Uncovering Multiple domains in Social Movement

——investigating the #Metoo movement with an NLP approach

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06/10/2020

Abstract

The #MeToo movement is among the most impressive social movements of recent years that have changed social mindsets. After the rapid expansion of this movement, the scope of #MeToo has become somewhat broader with this expansion. To provide a deeper understanding of the multiple domains and cultural patterns of the movement, this paper explores the user-generated text content of 91,653 tweets with #MeToo hashtag through using natural language processing. To this end, a text-mining methodology is performed to extracts tweet data from Twitter API to analyze cultural background and sentimental information behind the Metoo movement. Then, a Latent Dirichlet Allocation (LDA) model is applied to this database to identify topics. I further classify the test data into one the three categories (positive, neutral, and negative) and explore the content using Natural Language Analyses with NLTK. It shows that the movement has extended into other semantic domains outside of sexual assault such as "white supremacy" and "police violence". The colonial theory is used to explain the colonial ideologies and eurocentrism identified in the movement. These identified topics can be a starting point for future research on social movements, sociology, sexuality, racism and gender inequity.

Keywords: MeToo movement, LDA Topic Modelling, Text Analysis, Sentiment Analysis

1. Introduction

The #MeToo movement, initially voiced by sexual harassment survivor and activist Tarana Burke, is an international movement against sexual harassment and sexual assault (Ohlheiser 2018). The movement went viral as a hashtag on social media, following the exposure of the widespread sexual-abuse allegations against Harvey Weinstein in October 2017. Organizers including Alyssa Milano, Anna Paquin and Lady Gaga called on all women who have been sexually assaulted to come forward and speak out of their painful experiences to raise social attention. Women from all over the world have come forward to share their story of being sexually harassed. They have done it on social media using the hashtag "MeToo", which aims to show the magnitude of sexual assault. In addition to Hollywood, the #MeToo Manifesto has also sparked extensive discussions in the political field, academic field, cultural field and other fields related to incidents of sexual harassment and assault. The original purpose of "MeToo" was to empower women through empathy, especially young and vulnerable women. After millions of people started using the phrase, it spread to dozens of other languages, the purpose of the movement changed and expanded. As a result, it has come to mean different things to different people. The #MeToo movement not only seeks for justice for sexual harassment survivors and marginalized people, but also provides insights for policing practice, race and gender equality.

In this context, the goal of this paper is to answer these research questions: What issues arise around the powerful #MeToo movement? Can such a social movement be analyzed using user-generated content (UGC), and would such analysis reveal active agents that influence its development? Such investigation can provide meaningful insights for further research in terms of identification, awareness, and communication actions with regard to sexual harassment and women's inclusion. The results can also help professionals to better understand the challenges posed by the #MeToo through the analysis of publications shared by users on Twitter.

Previous research on tweets with specific hashtags (Sumiala et al., 2016) demonstrated the usefulness of the content published on social networks for studying terrorism, racism, gender equality, or sexual harassment. Manikonda (2018) analyzed social movements based on UGC in Twitter and classified this content according to sentiments expressed in corresponding tweets. In another relevant study, Field et al. (2019) used what they called 'affective analysis' to study sexual harassment; and it showed that social networks have become an information vehicle, a channel that can be meaningfully used by companies to support social movements or to fight against injustices. The present study continues previous research by Manikonda et al. (2018) and Field et al. (2019). Along with these studies, my research highlights the need to investigate the multiple domains in MeToo movement.

In this work, I use natural language processing (NLP) techniques to analyze online tweet data of the #MeToo movement. Through LDA topic modelling and sentiment analyzing, I identified several heated topics in the movement and classify the sentiment information of each tweet. Overall, the #MeToo movement can be interpreted as a feminist movement to protect sexual harassment survivors. Clearly, the scope of this interpretation is limited. According to my exploration about tweet data, people from different gender and race groups shared the fact that they have been the victim of unwanted sexual aggression or police oppression. The scope of this movement has changed and expanded to a broader field.

The following is a brief view of the paper. After the literature review in Section 2, I present the data in Section 3. Then, I introduce the methodology and report the results in Section 4 and Section 5 respectively. Finally, the conclusions and further discussions are summarized in Section 6-7.

2. Literature Review

2.1 Twitter-based UGC analysis in social movement

In recent years, the use of social platforms has increased dramatically. Many scholars believe that it is necessary to study user-generated content (UGC) on social platforms, which fully reflects the development of social movements in the digital world. The main advantage of social platforms in social movements is that users are networks of individuals with similar views and opinions (Palos-Sanchez et al., 2018). Many users visit social platforms to tell others about their daily activities and experiences and share their views. Importantly, if the stories of users of social platforms are widely disseminated and thus have a larger audience than a particular group of followers, a social networking campaign will be launched (Reyes-Menendez et al., 2018).

Twitter is one of the most commonly used social platforms for generating content on specific topics. This popularity of Twitter makes it a valuable source of data for many studies. Discussions on various topics can be conducted around your profile (such as @MMIW) or around hashtags (#) (such as #MeToo). In this way, all comments on such personal data or tags can be studied (Saura and Bennett, 2019). Sumiala (2016) research on tweets with specific tags also proves the usefulness of content posted on social networks to study terrorism, racism, gender equality or sexual harassment. Platform, users are organized in the network, which makes it possible to investigate people or communities with common interests rather than personal data or personality. Therefore, based on data from social networks and digital platforms, influencers or opinion leaders can also be identified, that is, different types of messages sent to the community can be used to lead the campaign and encourage other users to follow their users (Saura et al., 2019). Similarly, based on the classification of content generated for specific reasons (usually organized around hashtags), researchers can identify indicators and insights that are critical to a company's digital strategy or understanding social activities (Stieglitz et al., 2018).

In addition, through user comments, Twitter users can also influence other users' decisions. The aforementioned characteristics and the large amount of data generated on the Twitter platform have led many researchers to use the content generated on the social platform to obtain information about terrorism, racism, and sexual harassment in private life and work. Similarly, content generated on Twitter and other social networks is also used to investigate social activities, such as #JeSuisCharlie or #TimesUp (Ward-Peterson and Chang, 2018). Therefore, this analysis can be viewed as an opportunity for improvement by companies, public institutions and non-profit organizations.

Based on the previous researches, my study will focus on the Twitter-based UGC to analyze the cultural background and sentiment information of MeToo movement. The analysis of UGC topics in the movement can be used to obtain helpful insights for researchers to better understand their followers or target audiences and, therefore, to better informed about the ways to create appropriate and relevant messages for social network users.

