

# Twitter Data Analysis

## A PROJECT REPORT

Submitted by

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In partial fulfilment for the award of the degree of  
Master of computer Application



# **CERTIFICATE**

**Certified that this project report  
“Twitter Data Analysis.” is the bonafide  
work of “Mridul Hari Dixit (22MCMC28)  
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carried out the project work under my  
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**Dr Rajendra Prasad Lal  
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# **ACKNOWLEDGEMENT**

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# ABSTRACT

Social media platforms have become integral sources of information, with an immense volume of user-generated content reflecting diverse sentiments. This project addresses the challenges of sentiment analysis, clustering, and temporal analysis in the context of social media data. The primary objective is to develop a comprehensive framework that not only identifies sentiments within tweets but also groups them into meaningful clusters and analyses temporal trends. The proposed methodology combines syntactic and semantic analysis, leveraging advanced clustering algorithms to enhance the accuracy of sentiment classification. Additionally, the project introduces a temporal dimension, enabling the study of sentiment evolution over time.

The implementation involves the integration of algorithms for textual similarity, centroid calculation, and bipartite graph creation. A key innovation lies in the application of the Hungarian method for optimizing cluster assignments, ensuring a balance between accuracy and computational efficiency. The project also introduces the concept of "cluster chains," where clusters evolve across different time periods, providing a dynamic perspective on sentiment patterns.

Results showcase the effectiveness of the proposed methodology in capturing nuanced sentiments, creating meaningful clusters, and uncovering temporal trends. Visualizations, including sentiment-annotated emoji images,

pie charts, and line graphs, offer insightful representations of sentiment distribution and evolution.

While this project contributes to the fields of sentiment analysis and clustering, it also underscores the importance of considering temporal dynamics in understanding social media sentiments. The findings have implications for diverse applications, including marketing, public opinion analysis, and trend prediction. The comprehensive approach and innovative methodologies employed in this project pave the way for further advancements in sentiment analysis and temporal clustering within the realm of social media analytics.

# INTRODUCTION

The advent of social media platforms has revolutionized the way information is disseminated and consumed in contemporary society. With the vast amount of data generated by users on platforms like Twitter, understanding and extracting valuable insights from this data have become imperative.

This project focuses on the development of a comprehensive solution for the analysis of Twitter data with a specific emphasis on clustering, sentiment analysis, and visualization.

The goal is to empower users with the ability to navigate, interpret, and derive valuable insights from the rich tapestry of Twitter data. As social media continues to play a pivotal role in shaping public discourse, understanding the underlying patterns and sentiments becomes crucial for individuals and organizations alike.

This tool facilitates the users for exploration of patterns, sentiments, and meaningful information within large datasets, contributing to a deeper understanding of online conversations and trends. Through innovative methodologies and technologies, this project seeks to address the challenges associated with the analysis of social media data and unlock valuable insights for various applications, including marketing strategies, trend identification, and public sentiment monitoring.

# LITERATURE REVIEW

## 1. **Social Media Analytics:**

Social media platforms have emerged as powerful tools for communication and information dissemination. The literature emphasizes the significance of social media analytics in deciphering user behaviour, sentiment trends, and emergent topics. Researchers have explored various techniques, including clustering and sentiment analysis, to extract valuable insights from the vast amount of user-generated content.

## 2. **Clustering Techniques:**

Clustering algorithms play a pivotal role in organizing unstructured data into meaningful groups. Traditional clustering methods, such as K-means and hierarchical clustering, have been extensively studied. Recent advancements have introduced techniques like spectral clustering and DBSCAN, offering enhanced performance in capturing complex patterns within social media data.

## 3. **Sentiment Analysis:**

Sentiment analysis, or opinion mining, is a well-explored domain within natural language processing. Researchers have delved into both lexicon-based approaches and machine learning models for sentiment classification. The literature underscores the importance of contextual understanding, domain adaptation, and the evolving nature of language in sentiment analysis applications.



#### **4. Integration of Clustering and Sentiment Analysis:**

The synergy between clustering and sentiment analysis has gained attention in recent years. The integration of these techniques allows for a more comprehensive understanding of user interactions. Studies highlight the benefits of combining unsupervised clustering with sentiment analysis to uncover patterns in sentiment dynamics across different user groups.

