Social Sentiments and Mimetic Outcome - Implications on Brand Metrics

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Abstract— This study explores the relationship between social media sentiments and mimetic behavior using visualization techniques. Specifically, this study examines the characteristics of Twitter information diffusion surrounding two recent events of worldwide attention in order to understand whether the emotional aspects of mimetic behavior are similar. The Mimetic Theory of desire contends that a subject (S), imitate the behavior of a Model (M), in relation to an object of desire (O). With all desires being the desire of others; this study premise that the emotional arousal that O causes similar reaction in S in relation to M. In the presence of an external mediator, the reaction is also exclusively mimetic. This study collected a number of tweets bearing the hashtag of a recent event that received worldwide attention and classified the tone of the tweets using sentiment analysis as positive, neutral or negative. The same analysis is replicated on a corpus collected on tweets bearing the fake news tag. The sentiments are first visualized before applying the post-truth[1] diffusion proposition to show the presence of mimesis and its relation to sentiment are similar in both cases. This study concludes by discussing the applicability of Mimetic Theory on both real and fake news diffusion and the implications on marketing efforts.

Keywords— Social Media, Diffusion, Influencer, Mimetic, Sentiment, Post-Truth, Branding

I. INTRODUCTION

Word of mouth (WOM) and virality metrics are inherent in social media sites like Twitter, Facebook and Instagram. They provide valuable insights in mass behaviour and choices. Studies have shown that these factors can impact key metrics in branding awareness, both negatively and positively [1, 2]. This study extends current work by looking at the behavior of social media in terms of misinformation by looking at datasets related to a recent event that gained virality and compared the results to another dataset that co-occurs with the word FakeNews by employing a methodology of community detection to identify whether similar patterns occur in terms of diffusion. Post-truth, is defined as "relating to or denoting circumstances in which objective facts are less influential in shaping public opinion than appeals to emotion and personal belief" [3].

This paper presents a discussion on the mimetic behavior of users on social media and its impact on brand metrics in the following aspects, termed as soft-brand metrics using examples of recent events that gained worldwide attention.

- Public Relations – Social media has given an entirely new sphere for companies to build and establish wholesome relations with customers and to know more about the customers of its competitors. Businesses can develop competitive benchmark strategy by comparing customer sentiments and also identify needs that may not be met by competitors [2, 4, 5]
- Customer Engagement – Customer engagement has become one of the most important metrics in today's business environment showing direct positive influence on customer stickiness and value creation [6]. Online engagement is key to improving satisfaction and loyalty rates, and revenues [7, 8]. Social media provides and avenue for customers to interact and voice their opinion and feedback and many customers also depend on the feedback of past customers. A dissatisfied customer can have detrimental effects on customers as they are more than ready to convert.
- Customer retention – A positive effect that can be derived from engaged customers is relational benefits such as retention [9] through trust and positive word-of-mouth activity [10, 11]. An engaged customer can in itself become a channel for sales, public relation and also customer service. It is therefore crucial that companies understand the implicit and explicit implications of a successful social media success.

II. RELATED WORK

Social media is defined as "a group of internet based applications that builds on the ideological and technological foundations of Web 2.0, and it allows the creation and exchange of user-generated content" [12]. This definition implies that content is produced, shared and consumed by users actively generating content [13]. In the review of literature on social communities, psychological need is one of the many incentives for people to join. People need to feel socially connected and gratifies a need for connection [14]. This study advances research in the area by applying the principles of the Rene Girard's Mimetic Theory of Desire [15] in examining how users connected on the internet seek out an influencer to mediate behaviour towards a particular object. The testbed for this study is based on two events of contrasting nature to examine whether the concept of mimesis based on external mediation is imitative nature and dependent on the Model of mimesis.

