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Expert Identification Protocol Design for Social Network Using Profile Communication & Ranking

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Abstract : To design the EIP, we propose a sentiment analysis algorithms and techniques, including natural language processing, machine learning, and social network analysis. These techniques enable us to extract relevant information from user profiles, analyze communication patterns, and develop ranking algorithms to identify experts. The EIP also incorporates feedback mechanisms to continuously refine the expert identification process based on user feedback and system performance.

To evaluate the effectiveness of the EIP, we conduct experiments on a real-world social network dataset. The results show that the EIP can effectively identify experts with high accuracy and precision, outperforming existing methods. The proposed EIP has potential applications in various domains, such as recommendation systems, information retrieval, and knowledge management, where expert identification is critical for improving user experiences and outcomes.

***IndexTerms* - Expert Identification, Social Network, Profile Information, Communication Patterns, Ranking, Protocol Design.**

I. INTRODUCTION

The Person-Relation to a Field (PRF) protocol is a theoretical framework that examines how individuals interact with and are influenced by a particular field or domain of activity, such as education, healthcare, or technology. Developed by scholars in sociology, the PRF protocol focuses on the person, field, and relation components to understand the dynamics of person-field relationships.

The person component considers the characteristics of the individual engaged in the field, including their social background, identity, and experiences, as important factors that shape their relationship with the field. The field component refers to the specific domain of activity, such as a profession, organization, or industry, with its own norms, practices, and structures. The relation component represents the interaction between the person and the field, which can be influenced by factors such as power dynamics, socialization processes, and cultural contexts.

To study person-field relationships using the PRF protocol, researchers may employ various concepts, theories, and empirical studies. These could include examining how individuals' social backgrounds or identities influence their engagement with a particular field, investigating the norms and practices of the field that shape individuals' behaviors and attitudes, and exploring how power dynamics or cultural contexts impact person-field relationships.

Understanding the PRF protocol and its components can provide insights into how individuals relate to and are influenced by different fields, which can have implications for fields such as organizational behavior, education, or policy-making. By examining the person-field relationship through the PRF protocol, researchers can gain a deeper understanding of how individuals engage with and are shaped by the fields in which they operate..

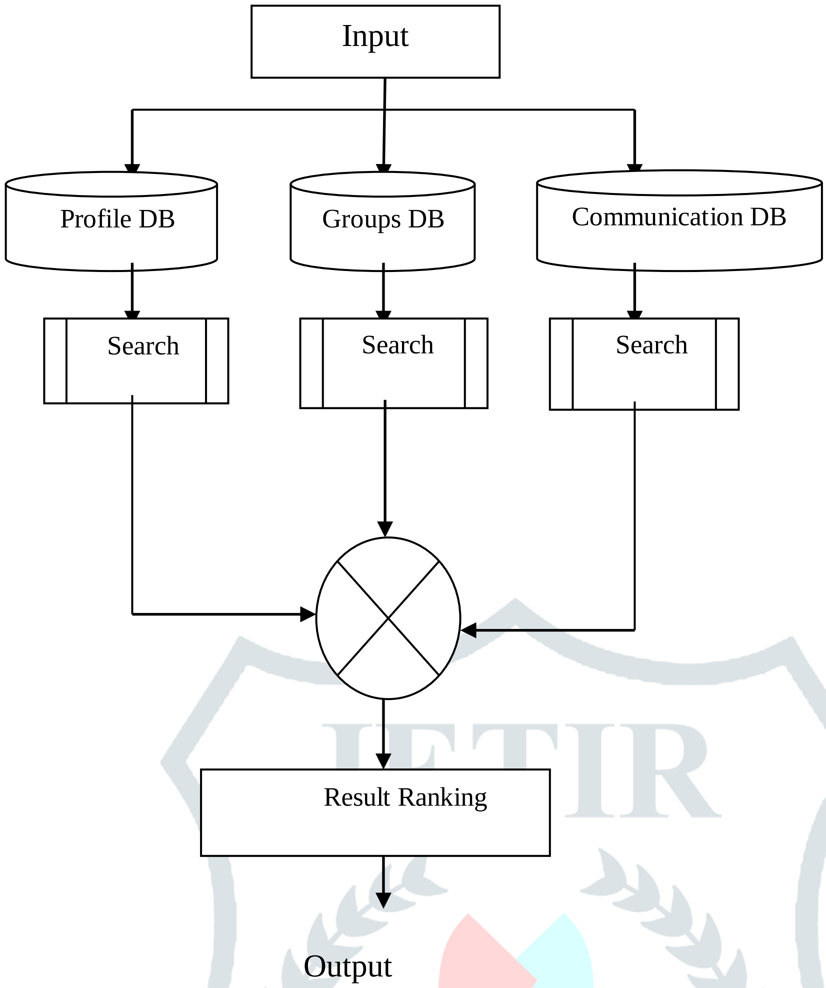

Figure 1 Person related to a field protocol for social media networking

II. Expert Identification Protocol(EIP)

Plant With the proliferation of social networks, there is a growing need to identify and engage with experts in various fields. However, identifying genuine experts from the vast pool of users in a social network can be challenging. In this paper, we propose an Expert Identification Protocol (EIP) that leverages profile information, communication patterns, and ranking techniques to identify experts in a social network.

