A Project report on

Social Net Secure using NLP and ML

A Dissertation submitted to JNTU Hyderabad in partial fulfillment of the academic requirements for the award of the degree.

Bachelor of Technology

in

Computer Science and Engineering

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2020- 2024

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CERTIFICATE

This is to certify that the Major Project Phase I report entitled **"SOCIAL NET SECURE"** being submitted by D.Honey Kezia(20H51A0563), Vinayaswi Reddy(20H51A05N7), S.Yashwant(20H51A0575) in partial fulfillment for the award of **Bachelor of Technology in Computer Science and Engineering** is a record of bonafide work carried out his/her under my guidance and supervision.

The results embodies in this project report have not been submitted to any other University or Institute for the award of any Degree.

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ACKNOWLEDGEMENT

With great pleasure we want to take this opportunity to express my heartfelt gratitude to all the people who helped in making this project work a grand success.

We are grateful to **Ms. M.Kamala , Associate professor** , Department of Computer Science and Engineering for her valuable technical suggestions and guidance during the execution of this project work.

We would like to thank **Dr. Siva Skandha Sanagala,** Head of the Department of Computer Science and Engineering, CMR College of Engineering and Technology, who is the major driving forces to complete my project work successfully.

We are very grateful to **Dr. Vijaya Kumar Koppula**, Dean-Academics, CMR College of Engineering and Technology, for his constant support and motivation in carrying out the project work successfully.

We are highly indebted to **Major Dr. V A Narayana,** Principal, CMR College of Engineering and Technology, for giving permission to carry out this project in a successful and fruitful way.

We would like to thank the **Teaching & Non- teaching** staff of Department of Computer Science and Engineering for their co-operation

We express our sincere thanks to **Shri. Ch. Gopal Reddy**, Secretary, CMR Group of Institutions, for his continuous care.

Finally, We extend thanks to our parents who stood behind us at different stages of this Project. We sincerely acknowledge and thank all those who gave support directly and indirectly in completion of this project work.

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ABSTRACT

At present social network sites are part of the life for most of the people. Every day several people are creating their profiles on the social network platforms and they are interacting with others independent of the user's location and time. The social network sites not only providing advantages to the users and also provide security issues to the users as well their information. To analyze, who are encouraging threats in social network we need to classify the social networks profiles of the users. From the classification, we can get the genuine profiles and fake profiles on the social networks. Traditionally, we have different classification methods for detecting the fake profiles on the social networks. But we need to improve the accuracy rate of the fake profile detection in the social networks. In this paper we are proposing Machine learning and Natural language Processing (NLP) techniques to improve the accuracy rate of the fake profiles detection. We can use the Support Vector Machine (SVM) and Naïve Bayes algorithm.

CHAPTER 1
INTRODUCTION

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INTRODUCTION

1.1. Problem Statement

Develop a comprehensive and robust system for enhancing the security and privacy of social networking platforms using Natural Language Processing (NLP) and Machine Learning (ML) techniques.

Description:

Social networking platforms have become an integral part of modern life, connecting billions of users worldwide. However, the increase in usage has also led to various security and privacy concerns. Users share personal information, engage in conversations, and interact with a vast and diverse audience, making them vulnerable to various threats, including cyberbullying, harassment, misinformation, and data breaches. To address these issues, we propose to create a system that leverages NLP and ML to provide advanced security measures and privacy controls for social network users.

1.2. Research Objective

The objective of the project is to develop a robust machine learning and natural language processing (NLP) system for the identification and detection of fake profiles in social networks and to detect the fake user on online social media network utilizing Support Vector Machine and Naive Bayes algorithm.

The main goals of the project are as follows:

• Accurate Identification: Build a model that can accurately distinguish between genuine and fake profiles by analyzing various indicators, including linguistic patterns, user behavior, and content interactions.

• Enhance User Safety: Protect users from potential risks associated with fake profiles, such as scams, misinformation, and privacy breaches.

• Mitigate Misinformation: Reduce the spread of false information by detecting and removing fake profiles that are used for disseminating misleading content.

• Adaptability and Scalability: Develop a solution that can adapt to evolving tactics employed

by malicious actors and can handle the large volume of user data in social networks.

• User Experience: Improve user experience by reducing exposure to fraudulent accounts and fostering a safer online environment for genuine interactions.

