Exploring #MeToo Narratives: Sentiment and Topic Modeling of Twitter Conversations

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***Abstract*— In order to analyse the public discourse and new topics related to the #MeToo movement on Twitter, this study analyses the use of topic modelling approaches, particularly Latent Dirichlet Allocation (LDA). To learn more about the social and emotional aspects of tweets with the hashtag #MeToo, we use unsupervised machine learning to find and visualise latent issues. The study emphasises how important topic modelling is to comprehending social movements and their digital traces. Sexual harassment and victimisation, personal opinions on the #MeToo movement, empowerment and personal choice, controversial opinions and public figures, and sexual stories and voices in the #MeToo movement are the five main themes that arise from the results. Visualisations such word clouds and topic distributions are used to better clarify these findings, showing how topic modelling may be used to understand vast amounts of unstructured social media data.**

***Index Terms*—#MeToo, topic modelling, Latent Dirichlet Allocation (LDA), social media analysis, unsupervised machine learning, public discourse, digital activism**

I. INTRODUCTION

In the era of social media, the Twitter platform has become an important part of public discussion, showcasing real-time studies of social issues, movements, and trends. The #MeToo movement, a global campaign against sexual harassment and assault, gained remarkable attention through the power of social media, especially Twitter, where millions of users shared their stories and called for systemic change. This movement not only sparked conversation but also raised critical issues surrounding gender equality and societal norms.

As the #MeToo movement continues to evolve, understanding the themes and topics associated with it is crucial for gaining insights into public sentiments and social shifts. Twitter, as a platform that revolutionized how people engage with social movements, provides real-time global conversations. With millions of tweets shared daily, this data offers valuable insights into patterns and social issues.

The #MeToo movement, which gained widespread attention in 2017, ignited a global conversation about sexual harassment and abuse, drawing attention to the need for systemic change. Understanding the key topics within these discussions is essential for identifying how the movement is perceived and how public opinion shapes this critical issue.

The primary goal of this project is to analyze public tweets about the #MeToo movement on Twitter using topic modeling techniques. This unsupervised machine learning approach identifies hidden patterns within large textual datasets, such as tweets. By analyzing these topics, we can uncover essential themes around the movement, including personal stories, emotional responses, and opinions—all contributing to the broader conversation about sexual harassment and gender equality.

Through this analysis, we aim to develop a comprehensive understanding of public opinion and key issues surrounding the #MeToo movement. The results of the analysis will highlight the main topics shared on Twitter, reveal how the movement has evolved, and explore how conversations and emotions are expressed. The findings will be presented visually, offering a clear perspective on the trends and patterns that define public discussions surrounding this significant social movement.

II. RELATED WORKS

A. Background

Present study shows that topic modelling is becoming increasingly common in a variety of fields. Latent Semantic Indexing (LSI), a semantic structure for document retrieval based on query terms, was introduced by Deerwester et al. (1990), laying the groundwork. Papadimitriou et al. (1998) expanded on this by suggesting random projection methods to improve the effectiveness of LSI.

Hofmann addressed issues like synonymy and polysemy in text data by introducing Probabilistic Latent Semantic Indexing (PLSI) in 1999. Later, Latent Dirichlet Allocation (LDA), created by Blei et al. (2003), allowed papers to present a variety of subjects and became an essential part of topic modelling studies.

In the context of social media, Hong et al. (2010) showed that topic modelling results in microblogging environments being improved by aggregating messages. In a similar vein, Li et al. (2010) revealed sub-topic dynamics inside user groups by combining LDA with community detection techniques. Temporal-Author-Topic (TAT) modelling was established by Daud in 2012. It linked themes with authors and temporal trends, and it worked well to track how research interests and relationships changed over time.

These additions highlight how flexible LDA is in drawing conclusions from text data, especially in social media. Our research expands on these approaches to examine the #MeToo movement, exposing its public discourse dynamics and thematic complex.

