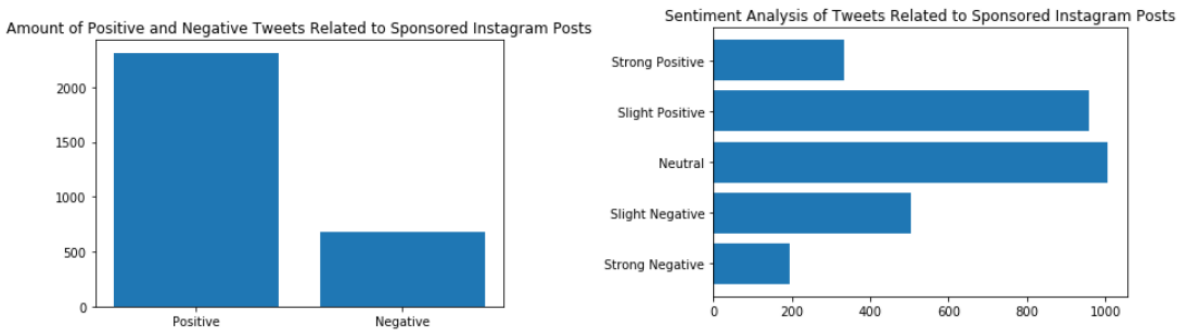


Fig 6.17

6.5 Regression Analysis on Survey

The answers to all the survey questions can be found in the Appendix section. Here, I will show the results of performing regression analysis on the survey data.

The survey had 49 responses, but 3 of the responses had unanswered questions (an error I made during survey creation, not making every question required to answer before moving on). To keep the data reliable, I removed these responses with empty answers when performing regression analysis. I plotted the independent variables individually with the dependent variable, and then plotted all independent variables.

Here is the regression analysis of the dependent variables and all the independent variables being used:

DEPENDENT VARIABLE/STATEMENT	R-VALUE WITH ALL INDEPDENT VARIABLES USED
"I feel like I have a relationship with the companies/political parties I interact with on social media sites"	0.252
"Interacting with companies/political parties online allows me to gain information that others might not be able to"	0.582
"The strategies that companies/political parties employ on social media sites to attract people are effective"	0.495

Fig 6.18

Below are tables showing the correlation between the dependent variables/questions each independent variable (engagement with specific strategy).

6.5.1 Relationship with Organisation

INDEPENDENT VARIABLE/STRATEGY	R-VALUE
Video Advertisements	0.031
Personalised/Targeted Adverts	0.136
Competitions, Discounts & Giveaways	0.095
Sponsored Posts	**0.187**
Consumer-based Interaction	0.091

Fig 6.19

6.5.2 Gaining Information via Interacting

INDEPENDENT VARIABLE/STRATEGY	R-VALUE
Video Advertisements	0.135
Personalised/Targeted Adverts	0.226
Competitions, Discounts & Giveaways	**0.484**
Sponsored Posts	0.028
Consumer-based Interaction	0.095

Fig 6.20

6.5.3 Effectiveness of marketing strategies

INDEPENDENT VARIABLE/STRATEGY	R-VALUE
Video Advertisements	0.038
Personalised/Targeted Adverts	0.044
Competitions, Discounts & Giveaways	0.111
Sponsored Posts	0.126
Consumer-based Interaction	**0.375**

Fig 6.21

7. Analysis

7.1 Video Advertisements

In the survey, little or no engagement with YouTube advertisements were shown. Over 93% of the answers showed that people skip adverts frequently/very frequently. 82% of people did not click on the links provided by the adverts, and a further 90% of answers showed that people did not forward these video adverts to friends. This can be because the participants just want to watch the videos of the content creators they support, and therefore do not pay attention to these advertisements and skip them as soon as possible. Video advertisements was also shown to have no correlation with the concluding statements, meaning that although it is a strategy employed very frequently, people do not seem to interact with the material promoted very often.

As you can see, sentiment analysis performed on the tweets collected about YouTube adverts indicate that more tweets are positive than negative. In Fig 6.1, model A shows a large proportion of the tweets were positive, whereas model B shows that there were a lot of tweets that were neutral, but still a substantial number of tweets were positive than negative. A large majority of YouTube adverts can be skipped after a short 5 seconds. As people understand that these adverts are necessary for the platform to remain free, and that the adverts support content creators, it is understandable for them to be received in a positive light.

Furthermore, as YouTube ads can be skipped after 5 seconds, companies do their best to try capture the viewer's attention within these 5 seconds. This can lead to smart and successful advertising campaigns, one example being the Raid Shadow Legends campaign.

7.1.1 Raid Shadow Legends

Sentiment analysis on the tweets close to the release of the RSL commercials (Fig 6.2) show that a large proportion of the tweets are in a positive sentiment. This can be due to the high quality and production of these adverts, something that can be very appreciated for avid users of the platform. Furthermore, the humour of these adverts, mixed with its relevancy towards the promoted material (regularly, mobile game ads on YouTube show false gameplay or straight up ripped content from other games) are strong reasons as to why the adverts were received well. This is supported by Fig 6.4 and Fig 6.5. Fig 6.4 shows a large proportion of the YouTube comments are positive, and Fig 6.5 shows that the videos have almost barely any dislikes relative to the amount of likes it has received. This backs up the fact that the commercials have been received well by the users of the respective social media platform.

However, looking at Fig 6.3, model A shows there the split between the positive/negative tweets has decreased, whereas model B still maintains its shape from Fig 6.2. As the game has become well known now, with the adverts having released more than half a year ago, seeing them constantly can become repetitive. With more content creators being sponsored by RSL, it is no surprise that people feel that the novelty of the commercials has worn off. This shows that even though the adverts were at first received well, it is important that an organisation continues to evolve and not constantly promote the same material, otherwise people will lose interest.

7.1.2 Labour Party videos

Political promotional material has always been touchy, with the followers of the party being very vocal in their support, and the opposition being very outspoken in their disagreements. The comments on the videos (Fig 6.6) can surprise someone with the higher number of positive comments, but this could just be from Labour supporters only. Fig 6.7 shows that the likes & dislikes are more even than the RSL videos, with numerous videos having a near 50/50 split. This is understandable as politics is a very polarising subject, and not everyone agrees with what the Labour party are saying.

7.1.3 Videos shared from Twitter Links

Analysing the videos that were shared the most on Twitter, I saw that from the top 4 shared YouTube links, 3 of the 4 were about American politics, with 2 being posted by the same channel, and all 3 being related to each other. Initially, there seems to be a disparity between the likes/dislikes of these videos (Fig 6.8), and the sentiment analysis of the comments (Fig 6.9). However, the negative comments could be those bashing the people spoken about in the video, with the titles indicating that the video will not speak positively about the target person (e.g. “Biden ad panders to young people with zero substance” – clearly this video will speak negatively about Biden and the target audience of his adverts).

Due to the current climate in the world, with political scandals coming to light frequently, and the actions of world leaders being under heavy scrutiny, it is no surprise that conversations on social media and links being shared are politically-fuelled. I was not surprised to see that the most shared links were those of a political nature.

7.1.4 Gephi Visualisations

Through Gephi, we can analyse the network of related videos (see Section 5.3).

Raid Shadow Legends Visualisation (can be found at *RSL-videos-network.gephi*)

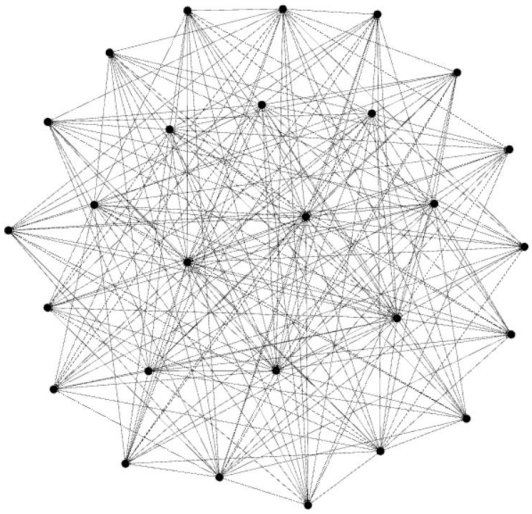


Fig 7.1

As you can see, using the ForceAtlas2 algorithm, this graph has every node/video connected to at least 2 or more nodes. There are not any anomalies being made, as the videos relate to the mobile game.