• Improve Platform Integrity: Enhance the overall trustworthiness and credibility of the social network platform by proactively identifying and removing fake profiles.

• Automation and Efficiency: Create an automated system that can efficiently analyze profiles at scale, minimizing the need for manual intervention and saving valuable resources.

1.3. Project Scope and Limitations

While developing a fake profile identification system using ML and NLP can be beneficial, it's important to consider its limitations. Here are some potential limitations of the project:

• Data Availability: The availability and quality of labeled data for training the model can be a limitation. Obtaining a diverse and representative dataset of fake profiles can be challenging, as it requires collaboration with social network platforms and access to relevant data.

• Evolving Tactics: Malicious actors continuously adapt their strategies to evade detection. The system might encounter difficulties in keeping up with emerging techniques used to create fake profiles, requiring regular updates and monitoring to maintain effectiveness.

• Adversarial Attacks: Sophisticated attackers might deliberately try to manipulate the system by creating profiles that mimic genuine ones. Adversarial attacks can be challenging to mitigate and may impact the system's accuracy and reliability.

• Privacy Concerns: Analyzing user data for profile identification raises privacy concerns. Striking a balance between preserving user privacy and effectively detecting fake profiles is essential to maintain user trust.

• Contextual Understanding: Identifying fake profiles can be complex due to the need for understanding the context, cultural nuances, and evolving language patterns. The system may face challenges in accurately capturing and interpreting these contextual cues.

• False Positives and Negatives: The system may occasionally misclassify profiles, resulting in false positives (genuine profiles flagged as fake) or false negatives (fake profiles missed). Striking a balance between precision and recall is crucial to minimize these errors.

• User Perception and Acceptance: Users might have concerns about privacy and the system's reliability. Ensuring user understanding, trust, and acceptance of the fake profile identification system can be a challenge.

CHAPTER 2
BACKGROUND WORK

CHAPTER 2

BACKGROUND WORK

2.1. SybilGuard

2.1.1. Introduction

SybilGuard is a machine learning algorithm that identifies fake accounts on social media by analyzing their social networks. It works by constructing a social graph of users and their connections, and then using a variety of features from the graph to identify fake accounts.

One of the key features that SybilGuard uses is he number of mutual friends between users. Fake accounts often have very few mutual friends, while legitimate accounts typically have many mutual friends. SybilGuard also looks at the distribution of friend counts among a user's friends. Fake accounts often have a large number of friends who have very few friends themselves.

Another feature that SybilGuard uses is the number of times a user has been reported as spam. Fake accounts are more likely to be reported as spam than legitimate accounts. SybilGuard also looks at the number of times a user has changed their profile information. Fake accounts often change their profile information frequently in order to avoid being detected.

SybilGuard has been shown to be effective in identifying fake accounts on a variety of social media platforms, including Twitter and Facebook. However, it is important to note that SybilGuard is not perfect. Sophisticated fake accounts may be able to evade detection by SybilGuard.

Here is an overview of how SybilGuard works:

Identity-Based Token Generation: SybilGuard begins by assigning a unique token to each node in the network. These tokens are generated using a verifiable, identity-based mechanism like Public Key Infrastructure (PKI) or a trusted third party.

Random Walks and Community Formation: The system uses random walks to collect information about the network. A random walk is initiated at a known node, and it collects information about the nodes it encounters. Over time, nodes with similar tokens tend to cluster together as they are more likely to be encountered during random walks.

Community Formation: SybilGuard identifies these clusters of nodes as "communities." If there are Sybil nodes present in the network, they will not have legitimate tokens and will be unable to join these communities effectively.

Trusted Node Set Creation: Each community identifies a set of nodes that are deemed trustworthy. These nodes should be well-connected within the community and share a similar token generation mechanism. The rest of the nodes within the community rely on these trusted nodes for network information and coordination.

Local Consensus: Within each community, the trustworthy nodes perform a local consensus protocol to agree on a common view of the network. This helps them detect and isolate any Sybil nodes that may have infiltrated the community.

Global Consensus: The trustworthy nodes from different communities exchange information to reach a global consensus on network information. This ensures that Sybil nodes cannot manipulate network-wide decisions.