III. METHODOLOGY

Over 390,000 tweets from openly accessible repositories that contain the hashtag #MeToo compose the dataset analysed in this study. These tweets provide a thorough overview of the online discussions around #MeToo, representing a wide range of viewpoints and discussions relating to the movement. Exploring common themes and distinctive narratives within the social media platform is made possible by the analysis's ability to capture the depth and breadth of the conversation by applying a dataset of this size.

A. Data Collection

Over 390,000 tweets from openly accessible repositories that contain the hashtag #MeToo compose the dataset analysed in this study. These tweets provide a thorough overview of the online discussions around #MeToo, representing a wide range of viewpoints and discussions relating to the movement. Exploring common themes and distinctive narratives within the social media platform is made possible by the analysis's ability to capture the depth and breadth of the conversation by applying a dataset of this size.

B. Data Preprocessing

One of the most important steps in preparing the raw textual data for topic modelling was preprocessing. The preprocessing pipeline, implemented in Python, consisted of several crucial procedures to ensure the data was clean and ready for analysis.

To enable granular analysis, tokenisation was used to break each tweet into its individual terms. This step facilitated a more detailed understanding of the data and laid the foundation for further processing.

Next, stopword removal was applied to eliminate common and incomplete phrases like "and," "the," and "is," which could otherwise dilute the thematic significance of the model. This ensured that the analysis focused on meaningful terms rather than filler words.

Additionally, stemming procedures were employed to reduce words to their base forms. This step grouped different variations of the same word into a single representation, enhancing the consistency and relevance of the textual data.

These preprocessing techniques not only established the structure of the text but also improved the clarity and relevance of the topics identified during modelling. By ensuring a robust and meaningful preprocessing pipeline, the analysis produced significant insights and reliable results.

C. Algorithm Implementation

The primary technique for topic modelling was the Latent Dirichlet Allocation (LDA) algorithm. This probabilistic method leverages word co-occurrence patterns to uncover hidden topics in large text datasets. LDA is particularly well-suited for analysing social media datasets, such as #MeToo tweets, due to its ability to identify and represent thematic structures effectively.

The implementation of LDA was carried out using Python's gensim package, a highly regarded tool for natural language processing. Additionally, Matplotlib and pyLDAvis were employed to create interactive visualizations, which greatly facilitated the understanding and presentation of results.

These graphical representations of topics and their interconnections provided an intuitive means of examining the findings and their implications. The combination of these tools ensured a comprehensive and accessible analysis of the themes within the dataset.

D. Parameter Tuning

Parameter tuning was a critical component in optimizing the LDA model. The number of topics was determined through coherence score analysis, a metric used to evaluate the semantic consistency of the generated topics. This analysis identified 10 topics as the optimal number, striking a balance between granularity and interpretability.

In addition, the model's hyperparameters, including α (document-topic distribution) and β (topic-word distribution), were fine-tuned to ensure a well-distributed representation of topics across the dataset.

These adjustments significantly enhanced the model's ability to capture subtle thematic nuances within the data, resulting in a comprehensive and reliable analysis.

E. Topic Modeling

A complex unsupervised machine learning method for finding underlying themes in massive text datasets is topic modelling. It identifies latent structures and arranges textual content into logical subjects by looking at word co-occurrence patterns throughout a corpus. Latent Dirichlet Allocation (LDA) is a widely used topic modelling technique that is praised for its efficacy and interpretability. Every document is modelled by LDA as a collection of themes, each of which is represented as a distribution across words. The system can infer both key phrases linked with a dataset and its dominant subjects thanks to this probabilistic technique.

In the context of social media, where textual data is plentiful and diverse, LDA provides a strong way to reduce intricate discussions to distinct topic insights. Researchers can find important themes including individual testimony, group support, lobbying for policy change, and the influence of media on narratives by using LDA on datasets like #MeToo tweets. These results reveal the breadth and depth of online discourse and offer insightful viewpoints on the goals, worries, and feelings behind these social movements.