A. Mimetic Theory

Crucial in Girard's Mimetic Theory is the notion of Mimetic desire viewed as the main source of aggression characterizing a person's action. The intrinsic value of the objects of our desire lies solely on the fact that the target of object is the desire of the others. What this means is that the meaning acquired with imitation consists desirable qualities possessed by the person who is being imitated and is therefore viewed as a reflection of them. This, is the essence of why people imitate and its implication is that social media can be seen in the form of influencers. Rivalry is seen not only amongst groups that one interacts with but also among reference groups that are created through formations of polarized groups. Burns (2010) proposes a theory of marketing based on the role of taste in fashion as a means of influence between others and one's fashion understanding and subsequent fashion choices. When another is viewed as desiring a product (as is noted by their desire for the product or their ownership of the product), an individual is alerted to the desirability of the product – a fashion trend has begun [16]. Ahmed & Mort (2016) offers a framework based on the concept of mimesis for an enhanced perspective to understand consumer motivations with regards to products, supply, sell, buy and use of counterfeits. In a study of online food image sharing, desire is conceptualized as energetic, connective, systematic and innovative, it was found that networks of desires create a passionate universe of technologically enhanced desire. According to this study, technology increases the passion to consume and effects depend upon participation in the network which can be private, public or professional [17].

In Twitter network, users can follow conversations of a community and when their posts appear on their newsfeed, they can show different forms of engagement: mark as favourite, retweet the content by adding the information to their own timeline and they can create own feed using the information received by mentioning the original author of the post. The number of profiles following a user indicated popularity (Bigonha, Cardoso, Moro, Almeida & Goncalves, 2010) and social influence increases when a larger number have access to the influencer's tweets. A social influencer therefore not only has a large number of followers but also follows a huge number of users to create strong ties in the virtual community (Okazaki, Díaz- Martín, Rozan-Suplet, and Mene ndez-Benito, 2014). A social influencer as such, has the potential of asserting mimetic pressure as well as creating mimetic action from followers.

B. Sentiment Analysis

Sentiment Analysis is the process of determining whether a piece of writing (product/movie review, tweet, etc.) is positive, negative or neutral. It can be used to identify the customer or follower's attitude towards a brand through the use of variables such as context, tone, emotion, etc. Marketers can use sentiment analysis to research public opinion of their company and products, or to analyze customer satisfaction. Organizations can also use this analysis to gather critical feedback about problems in newly released products.

Sentiment analysis not only helps companies understand how they're doing with their customers, it also gives them a better picture of how they stack up against their competitors. Fan (2013) uses the ideodynamic model to predict opinion over time about the commercial brand of Toyota when media coverage was used as predictors. The same study showed that good predictions could be made from a variety of media channels including online news, blogs and forums.[18] Knowing the sentiments associated with competitors helps companies evaluate their own performance and search for ways to improve their public relation crisis management [19].

When members belong to a virtual community, they develop a social identity. Users who simultaneously engage many communities form relationships with existing users and become loyal to the community [20] that can enhance brand loyalty [21]. The Theory of Mimetic Desire, is fundamental concept used in this study to explain the diffusion behaviour on social media. The presence of an influencer is crucial as the external mediator. When users identify with and feel comfortable with the group, they often "share", by means of a retweet, content that other users could find interesting or relevant. By passing a tweet along, not only do users amplify the message, but they also validate it. Retweeting can be a form of social advocacy where members become supporters of a user or a brand [22].

III. METHODOLOGY

This section details the methodology that is used to gather the data for analysis. This paper first discusses the #FakeNews by looking at the sentiments and social relationship with implications on branding. Then, this paper presents the findings of similar analysis on #PokemonGo. Data collection was completed via Twitter Search API and subsequently visualized using two methods: Scatterplot graph and network graph using OSoME API [23]

A. Data Collection

This study was conducted on two datasets in conjunction, both obtained from Twitter. The first dataset was collected to monitor narratives and discussions surrounding fake news. To do so, this study performed simultaneous data collections using the Twitter Search API to search for tweets mentioning specific keywords (Figure 1).

- In the first step, tweets in English containing the hashtags #FakeNews and #PokemonGo are collected simultaneously. The limit set on each category of tweet is 5000.