2.2 Topic identification in MeToo study

Since 2017, the #MeToo movement has gained worldwide research interest. In a recent study, Johansson et al. (2018) emphasized the importance of Swedish women mobilizing more actively around #MeToo than Danish women. Specifically, Johansson et al. (2018) identified the following five factors that promote the #MeToo campaign to mobilize Twitter users: (1) government support; (2) political opportunities; (3) culture; (4) development process, and (4) previous mobilization. In another study on user intent that posted #MeToo tweets, Wood (2018) divided user intent into the following six categories: (1) unity; (2) narrative; (3) self-confidence; (4) objection, (5) Activism and (6) Criticism. These results prove the social significance of the #MeToo social movement and its potential impact on different industries.

On the other hand, using the topic modeling techniques, Clohessy (2018) identified the following three themes in the UGC tweets posted by users: (1) criticism of women; (2) sports against men Influence; (2) the political influence of the movement. The author concludes that these topics include the urge and behavior of Twitter users to express their views and support for the #MeToo movement.

Other authors seek to go beyond topic recognition and use sentiment analysis techniques to investigate the sentiment of Twitter users expressed in corresponding posts. For example, Manikonda, etc. (2018) analyzed the sentiment expressed in the #MeToo tweet to understand the user’s attitude towards the issue; the results yielded some examples where users shared negative and positive connotations about the sport. Similarly, Saura et al. (2018) determined the sentiment of the tweet to determine the user's attitude towards the research topic. Other authors, such as Field, etc. (2019), using sentiment analysis (combination of topic recognition and sentiment analysis) to study #MeToo movement.

My research will first perform topic modelling on text data with LDA model, so as to obtain the most salient topics in the MeToo tweets. Then I will further investigate the sentiment information of the tweets to learn the feelings of individual users in Twitter.

2.3 Natural language processing in MeToo study

To better understand the data collected from social networks, different methods based on natural language processing (NLP) have been used. For example, Saura, etc. (2019) uses sentiment analysis to analyze user-generated content (UGC) related to Twitter-based startups from the perspective of user experience. In this analysis, indicators in the form of key points for the development of startups are extracted. This allows the author to establish that for success (and positive reviews from users), startups should use team leadership, technology, and tools. Similarly, Reyes-Menendez et al. (2018a) Use sentiment analysis and text analysis to investigate users' opinions on the hotels that users express in TripAdvisor reviews. This allows the author to identify factors and indicators that are positively related to hotel service quality and sustainability policies. Similar analysis methods are also used to analyze user-generated content related to social activities (eg Hysa and Spalek, 2019).

One technique used globally in natural language processing is text analysis. When analyzing text content, researchers focus on expressing the meaning of messages, adjectives or words (Marengo et al., 2019). Finally, the types of analysis briefly reviewed above can also be meaningfully supplemented by machine learning, data mining techniques, or other artificial intelligence tools. The advantage of the latter group of methods is that the training machine analyzes the data to analyze more content (Krippendorff, 2013).

Along with textual analyses, another technique to analyze UGC is using sentiment analysis. Some previous studies analyzed social activities based on UGC on Twitter and classified the content according to the emotions expressed in the corresponding tweets (Manikonda et al., 2018). In a related study, Field et al. (2019) use the sentiment analysis to study sexual harassment, while Saura et al. (2019) Identified relevant topics and then performed sentiment analysis on the data. Therefore, social networks have become an information tool that can be used meaningfully by companies to support social movements or to fight injustice (Field et al., 2019).

My research will combine the textual analysis and sentiment analysis to uncover practical implications of the topics and sentiments around the #MeToo movement, as well as to explore their theoretical importance for the theoretical investigations.

3. Data

My total sample data combines two datasets: one dataset contains approximately 390,000 tweets (downloaded from data. world) and another dataset contains 13,487 tweets (crawled from twitter API). Only two columns are kept in the datasets: ‘text’ and ‘dataoftweet’.

I first extracted a total of 13,487 tweets and merge the dataset with the existed dataset; after preprocessing, the final dataset contains 91,653 tweets. These tweets were in English and had #MeToo as the hashtag.

After data collection, I filtered and cleaned the data using NLTK package in Python. The initial sample was then cleaned to remove repeated tweets and retweets. Tweets with pure numbers were also deleted. Of note, tweets can contain either a hashtag (#) or a reference to a user profile (@). The replies were analyzed as independent tweets, considering the expressions related to the same subject under the same hashtag. Images, videos, and multimedia content were not analyzed. Instead, I focused exclusively on text and analyzed it using natural language processing (NLP). For filtering, I eliminated URLs that contained the tweets, as well as emoticons and special symbols that did not include capitalization or punctuation.

4. Methods

4.1 Topic modeling with LDA

Topic Modeling is a technique to extract the hidden topics from large volumes of text. In order to identify the topics, I used the Latent Dirichlet Allocation (LDA). LDA is a popular algorithm for topic modeling with excellent implementations in the Python’s Gensim package. It processes many “documents” and outputs the most relevant words for each topic. Using the LDA model, my objective was to identify keywords in the database. Each word was encoded in a separate document. Then, using the identified keywords, I performed an identification of the topics. The workflow of topic modeling is as follows:

1. Preprocess the data

2. Create Bigram and Trigram Models

3. Create the Dictionary and Corpus

4. Create the Dictionary and Corpus

5. Build and visualize the LDA model

Fig 1 Workflow of topic modeling

4.3 Sentiment analysis

After topic identification, I used an algorithm developed in Python to classify tweets according to sentiments expressed in them. The Sentiment Analysis (SA) approach, also known as Opinion Mining (OM), relies on using the systems that can detect the feelings expressed in a text or textual content—in our case, the tweets with the hashtag #MeToo. For the development and use of the SA approach, several training approaches are available. For instance, interfaces can be used to improve the algorithms that work with machine learning. There are also techniques that develop SA with artificial intelligence or hybrid models that require both the machine learning technology and data-mining training. The workflow of sentiment analysis is as follows:

1. Preprocess the data

2. Calculate the sentiment score

3. Splitting the dataset

4. Plot word clouds

Fig 3 Workflow of sentiment analysis

4.3 Text analysis

Finally, I use TF-IDF to identify the most frequently used terms in the downloaded tweets.TF-IDF, short for term frequency–inverse document frequency, is a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus. The tf–idf value increases proportionally to the number of times a word appears in the document and is offset by the number of documents in the corpus that contain the word, which helps to adjust for the fact that some words appear more frequently in general. Based on tf-idf value, I then drew a bar chart and a word cloud to show the most salient phrases in Metoo movement. The workflow of topic modeling is as follows:

1. Preprocess the data

2. Calculate the tf-idf of each word

3. Plot a word cloud

4. Ploy most frequent Bi-grams

Fig 2 Workflow of text analysis

5. Results

5.1 Identification of topics with the LDA model

After the analysis with the LDA model, 20 topics linked to the #MeToo movement and top-30 most relevant terms for topics were identified (see Table 1 and Fig 4). During this process, the keywords corresponding to each of the sentiments in topics were categorized. On finding 10–30 keywords, these words were used to formulate the topics. In this process, to the goal was to formulate a phrase that contained 7 most repeated words and try to order them to make sense. Thus, the name of the topic was the result of the combination of these phrases and the formulated content.