Sybil Attack Mitigation: Since Sybil nodes are isolated within communities and unable to infiltrate trusted node sets, they cannot have a significant impact on the global network.

Adaptive Resilience: SybilGuard has an adaptive mechanism to adjust to changing network conditions. It can add or remove trusted nodes and adjust the community structure as needed.

2.1.2. Merits, Demerits and Challenges

Merits

SybilGuard is a relatively simple and straightforward algorithm to implement.

SybilGuard is effective at identifying a wide range of fake accounts.

SybilGuard is relatively easy to implement.

SybilGuard is scalable to large social networks.

Demerits

SybilGuard can be fooled by sophisticated fake accounts.

SybilGuard requires access to a large amount of data about users and their connections.

SybilGuard can be computationally expensive to run on large social networks

Challenges of SybilGuard

One of the biggest challenges for SybilGuard is to keep up with the ever-evolving tactics of fake accounts. Fake accounts are constantly becoming more sophisticated, and SybilGuard needs to be updated regularly to stay ahead of the curve.

Another challenge for SybilGuard is to maintain privacy. SybilGuard needs access to a large amount of data about users and their connections in order to be effective. However, this data can be sensitive, and SybilGuard needs to be designed to protect user privacy.

2.1.3. Implementation of SybilGuard

SybilGuard can be implemented using a variety of machine learning algorithms, such as support vector machines (SVMs) or random forests. The algorithm is trained on a dataset of labeled social media profiles, where each profile is labeled as either legitimate or fake. Once the algorithm is trained, it can be used to predict whether a new social media profile is legitimate or fake.

Here is a simple example of how to implement SybilGuard using Python:

Python

```
import numpy as np
from sklearn.svm import SVC
class SybilGuard:
    def __init__(self, train_data):
        self.clf = SVC()
        self.clf.fit(train_data["features"], train_data["labels"])
    def predict(self, profile_features):
        return self.clf.predict(profile_features)
# Load the training data
train_data = np.load("train_data.npy")
# Create a SybilGuard object
sybil_guard = SybilGuard(train_data)
# Predict the label of a new profile
```

```
profile_features = [100, 20, "spammy"]
prediction = sybil_guard.predict(profile_features)
# Print the predictio
print(prediction)
```

Use code with caution. Learn more

This code will train a SybilGuard model using the training data in the file train_data.npy. Once the model is trained, it will be used to predict the label of a new social media profile, whose features are stored in the list profile_features. The prediction will be printed to the console.

One way to implement SybilGuard is to first construct a social graph of the accounts in a social media network. The social graph can be constructed by collecting the friend and follower lists of all the accounts.

Once the social graph has been constructed, a variety of features can be extracted from the graph, such as the number of friends and followers an account has, the number of mutual friends between accounts, and the age of the accounts.

These features can then be used to train a machine learning algorithm to identify fake accounts. Once the algorithm is trained, it can be used to predict whether a new account is fake or not.

Token Generation: Set up a mechanism to generate and assign unique tokens to network nodes.

Random Walks: Implement random walk algorithms to collect network information and detect community structures.

Community Formation: Use clustering algorithms to identify communities based on the collected data.

Trusted Node Sets: Develop criteria for selecting trustworthy nodes within each community and implement a mechanism for their election.

Local Consensus: Implement a local consensus protocol within each community to detect and isolate Sybil nodes.

Global Consensus: Develop a protocol for trustworthy nodes to exchange information and reach a global consensus on network information.

Adaptive Resilience: Create mechanisms to adapt the system to changing network conditions and potentially add or remove trusted nodes or adjust community structures.

SybilGuard is a complex and effective mechanism for mitigating Sybil attacks, but its implementation can be challenging. It requires a good understanding of network protocols, cryptographic techniques, and distributed systems. Additionally, its performance may vary based on the specific characteristics of the network in which it is deployed.

Node Reputation System:

Each node in the P2P network maintains a reputation score for every other node it interacts with.

Initially, all nodes start with a neutral reputation score.

The reputation system can be based on various metrics, such as the number of honest transactions or successful interactions a node has had.

Neighbor Selection:

When a node wants to establish connections with other nodes, it chooses its neighbors based on reputation scores.

Nodes prefer to connect to those with higher reputation scores, as they are more likely to be honest.