- Every 15 minutes Twitter's Search API extract general tweets that include the most relevant URLs stored, and meta-data about the users who tweeted about them.

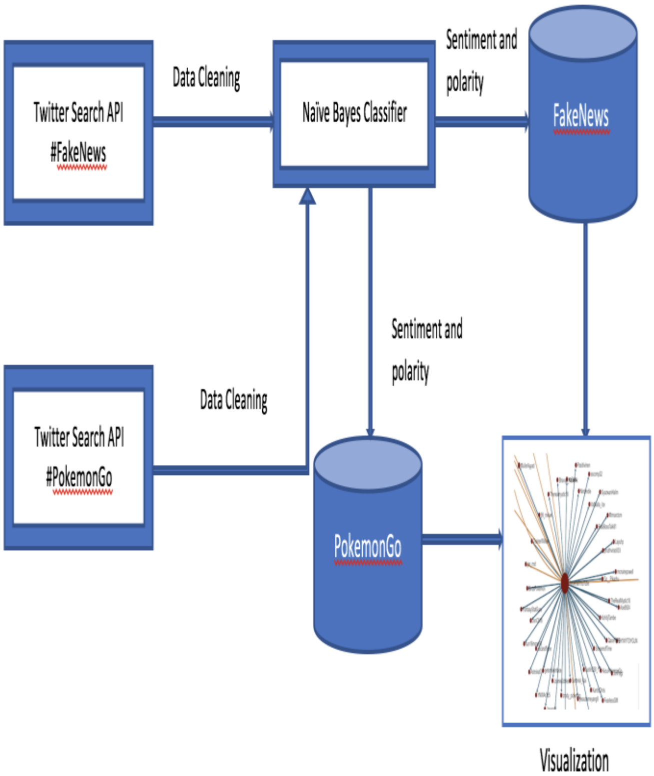

Fig. 1: Methodology for Retrieving Tweets, Classifying Tweets and Visualization

The goal of this double-dataset collection is to build a more complete view of the #FakeNews and #PokemonGo datasets of very different nature: to study the diffusion pattern and sentiments of both both users who are referring to a content (i.e. an URL or another tweet) as a potential source of news, and users who are citing, propagating or interacting with the same content without attaching to it the label. The methodology that is used in this study draws inspiration from Ribeiro's paper on Spread of Fake News that uses a double data-collection mechanism from both Search API and Twitter Stream. [24]

B. Sentiment Analysis

This study adopted a natural approach to how twitter users reacted to news items with the hashtag #FakeNews and #PokemonGo. Sentiment analysis is applied to tweets collected to examine the emotions that manifested in Tweets. The analysis is limited to all tweets in English. This project analyzed the emotions at the word level; that is, words with various discrete emotions were tabulated and counted. The more detailed procedure is as shown in Figure 2. The tools used are Python and the Natural Language Toolkit (NLTK), a platform with resources and programming libraries suitable for linguistic processing [25].

