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IDENTIFYING EMOTIONS DURING COVID-19 USING TOPIC MODELLING APPROACH

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Abstract

The purpose of this paper was to study the emotions of large population under the unique situation like the COVID-19,

a). How to capture the emotions of large population without the direct observation of the respondent and his facial expression while the distressed situation is ongoing?

b). Will the basic emotions remain the same or will they be different while the respondents are not directly involved?

Resent researchers propose that "emotional experiences also can be investigated using qualitative

methods such as the coding of written or oral narratives" such as sentiment analysis of Tweets. Therefore, this study was carried out by identifying #COVID-19 Tweets during first seven-day stretch of August-2020 utilizing supposition study and point of demonstrating utilizing Latent Dirichlet Allocation(LDA) post preparing. The study reasoned that the data stream was exact and dependable identified with COVID-19 outbreak with least deception.

From the data analysis we found that the oral narratives of large population related to #COVID-19 have represented the basic emotions same as individual facial expression or self-reported questionnaires that are; "fear", "sadness", "joy", "surprise", "anger", and "disgust", Therefore, we can conclude that the Topic Modelling Approach" or LDA methodology can be used for twitter hashtags analysis with equal reliability as that of observation and self-reporting studies. In addition, the advantage can be a quicker process with a large number of respondents that gives better reliability of the data. We also found that using Topic Model Approach, one aspect of measurement may serve as a proxy for others

Key words: Identifying Emotions, Twitter Analysis, COVID-19, Topic Modelling Approach, Latent Dirichlet Allocation.

Introduction

Global lockdowns due to COVID-19 has impacted the family and economic situation and also the control measures such as social distancing, wearing face mask, continuous hand sanitization, etc. have triggered various emotional imbalances in the people. World Health Organization (WHO) is leading everyday media meetings to alleviate the feelings of trepidation and furthermore train the administrations over the world to execute explicit measures. Online networking organizations like Twitter, Facebook, YouTube, and so forth are exceptionally wary about the fear inspired notions and misinformation being spread about COVID-19. In spite of the best efforts of this internet based firms' part of disinformation is spreading since the novel strain of virus containment spread over the globe. It is important to understand what are the large scale emotions felt by the people for governments, NGOs, and social organizations to develop policies and emotional support to those who are most affected by the situation.

Ekman & Freisen (1975) found six basic emotions of facial expression; anger, fear, sadness, disgust, happiness, and surprise. Kemper (1987) identified a set of primary emotions: anger, fear, depression, and satisfaction parallel Ekman's set of basic emotions. Sociological aspects of primary emotions are described by Turner (2002) as; assertion-anger, aversion-fear, disappointment sadness, and satisfaction-happiness. Thoits' (1990) indicated that an emotion has four interconnected components: (1) situational cues, (2) physiological changes, (3) expressive gestures, and (4) an emotion label that names the specific configuration of components. For example, Physiologically, fear is associated with greater decreases in blood pressure and blood flow to the extremities (Levenson, 1992). Stets (2006) argue that, "the universality of these facial expressions provided compelling evidence that these emotions are basic to humans. Individuals are socialized into what emotion label to apply to situations and to physiological changes. For this reason, emotions and sentiments are intimately social".

In a normal situation individual emotions are identified by observation or self-administered reports of survey, which ask participants to recall from memory situations that evoked a set of emotions. Some researchers argue that, "emotions have no distinct facial expression (e.g. jealousy; Buss, 2013), or do not appear to serve a signaling function at all (e.g., regret; Galperin et al., 2013). Many evolved emotions not to have discernible outward signals (Al-Shawaf et.al.2016). Stets (2010) suggested, "more research is needed on the consequences of emotions for larger entities such as relationships and groups, since this has implications for understanding stable (and unstable) social structures". Therefore, we wanted to study the emotions of large population under the unique situation like the COVID-19,

a). How to capture the emotions of large population without the direct observation of the respondent and his facial expression while the distressed situation is ongoing?

b). Will the basic emotions remain the same or will they be different while the respondents are not directly involved?