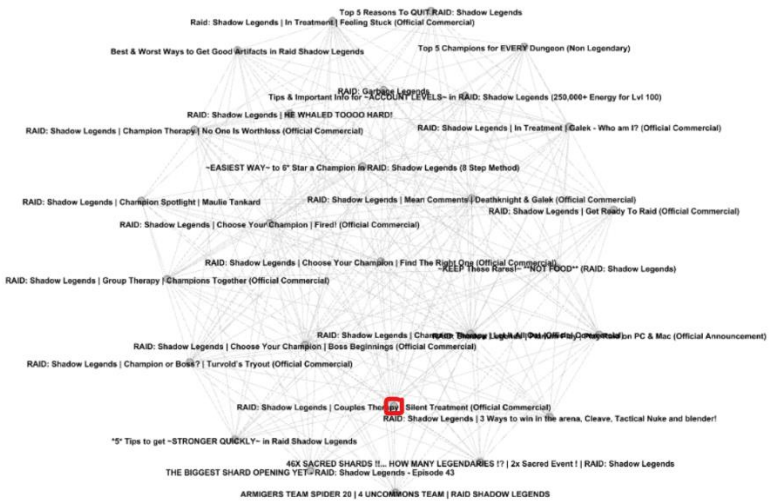


Fig 7.2 – selecting a video and seeing what is connected to it

I selected the node circled red, and as you can see, all the videos related to it are about RSL. This shows that the videos have a significant reach, as the related videos are still relevant to the original material.

Labour Party Visualisations (can be found at *labour-videos-network.gephi*)

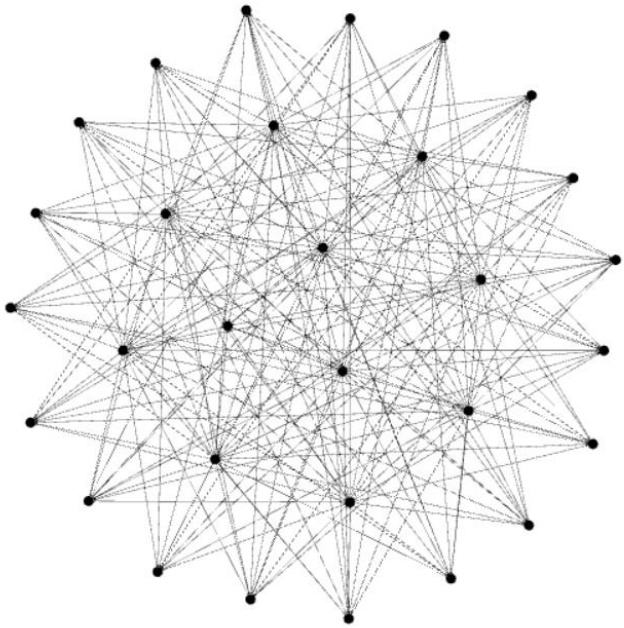


Fig 7.3

A similar shape produced in the previous graph; this one has one node also connected to multiple nodes.

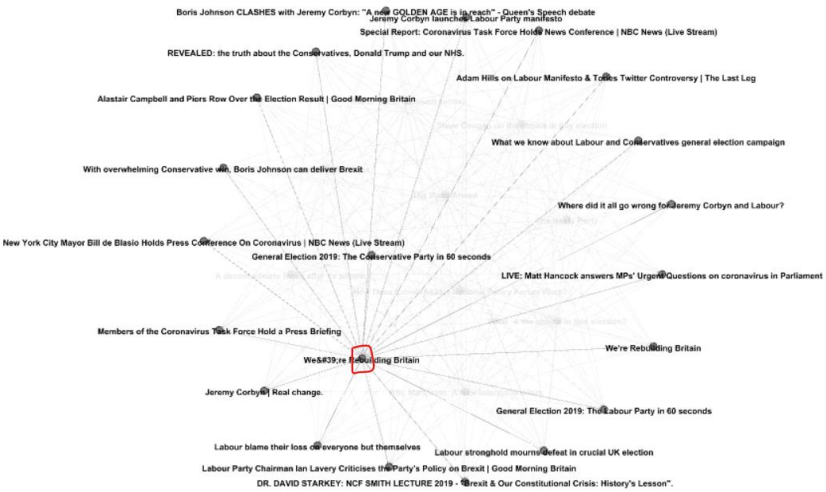


Fig 7.4

However, some of the related videos are not on same the subject matter of advertising the Labour Party. This shows that the reach of these videos is lesser than those of RSL, with videos speaking negatively about the Labour Party being related. Videos of the opposition Conservative party are also appearing.

Political videos shared on Twitter (can be found at *shared-videos-network.gephi*)

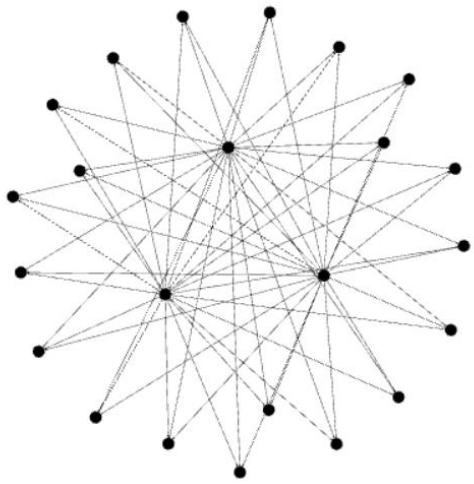


Fig 7.5

A much smaller graph in comparison is produced (with only 3 videos being passed through as seed videos).

Fig 7.6

As you can see, the same videos have been related for the original videos. This shows that the seed videos are indeed related, but then it also means that their reach is marginal. This is in contrast to the fact that these videos were shared the most from a few thousand tweets.

7.2 Personalised/Targeted Adverts

57% of people did not have personalised adverts settings turned on. This makes sense, as with personal data breaches like Cambridge Analytica scandal coming to light, people have become more aware of companies & social media using their personal data, with some taking steps to restrict this. 51% felt indifferent about being encouraged to purchase a product/follow a company because of personalised adverts. 29% felt that they were not encouraged, with 20% slightly agreeing with feeling encouraged. Finally, 35% of people actually engaged with personalised adverts. This strategy also had little to no correlation with the concluding statements.

Surprisingly, sentiment analysis on tweets related to personalised adverts show that there is a greater number of positive tweets than negative tweets (Fig 6.10). A reason for this can be the relevance of these adverts; if one were to see adverts online, it would be more beneficial for these to be related to what they are interested in. This can lead to potentially purchasing a product from these targeted adverts. The negative tweets can be posted by individuals who feel that this type of marketing relies on personal data, and also is not always accurate.

Altogether, this shows that although the majority of survey responses do not engage with personalised adverts (with some even disabling the setting), some still do engage with this method of marketing, and the number of positive tweets indicate that this strategy has some effectiveness in gaining customer attention by being received well.

7.3 Competitions, Discounts & Giveaways

7.3.1 Survey Responses

69% of people did not enter any competitions or giveaways in the specified time-period, whilst 31% did. The majority of people disagreed with competitions or giveaways being worthwhile (51%). 41% were indifferent, with only 8% slightly agreeing. 43% of people had used discount codes acquired from social media, with a further 20% having used between 3 & 6 discount codes. On the other hand, 57% of people did not use any discount codes.

Regression analysis showed that there was a positive correlation between the number of interactions with this method and gaining information online (Fig 6.20), but not with the other concluding statements. This shows that this method is effective in allowing customers to gain information that others may not be able to, which is a very positive.

7.3.2 Sentiment Analysis

Sentiment analysis gathered about the discounts offered by the different apps showed that there were more positive tweets than negative tweets, but the two models showed a difference in the overall split (Fig 6.11, 6.12, 6.13). Model B showed a larger number of positive tweets compared to negative. People will feel more inclined to purchase a product if they know it is available for a cheaper price, and with the frequency that these services provide discount codes, it is no surprise that people feel positive about this. However, the number of negative tweets provided by Model A can be explained by the actual type of discount. Some of these discounts are designed in a way where you do not save as much as anticipated; a 25% off offer from UberEats may only remove the delivery fee, but the food will cost the same price. Misleading discounts like this can lead to customer dissatisfaction, which can explain why model A showed more negative tweets.

