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The Sentiment Spectrum of Fourth Wave Digital Feminism on Instagram

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Abstract: This paper represents a comprehensive analysis of the sentiment behind the revolutionary social movement, "Feminism" and its recent improvements in the digital scope with the advent of the fourth wave of Feminism. Social Media platforms like Instagram, Twitter and Facebook have provided with tools that are optimized to propagate Digital Feminism. Hashtag Activism has emerged in the recent years which received mixed inputs from the community. Here, we analyze the sentiment behind the posts that carry respective hashtags and understand the varying intensities of emotion and subjectivity of matter that map onto the polarity of features that the fourth wave currently resides over, under observing the eye of Computational Social Science. The platform of Social Media used in the paper is relatively increasing in demand, which is Instagram.

Keywords: Computational Social Science, Feminism, Hashtag, Instagram, Sentiment Analysis, Social Media..

1. INTRODUCTION

Sentiment analysis is one of the fastest growing computational methods that can identify the emotion behind data and with growing accuracy, on the note of the advent of accurate and efficient algorithms in the rise [1]. The same is applied here to study the Feministic spectrum of sentiment on the social media platform of Instagram, with special attention to the Hashtags that have become increasingly popular to propagate Feministic activism or Hashtag activism.

Fourth Wave of Feminism:
Feminism has been around for over decades now, and the scope of its definition has been evolving ever since. It covers a wide range of political and social view points while dealing with equality and beating gender stereotypes. Significant results have been achieved from the feminist movement and the reach has only quadrupled or more with the digital domain occupying the frontiers of Feminism.

Here we mainly focus on the Fourth wave of Feminism which is mostly driven out on the social Media platform. The Fourth wave is "defined by technology", with the use of Facebook, Instagram, Twitter and the like. Social Media activism has made all the difference between the latter model of feminism, thereby extending communication.

Hashtag Feminism has a strong presence on social media platforms, including Instagram, Facebook and Twitter. Some of the hashtags within the movement include "#MeToo "#BodyPositivity", "#EverydaySexism", and "#LoveIsLove", which have become an essential part of this wave [3][4].
This paper and the results focused on is analyzing the sentiment of the specified hashtags and understand the social implications that have developed so far. As we acknowledge the positive and negative alignment of specific hashtags.

II. DATA EXTRACTION

While performing sentiment analysis on the posts retrieved of the chosen hashtags, the process of retrieval comes first which is done using the Instagram's Graph API. The sentiment analysis is done twice, using two different libraries, for higher accuracy and efficient cross plotting. One being the Textblob and the other is the Sentiment Intensity Analyzer from Vader.

Using the Graph API:
The Instagram Graph API is in fact merged with the counterpart Facebook's Graph API [2], while the former developed very recently. An Instagram Business User needs to be registered with the respective Public Facebook page before accessing the respective public Instagram page. The following query shown below is used to extract posts related to the specific tag, "feminism". Here locale is set to "en_US", as Instagram supports multiple languages and the sentiment analyzer has been designed for English language only.

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Vol 6, Issue 5, May 2019

```
graph_url = 'https://graph.facebook.com/v3.3/'
req_url = 'ig_hashtag_search?user_id='+user_id+'&q=feminism&locale=en_US'
final_url = graph_url + req_url
```

The final_url is used to pull the data related to that specific hashtag, which is usually retrieved in JSON format. An example of the data is found below.

```
{'data':
    [
      {'caption': 'Girls united for the long run #feminism #girlpower #happy #life #loveislove'}
    ]
}
```

The following JSON data is further converted to readable and programmable table format, after rigorous data cleaning and grooming procedures.

There are also some limitations specified by the Instagram hashtag search functionality provided by Facebook has some limitations specified. A maximum of 30 hashtags are supported on a 7-day rolling period and the feature is only supported on posts only, does not support Instagram stories.

III. SENTIMENT ANALYSIS

After the data extraction and grooming, comes the sensitive issue of dealing with emotion and sentiment. Sentiment analysis in a nutshell is a series of methods, techniques, and tools about detecting and extracting subjective information, such as opinion and attitudes, from language [5]. Traditionally, sentiment analysis has been about opinion polarity, i.e., whether someone has positive, neutral, or negative opinion towards something [6].

In this paper, we reflect on two methods of sentiment analysis that was used.

TextBlob:
Natural language processing is a sub-field of computer science that deals with how to process natural data by programming computers identically. Python has a huge library of Natural Language Processing called the NLTK library and the TextBlob is built on the shoulders of NLTK library.

TextBlob is a python library and offers a simple API to access its methods and perform basic NLP tasks. There is a specific function called the sentiment function in the following library which returns polarity and subjectivity. Polarity is float which lies in the range of [-1,1] where 1 means positive statement and -1 means a negative statement. Subjective sentences generally refer to personal opinion, emotion or judgment whereas objective refers to factual information. Subjectivity is also a float which lies in the range of [0,1] [7].