Since individuals are scanning on the web for data about COVID-19 outbreak and they are especially depending on the previously mentioned internet based life stages and online news destinations. Recently many researchers have used Twitter to determine the emotions on almost every situation for example, (Jagdale et.al 2019), movies (Uma et.al 2018), politics (Ravikuma 2015), digital technology (Maidola et.al 2018) and natural calamities (Wyang et.al. 2014) On the same lines, we believed the automatic sentiment analysis can address our question of identifying the emotions by referring to the tweets of the people globally by finely tuned algorithms. Therefore, we conducted sentiment analysis of 10,000 tweets and identified the emotions of people findings are compared with previous research.

This paper is organized as follows, second section presents the literature review on use of Twitter during the past pandemics and findings, third section presents the research methodology, fourth section presents the findings and analysis fifth section presents the conclusions and direction for further research.

Literature Review - Measuring Emotions

Emotions represent intense affective, valenced reactions and are directed at a specific cause (e.g., fear over COVID-19). Sates (2010) argued that "emotions can move from negative to positive, and back again to negative, in rapid succession and within a matter of minutes. They can start out positive, and feelings such as happiness and satisfaction may persist throughout most of an interaction, but then an unexpected event may end the interaction with feelings of hostility. Still yet, individuals initially may get trapped in a negative feeling state throughout an interaction, unable to change its course or extricate themselves from it. More sociological theory is needed that explains how early events and emotions influence later events and emotions". The context and the purpose of measurement of emotions should dictate the type of affect assessed. For example, interest in how people feel after hearing the news of with particular service people dying after getting infected with COVID-19. These types of affect are ephemeral and linked to discrete events. One of the important decisions is determining which aspect(s) of emotional responding to assess. Typically, interest centers on emotional *experience*, or one's subjective assessment of emotion. In some cases, though, other phenomena, such as emotional awareness (the ability to recognize emotions in oneself and/or others), emotional expression (outward display of emotions), emotional regulation (the process of influencing emotional experience and expression), and/or psychophysiological response are of interest (Sloan & Kring, 2007). The issue of ultimate scientific and/or applied concern must drive the measurement strategy. Measurement of one aspect does not necessarily serve as a proxy for others. Assessing multiple emotional phenomena, and using multiple measures to assess each, will be the most appropriate and informative strategy. Some researchers suggest that emotional experience can be captured by a set of underlying dimensions. According to one dimensional framework, valence (also known as "hedonic tone" or pleasantness-unpleasantness) and activation (also known as arousal) are the two fundamental dimensions organizing emotional experience (Russell & Barrett, 1999). In another popular model, the two primary factors (i.e., dimensions) of emotional experience are positive activation and negative activation (i.e., Tellegen et.al 1999). Considerable evidence supports the dimensional perspective. For instance, many emotions (e.g., guilt, anxiety) often co-occur, implying that they reflect the same underlying dimensions and processes (Watson et al., 1999). Also, many measures can distinguish among emotions at opposite poles of a dimension (e.g., positive vs. negative emotions), but cannot distinguish well between specific emotions closely located on that dimension (e.g., fear vs. shame along the negative dimension). A well-known alternative view is that there are a certain number of discrete emotions, (e.g., anger, fear, disgust), each of which corresponds to and represents a unique pattern of emotional experience, behavior, and physiology (e.g., Ekman, 1999). Adherents of this view argue that, by collapsing distinct emotions (e.g., guilt and anxiety) into dimensional emotional experiences (e.g., high negative activation), the uniqueness of each emotion is lost. The purpose and context of the measurement must be the focus when choosing a measurement strategy. Observational methods offer several notable benefits and can overcome many of the drawbacks associated with self-reports. For instance, observational methods can provide insights into emotional experiences that individuals may not recognize or be willing to divulge (Tracy & Robins, 2007). Observational methods generally are most useful when research interest is in the display (versus the experience) of emotion. According to Barclay & Skarlicki, (2005), "emotional experiences also can be investigated using qualitative methods such as the coding of written or oral narratives". These methods are especially useful in assessing particular, discrete emotional experiences (e.g., a bad mood at work on a particular morning) and in identifying the specific conditions that give rise to them (e.g., a child's illness). Also, writing narratives about one's own work and the emotions it generates can improve respondents' well-being.