The giveaways for the popular games was overwhelmingly positive from both models (Fig 6.14, 6.15). This is no surprise, as getting a chance to play a popular game for free is very enticing.

In conclusion, competitions, discounts, and giveaways are received very positively by consumers, as the partial or complete reduction of the price of a product/service is received very well by people. The only negative aspects are the misleading offers, which can be prevalent, and the low chance of winning a competition, if it is for something very popular.

7.4 Sponsored Posts

42.9% of survey respondents agreed with sponsored posts dissuading them from following the account that posted them. This is obviously detrimental for the accounts that post the advertised material, as they do not want to lose touch with their audience for partnering with a company. 30.6% disagreed with the statement, and 26.5% were indifferent.

37% of people interacted with sponsored posts, with the majority interacting only once or twice. 61% of people did not interact.

The interaction with sponsored posts had little positive correlation with feeling a relationship with an organisation.

Sentiment analysis performed on the tweets about sponsored posts indicated more positive tweets than negative (Fig 6.16, 6.17). This can be due to the fact that individuals relate to the influencers that they follow online, and the content promoted by these influencers would resonate with them (if the company that partner with the influencer correctly identified the target audience). Furthermore, people know that interacting with these pieces of promotional content will be beneficial for the

account that they follow, which would persuade those to interact with and take an interest in those services.

Posts sponsored by an organisation can lead for people to believe the account that they follow which posted this content has 'sold out', leading to people not wanting to engage with these accounts anymore. Furthermore, the legal obligation of stating that the material is sponsored can further this perceived 'sell out' image. However, it is still an effective way of engaging with users, as a specific target audience already amassed can be interacted with directly.

7.5 Consumer-based Interaction

7.5.1 Survey Responses

44.9% of people agreed with feeling influenced to take an interest in an organisation if they see their peers sharing or re-posting them onto social media platforms. Only 24.5% disagreed, with 30.6% staying impartial.

85.7% did not re-post anything from a company onto their social media accounts, with the remaining 14.3% only doing so between 1 to 4 times in the specified time frame.

However, only 36.7% did not click on something re-posted by a peer. 46.9% interacted with these re-posts 1 to 4 times. 10.2% interacted with these 5 to 8 times, and 3 (6.1%) people interacted with these posts more than 10 times.

Interactions between consumers about companies had a relative positive correlation with feeling that social marketing strategies are effective (Fig 6.21). This makes sense, as the more people talk about a company online (and verbally), the more they feel that the marketing strategy is effective.

7.5.2 Gephi Visualisations

Here, I will go over the two different giveaways analysed (Call of Duty & Grand Theft Auto V). I will be looking at the interactions between the accounts and see if anything interesting can be found.

Call of Duty Visualisation (can be found at *cod-tweets.gephi*)

Using the Fruchterman Reingold algorithm [41]:

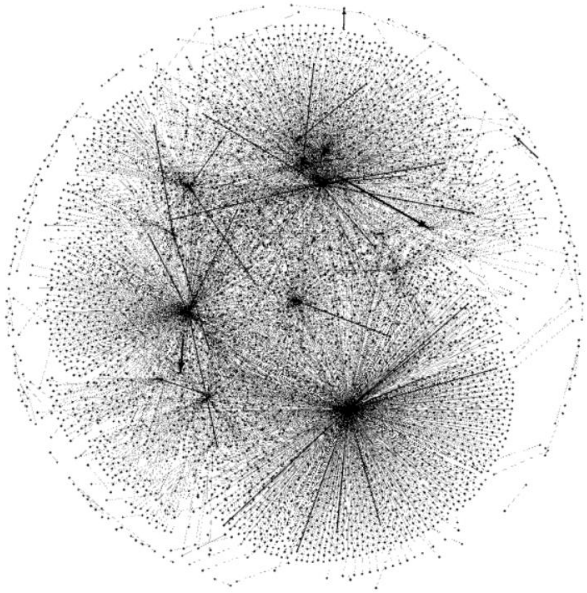


Fig 7.7

As you can see, the graph created by the tweets show that a large amount of them are connected, with a few anomalous tweets found around the outside of the shape produced.

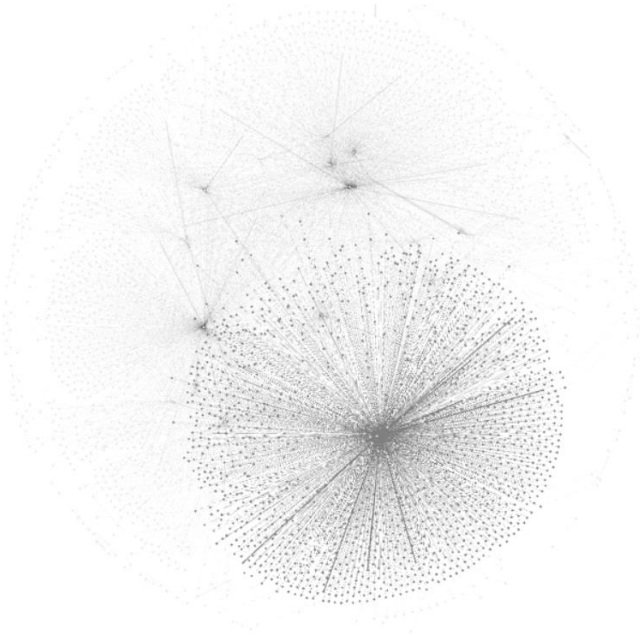


Fig 7.8 – Call of Duty UK account

The node in the centre of the highlighted space is the Call of Duty UK account. It is no surprise that this account has a large amount of connections with the other nodes/accounts.

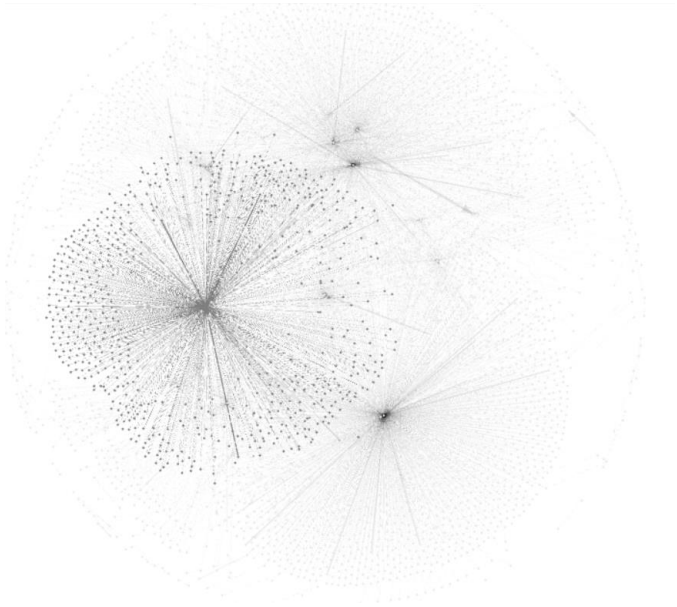


Fig 7.9 – Nvidia GeForce France Account

This time the highlighted account is a sponsor of the competition and the brand as a whole. Nvidia is well known for its manufacturing of graphic processors for gaming PCs, and has had ties with the Call of Duty franchise for a while.