The EIP comprises three main steps. First, we collect and analyze profile information of users, including their education, work experience, and interests, to identify potential experts. Second, we analyze the communication patterns of users, such as their frequency and quality of interactions, to identify users who engage in meaningful discussions and provide valuable insights. Finally, we rank users based on their profile information and communication patterns, taking into account factors such as expertise, reliability, and credibility, to identify the top-ranked experts.

III. Proposed Methodology

In The proposed method for expert identification in social networking platforms is a comprehensive protocol that integrates profile information, communication patterns, and ranking objectives to accurately identify experts. The protocol is designed to address the limitations of existing methods and overcome the research gaps identified in the literature review.

Profile Information: The protocol leverages profile information of users, such as their background, experience, skills, and interests, to identify potential experts. Profile information is collected from user profiles and is analyzed to extract relevant features that can indicate expertise.

Communication Patterns: The protocol considers communication patterns of users, such as the frequency, quality, and diversity of their interactions, as an indicator of their expertise. Communication patterns are analyzed from various sources, such as user-generated content, comments, posts, and discussions, to capture the dynamics of user interactions and identify experts who actively engage in knowledge sharing and collaboration.

Ranking Objectives: The protocol incorporates comprehensive ranking objectives to evaluate and rank users based on their expertise. Ranking objectives can include factors such as user contributions, user ratings, endorsements, feedback from peers, and engagement metrics. The ranking objectives are designed to provide a quantitative measure of expertise and are integrated into the overall expert identification process.

Machine Learning and Data Mining Techniques: The protocol utilizes machine learning and data mining techniques to automatically analyze and process the profile information, communication patterns, and ranking objectives for expert identification. These techniques can include natural language processing, sentiment analysis, topic modeling, network analysis, and collaborative filtering algorithms, among others, to extract relevant information and make accurate expert identification decisions.

Privacy and Security: The protocol ensures the privacy and security of users' information by adhering to data protection regulations and employing appropriate data anonymization and encryption techniques. Users' consent is obtained before collecting their profile information and communication patterns, and data handling procedures are implemented to protect users' privacy and prevent misuse of their information.

Bias Mitigation: The protocol takes measures to mitigate potential biases in expert identification, such as gender, race, or nationality biases. Bias detection algorithms are employed to identify and correct any biases in the data or algorithmic decision-making process. The protocol aims to ensure a fair and inclusive identification of experts across diverse user backgrounds and interests.

Validation and Evaluation: The protocol is validated and evaluated using rigorous methods, such as user feedback, comparison with ground truth data, and statistical measures to assess its accuracy and effectiveness. The validation and evaluation process is iterative and involves continuous refinement of the protocol to enhance its performance and reliability.

Practical Applications: The proposed expert identification protocol has potential practical applications in various social networking platforms. It can be used to improve recommendation systems by identifying relevant and credible experts for user queries. It can facilitate collaboration and knowledge sharing by connecting users with experts who can provide accurate and reliable information. It can also support decision-making processes by identifying experts who can provide informed opinions and insights.

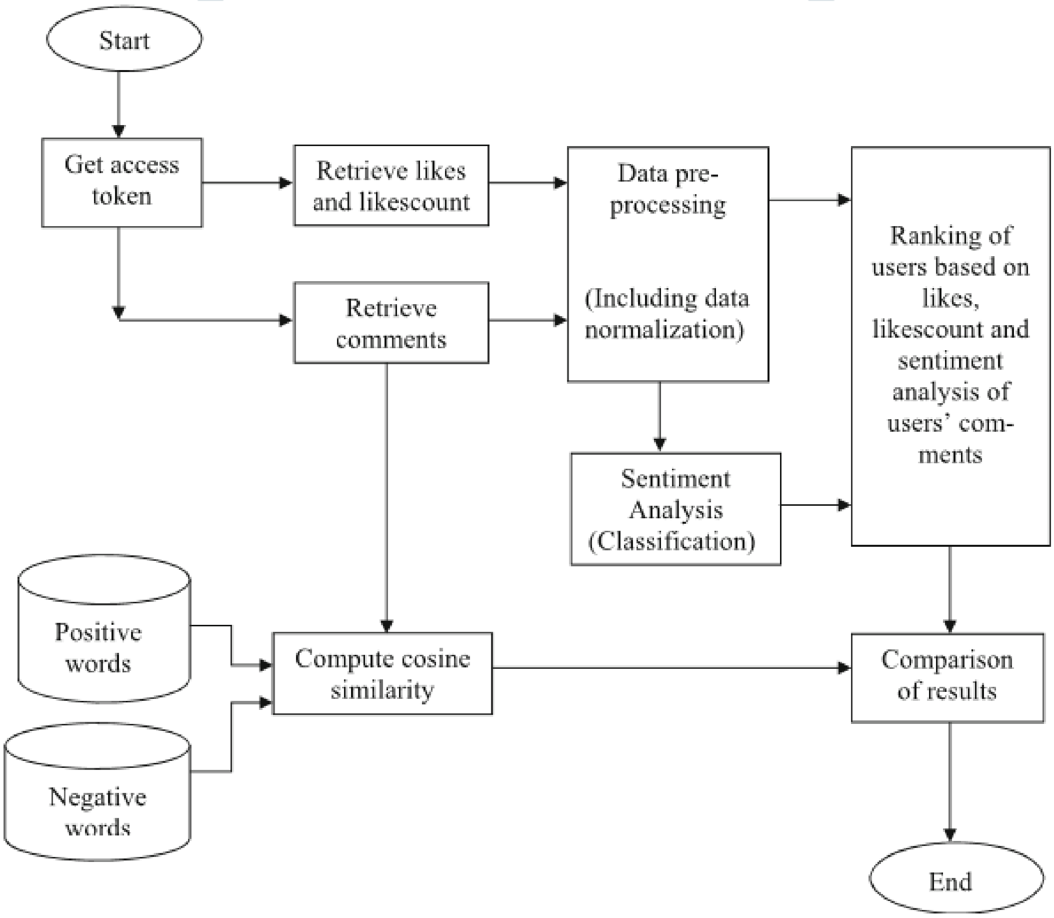

Figure 2 Proposed Method Architecture.