Fung et al. (2014) arbitrary test tweets identified with Ebola episode and inferred that the vast majority of the tweets started in USA, while illness outbreak was in Guinea, Liberia and Sierra Leone because of the way that internet get to was minimal in these nations. Negative feelings, for example, anxiety, anger, swearing and death ruled the tweets which features the elevated levels of anxiety identified with Ebola. They further reasoned that twitter can be viably be utilized by the specialists and health experts to give applicable exact data identified with illness and can decrease frenzy and anxiety in irrelevant zones where there is no episode (Fung ICH T. Z., 2014). Oyeyemi et al. (2014) studied the misinformation that spread during the Ebola outbreak that created panic and anxiety and concluded most of the tweets were misinformation and had a wide reach compared to correct information. Zika outbreak in Latin America related tweets were concentrated by Kung-Wa Fu et al. (2016) where in the analysts distinguished tweets with numerous subjects like the societal effect of the outbreak, sway on pregnant ladies and unborn kid, reaction of government and health specialists identified with the outbreak and how the infection spread across geographical areas. Chew and Eysenbach (2010) examined 2 million tweets identified with H1N1 or swine flu episode and directed investigation to understand the "infoveillance" which they proposed to screen the progression of data identified with outbreak on twitter. They proposed utilizing social media for potential "infodemiology" contemplates and finished up the tweets were utilized to spread data identified with episode from dependable sources and additionally clients voiced their suppositions and concerns generally. Further proposed wellbeing specialists can principally utilize twitter for spreading information and control concerns (Chew C, 2010).

The study focused around the data stream on twitter during the corona virus outbreak. Tweets identified with #coronavirus are considered utilizing sentiment investigation and topic demonstrating utilizing Latent Dirichlet Allocation(LDA) post preprocessing. The study inferred that the data stream was precise and dependable identified with corona virus outbreak with least deception. LDA study had distinguished the most applicable and exact topics identified with corona virus outbreak and sentiment investigation affirmed the pervasiveness of negative emotions like dread alongside positive emotions like trust. Governments and Healthcare specialists and organizations viably used to spread exact and solid data on twitter (Dr. Rajesh Prabhakar Kaila, 2020).

Topic Model-Latent Dirichlet Allocation:

Topic modeling is the process of three components like input, Latent Dirichlet Allocation and output. Input is a document term matrix, it is a matrix where the rows are different documents and the columns are of different terms. And the values in the matrix are the word counts. It deals with the bag of words format. LDA is an algorithm used popularly in topic modelling technique. Output is basically functions to find themes across various routines and tend to talk about which terms are latent Dirichlet Allocation. LDA is an another word for hidden, and it finds the hidden topic from the text, and Dirichlet is a type of probability distribution. For simple understanding of the Function of LDA, if there are n documents of m themes of documents p documents and q documents having the mix of p documents. LDA allocates the themes in p documents as per the probability distribution of different themes according to the topics.

In this investigation Topic modeling method Latent Dirichlet Allocation (LDA) is actualized on the Document term matrix made from text corpus. Topic modeling distinguishes topics from a set of documents which are a set of words dependent on the accompanying supposition that each document can depicts by a dispersion of topics and every topic can be portrayed by a distribution of words. In a document-term matrix, rows relate to documents in the assortment and segments compare to terms.

Latent Dirichlet Allocation starts with recognizing the words in each document, makes a topic blend for the document identified with a fixed set of topics picked and topic determination is absolutely founded on document's multinomial distribution followed by picking of words dependent on multinomial distribution. Fundamentally, LDA is an unsupervised algorithm used to recognize the semantic connection between words a gathering with the assistance of related markers. Researchers had utilized Topic Modeling Especially Latent Dirichlet Allocation for distinguishing topics in tweets, which are (Prabhakar, 2016) executed LDA on climate change tweets, Prabhakar, K.R and Satish. D (2016) executed LDA on tweets related Fort McMurray Wildfire debacle.