I was also surprised to see a number of accounts that were involved in this competition and held a significant number of interactions with the users participating. An example of this is Three UK:

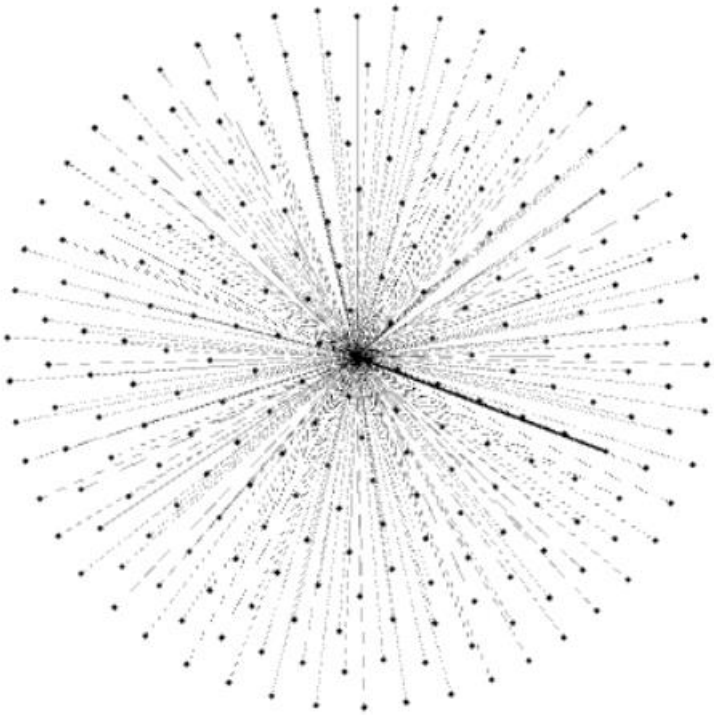


Fig 7.10 – Ego network of Three UK account

Using the ego network filter, you can see that the Three UK account (directly in the middle) holds a large number of interactions with other users. There are various reasons as to why a telecommunications company may be involved in a video game giveaway: they have been paid by Call of Duty/Activision to promote the material, or they have an already existing sponsorship with them. It is still interesting to see them involved in this competition.

GTA Visualisation (can be found at *gta-tweets.gephi*)

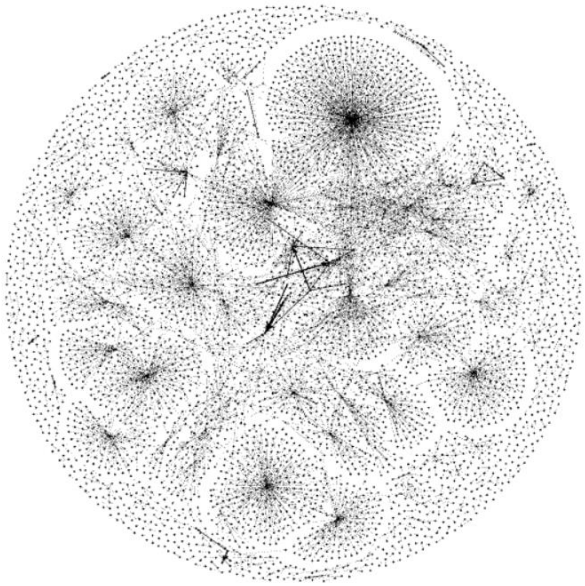


Fig 7.11

Using the F.R algorithm, you can see that these tweets are more spread out, with more circles of engagements than the COD giveaway. There are also more nodes located around the outside of the inner circles.

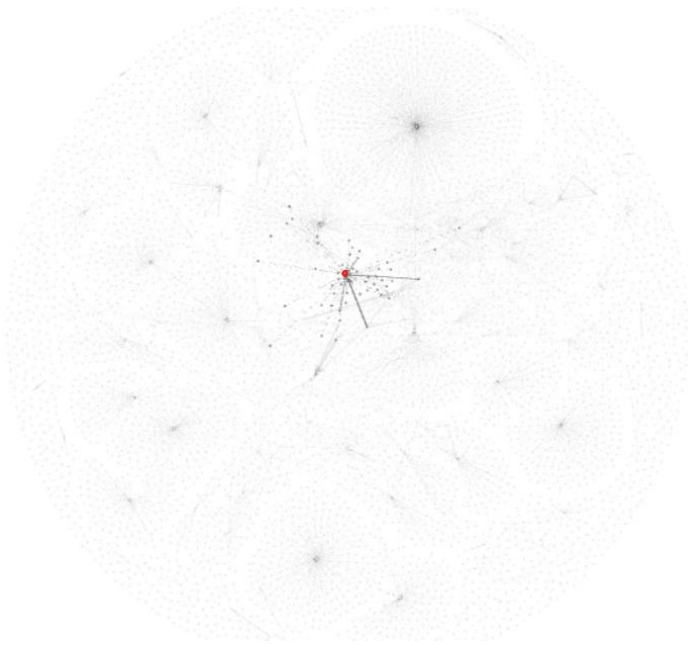


Fig 7.12

Here you can see the publisher of the game, Rockstar Games (circled in red), holding very little interaction with users. This is because the giveaway was not directly held on Twitter, meaning the engagements here are more so interactions between users displaying their reactions.

This also includes those giving out codes. An example of this is user @I_AM_WILDCAT:

Fig 7.13

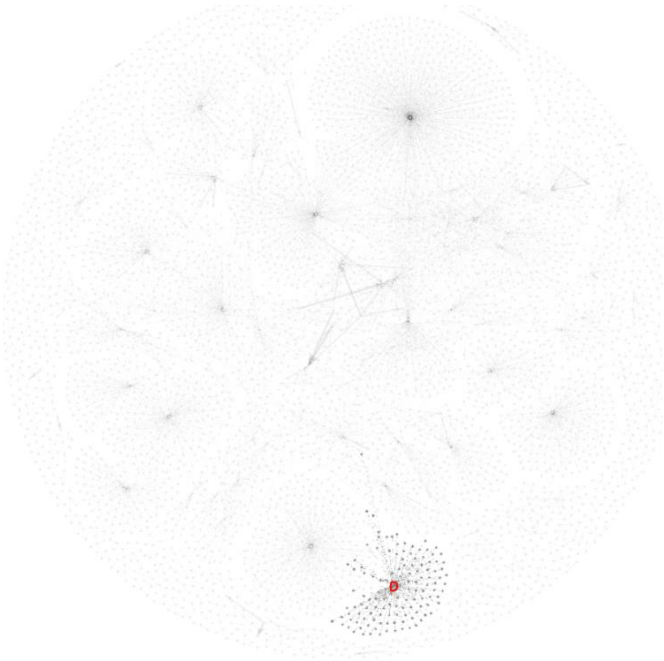


Fig 7.14

As you can see, @I_AM_WILDCAT (circled) holds a significant number of interactions from one of the circles in the graph. As the game is available free to everyone, there would be no benefit for companies to get involved unless directly being paid by Epic Games to promote this (this would be pointless as simply releasing the game for free gained a lot of attention for Epic Games). Therefore, those partnered with Epic, such as @I_AM_WILDCAT, can benefit by having people use his code.

7.6 Regression Analysis

By plotting all the variables (strategies) together against the concluding questions, you can see how well these strategies are for predicting how survey respondents feel about the statements (Fig 6.18).

There was little positive correlation between the strategies and the users feeling like they had a relationship with the organisations. This can be due to people understanding that companies see them as consumers only, and therefore there is no need of a relationship with these organisations. It could also be because these strategies do not induce the feeling of a relationship with the company/political party.

There was a strong positive correlation between these strategies and gaining information. As these strategies are all present on social media, the information conveyed can easily be shared across these platforms. In particular, competitions, discounts and giveaways had a solid positive correlation with feeling like gaining information that others do not have access to.

Finally, there was a positive correlation between the variables and the conclusion that these strategies are effective. With sentiment analysis showing more positive tweets/comments than negative ones, as well as the number of likes/dislikes on the YouTube videos, and the number of engagements between users presented in the graphs in Gephi, it makes sense that these strategies can be seen as being effective.

8. Conclusions

8.1 Research Success

Personally, I am happy with the results conducted by the research. A lot of data was gathered from various sources, showcasing my ability to work with different pieces of software, as well as increase the reliability of the conclusions drawn by using a wide range of data to support arguments made. I am happy with the sentiment analysis models working with a wide range of different sentences and producing sentiment results that make sense. I also feel like the research done is original compared to other studies performed.

The regression analysis of the strategies produced results that I am satisfied with. Some strategies showed positive correlations with the concluding questions, which supports my decision to analyse these marketing strategies as those deemed prevalent and frequent.