The identified topics provide important insights about user behavior and their perceptions of the #MeToo movement. In particular, I find #BlackLivesMatter in the topic description. The # BlackLivesMatter are specifically created for Indigenous women but still receive almost no attention, despite the high rates of violence against Indigenous women. I also identify words like racism and police in top-30 most relevant terms for these topics. This is to say, while #Metoo is now generally raise awareness of sexual harassment, it also raised a problem related to race inequity.

Table 1 Description of topics in #Metoo tweets

	Dominant_Topic	Topic_Keywords	Num_Doc	Per_Doc
0	11.0	metoo, late, news, listen, check, daily, women...	9308.0	0.1016
1	9.0	rape, victim, sex, claim, case, rapist, blame,...	5627.0	0.0614
2	17.0	man, woman, put, white, powerful, harass, supremacy...	4389.0	0.0479
3	18.0	people, show, talk, matter, life, problem, black...	5084.0	0.0555
4	19.0	sexual, harassment, assault, accuse, allegatio...	4533.0	0.0495

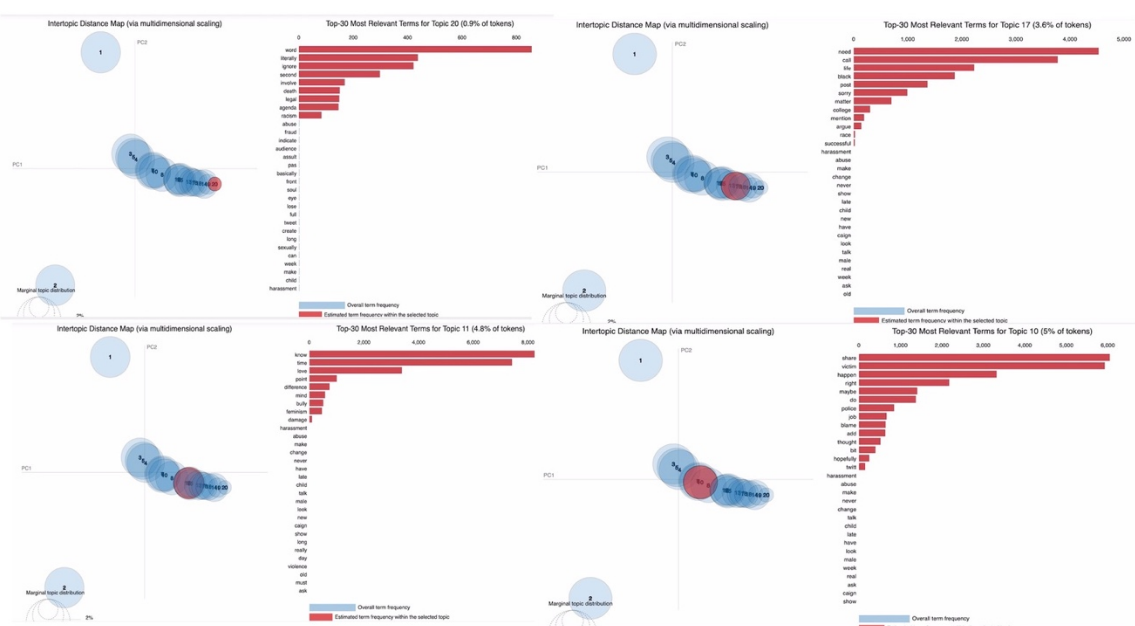

Fig 4 Intertopic Distance Map

5.2 Sentiment Analysis Results

On identification of the sentiments in the complete sample of tweets, Table 2 shows the date of tweet, corresponding words, sentiment score, and sentiment. All the tweets are divided into three categories based on the sentiment scores: positive, negative and neutral. The next step is splitting the dataset into train and test set. Based on my training data, I draw two word clouds to show the most salient positive words and negative words in MeToo tweets.

Table 2 Sentiment Score of #MeToo Tweets

	dateoftweet	text	sentiment	sentiment_score
0	06/03/2020	israeli priviledge matt lauer somehow jail bac...	negative	-0.4767
1	06/03/2020	normal viewing documentary netflix essential s...	positive	0.4767
2	06/03/2020	wish say story need voice suppo metoo	positive	0.4019
3	06/03/2020	psst saw bit blackout tuesday point previous t...	neutral	0.0000
4	06/03/2020	rivera hus hea see many former female student ...	negative	-0.7430