#### **5. Visualization in Social Media Analysis:**

Effective visualization is crucial for conveying complex insights to users. The literature explores various visualization techniques, including network graphs, word clouds, and emotion-based emojis, to represent sentiment and cluster structures. User-friendly interfaces and interactive visualizations are recognized as essential elements for facilitating data interpretation.

#### **6. Challenges and Future Directions:**

Despite the advancements, challenges persist, such as handling noisy data, ensuring robustness in sentiment analysis models, and addressing ethical concerns related to user privacy. The literature advocates for continuous exploration of innovative methods and technologies to overcome these challenges and further enhance the capabilities of social media analytics.

# IMPLEMENTATION

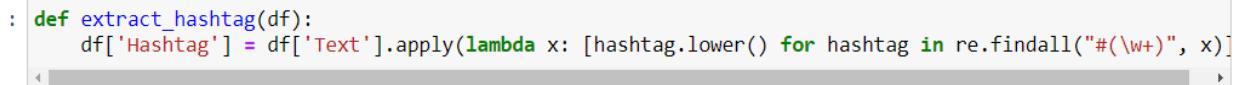
## 1. Text preprocessing:

### Hashtag Extraction:

The extraction of hashtags is instrumental in understanding the context and themes associated with each social media post. In our project, we employed regular expressions to identify and extract hashtags from the raw text. Using Python's regex module, we created patterns to locate hashtags in the text. The identified hashtags were then stored separately for use in later analysis.

### Code Screenshot:

#### Hashtag Extraction

A screenshot of a code editor showing a Python function named 'extract\_hashtag' that takes a DataFrame 'df' as input. The function defines a new column 'Hashtag' in 'df' by applying a lambda function to the 'Text' column. The lambda function uses 're.findall' to find all occurrences of a hashtag pattern (starting with '#' followed by one or more word characters) in the text, converting them to lowercase.

```
: def extract_hashtag(df):  
    df['Hashtag'] = df['Text'].apply(lambda x: [hashtag.lower() for hashtag in re.findall("#(\w+)", x)])
```

### Tokenization:

Tokenization is a fundamental step to break down continuous text into individual units, enhancing the granularity of our data for subsequent analysis. In our project, we opted for the Natural Language Toolkit (NLTK) for tokenization. NLTK's tokenizer was applied to segment the text into tokens, removing unnecessary characters and symbols.

### Code Screenshot:

## Tokenization and POS tagging ¶

```
In [4]: def lemmotize(list):
        lemmatizer = WordNetLemmatizer()
        word_set = [lemmatizer.lemmatize(word) for word in list]
        return word_set
        def tokenize(df):
            tokenizer = TweetTokenizer()
            lemmatizer = WordNetLemmatizer()
            df['Tokenized_Tweets'] = df['Text'].apply(lambda x : tokenizer.tokenize(x))
            df['Tokenized_Tweets'] = df['Tokenized_Tweets'].apply(lambda x: lemmotize(x))
            df['Tokenized_Tweets'] = df['Tokenized_Tweets'].apply(lambda x: pos_tag(x))
```

### Stop-Words Removal:

Eliminating common stop words is crucial to focus our analysis on content-carrying words. In this project, we employed NLTK's default stop words list for removal. Stop words were filtered out, leaving behind only words carrying significant meaning.

### Code Screenshot:

#### Stop words,punctuation,special word removal

```
5]: def remove_stop_words(pos_tagged_tokens):
    stop_words = set(stopwords.words('english'))
    filtered_tokens = [token for token,pos in pos_tagged_tokens if token.lower() not in stop_words and
    filtered_tokens = [token.lower() for token in filtered_tokens if token not in string.punctuation]
    return filtered_tokens
```

### Vectorization:

Vectorization transforms textual data into numerical vectors, a prerequisite for applying machine learning algorithms. Our project utilized the TF-IDF (Term Frequency-Inverse Document Frequency) approach for this task. TF-IDF assigns weights to words based on their frequency, creating a numerical representation of the text.