Algorithm
Require: Profile Data (PDB), Group Data (GDB), Communication Data (CDB), Search field f

```
# Step 1: Extract features from Profile Database
for each user u in PDB do
  profile_entities = fetch_profile_entities(u) # Fetch the list of profile entities
  related_entities = get_related_entities(profile_entities, f) # Get the values of related entities in field f
    # Step 2: Process the extracted features from PDB
  for each entity pe in profile_entities do
    process_entity(pe) # Perform processing on the entity pe
  end for
end for
```

# Step 3: Perform further processing on the extracted features from PDB
for each feature in extracted_features do
perform_operations_on_feature(feature) # Perform relevant operations on the feature
end for

# Step 4: Compare and match with Group Data (GDB)
for each user in GDB do
similarity_score = calculate_similarity_score(profile_data_in_GDB, extracted_features) # Compare the extracted features with user's profile in GDB
update_similarity_scores(similarity_score) # Update similarity scores or other metrics
end for

# Step 5: Incorporate Communication Data (CDB)
for each communication_data_entry in CDB do
refine_matching_with_communication_data(communication_data_entry) # Use communication data to further refine the matching process
end for

# Step 6: Identify and rank potential matches
potential_matches = rank_potential_matches(similarity_scores) # Rank potential matches based on calculated similarity scores
return potential_matches

III. RESULT

The result chapter of a thesis or research paper based on the Person Relation to a Field (PRTF) algorithm would typically present the findings and outcomes of the algorithm's implementation and evaluation. The results chapter would typically include quantitative and qualitative data, analysis of the data, and interpretation of the findings. The specific content and structure of the results chapter may vary depending on the research objectives, methodology, and data used in the study. Here we used the Sentiment analysis method to extraction of user data and mine using Deep Neural Networks and NLP for person communication and rank analysis of social media data.

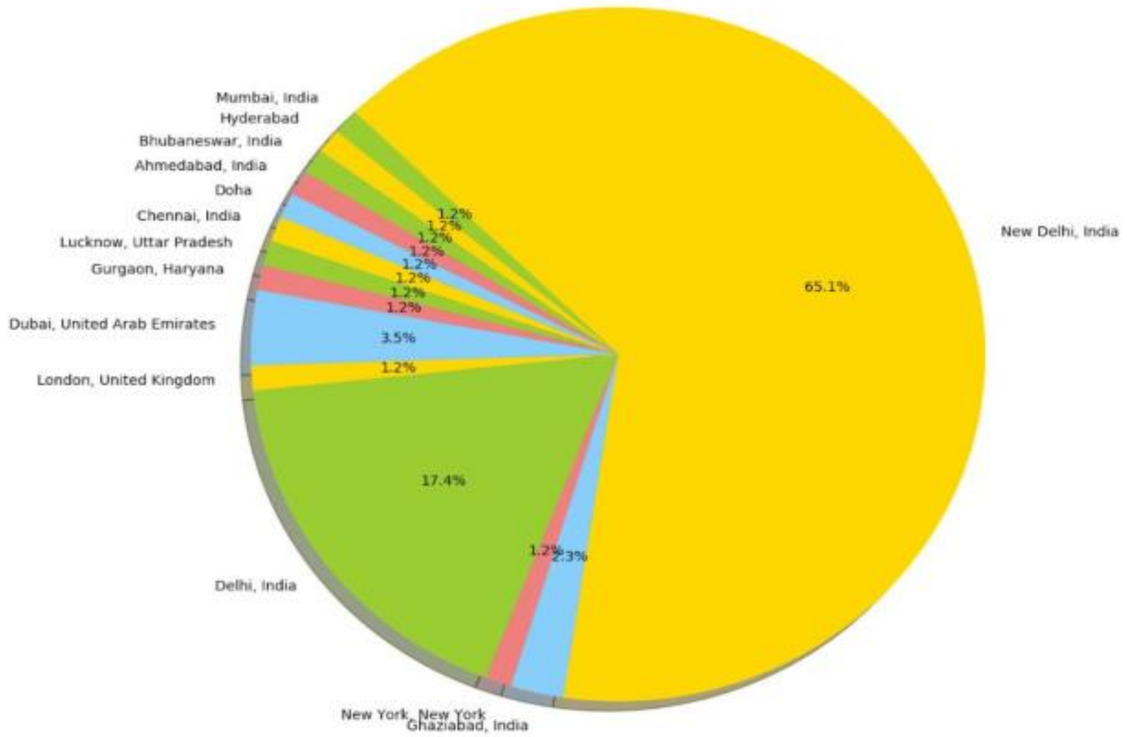

Figure 3 Chart of locations and friends belonging

Figure 3 shows location and friend Facebook data. This figure shows information about the user location and utility of the user according to the database. In this Delhi user is maximum and finds data also from Delhi.