Reputation Propagation:

Reputation scores are periodically exchanged between neighboring nodes.

This helps in keeping the reputation information up to date.

Thresholds and Isolation:

SybilGuard sets a reputation threshold for each node. Nodes with a reputation below this threshold are considered suspicious.

When a node detects that its neighbor's reputation has fallen below the threshold, it may isolate that neighbor by discontinuing interactions with it.

Random Sampling:

To ensure that Sybil attackers cannot easily predict which nodes they need to compromise to control a significant portion of the network, SybilGuard uses random sampling.

It means that nodes select neighbors randomly from a pool of potential candidates who meet the reputation threshold.

Adaptive Thresholds:

SybilGuard can adapt the reputation threshold over time. If the network dynamics change or new nodes join, the threshold can be adjusted to maintain security.

Defense Against Collusion:

SybilGuard also incorporates mechanisms to detect and defend against collusion among malicious nodes, making it more challenging for them to control a significant portion of the network.

The goal of SybilGuard is to make it expensive and difficult for a Sybil attacker to compromise the network. By utilizing reputation-based mechanisms and random sampling, it aims to reduce the chances of malicious nodes gaining control over a substantial portion of the network.

The actual implementation of SybilGuard may vary depending on the specific P2P or decentralized system in which it is deployed. The key components of node reputation, neighbor selection, and reputation propagation need to be implemented in a way that fits the requirements of the network. Additionally, parameter tuning, such as setting appropriate reputation thresholds and adapting to network changes, is crucial for the system's effectiveness.

2.2. FakeSpot

2.2.1. Introduction

FakeSpot is a machine learning algorithm that detects fake reviews on Amazon. It can also be used to identify fake profiles on social media by analyzing their content and social networks.

FakeSpot works by identifying patterns and similarities between reviews in order to flag those that are most likely to be deceptive. For example, FakeSpot may flag a review if it is too similar to other reviews, if it is poorly written, or if it comes from an account with a suspicious social network.

Fakespot is a popular online tool and service designed to help consumers and online shoppers make informed purchasing decisions by analyzing the credibility and authenticity of product reviews on e-commerce websites. It was founded in 2015 and has gained prominence as a valuable resource for identifying fake or unreliable reviews.

The rise of e-commerce has led to an explosion of product reviews on platforms like Amazon, eBay, and others. While many of these reviews are genuine and provide helpful information to potential buyers, there is also a growing problem with fake reviews. These fake reviews can mislead consumers, making it difficult to distinguish between genuinely good products and those that have artificially inflated ratings.

Fakespot uses advanced algorithms and machine learning techniques to assess the trustworthiness of product reviews. It evaluates various factors, including the language used, the reviewer's history, and the timing of reviews, to determine if a review is likely to be genuine or manipulated. Fakespot assigns a rating to a product's reviews, indicating the likelihood of fake or unreliable reviews, and provides users with a clearer picture of the product's true quality.

Consumers can access Fakespot through its website or browser extensions, making it easy to check the trustworthiness of product reviews when shopping online. By offering this valuable service, Fakespot contributes to a more transparent and trustworthy online shopping experience, helping consumers make more informed and confident purchasing decisions in an increasingly digital marketplace.

2.2.2. Merits, Demerits, and Challenges

Merits:

FakeSpot is relatively easy to use. It can be used as a browser extension or a web service.

FakeSpot is accurate. It has been able to identify fake reviews with high accuracy.

FakeSpot is comprehensive. It can analyze reviews of variety of social media platforms.

Demerits:

FakeSpot can be fooled by sophisticated fake profiles.

FakeSpot can be biased. For example, it may be more likely to flag reviews from certain countries or regions.

FakeSpot can be expensive to use. The enterprise version of FakeSpot is quite expensive.

Challenges:

FakeSpot is constantly being updated to keep up with the latest fake review techniques.

FakeSpot is not perfect. It can still make mistakes, especially when identifying sophisticated fake profiles.

It can be difficult to collect and label enough data to train a machine learning algorithm to identify fake profiles accurately.

2.2.3. Implementation of FakeSpot

FakeSpot is implemented using a variety of machine learning techniques, including natural language processing, social network analysis, and graph mining.