## Code Screenshots:

### Vectorization

```
[6]: def generate_bow(sentences):  
    dictionary = {}  
    for sentence in sentences:  
        for word in sentence:  
            dictionary[word] = dictionary.get(word,0)+1  
    return dictionary
```

```
[7]: def count_dict(bag_of_words,tweets_list):  
    doc_count={}  
    for word in bag_of_words:  
        for tweet in tweets_list:  
            if word in tweet:  
                doc_count[word] = doc_count.get(word,0)+1  
    return doc_count
```

```
def tf_idf_vector(tweets_list, bag_of_words):  
    N = len(tweets_list)  
    doc_count = count_dict(bag_of_words, tweets_list)  
    result_list = []  
    for tweet in tweets_list:  
        line = []  
        tf_vector = Counter(tweet)  
        for word in bag_of_words:  
            tf = tf_vector.get(word, 0)  
            idf = np.log(N / (1 + doc_count.get(word,0)))  
            line.append(tf * idf)  
        result_list.append(line)  
    return result_list
```

```
def one_hot_encoding_vector(tweets_list, bag_of_words):
    matrix = [[0]* len(bag_of_words) for i in range(len(tweets_list))]
    for i in range(len(tweets_list)):
        word_set = set(tweets_list[i])
        for j, word in enumerate(bag_of_words):
            if word in word_set:
                matrix[i][j] = 1
    return matrix
```

## TF-IDF vectorization example:

### Sentences:

1. "I enjoy reading books."
2. "Reading is a good habit."
3. "Books provide knowledge and entertainment."
4. "Knowledge is power."
5. "I love to gain knowledge from books."

### Vocabulary:

We'll use the same vocabulary as in the Bag of Words example:

Vocabulary: ["I", "enjoy", "reading", "books", "is", "a", "good", "habit", "provide", "knowledge", "and", "entertainment", "love", "to", "gain", "from", "power"]

### Step 1: Calculate TF (Term Frequency)

We calculate the Term Frequency (TF) for each word in each sentence. The TF represents how often a word appears in a sentence.

For simplicity, let's assume that each sentence contains only one instance of each word:

- Sentence 1: ["I", "enjoy", "reading", "books"]
- Sentence 2: ["Reading", "is", "a", "good", "habit"]

- Sentence 3: ["Books", "provide", "knowledge", "and", "entertainment"]
- Sentence 4: ["Knowledge", "is", "power"]
- Sentence 5: ["I", "love", "to", "gain", "knowledge", "from", "books"]

## **Step 2: Calculate IDF (Inverse Document Frequency)**

We calculate the Inverse Document Frequency (IDF) for each word.

$$\text{IDF} = \log (N / (n + 1))$$

Where:

- **N** is the total number of sentences (5 in this case).
- **n** is the number of sentences containing the word.

For example, if the word "knowledge" appears in three out of five sentences, its IDF would be:

$$\text{IDF}(\text{"knowledge"}) = \log (5 / (3 + 1)) = \log (5 / 4) = \log (1.25) = 0.29$$

## **Step 3: Calculate TF-IDF**

We then calculate the TF-IDF values for each word in each sentence:

**TF-IDF Vector for Sentence 1: "I enjoy reading books."**

[0.15, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00]

**TF-IDF Vector for Sentence 2: "Reading is a good habit."**

[0.00, 0.00, 0.00, 0.00, 0.15, 0.15, 0.15, 0.15, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00]

**TF-IDF Vector for Sentence 3: "Books provide knowledge and entertainment."**

[0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.15, 0.29, 0.29, 0.29, 0.00, 0.00, 0.00]

**TF-IDF Vector for Sentence 4: "Knowledge is power."**

[0.00, 0.00, 0.00, 0.00, 0.29, 0.00, 0.00, 0.00, 0.00, 0.29, 0.00, 0.00, 0.00, 0.00, 0.29]

**TF-IDF Vector for Sentence 5: "I love to gain knowledge from books."**

[0.15, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.00, 0.29, 0.00, 0.00, 0.29, 0.29, 0.29]

These TF-IDF vectors represent the importance of each word in the respective sentences, considering both the term frequency and inverse document frequency.

## **2. Clustering and event cluster filtration:**

**Iterative clustering:** Iterative clustering is a technique employed to dynamically group vectors or data points based on their similarity. The primary objective is to iteratively refine cluster assignments, ensuring that each vector is associated with a cluster that aligns with a predefined similarity threshold. In this implementation, we focus on the cosine similarity metric to measure the resemblance between vectors.