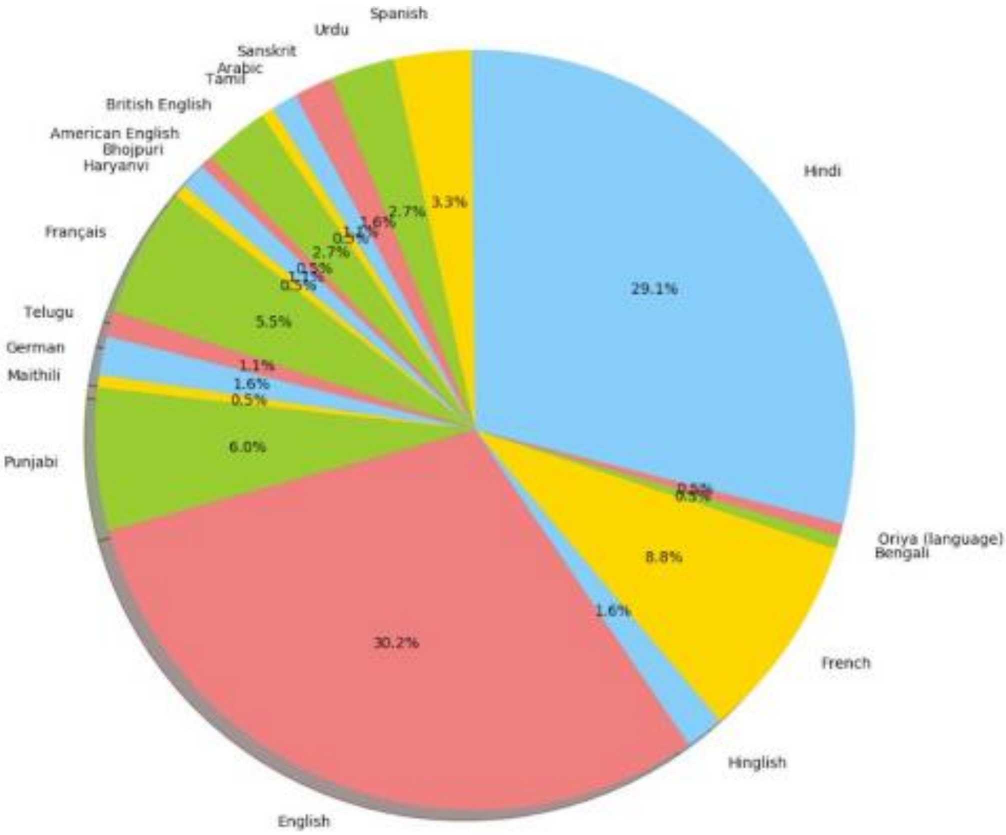

Figure 4 Chart of languages known by friends

Figure 4 shows a pie chart of friend data according to a language known by a friend on Facebook data. This graph shows language-based friend data distribution. This Hindi language used a high user rate of 29.1%.

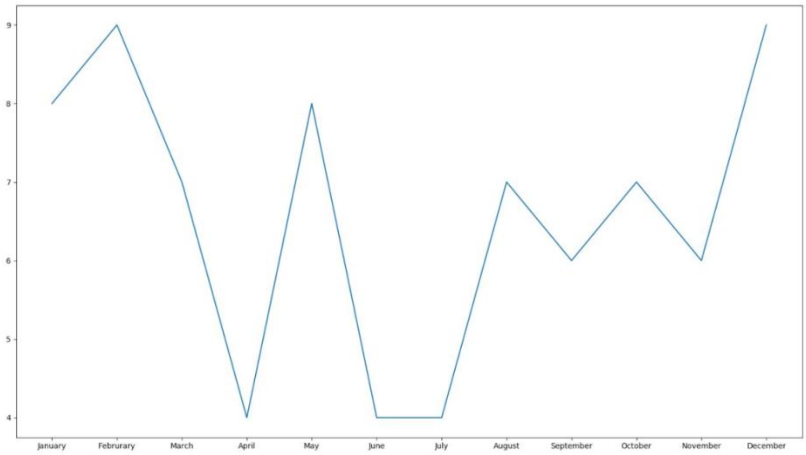

Figure 5 Time series graph of birthday of friends in months

Figure 5 show Time series graph of birthday of friends in months. This is a data output graph based friend's birthday month and rank.

The keys in the above dictionary are the months denoting the labels on x-axis.