The below are the results of the functionality described above:

```
Sentiment(polarity=0.0, subjectivity=0.0)
Sentiment(polarity=0.4, subjectivity=0.8)
Sentiment(polarity=0.0, subjectivity=0.0)
Sentiment(polarity=0.5, subjectivity=1.0)
Sentiment(polarity=0.0, subjectivity=0.0)
Sentiment(polarity=0.0, subjectivity=0.0)
```

VADER:
VADER stands for Valence Aware Dictionary for sEntiment Reasoning, it is a lexicon and rule-based sentiment analysis tool that is specifically attuned to sentiments expressed in social media, and works well on texts from other domains The correlation coefficient shows that VADER (r = 0.881) performs as well as individual human raters (r = 0.888) [8].

Typical use cases for sentiment analysis of VADER:
Some of them are, typical use of contractions as negations, conventional use of punctuation to signal increased sentiment intensity, conventional use of word-shape to signal emphasis, using degree modifiers to alter sentiment intensity, understanding many sentiment-laden slang words, understanding many sentiment-laden slang words as modifiers, understanding many sentiment-laden emoticons, translating utf-8 encoded emojis, understanding sentiment-laden initialisms and acronyms [8].
The results obtained after using the sentiment intensity analyzer looks like below:

```
{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}
{'neg': 0.0, 'neu': 0.82, 'pos': 0.18, 'compound': 0.5106}
{'neg': 0.0, 'neu': 0.641, 'pos': 0.359, 'compound': 0.6808}
{'neg': 0.0, 'neu': 0.775, 'pos': 0.225, 'compound': 0.4404}
{'neg': 0.0, 'neu': 0.817, 'pos': 0.183, 'compound': 0.4824}
```

The fields specified are ‘neg’, which stands for negativity. ‘neu’, which stands for neutrality, ‘pos’ which stands for

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Vol 6, Issue 5, May 2019

positivity and 'compound' is the compound score that is obtained.

The compound score is computed by summing the valence scores of each word in the lexicon, adjusted according to the rules, and then normalized to be between -1 (most extreme negative) and +1 (most extreme positive). This is the most useful metric for a single unidimensional measure of sentiment for a given sentence. Calling it a 'normalized, weighted composite score' is accurate [8].

Typical threshold values are:
1. positive sentiment: compound score >= 0.05
2. neutral sentiment: (compound score > -0.05) and (compound score < 0.05)
3. negative sentiment: compound score <= -0.05

A combination of parameters extracted from both TextBlob and VADER becomes the basis of Sentiment metrics that are used in the following understanding of the hashtags that are being analysed in this paper.

The final results of TextBlob and VADER are combined in a csv format to feed further for data analysis and visualization of patterns that were observed in the hashtags.

Format of the CSV generated:

Pol	Sub	Neg	Neu	Pos	Compound
0.2	0.2	0.213	0.628	0.159	-0.2732
0.2	0.2	0	1	0	0
0.2	0.2	0	1	0	0
0.2	0.2	0	1	0	0
0.2	0.2	0	0.738	0.262	0.5994
0.2	0.2	0.141	0.859	0	-0.3182

Table 1: CSV file generated

The above table of data is generated for each hashtag and prepared for drawing patterns of visualisation.

IV. DATA EXPLORATION AND VISUALIZATION

Tableau is a popular software that is used to generate beautiful data visualizations and explore the features of data while drawing in vast contrasts [9][10]. In the ever rising amount of data being generated, fine-tuned software for better estimating data are simultaneously emerging [11].

Both Qualitative and Quantitative analysis has been constructed from the collected data samples, while Qualitative analysis deals with expertise, quantitative analysis deals with count and measurement [12]. Both are conducted using statistical methods of visualisation thereby a mixed approach where both types of analysis converge to form a use case that is well applied in this specific case of Sentiment analysis. Multiple cases of analysis has been drawn to understand the State of sentiment of a particular hashtag.

Case 1:
Qualitative Analysis of Sentiment:
Subjectivity vs Polarity

Subjective sentence expresses some personal feelings, views, beliefs, opinions, allegations, desires, beliefs, suspicions, and speculations whereas Objective sentences are factual. Low Subjectivity infers Objectivity [13]. Positive Polarity values indicates positive sentiment, while Negative Polarity values indicate negative sentiment, which is extracted from TextBlob [14].