Research Methodology:

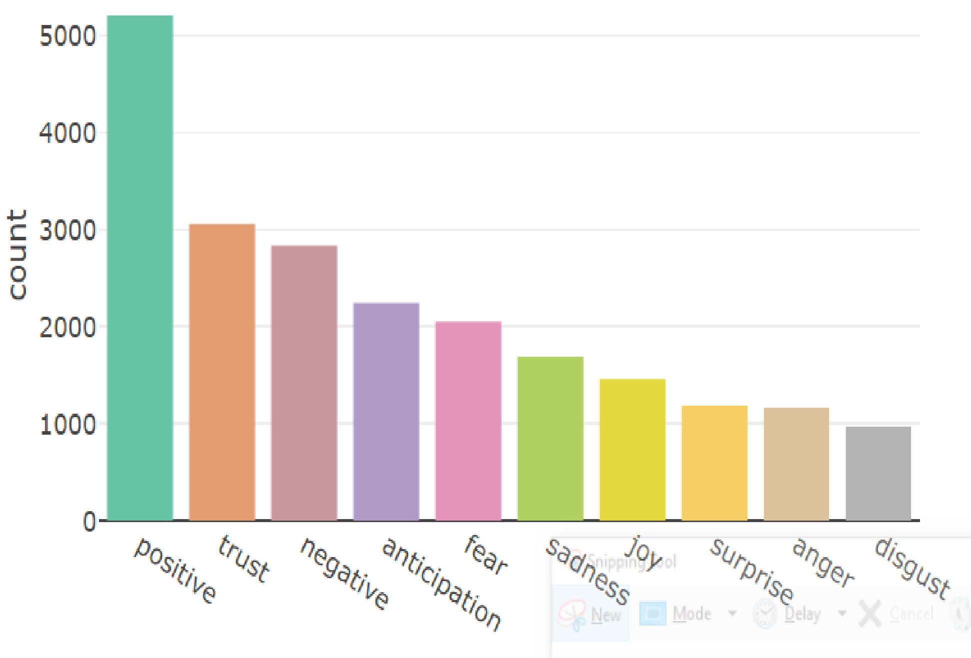
Using one of the author's Twitter app accpunt tweets of the # COVID -19 Tweets were downloaded and analysed using LDA model.

The examination centers around the tweets during the crown infection episode and a random example of 10000 tweets are downloaded utilizing the bundle "twitteR" in R. The example of 10000 tweets is picked as it is in general number of tweets that can be downloaded utilizing the bundle and using twitter API keys. The tweets are preprocessed utilizing bundle "tm" in R and changed over into a corpus of text. The preprocessing is confirmed utilizing a word cloud and there are no unique characters or any stop words. Sentiment analysis is directed on the cleaned tweets sentences before changing over tweets into a book corpus utilizing bundle "syuzhet" in R. For motivation behind sentiment analysis NRC sentiment word reference is utilized to ascertain the nearness of eight unique emotions and their relating valence. An information outline where each line speaks to a sentence from the first document. The sections incorporate one for every emotion type just as a positive or negative valence. The ten sections are as per the following: “positive”, “Trust”, “negative”, “anticipation”, “fear”, “sadness”, “joy”, “surprise”, “anger”, “disgust”. A Term Document Matrix is made from the content corpus which is a two-dimensional scanty network whose lines are the terms and segments are the archives, so every passage (I, j) speaks to the recurrence of term I in report j. Post making of term archive lattice, visit terms are recognized to approve whether the terms in tweets relate to corona infection outbreak or not. Relationship analysis led utilizing the term report network where in every vector holds coordinating terms from x and their adjusted connections fulfilling the comprehensive lower relationship limit.