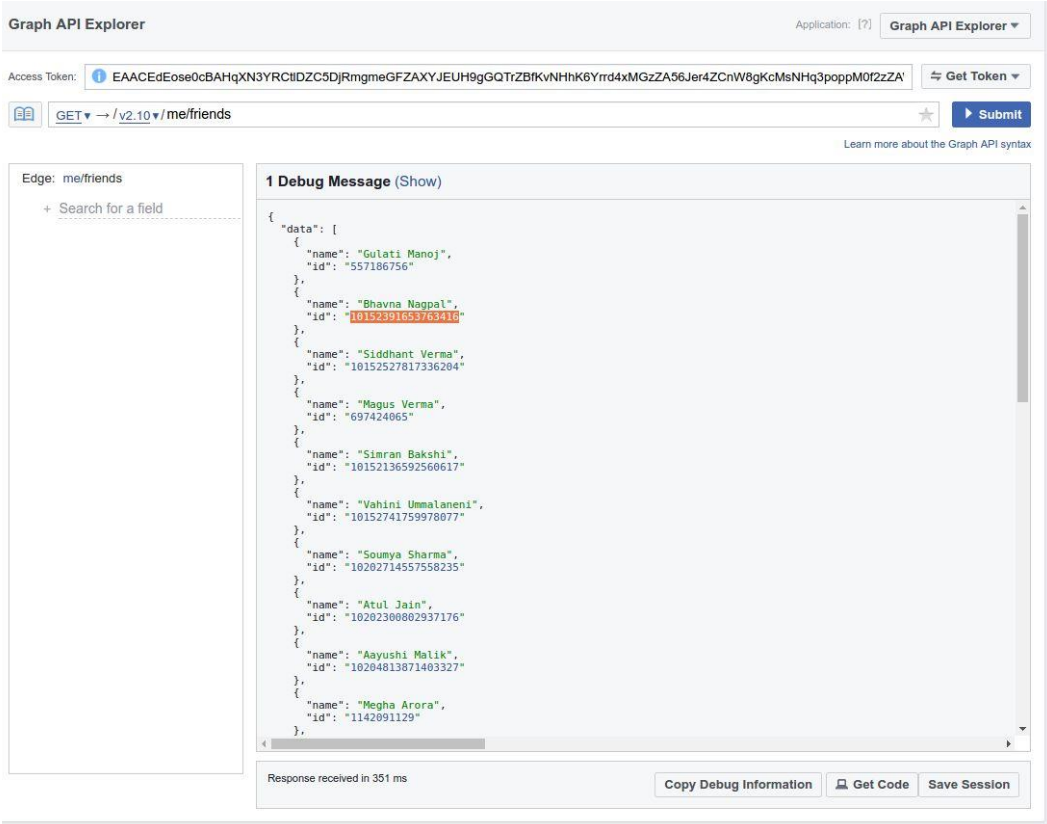

Figure 6 Collect data

Figure 6 show the Data collection framework. Yes, using the Graph API we can collect data of User B using token of User A. In the query, we just need to insert the ID of the user B for which we need to collect data and also the user B should have public access to the information we are extracting.

Suppose, I am the user A for which I have requested the friends I have using the query: 'me/friends' . Now I'll use the ID of a friend and change the query to get the information of the friends he/she has with query: 'user_ID/friends'

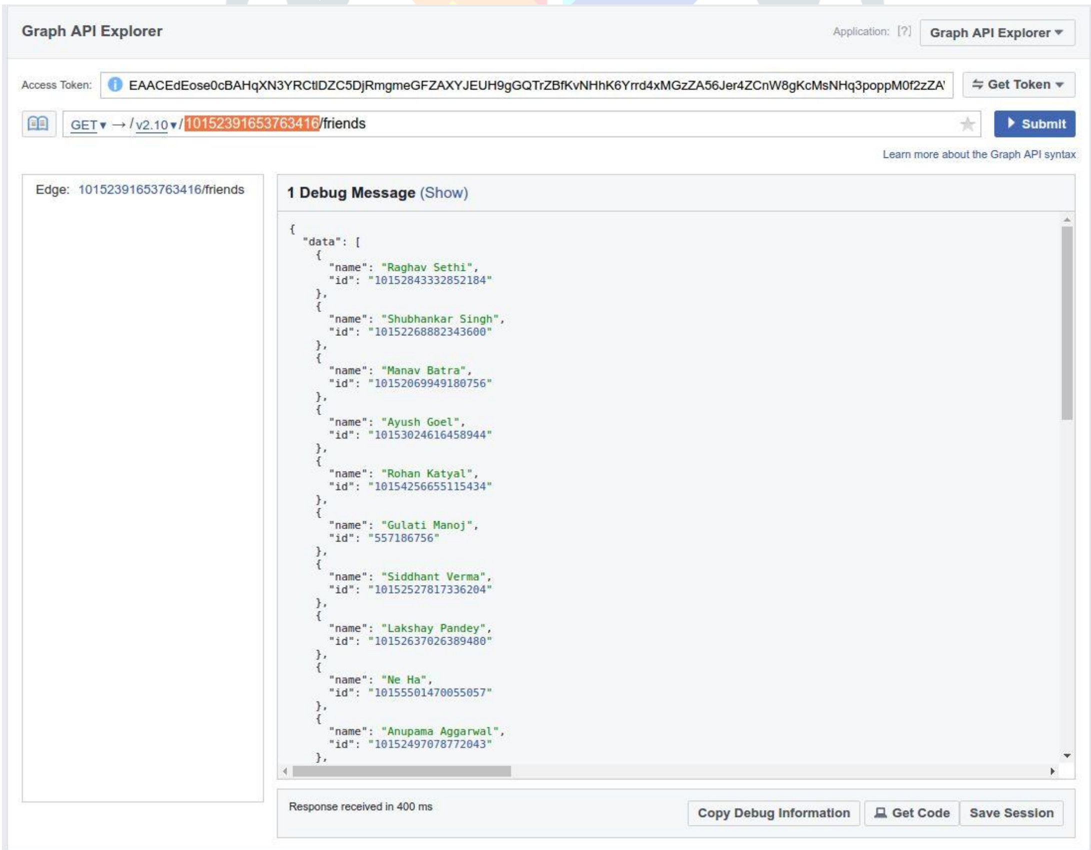

Figure 7 Collect data

Figure 7 show another data collection API framework. Here we have used the same token of user A (i.e. me) and got the information (which is here the friends a user has) for the user B. It can also be done/verified programmatically.