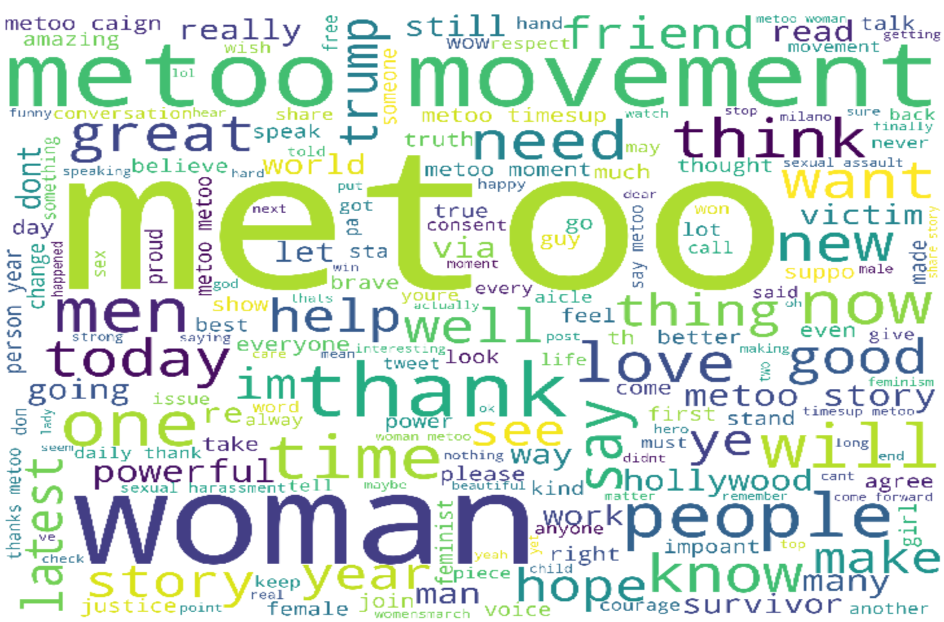

Fig 5 Positive Word Cloud

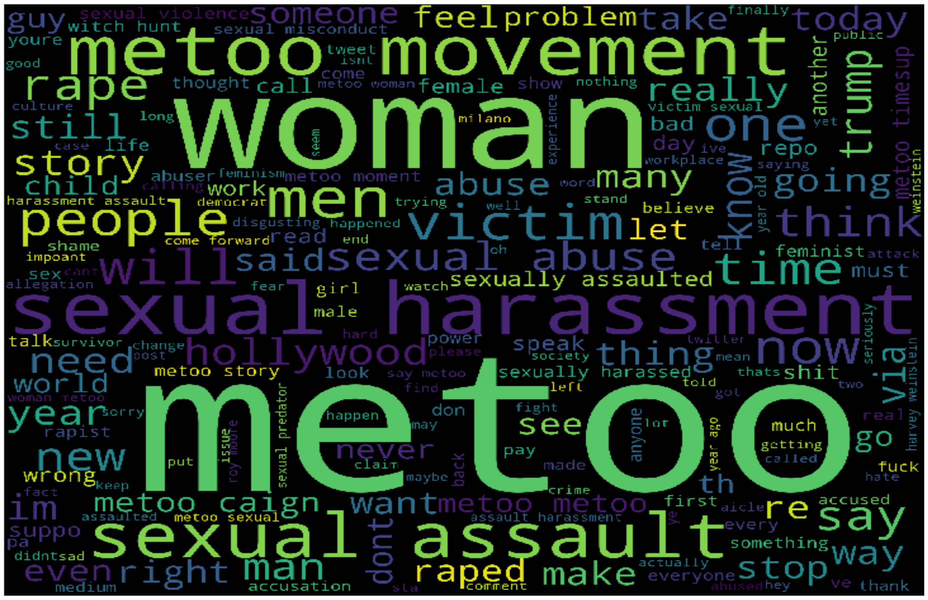

Fig 6 Negative Word Cloud

These word cloud images are used to show the most "important" words that are used in all tweets with #metoo hashtag. We can see words such as "feminist", "courage", "love", “truth” are identified as positive words, while words and phrases like “sexual assault”, “sexual harassment” and “abuse” are identified as negative words. These words are strongly corelated with the real movement.

Importantly, the sentiment of each topic encompasses the context surrounding each of the words that make up this topic. Accordingly, the identified words and phrases may be used in further research. For example, the topics that were identified in the present study as such that are associated with positive feelings can be used by researchers to elicit positive perceptions and evaluations on part of their target audiences.

5.3 Text Analysis Results

I first analyze the most commonly used adjectives to see if they are consistent with the intended interpretant of the #MeToo hashtag (See Fig 7). In the adjectives, we can see there is consistency in the way people use words like "sexual", "metoo", "new", "young", "viral", "important" and "public". Although there is still noise in the data, we can get some hints from the words mentioned above, for they are associated with the #MeToo movement. The #MeToo movement, initially voiced by sexual harassment survivor and activist Tarana Burke, is a movement against sexual harassment and sexual assault. Similar to other social justice and empowerment movements based upon breaking silence, the purpose of "Me Too", is to empower women through empathy and strength in numbers, especially young and vulnerable women, by visibly demonstrating how many women have survived sexual assault and harassment, especially in the workplace.

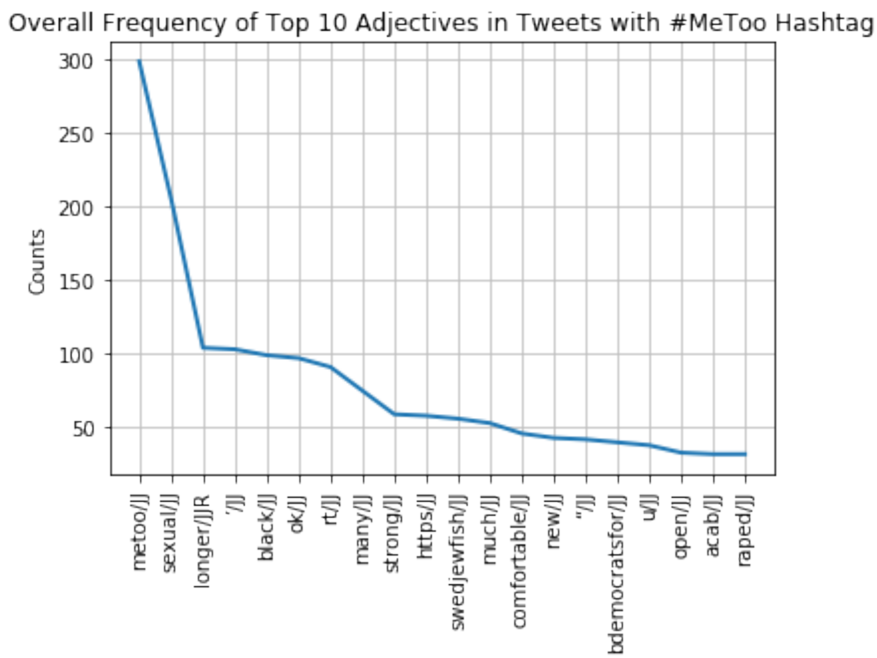

Fig 7 Overall Frequency of Top 10 Adjectives in MeToo Tweets

I then plot a word cloud image to show the most "important" words that are used in all tweets with #metoo hashtag (See Fig 8).We can see phrases such as "metoo movement", "sexual assault", "silence breaker", corresponding with the real movement. Apart from these phrases, I find some phrases include "white supremacy", "police violence". These indicate that the scope of #MeToo hashtag has become somewhat broader with this expansion, it has been more recently referred as an international movement for justice for marginalized people in marginalized communities.

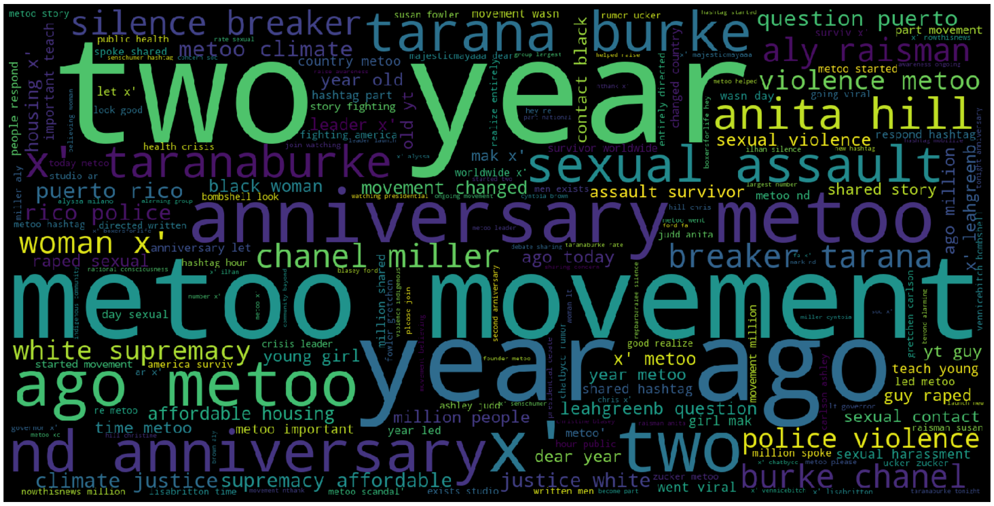

Fig 8 Word Cloud of MeToo Tweets

After plot the word cloud, I then calculate the frequency of Bi grams to further illustrate the importance of certain phrases used in tweets with #Metoo hashtag. For example, "police violence" was mentioned 383 times, while "white supremacy" was mentioned 381 times (See in Fig 9).