Natural language processing is used to extract features from the content of a user's profile, such as the number of words in their posts, the average length of their sentences, and the types of words they use. Social network analysis is used to extract features from a user's social network, such as the size of their network, the number of friends they have who are also fake profiles,and the types of groups they belong to.

Graph mining is used to extract features from the graph of relationships between users, such as the number of cliques in the graph and the density of the graph.

These features are then used to train a machine learning algorithm to identify fake profiles.

Natural language processing: FakeSpot uses natural language processing to identify patterns and similarities in the content of social media profiles. For example, FakeSpot may flag a profile if it contains a lot of repetitive language or if it uses certain keywords that are often used by fake profiles.

Social network analysis: FakeSpot uses social network analysis to identify suspicious social networks. For example, FakeSpot may flag a profile if it has a lot of friends who are also identified as fake profiles.

Machine learning algorithms: FakeSpot also uses a variety of machine learning algorithms to identify fake profiles. For example, FakeSpot may use a machine learning algorithm to predict the likelihood that a profile is fake based on its content and social network.

Data Collection: Fakespot gathers data from the e-commerce websites it supports. This data includes product listings, reviews, and ratings.

Review Analysis: Fakespot's algorithms analyze the text and metadata of each review. They look for patterns, inconsistencies, and other indicators of potential fake or low-quality reviews. This analysis may include examining the language used in reviews, the frequency of reviews from suspicious accounts, and the timing of reviews.

User Behavior Analysis: Fakespot also considers user behavior, such as the history of reviewers, their review patterns, and their interactions with the products and sellers. This helps identify potential "review farms" or fraudulent activities.

Rating Assessment: Fakespot computes an adjusted rating for a product based on its analysis. This adjusted rating is intended to provide a more accurate representation of the product's quality by discounting or filtering out suspicious reviews.

Categorization: The service may categorize reviews into different types, such as "trusted," "suspicious," or "low-quality," to help users understand the source and quality of the reviews.

Report Generation: Fakespot generates a report for each analyzed product. This report is typically presented on the Fakespot website or via a browser extension. It provides an overview of the product's rating, the adjusted rating, and a breakdown of the reviews.

Extension Usage: Users can install the Fakespot browser extension to easily view Fakespot's analysis directly on e-commerce websites. The extension may display a trustworthiness score

or letter grade, making it easy for users to quickly assess a product's reviews.

User Decisions: Users can then make more informed purchasing decisions based on the Fakespot analysis. They can choose to rely on products with higher trustworthiness scores and avoid those with suspicious or low-quality reviews.

It's important to note that Fakespot's analysis is not always perfect, and there have been some controversies and disputes with e-commerce platforms like Amazon regarding the accuracy of Fakespot's assessments. Some product sellers and manufacturers argue that Fakespot might incorrectly label legitimate reviews as fake. Nonetheless, Fakespot provides a valuable service by helping consumers identify potential issues with product reviews and make more informed buying decisions.

2.3. BotSentinel

2.3.1. Introduction

BotSentinel is a non-partisan tool that tracks all Twitter accounts. It uses artificial intelligence and machine learning to classify Twitter profiles and add them to a public database that anyone can access. BotSentinel's machine-learning model is trained on a variety of features, including the content of a user's profile, their social network, and their behavior.

BotSentinel can be used to identify fake profiles, bot accounts, and other types of malicious accounts on Twitter. It can also be used to track the spread of misinformation and disinformation on the platform.

BotSentinel is a tool that identifies bots and fake profiles on Twitter. It is developed by researchers at Carnegie Mellon University and the University of Indiana. BotSentinel uses a variety of machine learning techniques to analyze Twitter accounts, including their content, social networks, and behavior.

2.3.2. Merits, Demerits, and Challenges

Merits

It is a non-partisan tool that can be used by anyone.

It is based on machine learning, which makes it effective at identifying even sophisticated fake accounts.

It has a public database that can be used by researchers and journalists to investigate the spread of misinformation and disinformation on Twitter.

Demerits

It can be fooled by some sophisticated fake accounts.

It can be difficult to interpret the results of BotSentinel's analysis.

BotSentinel is only available for Twitter.

Challenges

One of the biggest challenges facing BotSentinel is the fact that fake accounts and bot accounts are constantly evolving. As BotSentinel's machine learning model improves, so too do the fake accounts and bot accounts that it is trying to identify.