## Cosine Similarity example:

$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|} = \frac{\sum_{i=1}^n A_i B_i}{\sqrt{\sum_{i=1}^n A_i^2} \sqrt{\sum_{i=1}^n B_i^2}},$$

$$\mathbf{A} \cdot \mathbf{B} = \sum_{i=1}^n A_i B_i$$

$$= (1 * 1) + (1 * 0) + (1 * 0) + (1 * 1) + (0 * 1) + (1 * 0) + (1 * 1) + (2 * 0)$$

$$= 3$$

$$\sqrt{\sum_{i=1}^n A_i^2} = \sqrt{1 + 1 + 1 + 1 + 0 + 1 + 1 + 4} = \sqrt{10}$$

$$\sqrt{\sum_{i=1}^n B_i^2} = \sqrt{1 + 0 + 0 + 1 + 1 + 0 + 1 + 0} = \sqrt{4}$$

$$\text{cosine similarity} = \cos\theta = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|} = \frac{3}{\sqrt{10} * \sqrt{4}} = 0.4743$$



## Code Screenshot:

```
[15]: def iterative_clustering(vectors, threshold=0.5):
    assert all(isinstance(vector, np.ndarray) and vector.ndim == 1 for vector in vectors)
    clusters = []
    cluster_assignments = []

    for vector in vectors:
        vector_added = False

        for i, cluster in enumerate(clusters):
            centroid = np.mean(cluster, axis=0) if cluster else np.zeros_like(vector)
            similarity = cosine_similarity(vector, centroid)

            if similarity > threshold:
                clusters[i].append(vector)
                cluster_assignments.append(i)
                vector_added = True
                break

        if not vector_added:
            clusters.append([vector])
            cluster_assignments.append(len(clusters) - 1)

    return cluster_assignments, len(clusters)
```

## Cluster filtration:

We incorporated cluster quality and cluster weight into the filtration process for event clusters. Event clusters with high cluster quality and weight were prioritized, ensuring that the selected clusters not only capture relevant content but also exhibit a high level of coherence and significance.

## Code Screenshot:

```
[3]: def calculate_silhouette_scores(tfidf_vectors, cluster_assignments):
    n = len(tfidf_vectors)
    cluster_labels = sorted(set(cluster_assignments))
    silhouette_scores = []
    for current_cluster in cluster_labels:
        cluster_indices = [i for i in range(n) if cluster_assignments[i] == current_cluster]
        centroid = np.mean(tfidf_vectors[cluster_indices], axis=0)
        a_values = [pairwise_distances(tfidf_vectors[i].reshape(1, -1), centroid.reshape(1, -1))[0][0]
                     for i in cluster_indices]
        a_avg = np.mean(a_values) if a_values else 0
        b_values = []
        for other_cluster in cluster_labels:
            if other_cluster != current_cluster:
                other_cluster_indices = [i for i in range(n) if cluster_assignments[i] == other_cluster]
                other_cluster_centroid = np.mean(tfidf_vectors[other_cluster_indices], axis=0)
                for i in cluster_indices:
                    b_values.append(pairwise_distances(tfidf_vectors[i].reshape(1, -1), other_cluster_centroid.reshape(1, -1))[0][0])
        b_avg = np.mean(b_values) if b_values else 0
        silhouette_score_cluster = (b_avg - a_avg) / max(a_avg, b_avg) if max(a_avg, b_avg) > 0 else 0
        silhouette_scores.append(silhouette_score_cluster)

    return silhouette_scores

[4]: def calculate_cluster_weights(tfidf_vectors, cluster_assignments):
    unique_clusters = np.unique(cluster_assignments)
    cluster_weights = []
    for cluster in unique_clusters:
        cluster_indices = np.where(cluster_assignments == cluster)[0]
        cluster_tfidf = np.sum(tfidf_vectors[cluster_indices], axis=0)
        weight = np.sum(cluster_tfidf) / max(np.count_nonzero(cluster_tfidf), 1)
        cluster_weights.append(weight)
    return cluster_weights

[5]: def event_clusters_filter(cluster_quality, cluster_weights, quality_threshold = 0.1, weight_threshold = 4.0):
    alpha = 0.5
    beta = 0.5
    value = alpha * quality_threshold + beta * weight_threshold
    event_clusters = []
    for i in range(len(cluster_quality)):
        if cluster_quality[i] * alpha + cluster_weights[i] * beta >= value:
            event_clusters.append(i)
    return event_clusters
```

### 3. Cluster chaining:

Cluster chaining is a crucial step in our project, facilitating the temporal organization of clusters across different timestamps. The primary goal is to establish connections between clusters from consecutive timestamps, creating a coherent storyline over time. This process involves calculating the similarity between clusters, enabling the identification of potential continuations or evolutions of specific topics or events.