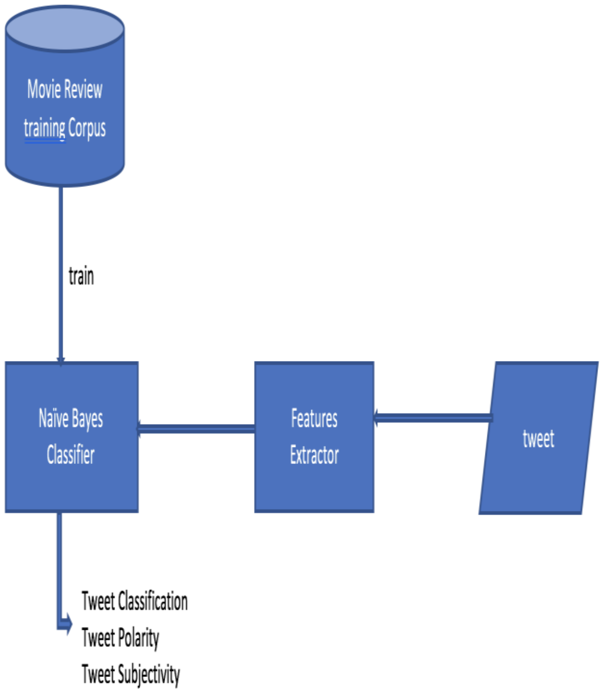

Fig. 2 Sentiment Analysis on Tweets using NLTK

Set A: #FakeNews

The dataset used in this study was retrieved via Twitter API based on 1760 tweets that were collected via Twitter API using the hashtag #FakeNews. TABLE 1 below shows the classifications of some tweets and the polarity that were determined using NaiveBayesian classifier available within the NLTK package.

The resulting tweets were visualized on a scatterplot showing the subjectivity of the tweets (Figure 3). The x-axis shows the subjectivity of tweets and the y-axis shows the time of creation of the tweets collected. This graph clearly showns distinct tweets that were reweeted along a line of same sentiment value.

The interactions were next visualized in a network diagram in Figure 4 and Figure 5 that shows a number of populous communities detected in both tweet and retweet larger networks and some smaller communities. A number of influential handlers were obvious in the network, namely:

- CNN
- POTUS
- RealDonaldTrump
- FoxNews

neg	0.347426471	0.652573529	@nytimes #FakeNews , maybe in 8 yrs.
neg	0.485043326	0.514956674	@CNN Not looking so good for you. #FakeNews https://t.co/qxYKMwKsit
neg	0.269237388	0.730762612	RT @SeldenGADawgs: @GeraldoRivera @realDonaldTrump Gee, that's not what #FakeNews says. They say in ONLY 8 months @realDonaldTrump has
pos	0.932815869	0.067184131	RT @SRuhle: Dear @realDonaldTrump, the people of Puerto Rico have no means to watch the #fakenews! THEY HAVE NO POWER #newsflash
neg	0.387986251	0.612013749	RT @theTrumpSpring: @CNN Another @CNN #fakenews story is about to explode spectacularly. When will you learn?
pos	0.737600507	0.262399493	RT @realDonaldTrump: Because of #FakeNews my people are not getting the credit they deserve for doing a great job. As seen here, they are Aâ€¦

Table 1: Sample data collected from Twitter Search API with hashtag #FakeNews that are classified (column 1) using NLTK NaiveBayesian Analyzer. Columns 2 and 3 are the polarity and subjectivity of the tweets.

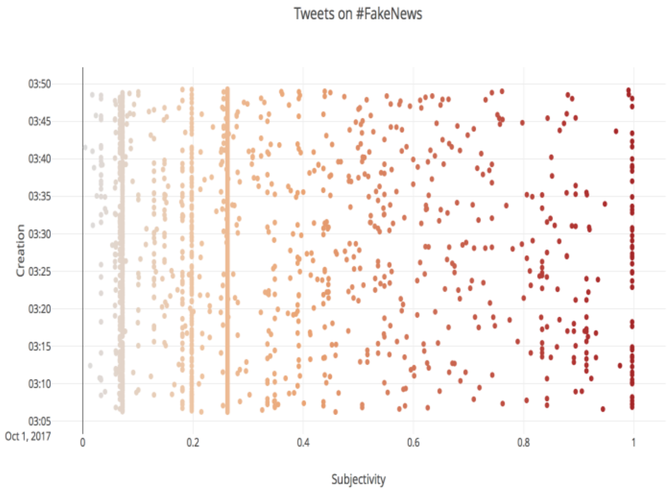

Fig. 3: Visualization of Sentiment Subjectivity on #FakeNews

Fig. 4: Visualization of Network Tweets and Retweets on #FakeNews generated 1 October 2017 (Period: 28 September 2017 until 30 September 2017)