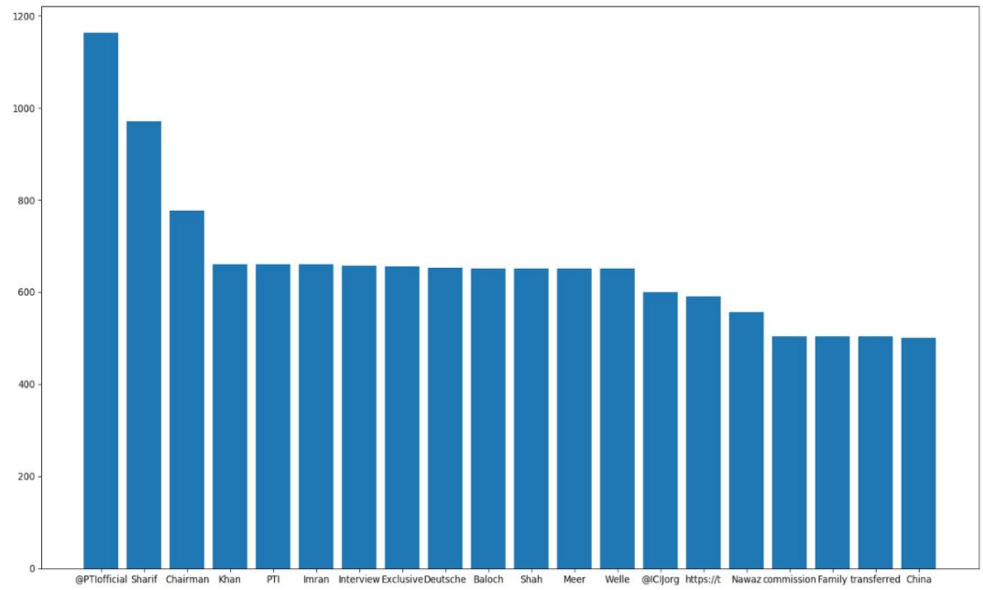

Figure 8 Histogram for Top-20 most frequent words in tweets

Figure 8 is a histogram that shows the top 20 most frequent words in tweets. A histogram is a graph that displays the distribution of a dataset by dividing it into intervals, or bins, and showing how many data points fall into each bin. In this case, the dataset is a collection of tweets, and the bins are the individual words that appear in those tweets.

The x-axis of the histogram shows the individual words, ranked in order from most to least frequent. The y-axis shows the frequency of each word, or how many times that word appears in the dataset of tweets. The bars on the histogram represent the number of tweets that contain each word, and the height of each bar corresponds to the frequency of that word in the dataset.

By looking at the histogram, you can see which words appear most frequently in the tweets. This information can be useful for understanding the topics and themes that are being discussed on social media, as well as for analyzing patterns of language use and sentiment.

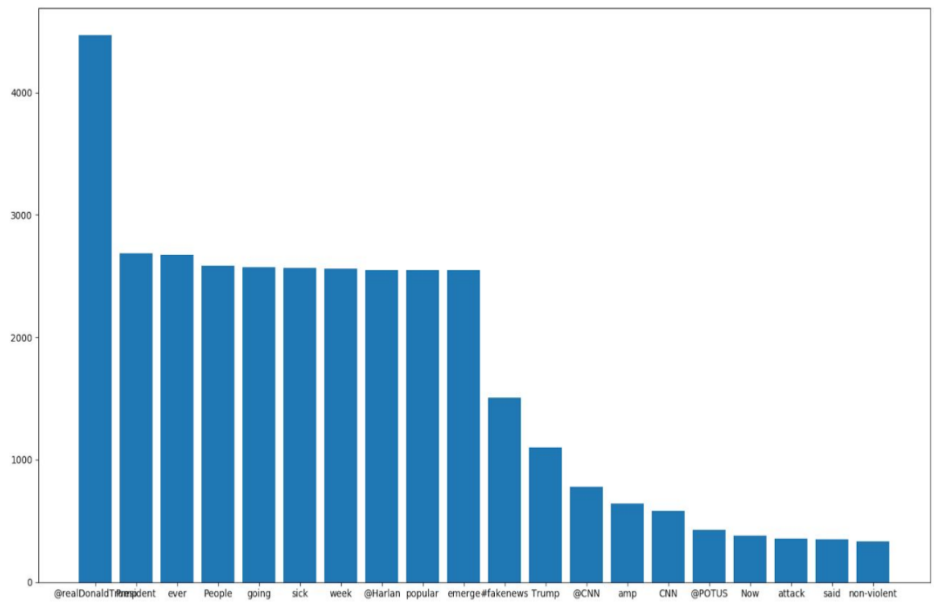

Figure 9 Fake News Analysis tweets Data

Figure 9 is a histogram that represents the frequency distribution of words in a dataset of tweets related to fake news analysis. The horizontal axis shows the frequency of occurrence of each word, while the vertical axis represents the number of words that fall into each frequency range.

The histogram is divided into several bars, with each bar representing a range of frequencies. For example, the first bar on the left represents words that occurred only once in the dataset, while the second bar represents words that occurred between 2 and 5 times. The histogram shows that there are a few words that occur very frequently, with a high frequency range of around 50-60. These words may be keywords or commonly used terms in discussions related to fake news analysis.