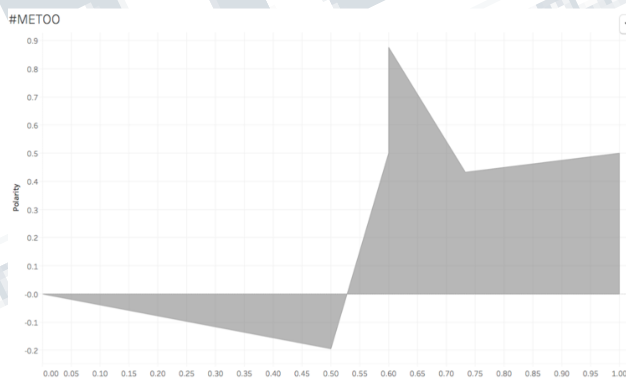

Fig 1: Subjectivity vs Polarity

Here the '#MeToo' features was considered for analysis.

We observe,
Low Subjectivity, No Polarity: As the subjectivity is low, there is no amount of Polarity detected.

Mid Subjectivity, Negative Polarity: While medium amounts of subjectivity indicates not much clarity in position and relatively vague details, which resulted in negative sentiment.

High Subjectivity, Wide Polarity: While the range of subjectivity is above 0.5, a wide range of Polarity plotting is observed.

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Similar observations were made on the same lines of Subjectivity vs Polarity for other chosen hashtags.

Case 2:
Quantitative Analysis of Sentiment:
Subjectivity vs Count of Polar Sentiment

The following method is used to observe the count of either Negative or Positive Sentiment that a particular Instagram post carries, and how it varies in accordance with the range of Subjectivity or otherwise the absence of Subjectivity, called Objectivity.

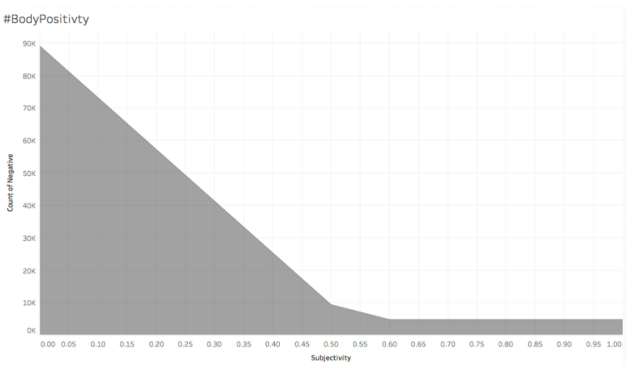

Fig 2: Subjectivity vs Count of Negative

Here, the '#BodyPositivity' features was considered for analysis.

Observations made:
A high number of posts seem to have Objective notion, which implies that they carry facts. The subjectivity of the post increases which holds that the number of the posts decreases.

Similar observations were made on the lines of other hashtags.

V. APPLICATION

Computational social sciences is a research discipline at the interface between computer science and the traditional social sciences [15]. Modern mathematics, and especially the mathematics of algorithms and statistics, get their objectivity from the intersubjective validity of formal proof. Algorithms implementing statistical inference, or scientific algorithms, are what distinguishes computational social science epistemically from other social sciences [16][17].

The social sciences developed from the sciences, or the systematic knowledge-bases or prescriptive practices, relating to the social improvement of a group of interacting entities [18][19]. In this paper, we better understand the relationship between the disciplines' varying incorporation of feminist perspectives and their progress towards organisational gender equity goals [20].
The field of Computational Social Science has defined applications which map onto the Feminist Social Science as well [21].

Below are the relevant observations, for relevant applications:

Human Cognition and Belief Systems:
Humans perceive images and immediate data for judgment and decision making, rather than basing our decisions on direct, unmediated data from the real world. Collective belief system maintains consistency, an important property or principle that is also known as cognitive balance. Observing real data instead of a hunch, could move us closer to the truth.

As in the case of how we have observed Sentiment grow with collective datasets of hashtag specific posts.

Decision Making Models:
A decision can be defined as a choice within a set of alternatives, each of which has a set of outcomes associated with each alternative. Socially stimulated humans do not neccesarily make decisions according to the validity of data, and most often include emotion. A Computational model would thereby aid.

Here, we understand the collective social nature by not mere opinion of an individual belief, but a set of collective beliefs that has been computed. Coming closer to the truth and objectivity has been made fairly easier, with the said computational social science applications.

VI. CONCLUSION

This article presents the various social states of trending hashtags. The reach, the polarity, the subjectivity and the prevailing belief system is identified over time from the posts that were collected from specific hashtags of the Feministic Society. The collective belief system has helped in moving closer to the understanding and effects on the current society, as well as studying the prevailing scenario regarding each movement or hashtag. Some hashtags chosen to study under this paper are

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Vol 6, Issue 5, May 2019

'#Feminism', '#MeToo', '#BodyPositivity', 'EverydaySexism' and '#LoveIsLove'. Relevant findings have been observed and documented. The field of Computational Social Science has been best leveraged to accurately proceed with the understandings.

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