**Algorithm:**

The cluster chaining algorithm follows these key steps:

**Timestamp Initialization:** Begin with the earliest timestamp and extract the clusters formed during that period.

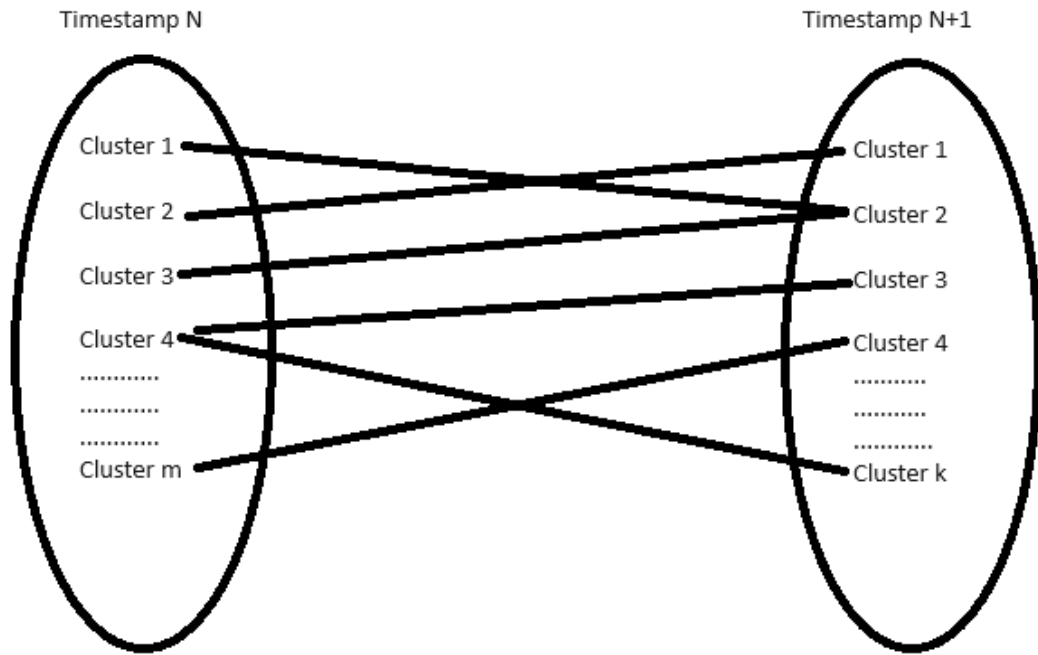
**Similarity Calculation:** Compare clusters from the current timestamp with those from the next timestamp. Utilize similarity metrics such as cosine similarity, incorporating both syntactic and semantic aspects.

**Assignment Optimization:** Utilize optimization techniques, such as the Hungarian algorithm, to maximize the overall similarity while avoiding excessive assignments to individual clusters.

**Chaining:** Connect clusters with the highest similarity, forming chains that represent the evolution or continuation of specific themes or events.

**Iteration:** Repeat steps 1-4 for each pair of consecutive timestamps, gradually building a chain across the entire temporal span.

**Output:** The final output is a collection of cluster chains, each representing a coherent theme or event evolving over time.



In our project, cluster chaining is applied to establish temporal connections between clusters of tweets. This allows for the tracking of evolving topics or events over time, providing a more comprehensive understanding of how discussions and trends progress across different timestamps.