This research project is very topical and relevant to today's socioeconomic climate. Undergoing the research for this project I feel I have a better understanding of marketing strategies, as well as user reception to these strategies, and for what reasons.

8.2 Limitations of Research

However, the results of this project are not conclusive, and is limited by certain factors. Firstly, and the most important, is that sentiment analysis does not produce an accurate result all the time. One thing that sentiment analysis models struggle to do is detect sarcasm. A simple sarcastic example of "I love the weather in England, rainy every day!" will most likely return as positive in the sentiment analysis model (whereas we humans understand that this sentence is in fact talking about English weather in a negative manner).

As such, the sentiment analysis models return more of an estimate of the sentiment of all the tweets and YouTube comments gathered. It should be used as a measure, and not is not definite.

Additionally, people use images, GIFs, and videos (not links) to portray how they feel about something. Unfortunately, none of the practical methods used offer a way to analyse these pieces of media. Media as part of a tweet is appended to the tweet as a link when the tweet is collected outside of Twitter, and only the string of the words in the tweet are used by the sentiment analysis models (with the links being removed from the string).

Furthermore, the use of the Twitter API would have allowed for more interaction with the platform.

The crux of this research project came from looking at Twitter and YouTube. There are various other social media platforms where people post their opinions, meaning there is potentially more data to analyse.

I also only looked at five different methods of marketing on social media. There are many more strategies used by companies, and these can sometimes be even more effective than the ones I chose to analyse.

Finally, although the survey produced good data, it was only answered by 49 people. More responses to the survey can increase the reliability of the data gathered, and in turn increases the confidence in the conclusions drawn.

8.3 Future Endeavours

If I were to continue working on this project, I would first find a way to train the sentiment analysis models to detect sarcasm in strings. This would aid in increasing the reliability of the conclusions.

I would then devise a method to analyse the media in the tweets. Tweets can sometimes be a few words followed by an image, GIF, or video that display the person's feelings towards the subject of the tweet. These tweets are just as important as those full of only words, and if a method of analysing the media posted by users on Twitter were created, then it would allow for more in-depth analysis.

I would also look at analysing more strategies. Social media marketing is not only limited to 5 strategies, and the strategies I did not analyse involve interacting with customers differently than just on Twitter and YouTube.

This leads into my next point, which is using other social media platforms. As I would have liked to analyse the media posted on Twitter, the same can be said about the content posted onto Instagram, and the posts made on Facebook. Reddit is another very popular platform as well. Using technologies/software to scrape information from these platforms would be something that can be done to gather more data.

8.4 Self Evaluation

To conclude, I am happy with the research objectives laid out and achieved in this project. As the subject matter of this project is broad, I feel that there is more that can be done, and I think that if work were to continue on this project, these avenues of gaining data would be pursued. I am interested to see how the online world evolves in the coming years, and how companies try to adapt to the ever-shifting playing field that is social media.

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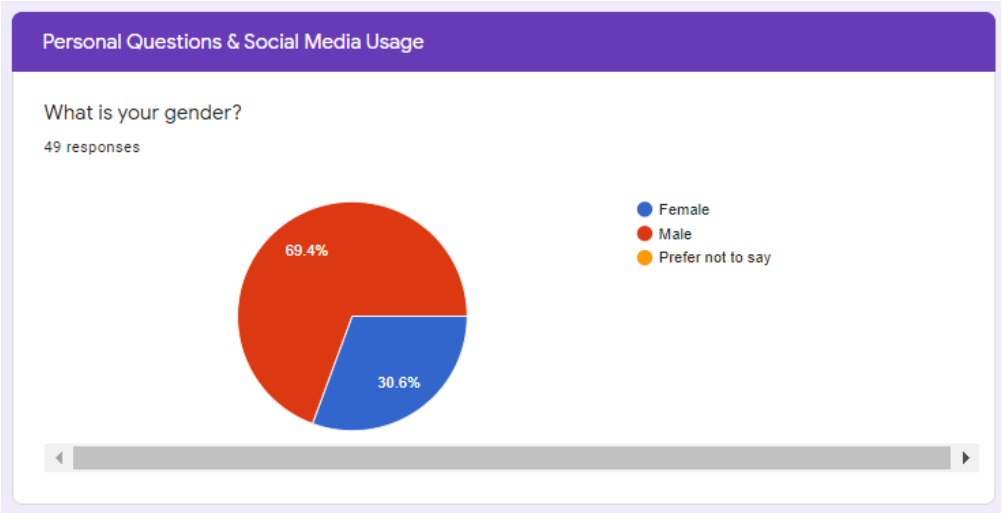
10. Appendix

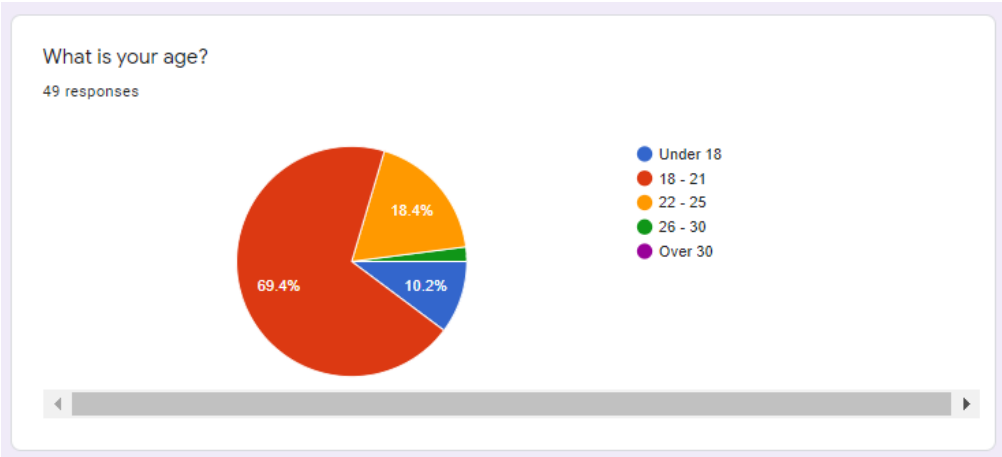
Appendix A – Link to GitLab/Code

Link to GitLab Repository – https://gitlab.doc.gold.ac.uk/jhiir001/3rdyearproject

Appendix B – Survey Questions & Answers

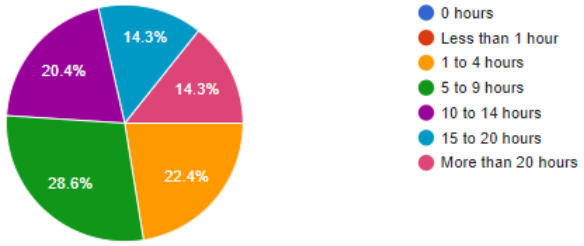
Section A – Personal Questions & Social Media Usage





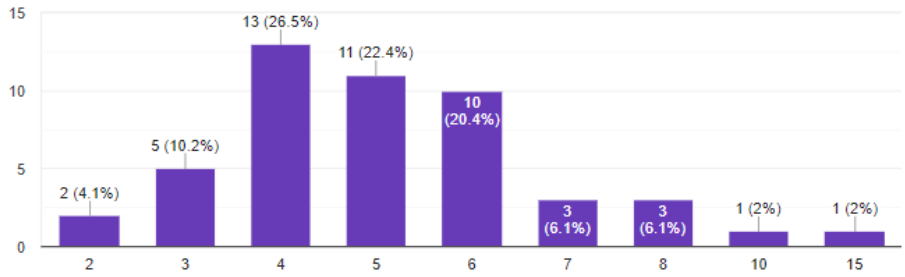
Roughly how much time do you spend on social media platforms per week? (You can check your phone's screen time to get a good estimate)

49 responses



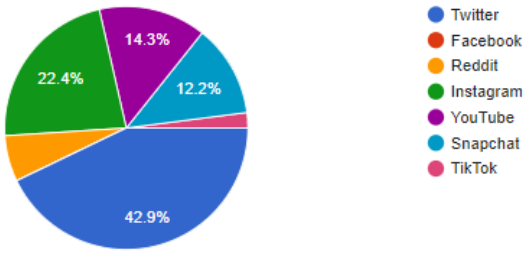
How many social media platforms do you have accounts with? Please insert a number:

49 responses



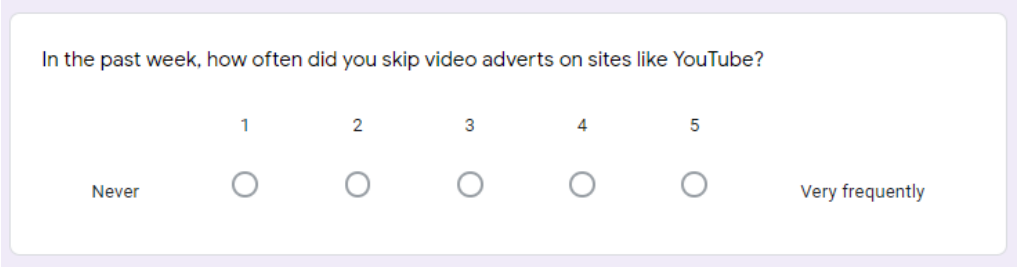
Which social media platform do you use the most?