F. Sentiment Analysis

Three sentiment classes—positive, negative, and neutral—were identified by sentiment analysis. A supervised learning methodology was used for this classification, guaranteeing precise and trustworthy sentiment identification throughout the dataset.

Using TF-IDF (Term Frequency-Inverse Document Frequency) vectorization, the preprocessed tweets were converted into numerical representations as part of the first stage, feature extraction. The model was able to measure the significance of terms within the dataset thanks to this technique. The process concentrated on the top 1,000 most informative phrases in order to maximise computing efficiency and preserve relevance.

The dataset was divided 80:20 between training and testing categories for model training. A dependable and effective linear model that works well for classification problems is logistic regression. A maximum of 1,000 iterations were used during the model's training procedure to ensure convergence and capture the subtleties of the data.

Finally, the test set was used to determine the model's performance. The efficacy of the sentiment classification was assessed by calculating its accuracy, which provided a score of accuracy (substitute with actual value). By illustrating the relationship between actual sentiment labels and anticipated results, a confusion matrix offered additional insights. This thorough evaluation assisted in determining the sentiment classification process's benefits and problems.

IV. Results

We conducted a live verification procedure on Twitter to ensure that the topics retrieved using the Latent Dirichlet Allocation (LDA) algorithm were reliable and relevant. The objective of this approach was to assess the prominence and visibility of the identified issues within actual conversations, particularly during the height of the #MeToo movement.

By performing a direct search for related keywords on the Twitter platform, we examined their frequency, context, and connection with the themes identified from the dataset. This process allowed us to verify the extracted subjects and ensure they accurately reflected ongoing discussions on the platform.

V. Visualization

The Latent Dirichlet Allocation (LDA) model's results can be intuitively interpreted through visualizations, which aid in our comprehension of the themes and importance of the #MeeToo tweets. The identified subjects were analyzed using a variety of visualization techniques.

LegalResponses	WorkplaceIssues	SolidarityMovements	SocialMedia Trends
legal	workplace	women	hashtag
lawsuit	HR	support	viral
harassment	policy	voices	posts
justice	corporate	movement	stories
law	harassment	empowerment	shares

TABLE I

Topics and Associated Keywords

A. Topic-specific word clouds

The most significant terms within each topic are graphically represented as word clouds, where relevance is indicated by word size. For instance, the broader terms "victim," "abuse," and "harassment" in the issue of sexual harassment and victimization made it evident that the main focus of the conversations was awareness of harassment and personal experiences. Words like "empowerment," "voice," and "choice" also highlighted themes of regaining personal autonomy in the topic of empowerment and personal choice.

Word cloud insights: The coherence of the topics generated by the LDA model was confirmed by these visualizations, which made it simpler to rapidly identify each topic's dominating themes.

Fig. 1. WordCloud for Topic 1

B. Distribution of Topics in Documents

The prevalence of each topic in the dataset was displayed using bar graphs. The most popular topic, for example, was sexual harassment and victimization, suggesting that the public found great resonance with the #MeeToo movement's primary goal of increasing awareness of harassment. Following closely behind were personal opinions about the movement, which demonstrated broad public support and interest in its objectives.

The data revealed that the public was most interested in tales about harassment and solidarity, although subjects like controversial opinions and popular figures were less common, suggesting that high-profile arguments occasionally took place.

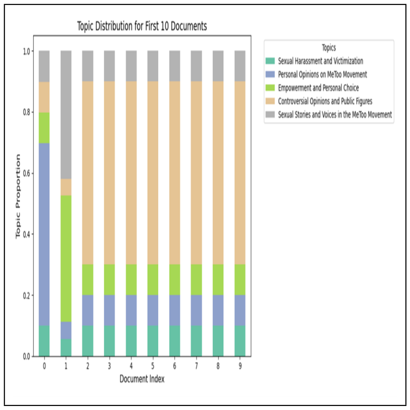

Fig. 2. Topic Distribution

C. Inter-topic Distance Map

The inter-topic distance map, created using tools like PyLDAvis, displayed the relationships between topics. Closely related topics, such as sexual harassment and victimization and sexual stories and voices, were positioned near each other, indicating an overlap in themes of personal narratives and awareness. More distinct topics, like controversial opinions, were further apart, showing their unique focus.