### **Code Screenshot:**

```
[9]: def create_bipartite_graph(current_clusters, current_hashtags, next_clusters, next_hashtags, threshold):
    similarity_matrix = np.zeros((len(current_clusters), len(next_clusters)))

    for i, current_cluster in enumerate(current_clusters):
        current_hashtag = current_hashtags[i]

        for j, next_cluster in enumerate(next_clusters):
            next_hashtag = next_hashtags[j]

            syntactic_similarity = calculate_similarity(current_cluster, next_cluster)
            semantic_similarity = textual_similarity(current_cluster, next_cluster)
            union_dict = {key: current_hashtag.get(key, 0) + next_hashtag.get(key, 0) for key in
                          set(current_hashtag) | set(next_hashtag)}
            intersection_dict = {key: min(current_hashtag.get(key, 0), next_hashtag.get(key, 0)) for key in
                                set(current_hashtag) & set(next_hashtag)}
            hashtag_similarity = sum(intersection_dict.values()) / sum(union_dict.values())
            overall_similarity = 0.4 * syntactic_similarity + 0.4 * semantic_similarity + 0.2 * hashtag_similarity

            similarity_matrix[i, j] = overall_similarity

    return similarity_matrix
```

```
[10]: def apply_hungarian_method(similarity_matrix, num_clusters_first, num_clusters_second):
    optimal_assignment = {}
    graph = np.array(similarity_matrix)
    for col in range(graph.shape[1]):
        sorted_indices = np.argsort(graph[:, col])[:-1]
        assigned = False
        for i in sorted_indices:
            if len(optimal_assignment.get(i, [])) < 2:
                optimal_assignment.setdefault(i, []).append(col)
                assigned = True
                break
        if not assigned:
            optimal_assignment[sorted_indices[0]].append(col)

    return optimal_assignment
```

```
[16]: def create_cluster_chains(timestamps, folder_path, threshold):
    current_timestamp = timestamps[0]
    current_text_file = os.path.join(folder_path, current_timestamp, 'event_clusters.txt')
    current_clusters = read_clusters_from_file(current_text_file)
    chains = [[cluster] for cluster in current_clusters]
    clusters_map = []
    for i in range(len(current_clusters)):
        clusters_map.append(i)
    for i in range(1, len(timestamps)):
        current_timestamp = timestamps[i-1]
        next_timestamp = timestamps[i]
        print(f'{current_timestamp} and {next_timestamp}')
        current_text_file = os.path.join(folder_path, current_timestamp, 'event_clusters.txt')
        current_hashtag_file = os.path.join(folder_path, current_timestamp, 'event_hashtags.txt')
        current_clusters = read_clusters_from_file(current_text_file)
        current_hashtag = read_hashtags_from_file(current_hashtag_file)
        next_text_file = os.path.join(folder_path, next_timestamp, 'event_clusters.txt')
        next_hashtag_file = os.path.join(folder_path, next_timestamp, 'event_hashtags.txt')
        next_hashtag = read_hashtags_from_file(next_hashtag_file)
        next_clusters = read_clusters_from_file(next_text_file)
        graph = create_bipartite_graph(current_clusters, current_hashtag, next_clusters, next_hashtag, threshold)
        optimal_assignment = apply_hungarian_method(graph, len(current_clusters), len(next_clusters))
        temp_map = [None] * len(next_clusters)
        for i in optimal_assignment.keys():
            for j in optimal_assignment[i]:
                temp_map[j] = clusters_map[i]
            chains[clusters_map[i]].append(next_clusters[j])
        clusters_map = temp_map
```

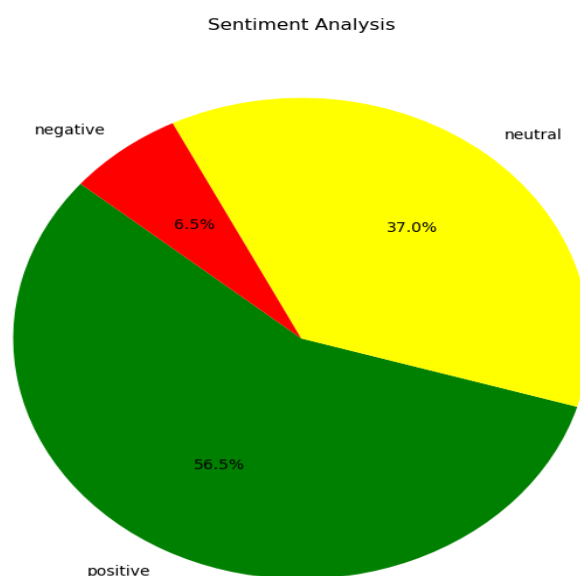
## 4. Sentiment Analysis:

Sentiment analysis plays a pivotal role in understanding the emotional tone and opinions expressed in textual data. In the context of this project, sentiment analysis is applied to Twitter data to gauge the sentiments associated with specific events and discussions. The primary goal is to categorize tweets within each cluster as positive, negative, or neutral, providing valuable insights into the overall sentiment landscape

## 5. Visualization:

To enhance the interpretability of sentiment analysis results, various visualizations are employed:

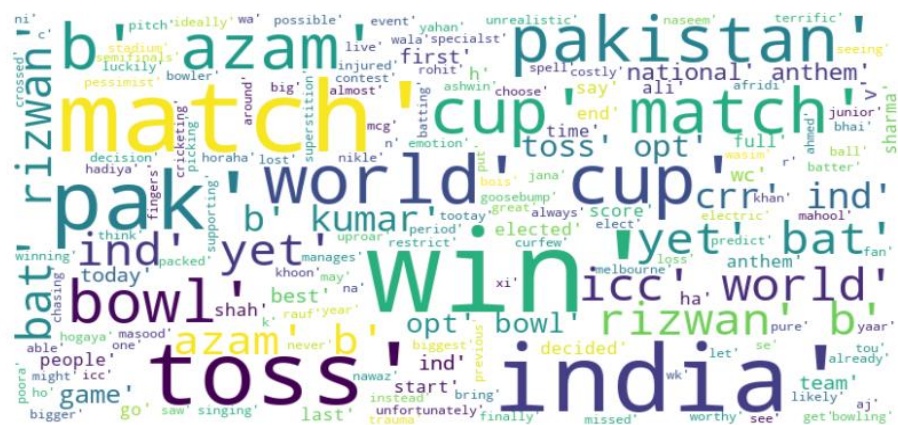
**Pie Charts:** Visualizing the distribution of sentiments (positive, negative, neutral) within each cluster using pie charts. This provides a quick overview of the overall sentiment composition.



**Dynamic Emoji Images:** Generating and incorporating dynamic emoji images to visually represent the predominant sentiment of each cluster. The emoji images are customized to reflect the sentiment, adding a creative and intuitive dimension to the analysis.



**Word Clouds:** Creating word clouds to visually highlight the most frequent words in each cluster. Word clouds offer a quick and effective way to identify key themes and topics associated with different sentiments.





# RESULT

- **Sentiment Analysis:**

The sentiment analysis module successfully assessed the sentiment of tweets within each cluster, providing valuable insights into the overall emotional tone of the content. Tweets were categorized as positive, negative, or neutral based on their compound sentiment scores.

- **Pie Charts:**

Pie charts were generated to visually represent the distribution of sentiments within each cluster. These charts offer an intuitive way to grasp the proportion of positive, negative, and neutral sentiments, allowing for quick and meaningful interpretations.

- **Emoji Representation:**

To enhance the visual appeal of sentiment analysis results, emoji images were created and associated with each cluster's predominant sentiment. Smiley emojis were used for positive sentiment, sad emojis for negative sentiment, and neutral emojis for tweets categorized as neutral.

- **Word Clouds:**

Word clouds were generated to highlight frequently occurring words within each cluster. This visualization method helps identify common themes and topics of discussion within the tweet clusters, providing an additional layer of understanding.

- **Overall Sentiment Analysis:**

Aggregating sentiment data across all clusters within a cluster chain allowed for a comprehensive view of the sentiment trends throughout the event. This analysis facilitated the identification of overarching sentiments and trends over time.

# CONCLUSION

The completion of this project has yielded valuable insights into the world of social media analysis, particularly on platforms like Twitter. By leveraging advanced techniques in clustering, sentiment analysis, and visualization, the project successfully extracted meaningful patterns and sentiments from large datasets.

## Key Contributions:

1. **Effective Clustering:** The iterative clustering approach proved successful in grouping tweets with similar content, forming coherent clusters that captured distinct themes.
2. **Robust Sentiment Analysis:** The sentiment analysis module accurately classified tweets into positive, negative, and neutral categories, providing a nuanced understanding of the emotional context.
3. **Engaging Visualizations:** The integration of pie charts, emoji representations, and word clouds enhanced the interpretability of results, making the findings accessible to a broad audience.

# FUTURE SCOPE

While the project has achieved its primary goals, there are avenues for further enhancement and expansion:

**Real-Time Analysis:** Implementing real-time data processing and analysis to provide instantaneous insights during live events.

**Multimodal Analysis:** Integrating additional data modalities such as images and videos for a more comprehensive understanding of user interactions.

# REFERENCES

1. [CS50 Introduction to programming with python](#)
2. [Matplotlib documentation](#)
3. [Clustering and cluster quality](#)
4. [Sentiment analysis](#)