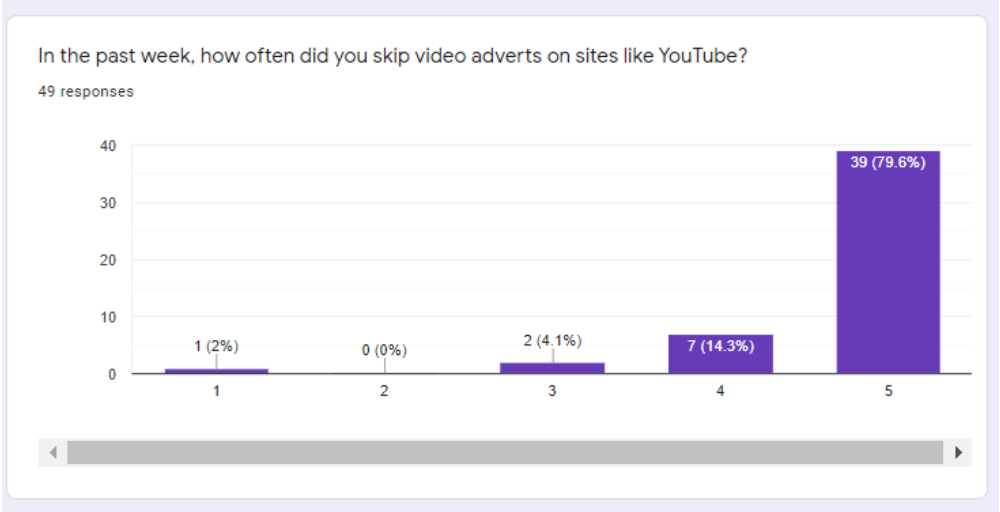
49 responses

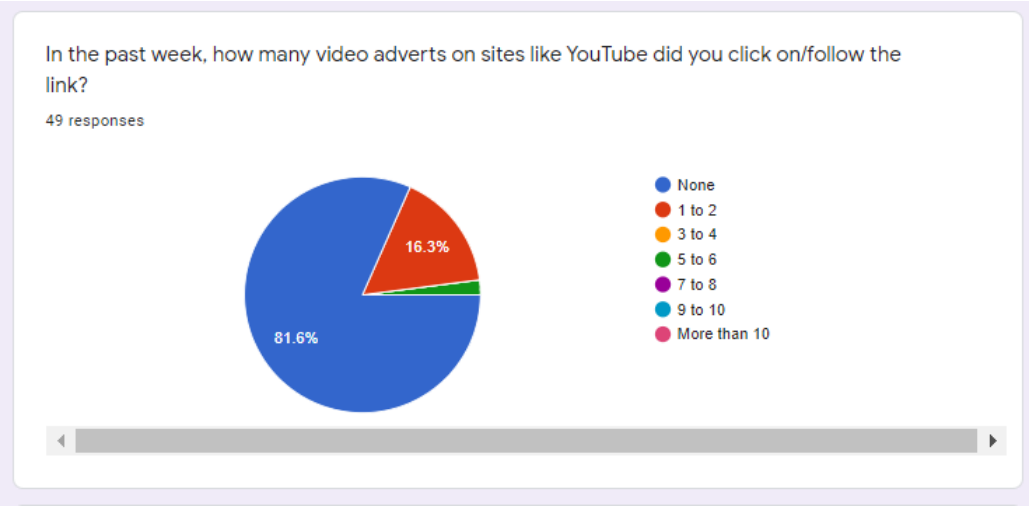


Section B – Questions about different strategies

Video Advertisements

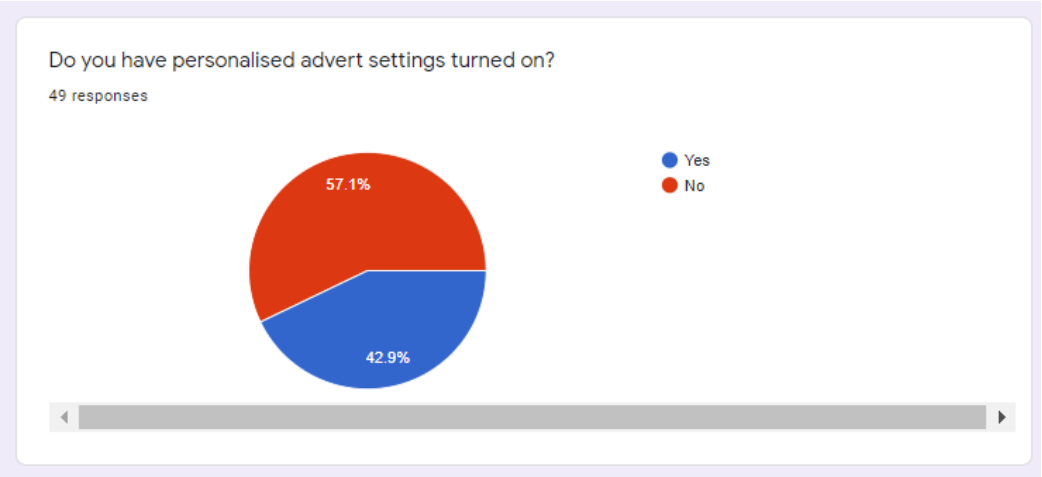


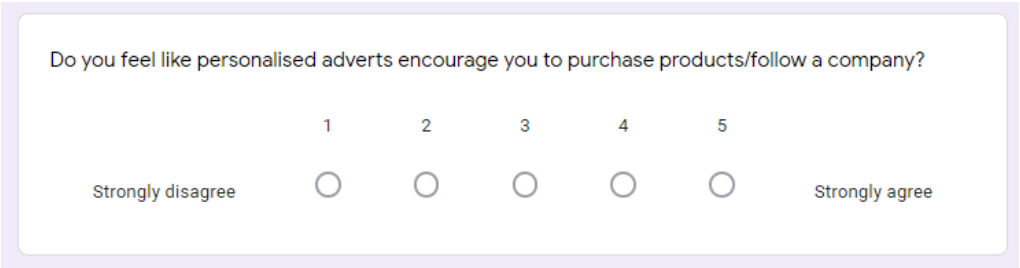


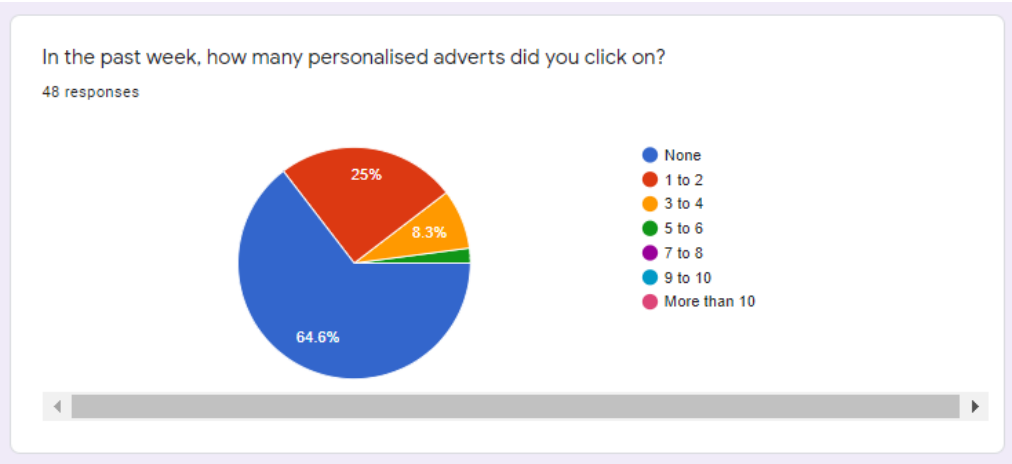


In the past week, how many video adverts on sites like YouTube did you send to friends?
49 responses
89.8%
None
1 to 2
3 to 4
5 to 6
7 to 8
9 to 10
More than 10