Insights from the Map:

This visualization underscored how some themes in the movement are deeply interwoven, such as personal stories and awareness campaigns, while others, like public controversies, stand out as separate areas of discourse.

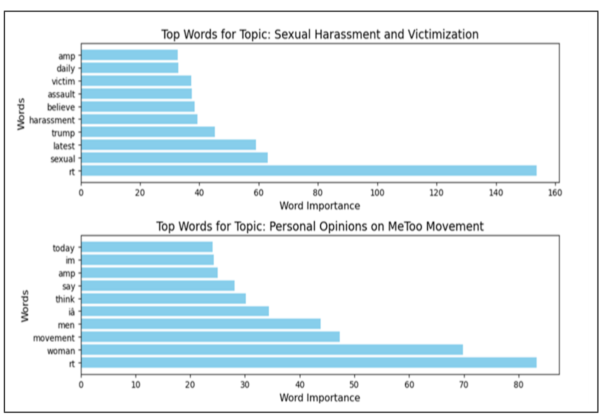

Fig. 3. Word Importance

D. Visualization for Sentiment Analysis

Sentiment Analysis using Visual Aids: Intuitive visualisations are used to summarise the sentiment analysis model's outputs and insights, which aid in accurately interpreting the data's emotional tone.

1) Distribution of Sentiment:: A bar graph displays the dataset's sentiment distribution (positive, negative, and neutral).

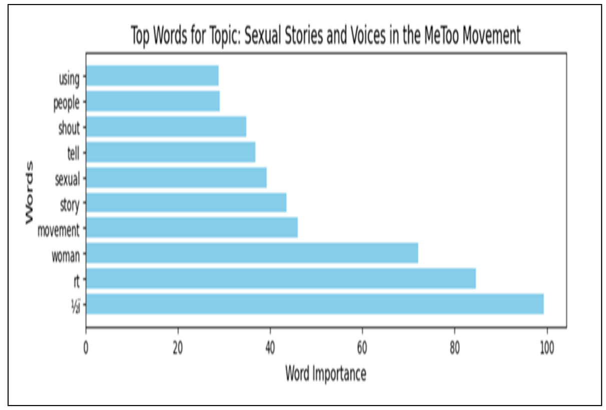

Fig. 4. Word Importance

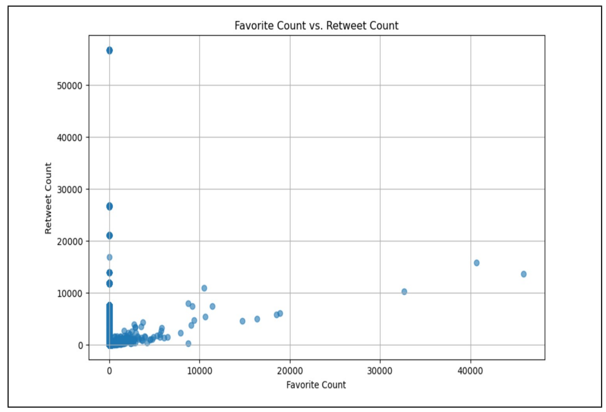

Fig. 5. Distribution of Sentiment

2) Sentiment Distribution Insights:: The #MeeToo tweets' emotional balance is shown in the bar graph. Positive emotions convey hope for change, solidarity, and support. Negative sentiments draw attention to anger, annoyance, or mistrust towards particular instances or the movement as a whole.