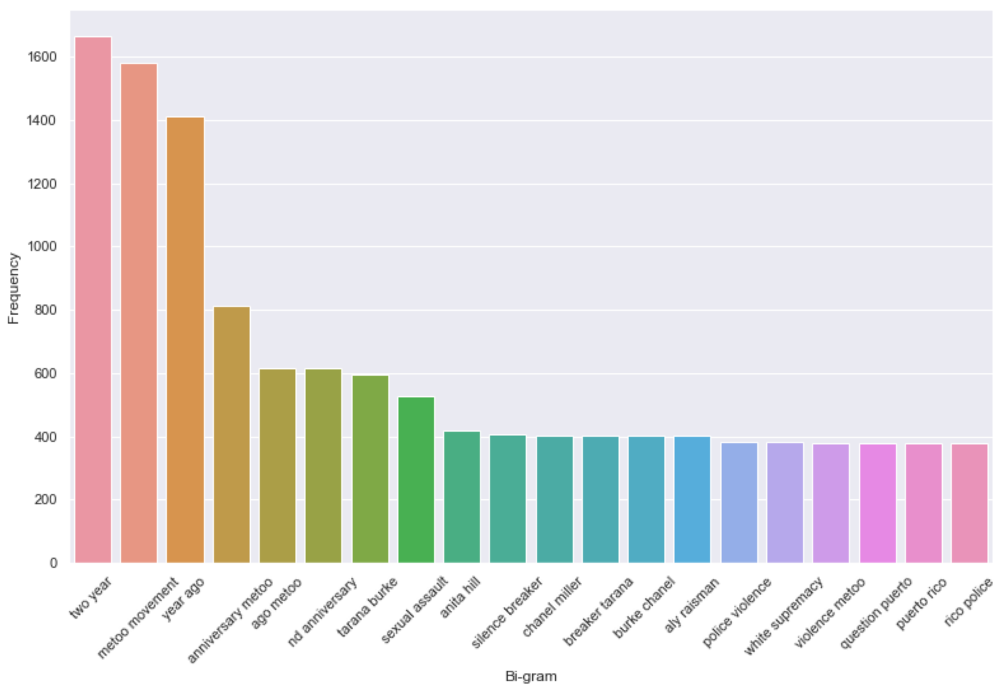

Fig 9 Bigrams of MeToo Tweets

The #MeToo movement can be interpreted as a feminist movement to protect sexual harassment survivors. Clearly, the scope of this interpretation is limited. According to my exploration about tweet data, people from different gender and race groups shared the fact that they have been the victim of unwanted sexual aggression or police oppression. The scope of this movement has changed and expanded to a broader field.

5.3.1 White supremacy in MeToo

In the wake of the initial accusations against Hollywood producer Harvey Weinstein, the hashtag #MeToo—the name of a movement launched 10 years earlier by writer and activist Tarana Burke, also a black woman—helped to harness collective outrage into a force that is reshaping workplaces around the country. This movement is the result of the collective labor of women of color who turned private agonies into public battles on behalf of justice.

However, there's an unsettling reality that a movement built largely on the labor of women of color has been co-opted by a discussion that prioritizes the experiences of victims who are white, wealthy, and privileged over those who are not(Angela Onwuachi-Willig,2018).When #MeToo entered the national consciousness, there were questions about whom the movement was really for. Headlines were largely dominated by stories of white, wealthy, straight, cisgender women, even though rates of sexual violence are disproportionally higher for poor women, women of color and LGBTQ people.

Racism and sexism are inextricably intertwined. Navigating a biased system exacts a toll, from lost career opportunities to the energy expended on internal calculations for dealing with inappropriate behavior and self-doubt. Many writers, activists, and scholars have worked tirelessly to highlight the cumulative impact of these experiences in the context of race and gender alike. But the justified outrage around sexual harassment has eclipsed the discussion on race while borrowing its language.

This kind of white supremacy can be explained by Stoler's theory about gender, race and colonial politics (Stoler,1991). The US has a long and sordid history of taking the labor of people of color for granted. When we attempt to explain the behavior of separating gender from race and class in MeToo movement, it will be helpful if we can understand how

European culture and class politics resonated in colonial settings, how class and gender discriminations were transposed into racial distinctions.

5.3.2 Police violence in MeToo

The #MeToo campaign turned a spotlight on power, consent, and sexual abuse. The hashtag describes a movement in which women, and some men share the fact that they have been the victim of unwanted sexual aggression, from harassment to rape. Thanks to the 2017 campaign, the public increasingly appreciates that power and authority impose new meanings on what might appear superficially as consensual encounters. When a person submits to someone who wields power over them, this may be deeply disturbing and coercive even for encounters that lack visible violence. These insights are equally applicable to policing.

More specially, the reason why "police violence" appears in the word cloud can be illustrated by the misconduct of Puerto Rican police in 2018.Puerto Rican Feminist groups organized a sit-in in front of Governor Ricardo Rosselló's residence, to protest the killing of a woman by her husband, a police officer. During the protests, the Puerto Rican police peppered sprayed the protestors and videos surfaced of the police pushing against the crowd at the gates of the residence.

Josephine Ross noted that the #MeToo movement is illuminating for policing practice known as stop and frisk (2018). While #MeToo movement reveals a hidden tsunami of sexual abuse in film studios and offices, it also points out that police sexual misconduct is extensive and underreported. Like other types of sexual harassment, police sexual misconduct ranges from unconstitutional overreach to criminal assault. Even constitutional frisks can feel like rape to those on the receiving end.

6. Conclusion

The present study aimed to analyze the #MeToo movement so that to help professionals to better frame their research topics with regard to MeToo movement. To this end, I analyzed a dataset containing 91,653 tweets with the hashtag #MeToo using a three-stage methodology.