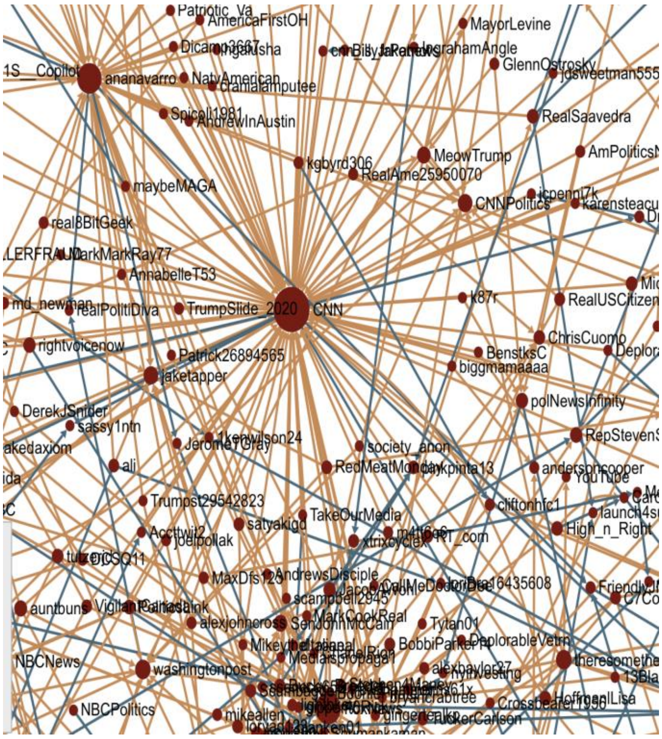

Fig. 5: Tweet and Retweet Network Structure of handle @CNN

Set B. PokemonGo

The dataset used in this study was retrieved via Twitter API based on 4946 tweets were collected via the Twitter API through TAGS using the hashtag #pokemonGo. Table 2 below shows the classification, polarity and subjectivity scores calculated on downloaded tweets. The sentiments were determined using NaiveBayesian classifier available within the NLTK package.

pos	0.544503496	0.455496504	RT @PokeGoNews2016: 'PokÃ©mon GO' Had 50 Times More Traffic Than Predicted - Forbes #PokeGONews24 #PokemonGO https://t.co/i53aBjEH1F
neg	0.290136091	0.709863909	First Suicune I saw but nobody to raid it ðŸ˜¡ #PokemonGo https://t.co/yQRo6sOH2S
pos	0.750423754	0.249576246	RT @PokeGoNews2016: This UK university lets students play PokÃ©mon Go as part of their degree - The Next Web #PokeGONews24 #PokemonGO https:â€¦
pos	0.501431917	0.498568083	RT @PokeGoNews2016: Pokemon Go helps express your inner hunting instincts! - The Indian Express #PokeGONews24 #PokemonGO https://t.co/drVeYâ€¦
pos	0.573985691	0.426014309	RT @SpringerOpen: New in our blog: Out in the city with #PokÃ©monGo by @carnby - https://t.co/6usOmZn0Bf

Table 2: Sample data collected from Twitter Search API with hashtag #PokemonGo that are classified using NLTK NaiveBayesian Analyzer