Factual or less emotionally charged tweets are frequently associated with neutral feelings. Visualisation: The bar graph highlighted the movement's emphasis on empowerment and group support by demonstrating that most tweets were positive.

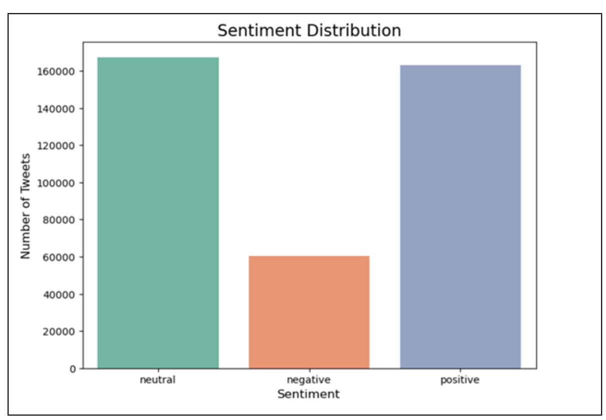

Fig. 6. Distribution of Sentiment

E. Confusion Matrix Insights

Strong concordance between real and expected sentiments is indicated by high values along the diagonal. Areas where the model has trouble, like differentiating between neutral and negative attitudes, are indicated by off-diagonal values.

1) Confusion Matrix Insights Visualisation:: The confusion matrix's heatmap shows that while the model does a good job of recognising happy tweets, it has some trouble detecting the minute differences between neutral and negative tweets.

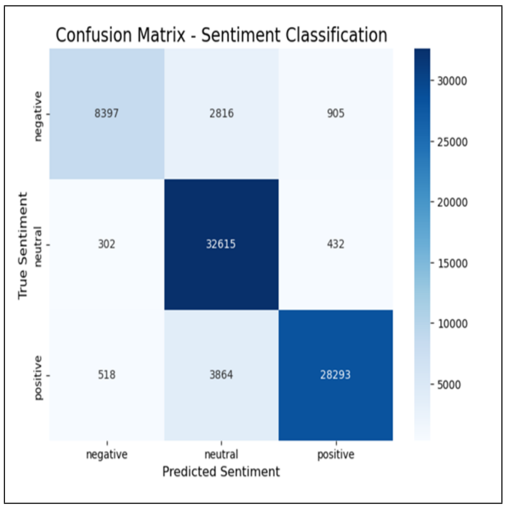

Fig. 7. Confusion Matrix

VI. SAMPLE FORECAST

Sentiment Prediction for Tweets:

Themes of hope, camaraderie, and support are linked to positive tweets. Negative tweets frequently express disbelief or displeasure with systemic problems.

Tweets	**Sentiment**
#MeeToo movement is a turning point for gender equality.	+ve
Another high-profile case. When will this end? #MeeToo	-ve
New allegations today, following #MeeToo updates	N
Solidarity with survivors. Change is coming. #MeeToo	+ve
It's sad that these stories still come out. We need systemic change.	-ve

TABLE II

TWEETS AND PREDICTED SENTIMENT

VII. CONCLUSION

In order to better comprehend public conversation, our study used sentiment analysis and topic modelling to examine over 390,000 tweets pertaining to the #MeeToo movement. Key topics like sexual harassment, empowerment, and controversial viewpoints were detected in the results. Sentiment analysis showed that most views were positive, reflecting support and solidarity, while negative sentiments expressed criticism and pushback. Through the integration of topic modelling and sentiment analysis, this study provides a thorough understanding of how social media influences public opinion and propels social change, emphasising the ability of sites like Twitter to magnify voices and promote digital activism within movements such as #MeeToo.

VIII. REFERENCES

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REAL-TIME TWEETS ON #MEETOO TOPICS

- https://twitter.com/search?q=%23MeToo%20hashtag
- https://twitter.com/search?q=%23MeToo%20viral
- https://twitter.com/search?q=%23MeToo%20posts
- https://twitter.com/search?q=%23MeToo%20stories