Results and findings:

Emotions analysis done on the pre-handled tweet sentences for #COVID-19 generated sentiments and emotions as shown in Fig.1 demonstrate intently both the "positive" and "trust" text as the greater part of tweets have both frenzy and encouraging words. Negative among the individuals rules the estimation followed by "anticipation" from the specialists. Interestingly, along with narratives such as 'positive', 'negative' 'trust' and 'anticipation' related to COVID-19, we also found the all the basic emotions like "fear", "sadness", "joy", "surprise", "anger", and "disgust",

Fig.1 Emotion Type for hashtag: #covid19



Frequent text from the word cloud as shown in Fig.2 generated from tweets term document matrix are likewise generally pertinent to the virus infection outbreak. Most regular words being "treat", health", "lead" affirm to the effected people with positive corona virus and advise them for treatment to convert in to negative effect that is to get cure from effect of corona virus. Covid 19 is not a death sentence, individuals shall maintain highest trust that every individual shall be from corona virus in a short time is the message from the most frequent words appearing under the trust dimension of the cloud. Oil showcase fallen and securities exchanges are likewise most exceedingly terrible influenced. Corona virus infection has gotten a pandemic. "disgust", "anger", and "fear" affirm that the people are panic regarding the spread of COVID-19.

Correlation Analysis as shown in Table-1,the association examination directed utilizing term document matrix made. There are numerous catchphrases with which correlation examination should be possible yet with the end goal of study, picked only word cloud sentiment words. The table underneath features the correlation with the explicit watchwords picked. Connected words are profoundly huge to the COVID-19 19 infection outbreak.

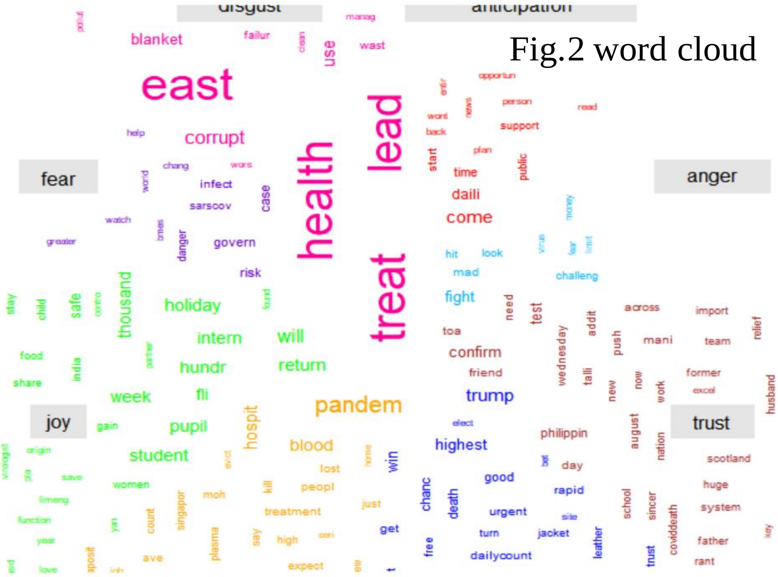


Fig.2 word cloud

Table-1 Correlation Analysis of emotions								
	anger	anticipation	disgust	fear	joy	sadness	surprise	Trust
Anger	1	0.9022	0.9753	0.9402	0.9459	0.9368	0.9455	0.876
anticipation	0.9022	1	0.878	0.8939	0.892	0.8901	0.8889	0.9688
Disgust	0.9753	0.878	1	0.905	0.9551	0.9269	0.9609	0.837
Fear	0.9402	0.8939	0.905	1	0.8832	0.977	0.881	0.9116
Joy	0.9459	0.892	0.9551	0.8832	1	0.894	0.9862	0.8592
Sadness	0.9368	0.8901	0.9269	0.977	0.894	1	0.8947	0.8901
Surprise	0.9455	0.8889	0.9609	0.881	0.9862	0.8947	1	0.8511
Trust	0.876	0.9688	0.837	0.9116	0.8592	0.8901	0.8511	1

From the above correlation matrix constructed between the emotions drawn from the word cloud, collected number of relations having from 80% to 100% with 5% bins difference as shown in Table-2.