My research questions are as follows: What issues arise around the powerful #MeToo movement? Can such a social movement be analyzed using user-generated content (UGC), and would such analysis reveal active agents that influence its development? With regard to these questions, my results demonstrate that the analysis of Twitter-based UGC can be meaningfully used to identify active agents of the #MeToo movement. Also, using sentiment analysis, I have linked each tweet with its related sentiment score, and demonstrated which word or phrase will be identified as positive or negative. Last but not the least, I find the limitation of MeToo movement by identify topics related to racism and policing practice.

Overall, the #MeToo campaign shed light on sexual abuse, police power, gender and race inequality. The original purpose of MeToo movement is to empower women through empathy and strength in numbers by visibly demonstrating how many women have survived sexual assault and harassment. As the movement continues to expand on a worldwide scale, the scope of #MeToo hashtag has become broader, it has been more recently referred as an international movement for justice for people in marginalized communities.

Although MeToo movement is successful to some extent, it doesn't address the problem of police misconduct and is lack of representation of minority women. Despite the prevalence of sexual misconduct mentioned in #MeToo movement, some have pointed out the lack of discussion regarding law-enforcement misconduct. As the #MeToo movement demonstrates, perceived consent is usually coercion when there’s an imbalance in power. Police sexual misconduct disproportionately affects women of color, though women from all walks of life are affected. In addition, it is also impossible to ignore the lack of representation of minority women in the #MeToo movement or its leadership. Most historical feminist movements have contained active elements of racism and have typically ignored the needs of non-white women despite the fact that minority women are more likely to be targets of sexual harassment.

In conclusion, MeToo movement is not merely an international movement against sexual harassment and sexual assault, it also provides significant insights to policing practice, gender and race inequality. These identified topics can be further investigated in the future research.

7. Limitations and Future Work

In this study, I used a machine learning-based process that was manually trained in the previous study. In addition, regarding the application of LDA, although it is a mathematical model, it requires qualitative intervention in the selection of topic names. My sentiment analysis was plagued by the huge noise in the training data set, which led to the misclassification of positive and negative words in tweets.

The results of this study provide meaningful theoretical hints for individuals, organizations, companies and institutions. In particular, my findings highlight the importance of gender equality, gender equality at work, and social network mobilization, especially in the #MeToo Twitter community. For future research, the identified themes can be used as independent structures or variables in further study and studied in quantitative models that can measure their importance relative to other themes. And I can extend the analysis undertaken in the present study to other social movements on Twitter as well.

8. Acknowledgement

I would like to thank my advisor Dr.Evans for his guidance and constructive suggestions.

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Appendix 1 Description of Cleaned Data

	dateoftweet	text
0	06/03/2020	israeli priviledge matt lauer somehow jail bac...
1	06/03/2020	normal viewing documentary netflix essential s...
2	06/03/2020	wish say story need voice suppo metoo
3	06/03/2020	psst saw bit blackout tuesday point previous t...
4	06/03/2020	rivera hus hea see many former female student ...

	dateoftweet	text
count	91653	91653
unique	105	90558
top	06/03/2020	ve now quaratine longer brock turner spent jai...
freq	2546	103

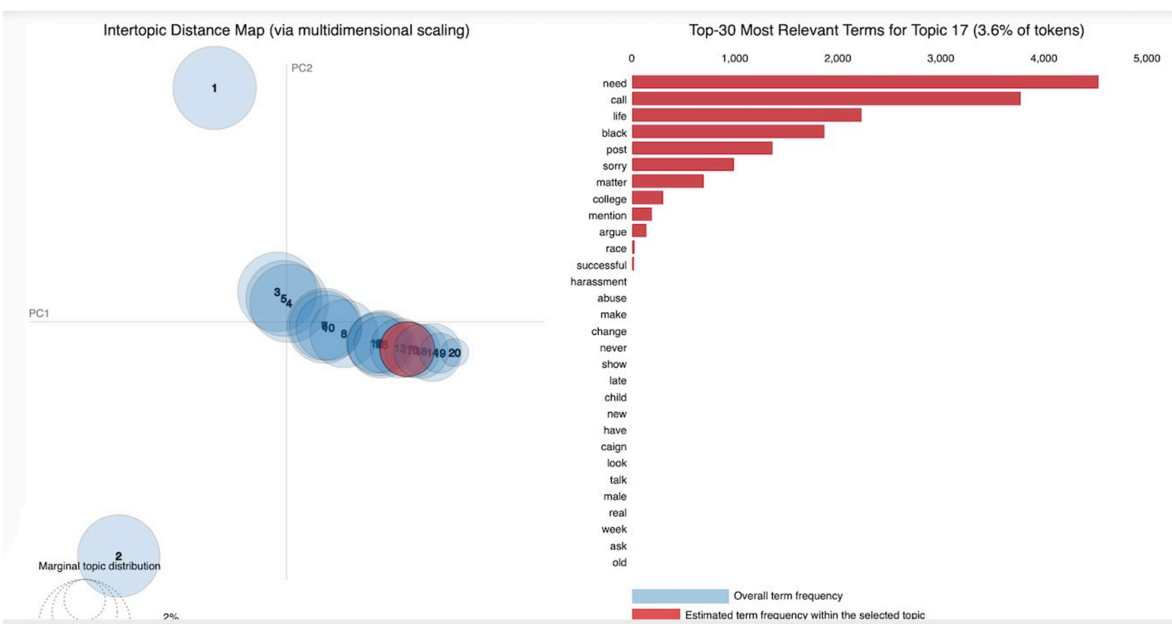
Appendix 2 Description of Dominant topics