The histogram also shows a large number of words that occur only once or a few times, which indicates a diverse vocabulary used in tweets related to fake news analysis.

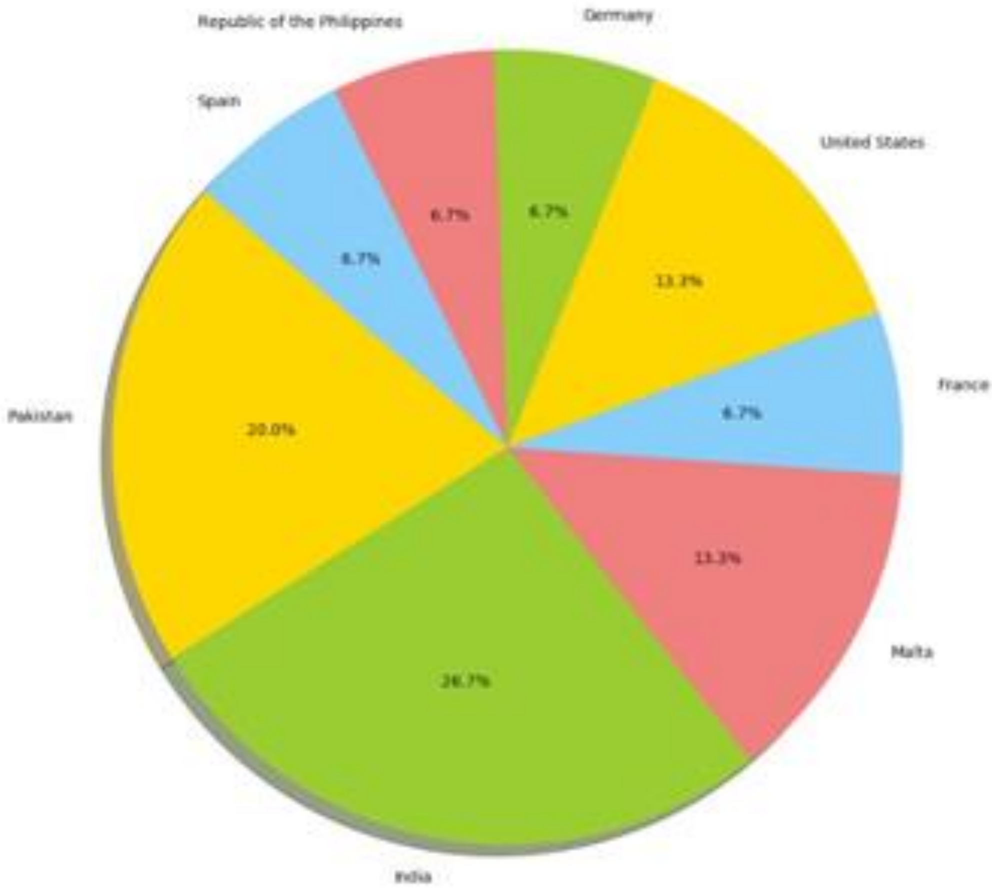

Figure 10 Pie Chart to analyze tweets from each country

Figure 10 is a pie chart that represents the proportion of tweets analyzed from each country in a particular dataset. The chart is divided into slices, with each slice representing a country. The size of each slice represents the proportion of tweets that were analyzed from that country. For example, if the chart shows slices for five countries, and the slice for the India is the largest, it means that the majority of tweets in the dataset were posted from the India. Similarly, if the slice for Pakistan is the second largest, it means that a significant portion of tweets were posted from Pakistan.

Pie charts are useful for visualizing the distribution of data among different categories or groups. In the case of Figure 5.8, the chart provides insight into the geographic distribution of the tweets analyzed in the dataset. This information can be useful for understanding the context and perspective of the tweets, and for identifying any patterns or trends that may be specific to certain countries or regions.