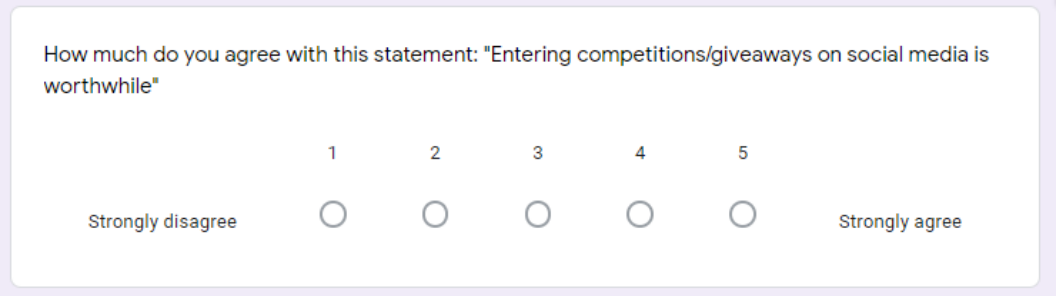
Personalised/Targeted Adverts

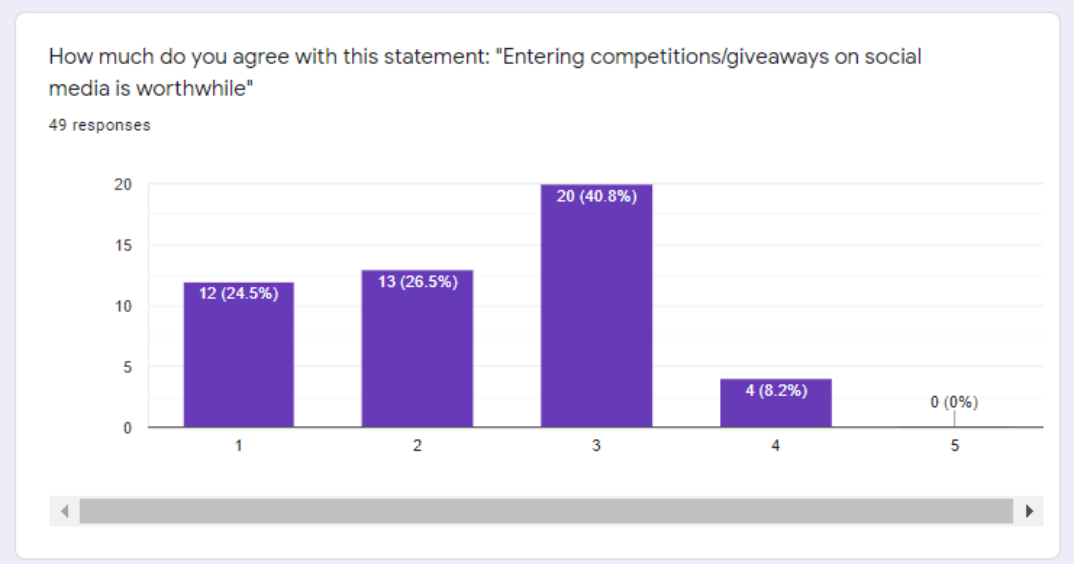





In the past week, how many personalised adverts did you click on?
48 responses
25%
8.3%
64.6%
None
1 to 2
3 to 4
5 to 6
7 to 8
9 to 10
More than 10

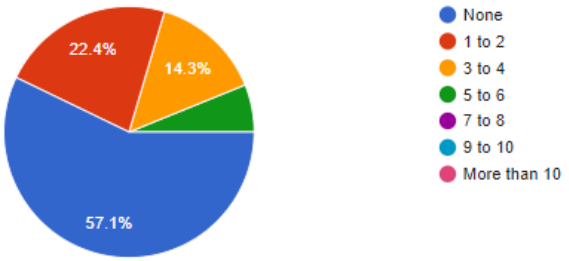
Competitions, Discounts & Giveaways



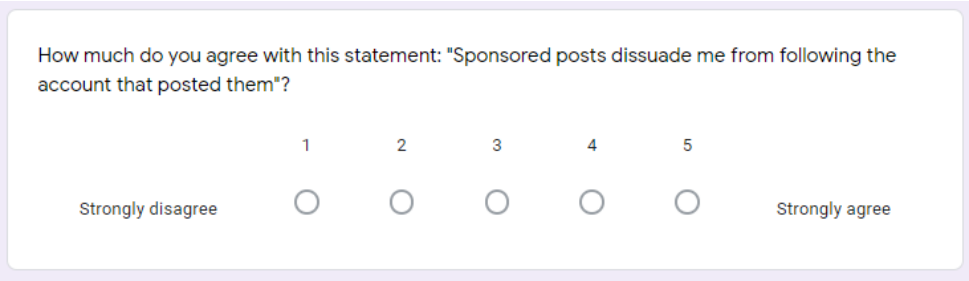


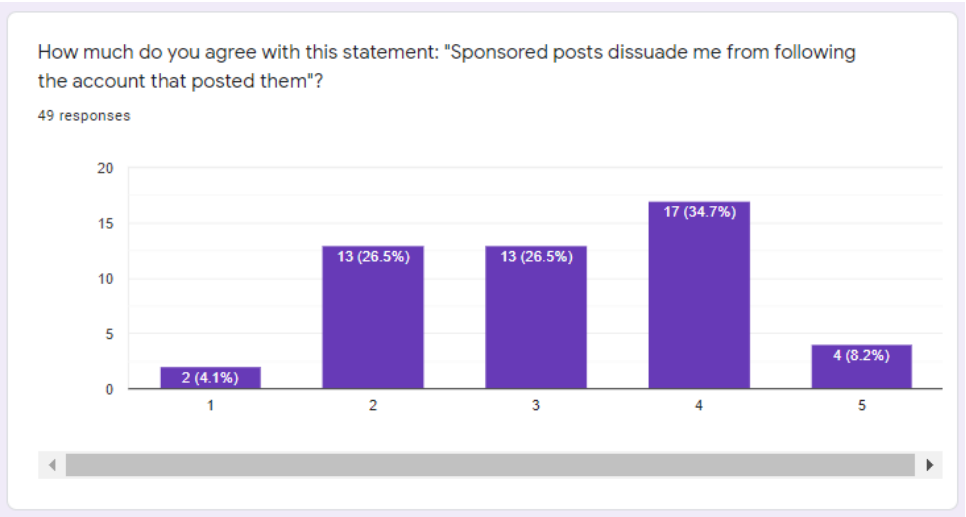
In the past month, how many discount codes have you acquired from social media sites (not including emails) and then used?