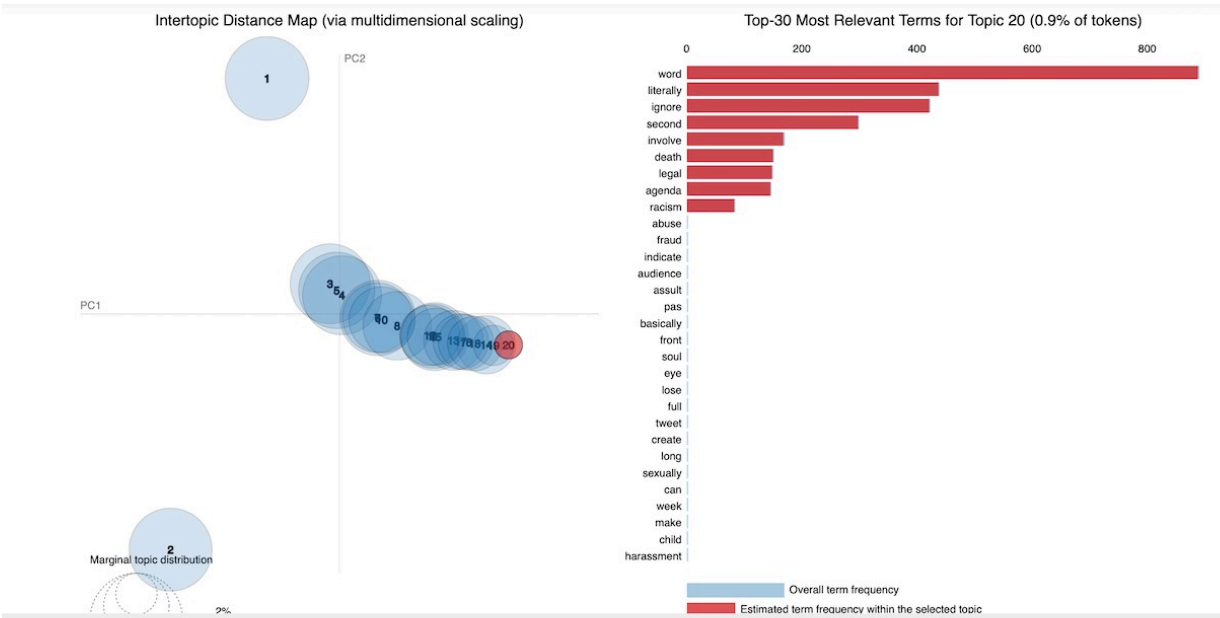
	Dominant_Topic	Topic_Keywords	Num_Documents	Perc_Documents
0	11.0	metoo, late, news, listen, check, daily, women...	9308.0	0.1016
1	9.0	rape, victim, sex, claim, case, rapist, blame,...	5627.0	0.0614

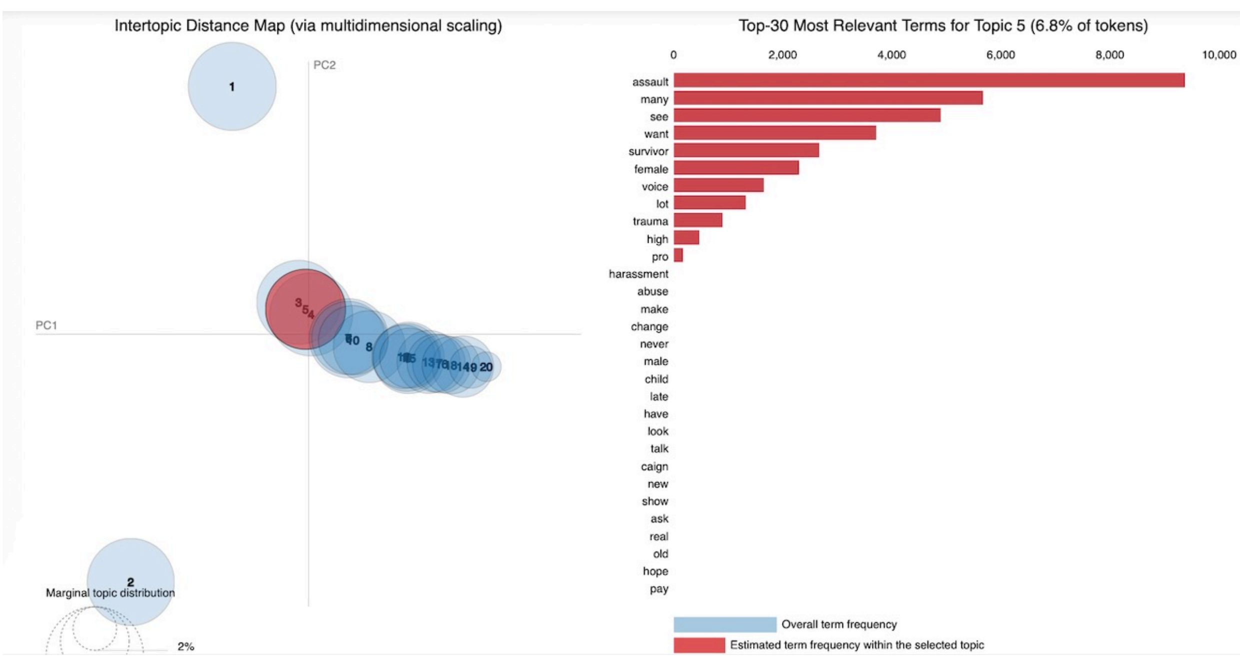
	Dominant_Topic	Topic_Keywords	Num_Documents	Perc_Documents
2	17.0	man, woman, put, white, powerful, harass, supremacy…	4389.0	0.0479
3	18.0	people, show, talk, matter, life, problem, black…	5084.0	0.0555
4	19.0	sexual, harassment, assault, accuse, allegatio...	4533.0	0.0495
5	8.0	metoo, hope, suppo, tweet, find, vote, resist,...	4325.0	0.0472
6	0.0	abuse, power, survivor, child, violence, end, ...	4672.0	0.0510
7	18.0	people, show, talk, love, life, problem, movem...	4465.0	0.0487
8	11.0	metoo, late, news, listen, check, daily, women...	4212.0	0.0460
9	4.0	man, woman, put, white, powerful, harass, beha...	4401.0	0.0480
10	14.0	read, write, great, piece, feminist, impoant, ...	4410.0	0.0481
11	18.0	people, show, talk, love, life, problem, movem...	4477.0	0.0488
12	12.0	movement, metoo, good, long, break, silence, l...	3659.0	0.0399
13	19.0	sexual, harassment, assault, accuse, allegatio...	4013.0	0.0438
14	8.0	metoo, hope, suppo, tweet, find, vote, resist,...	4061.0	0.0443