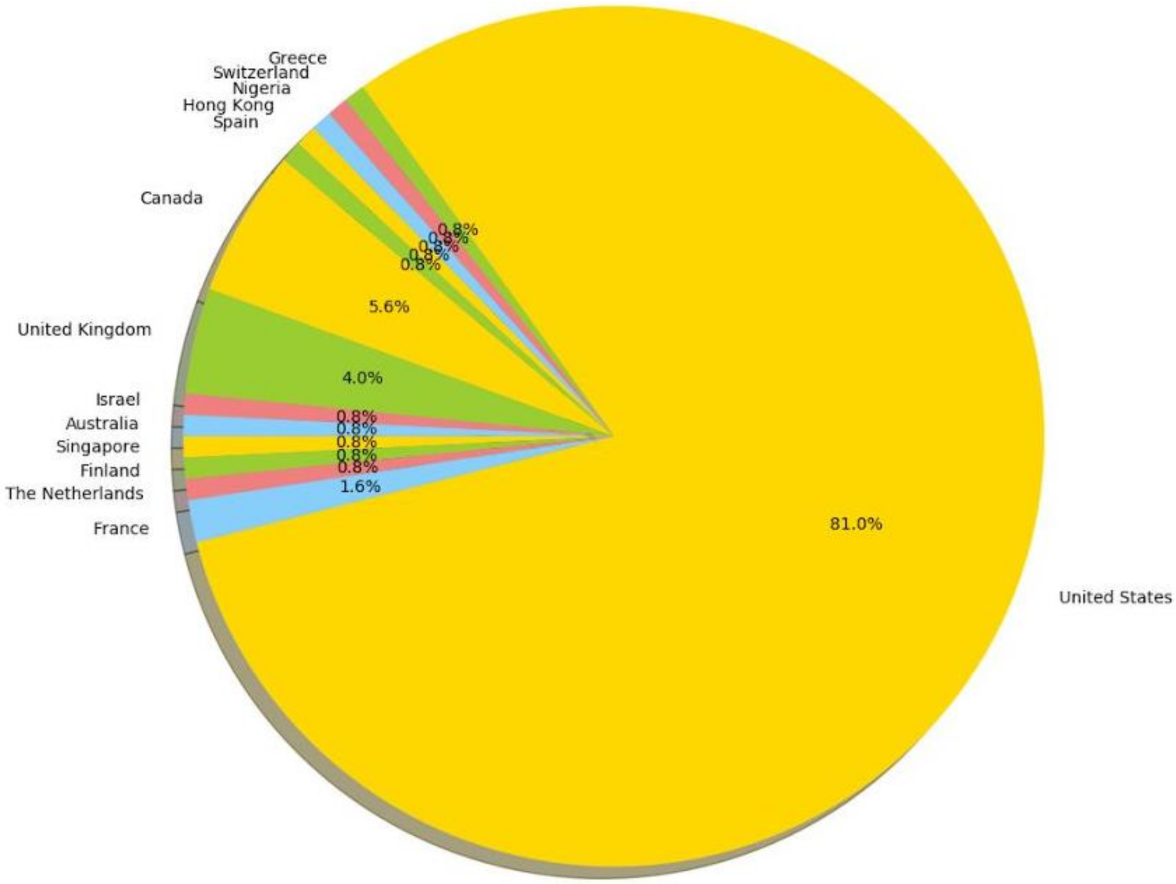

Figure 11 Pie Chart Fake News of tweet data

Figure 11 is a pie chart that represents the proportion of tweets analyzed from each country in a particular dataset. The chart is divided into slices, with each slice representing a country. The size of each slice represents the proportion of tweets that were analyzed from that country. In this chart United State is tweet fake news in twitter.

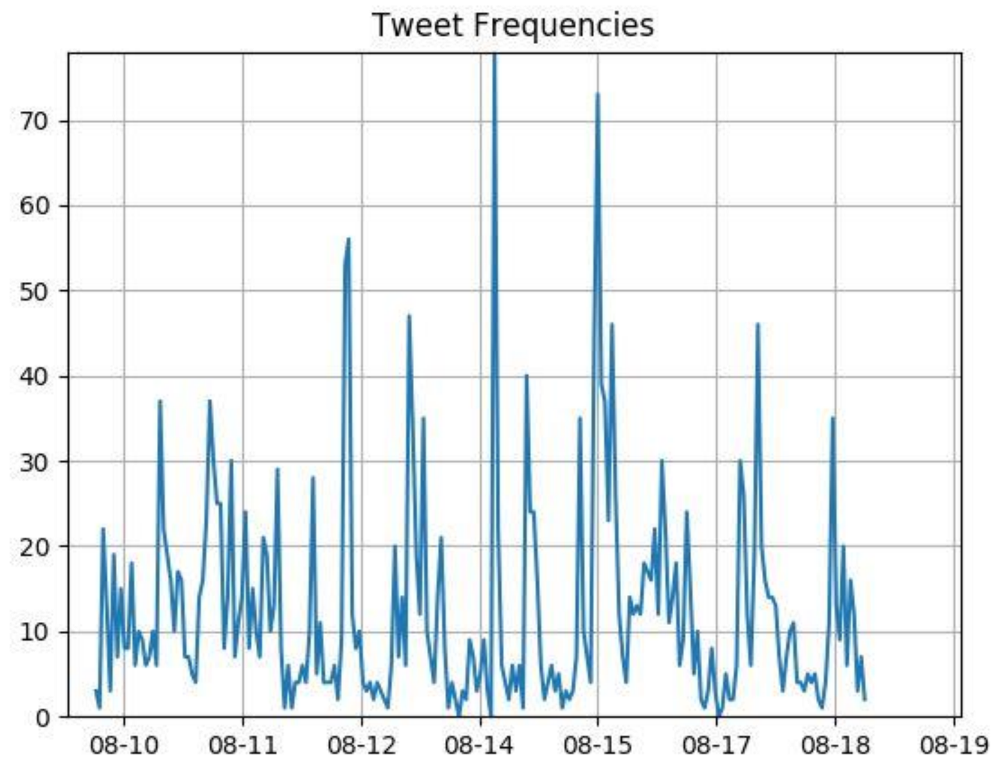

Figure 12 Tweet Frequency based on news

Figure 5.10 Show Tweet Frequency based on news for 10days tweet data.

X-axis: Time scale from 10/08/22 to 19/08/22 Y-axis: No. of tweets

IV. CONCLUSION

Person Relation to a Field (PRTF) algorithm outlined in this literature review and pseudo-code provides a framework for finding individuals related to a specific field based on their profile data, group data, communication data, and search field. The algorithm involves extracting features from profile data, processing the extracted features, comparing and matching with group data, incorporating communication data to refine the matching process, and identifying and ranking potential matches. In This paper, we used sentiment analysis of Facebook and Twitter data to check person data and according to activity decide the रैंक using machine learning and NLP method. This method mark rank according to the activity of the user.

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