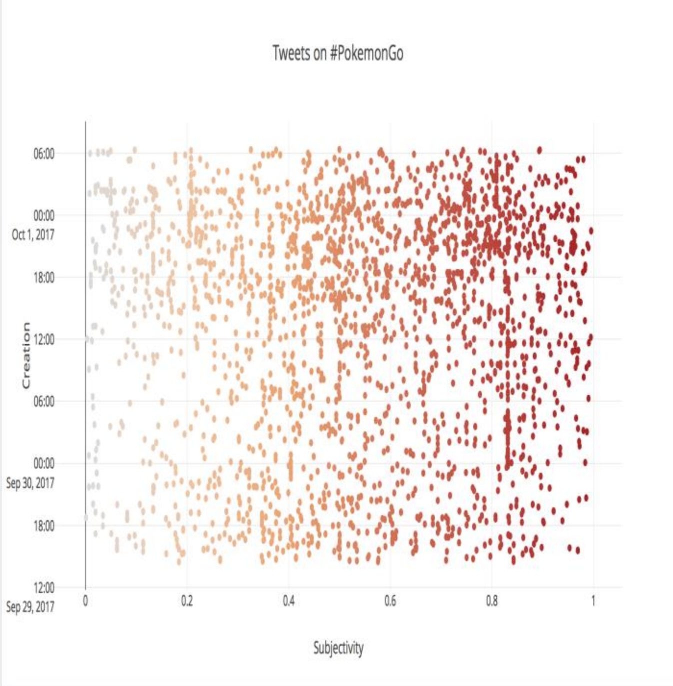

Fig. 6 Visualization of Sentiment Subjectivity on #pokemonGo

Figure 6 shows the sentiments plotted based on subjectivity (axis-x) of the tweets against time of creation (axis-y). The result we seen distributed over the graph.

Figure 7 showns the resulting network diagram generated and it shows several small communities that are tightly related. There are visibly more retweets and tweets in this community. The main influencers in this graph are:

- PokemonGoNews
- ReversalYoutube
- Cdiscount

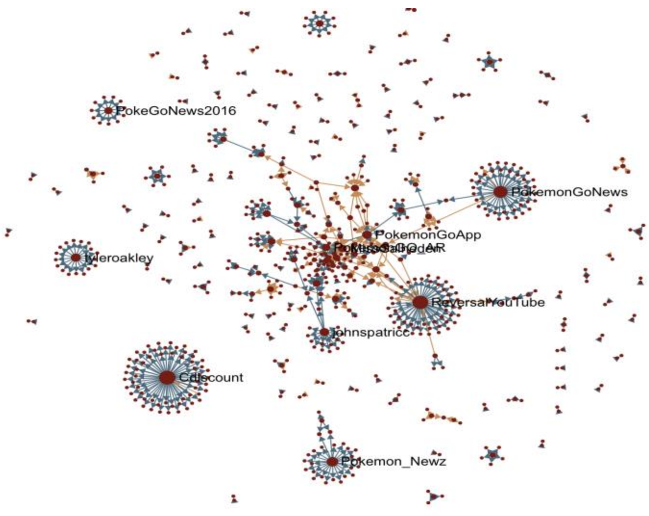

Fig. 7 Visualization of Network Tweets and Retweets on #PokemonGo generated 1 October 2017 (Period: 28 September 2017 until 30 September 2017)