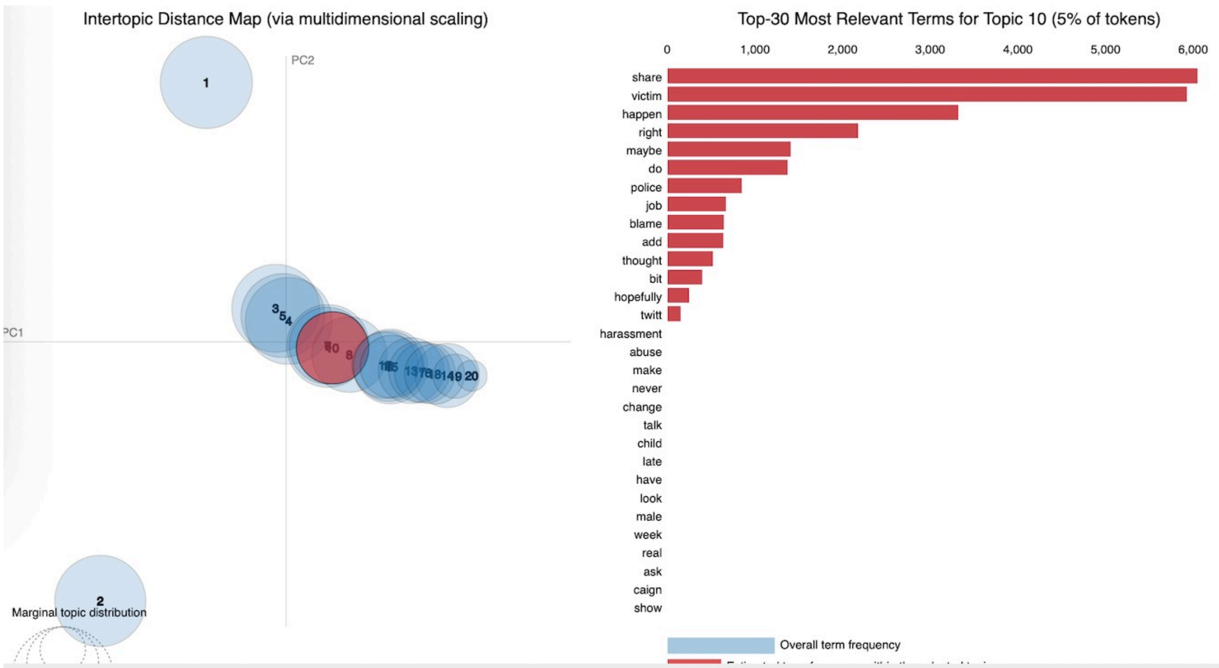
	Dominant_Topic	Topic_Keywords	Num_Documents	Perc_Documents
15	10.0	make, thing, feel, happen, bad, real, people, ...	4221.0	0.0461
16	18.0	people, show, talk, love, life, problem, movem...	3492.0	0.0381
17	18.0	people, show, talk, love, life, problem, movem...	3601.0	0.0393
18	7.0	stop, remember, agree, public, nee, true, fact...	3359.0	0.0366
19	1.0	today, watch, join, call, day, fire, week, res...	5344.0	0.0583

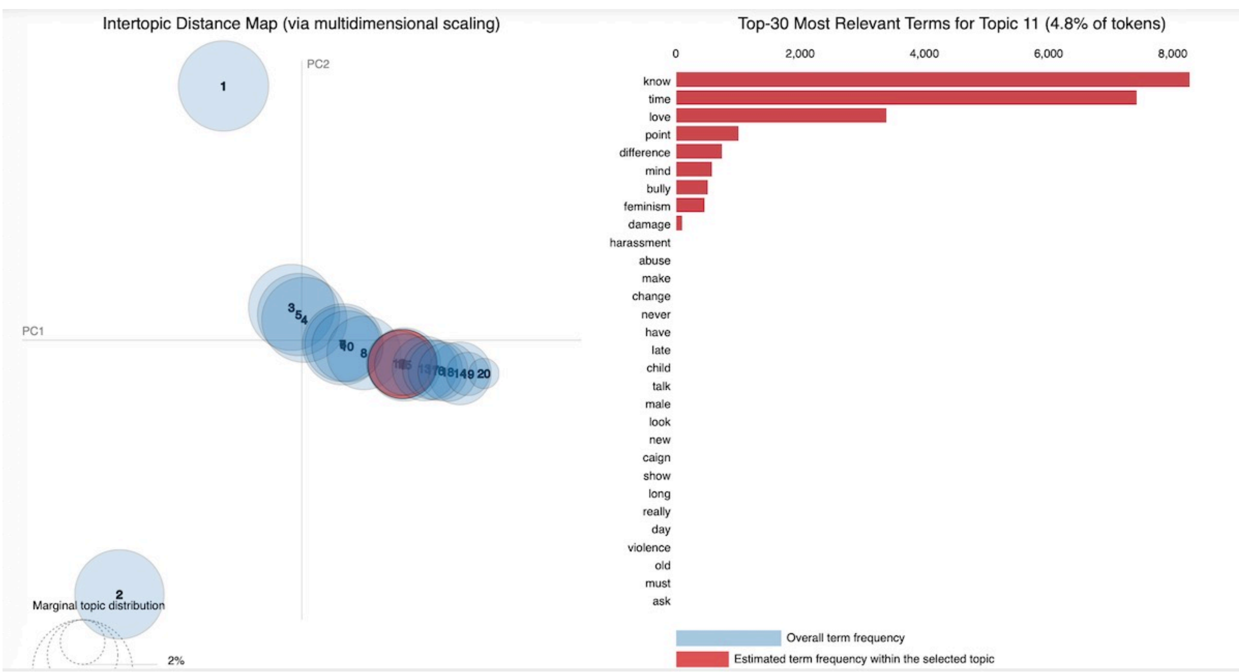
Appendix 3 Intertopic map and top-30 salient words




Intertopic Distance Map (via multidimensional scaling)
Top-30 Most Relevant Terms for Topic 20 (0.9% of tokens)
PC2
PC1
Marginal topic distribution
2%
0
200
400
600
800
word
literally
ignore
second
involve
death
legal
agenda
racism
abuse
fraud
indicate
audience
assult
pas
basically
front
soul
eye
lose
full
tweet
create
long
sexually
can
week
make
child
harassment
Overall term frequency
Estimated term frequency within the selected topic


Intertopic Distance Map (via multidimensional scaling)
Top-30 Most Relevant Terms for Topic 5 (6.8% of tokens)
PC2
PC1
Marginal topic distribution
2%
0
2,000
4,000
6,000
8,000
10,000
assault
many
see
want
survivor
female
voice
lot
trauma
high
pro
harassment
abuse
make
change
never
male
child
late
have
look
talk
caign
new
show
ask
real
old
hope
pay
Overall term frequency
Estimated term frequency within the selected topic


Intertopic Distance Map (via multidimensional scaling)
PC2
PC1
1
2
3
5
4
8
20
Marginal topic distribution
Top-30 Most Relevant Terms for Topic 10 (5% of tokens)
0
1,000
2,000
3,000
4,000
5,000
6,000
share
victim
happen
right
maybe
do
police
job
blame
add
thought
bit
hopefully
twitt
harassment
abuse
make
never
change
talk
child
late
have
look
male
week
real
ask
caign
show
Overall term frequency


Intertopic Distance Map (via multidimensional scaling)
PC2
PC1
1
2
3
5
4
8
20
Marginal topic distribution
2%
Top-30 Most Relevant Terms for Topic 11 (4.8% of tokens)
0
2,000
4,000
6,000
8,000
know
time
love
point
difference
mind
bully
feminism
damage
harassment
abuse
make
change
never
have
late
child
talk
male
look
new
caign
show
long
really
day
violence
old
must
ask
Overall term frequency
Estimated term frequency within the selected topic