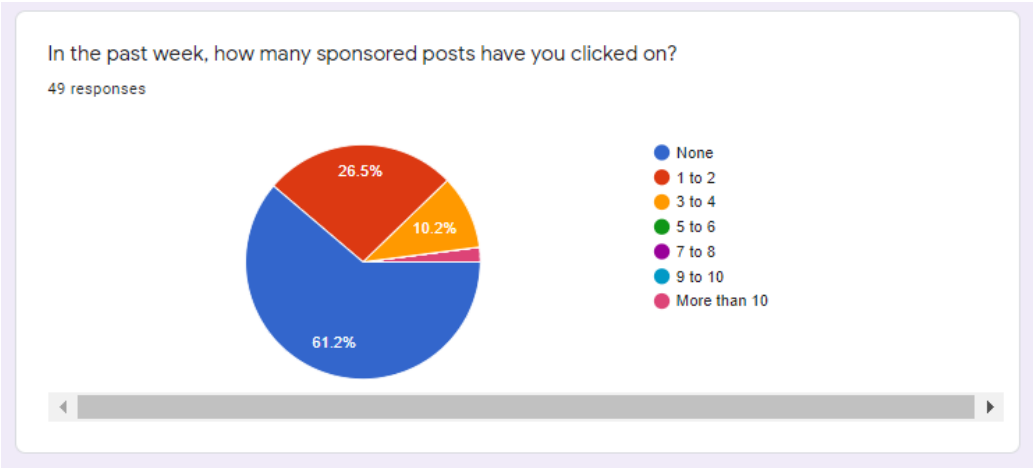
49 responses



Sponsored Posts/Adverts







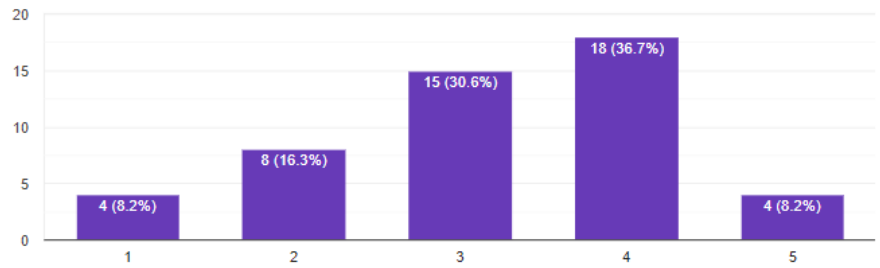
Consumer-based Interaction

Are you influenced to follow/take interest in a brand or company if you see your peers sharing or re-posting them on social media sites?

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

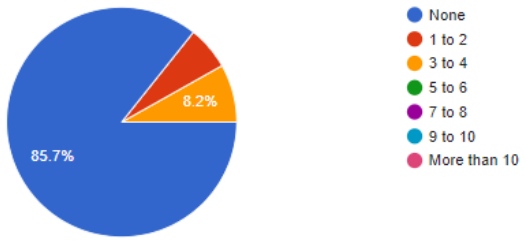
Are you influenced to follow/take interest in a brand or company if you see your peers sharing or re-posting them on social media sites?

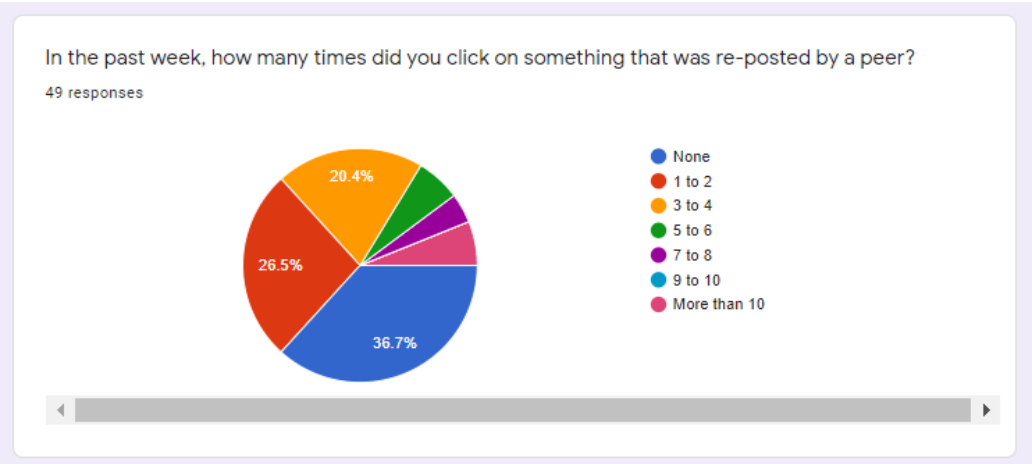
49 responses



In the past week, how many times did you re-post a company or brand's post on social media sites?

49 responses




In the past week, how many times did you click on something that was re-posted by a peer?
49 responses
20.4%
26.5%
36.7%
None
1 to 2
3 to 4
5 to 6
7 to 8
9 to 10
More than 10

Section C – Concluding Questions

How much do you agree with this statement: "I feel like I have a relationship with the companies/political parties I interact with on social media sites"?

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

How much do you agree with this statement: "Interacting with companies/political parties online allows me to gain information that others might not be able to"?

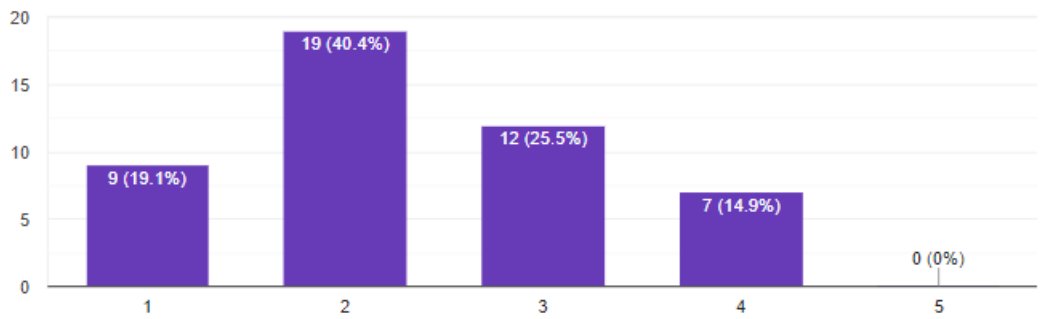
	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

How much do you agree with this statement: "The strategies that companies/political parties employ on social media sites to attract people are effective"?

	1	2	3	4	5	
Strongly disagree	○	○	○	○	○	Strongly agree

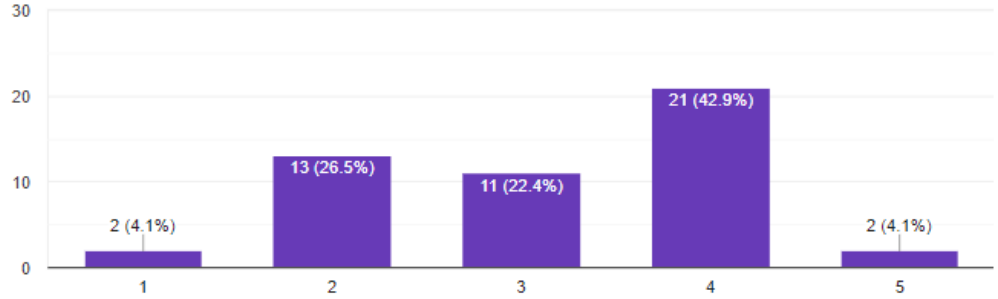
How much do you agree with this statement: "I feel like I have a relationship with the companies/political parties I interact with on social media sites"?

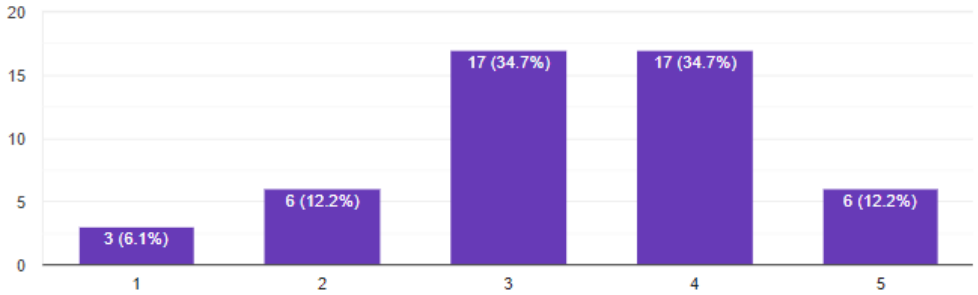
47 responses



How much do you agree with this statement: "Interacting with companies/political parties online allows me to gain information that others might not be able to"?

49 responses



How much do you agree with this statement: "The strategies that companies/political parties employ on social media sites to attract people are effective"?

49 responses