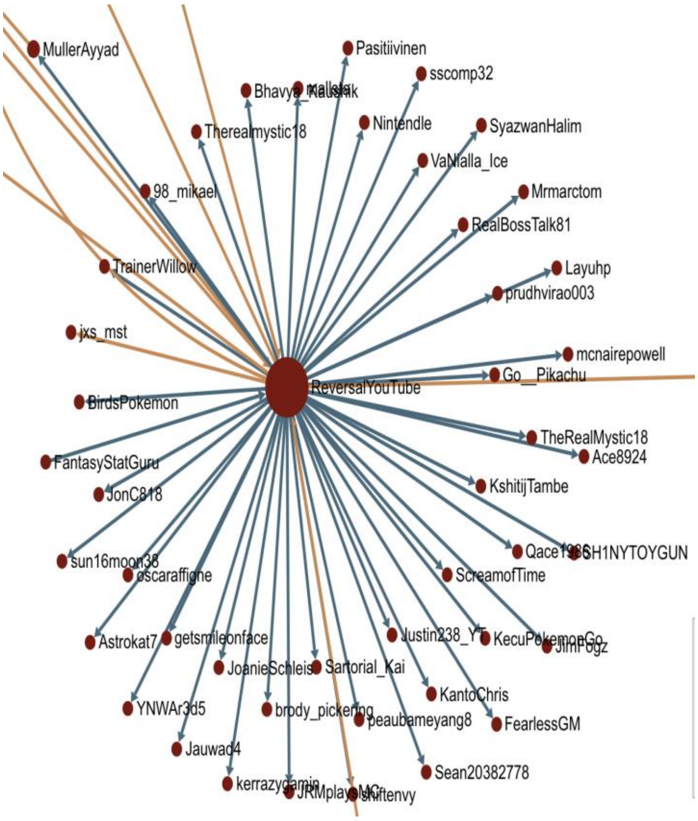

Fig. 8 Retweet Network Structure of user @ReversalYouTube

IV. RESULTS AND DISCUSSION

Implications of this study is derived mainly upon identifying the primary sentiments of populations in many markets. User sentiments can challenge the status of companies and individuals. As a result, companies develop a heightened sense of awareness of how things might be changing. These become a crucial insight for firms to decide and embark on long term strategic initiatives and crisis management. Combining the Theory of Mimetic Desire to understand diffusion behavior of social media users with Sentiment subjectivity offers the following advantages to companies' branding efforts:

- Identifying Latent Communication Channels through which information can be propagated - PokemonGo is an augmented reality game released in July 2016, that has an estimated 7.5 million downloads and a daily revenue of USD1.6 million as of July 11 2016 [26], it also became a massive online and offline experience. The game thrives on Poke-stops that are real-world locations for trainers to collect XP, Pokeballs and other related items. It has also created massive gatherings of like-minded gamers in cities. It has become a means for people to meet one another and also caused many online groups on social media sites like Facebook such as Pokemon Go Flash mob, Pokemon Go cosplay meetup. Yelp has also added Poke-stop nearby as a filter to help community find businesses that are doubling as poke-stops [27]. Graph visualization allows identification of links and patterns through which information is diffused. It also identifies small world communities which for a given topic, the link may remain uncovered.

- Identifying influencers - On Twitter, notable positive and negative Tweets can allow companies to identify who is contributing to the conversation in the tone that matches the company's campaign. A deeper look at different dates as shown in both cases of #FakeNews and #Pokemon, companies are able to determine what users are consuming in relation to the company as well as the competitor. As evidently shown in the case of #Pokemon, micro influencers (e.g. @ReversalYouTube) do afford as much swaying power as do macro influencers (e.g. @CNN). Knowing which influencer evoke which kinds of sentiments can therefore be useful for competitive intelligence and mitigate influencer marketing risks especially when the influencer falls out of favour.
- Social sentiment analysis allows brand-centric social media analysis - In the post-truth era, if one does not know whether anything is true or not, how does one choose what to stand against or which direction to expend targeted efforts? Companies are able to prioritize their engagement efforts to ensure that they are responding to crisis quickly. Keeping track shifts in perception by monitoring changes in average brand sentiment allow companies to take necessary actions to mitigate potential falls as in the case of misinformation (e.g. #FakeNews) that is circulating in regard to a particular company. Misleading customers can be disasterous but sharing FakeNews can be detrimental to a company's brand and efforts to build trust and sustain valuable reputation.
- Deriving insights for consumer engagement efforts - What this means for marketers is that they must understand the meanings behind the analysis and adopt impactful strategies for successful acquisition and retention of customer loyalty. Customer engagement remains crucial especially in the online sphere. Companies should take advantage of all the opportunities they have in engaging customers at every stage of their buying journey. Engagement happens when customers are connected to the brand both intellectually and emotionally. A company's understanding of who influences buying decisions is a critical component of successful influence marketing. Addressing sentiments of decision influencers can yield significant results.

V. CONCLUSION

This study considered the sentiments on social media in relation to two recent events that received global attention, and considered how it affected the organization in various aspects. One of the primary method of measuring social media success has been to look at the number of Likes (e.g. Facebook Page), the number of likes and retweets on posts (e.g. Twitter posts) as well as the amount of interaction amongst followers. Studies support the idea that Fans are certainly worth more than non-fans (citation required), which is essentially a measure of brand engagement. Once a fan is affiliated with the particular brand, they are also more likely to share content and communicate with their networks about a brand or product.

Online data can provide valuable behavioural and attitudinal insights. But these data require proper integration into existing data in order provide valuable and effective marketing indications for strategic effectiveness.

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