Table-2 bins differences				
	0.8 - 0.85	0.85 - 0.9	0.9 - 0.95	0.95 – 0.99
1	trust-disgust	trust-anger	anger-anticipation	disgust-anger
2		disgust-anticipation	fear-anticipation	trust-anticipation

3		fear-anticipation	joy-anticipation	joy-disgust
4		joy-antipation	sadness-antipation	surprise-disgust
5		joy-fear	surprise-anticipation	sadness-fear
6		surprise-fear	fear-disgust	surprise-joy
7		sadness-joy	sadness-disgust	
8		trust-joy	trust-fear	

Eight different correlation corresponding to 85%-90% and 90% -100% are identified. Among these relations, anticipation as a sentiment is more number of times correlated with the sentiments anger, fear, sadness and surprise. Topics are ascribed to freeze among individuals identified with corona infection episode like influenza.

Topic Modeling utilizing Latent Dirichlet Allocation (LDA) as shown in Table-3, with Gibbs Sampling strategy was directed on the document term matrix made from text corpus and decreased sparsity to 0.99.

Table – 3 Topic Modelling using LDA

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8
Covid	good	Care	Covid19	Virus	People	Virus	Trump
Outbreak	Hands	Government	Covid	Spread	Don't	One	Like
Positive	Health	Take	Outbreak	Corona	Know	Time	Will
Tested	People	Public	Must	Safe	Get	Test	Coronavirus
Journey	Take	Corona	Video	Stay	Flu	Home	Stop
Health	people	Hands	Coronavirus	Around	Panic	See	Cant
Safe	wash	health	News	latest	Think	due	Get

Topic one refers to outbreak on the journey or travel from one place to other places and quarantine measures are taken. Topic two attributes to advice by health and medical authorities to sanitize hands time to time and maintain good hygiene. Topic three suggests by the government to take care individuals from the unseen enemy corona. Topic four relates to news and videos being posted related to corona virus. Topic five is showing the spread of corona virus. Topic six can be ascribed to freeze among individuals identified with corona infection episode like influenza. Topic seven refers to self-testing suggested by the governments for people to stay home and observe symptoms like cold, cough and fever as there is no formal method of testing.

Conclusion:

From the data analysis we found that the oral narratives of large population related to #COVID-19 have represented the basic emotions same as individual facial expression or self-reported questionnaires that are; "fear", "sadness", "joy", "surprise", "anger", and "disgust", Therefore, we can conclude that the Topic Modelling Approach" or LDA methodology can be used for twitter hashtags analysis with equal reliability as that of observation and self-reporting studies. In addition, the advantage can be a quicker process with a large number of respondents that gives better reliability of the data. We also found that using Topic Model Approach, one aspect of measurement may serve as a proxy for others. Assessing multiple emotional phenomena, and using multiple measures to assess each, will be the most appropriate and informative strategy

a). “How to capture the emotions of large population without the direct observation of the respondent and his facial expression while the distressed situation is ongoing”?

Our second research question was

b). Will the basic emotions remain the same or will they be different while the respondents are not directly involved?

We found that using Topic Model Approach one aspect of measurement may serve as a proxy for others. Assessing multiple emotional phenomena, and using multiple measures to assess each, will be the most appropriate and informative strategy. Some researchers suggest that emotional experience can be captured by a set of underlying dimensions (Russell & Barrett, 1999).

The investigation infers that the data stream on twitter identified with corona infection outbreak was pertinent and for the most part exact with minor falsehood being spread. Contrasted with the previous Ebola and Zika infection outbreak where there was falsehood broadly spread among the twitter clients, there has been lesser deception spread during corona infection episode. Fear and frenzy were apparent among the twitter clients as the pandemic spread and passing’s ascend over timeframe. Be that as it may, governments and wellbeing specialists had additionally utilized twitter to spread exact and solid data identified with outbreak. Negative slants overwhelmed the tweet true to form as the infection exceptionally infectious and fatal which was apparent from assumption examination. Data spread was very precise and solid and twitter additionally ensured that deception is halted and erased right away. LDA examination had featured that all the subjects that are recognized from the tweets are most significant data to the covid19 corona virus infection outbreak. Twitter is as yet considered as one of the most favored mechanism for data spread during pandemics and profoundly successful, is demonstrated again from the current corona infection outbreak. Governments, Health Authorities and Institutions like WHO can depend on twitter for spreading data and controlling frenzy among people at large.

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