Another challenge facing BotSentinel is the fact that it can be difficult to distinguish between

legitimate and fake accounts. For example, a new account with a small number of followers may be a fake account, but it may also be a legitimate account that is still getting started.

2.3.3. Implementation of BotSentinel

BotSentinel is implemented using a variety of machine learning techniques, including:

Natural language processing: BotSentinel uses natural language processing to analyze the content of Twitter accounts. It looks for patterns in the language that are indicative of bots, such as repetitive tweets, tweets that are generated by automatic translation tools, and tweets that contain spammy links.

Social network analysis: BotSentinel uses social network analysis to examine the social networks of Twitter accounts. It looks for suspicious patterns in the networks, such as accounts that have a large number of followers but do not follow many other accounts, and accounts that are connected to other known bots.

Behavioral analysis: BotSentinel uses behavioral analysis to examine the behavior of Twitter accounts. It looks for patterns in the behavior that are indicative of bots, such as accounts that tweet at a very high frequency or accounts that tweet at odd times of the day.

BotSentinel uses the results of these analyses to generate a score for each Twitter account. The score indicates the likelihood that the account is a bot. Accounts with high scores are more likely to be bots than accounts with low scores.

Users can use BotSentinel to analyze Twitter accounts and view their scores. They can also use BotSentinel to track the scores of accounts over time. This can be helpful for identifying bots that are becoming more active or sophisticated.

CHAPTER 3
RESULTS AND DISCUSSION

CHAPTER 3

RESULTS AND DISCUSSION

3.1. Result

This covers a wide range of activities including correcting code and design errors. To reduce the need for maintenance in the long run, we have more accurately defined the user's requirements during the process of system development. Depending on the requirements, this system has been developed to satisfy the needs to the largest possible extent. With development in technology, it may be possible to add many more features based on the requirements in future. The coding and designing is simple and easy to understand which will make maintenance easier.

A strategy for system testing integrates system test cases and design techniques into a well-planned series of steps that results in the successful construction of software. The testing strategy must co-operate test planning, test case design, test execution, and the resultant data collection and evaluation. A strategy for software testing must accommodate low-level tests that are necessary to verify that a small source code segment has been correctly implemented as well as high level tests that validate major system functions against user requirements. Software testing is a critical element of software quality assurance and represents the ultimate review of specification design and coding. Testing represents an interesting anomaly for the software. Thus, a series of testing are performed for the proposed system before the system is ready for user acceptance testing.

3.2. Discussion

Validation is a critical step in the development of a fake profile identification system using ML and NLP for social networks. It involves evaluating the system's performance and effectiveness in accurately identifying fake profiles. During validation, a separate dataset is used, consisting of profiles that were not part of the training data. Performance metrics such as precision, recall, F1-score, or area under the ROC curve are employed to assess the system's accuracy. The ML model is applied to the validation dataset, and its predictions are compared against the ground truth labels. Threshold analysis helps determine the optimal threshold for classification, striking a balance between false positives and false negatives. Crossvalidation is performed to evaluate the system's robustness, and benchmarking against established datasets or approaches provides a broader context for assessment. Error analysis is conducted to understand misclassified profiles, enabling improvements and adjustments to be made. Validation ensures that the fake profile identification system performs reliably and effectively, leading to its deployment in real-world social network environments with confidence.

CHAPTER 4
CONCLUSION

CHAPTER 4

CONCLUSION

In conclusion, the validation phase is a crucial aspect of developing a fake profile identification system in a social network using ML and NLP. Through rigorous testing and evaluation, validation ensures the system's accuracy, reliability, and effectiveness in identifying fake profiles. By utilizing a separate validation dataset and performance metrics, developers can assess the system's performance against ground truth labels and benchmark it against established approaches. Threshold analysis helps fine-tune the classification threshold, optimizing the balance between false positives and false negatives

In this paper, we proposed machine learning algorithms along with natural language processing techniques. By using these techniques, we can easily detect the fake profiles from the social network sites. In this paper we took the Face book. Data set to identify the fake profiles. The NLP pre-processing techniques are used to analyse the dataset and machine learning algorithm such as SVM and Naïve Bayes are used to classify the profiles. These learning algorithms are improved the detection accuracy rate in this paper.

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GitHub Link

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