Detection Of Bot Accounts On Social Networks Using Big Data Mining Tools

U17CO002 Kaneesha Gandhi
U17CO023 Harshit Sodagar
U17CO028 Devanshi Bhatia
U17CO074 Jay Rathod

Guided by:
Dr. Dipti P. Rana

Introduction

- ONLINE SOCIAL NETWORKS ARE UBIQUITOUS.
- ATTRACTIVE TARGETS FOR MALICIOUS ENTITIES.
- SOCIAL BOTS ARE CAPABLE OF DOING THINGS WE CANNOT IMAGINE.
- ALL THIS TELLS HOW IMPORTANT IT IS TO IDENTIFY THESE FAKE ACCOUNTS.

Objectives

- TO COLLECT AND PROCESS DATA FROM ONE OR MORE SOCIAL MEDIA PLATFORMS.
- TO IDENTIFY WHETHER A GIVEN ACCOUNT IS A BOT OR A LEGITIMATE USER.

Literature Review

Authors like Bilge[1] worked on preventing automated attacks such as profile cloning and cross-site profile cloning. These were one of the most common identity thefts.

Furthermore, authors like Jin[2], Kontaxis[3] and Mohammed Razaei[9] analyzed the extensive social network patterns of any given user and compared the similarities of an input identity to the user over various networks.

Literature Review

Claudia[6] and Ragusa[6] put forth a technique which utilized sampling of non-uniform features inside a machine learning algorithm by the adaptation of random forest algorithm to recognize spammer insiders.

Lastly, authors like Deniz[7] and Gharge, collected Twitter datasets and used them for the detection of spam accounts. Deniz utilized the machine learning approach of Naive Bayes learning algorithm, before and after discretization of data. Gharge initiated a method, which was classified on the basis of two new features.

Proposed Framework

INTRODUCTION

- GOAL IS BINARY CLASSIFICATION : BOT OR LEGITIMATE.

- ALGORITHMS TO ANALYZE : DECISION TREE, NAIVE BAYES CLASSIFYING ALGORITHM, RANDOM FOREST,XG BOOST AND A HYBRID CLASSIFIER. THIS IS DONE WITH THE HELP OF TRAINING DATASET CONTAINING VARIOUS FEATURES.

- JACCARD SIMILARITY MODEL USING RECENT TWEETS OF THE USER.

- COMBINING BOTH THE MODELS FOR FINAL RESULT.

Bot
Detection

Flowcharts

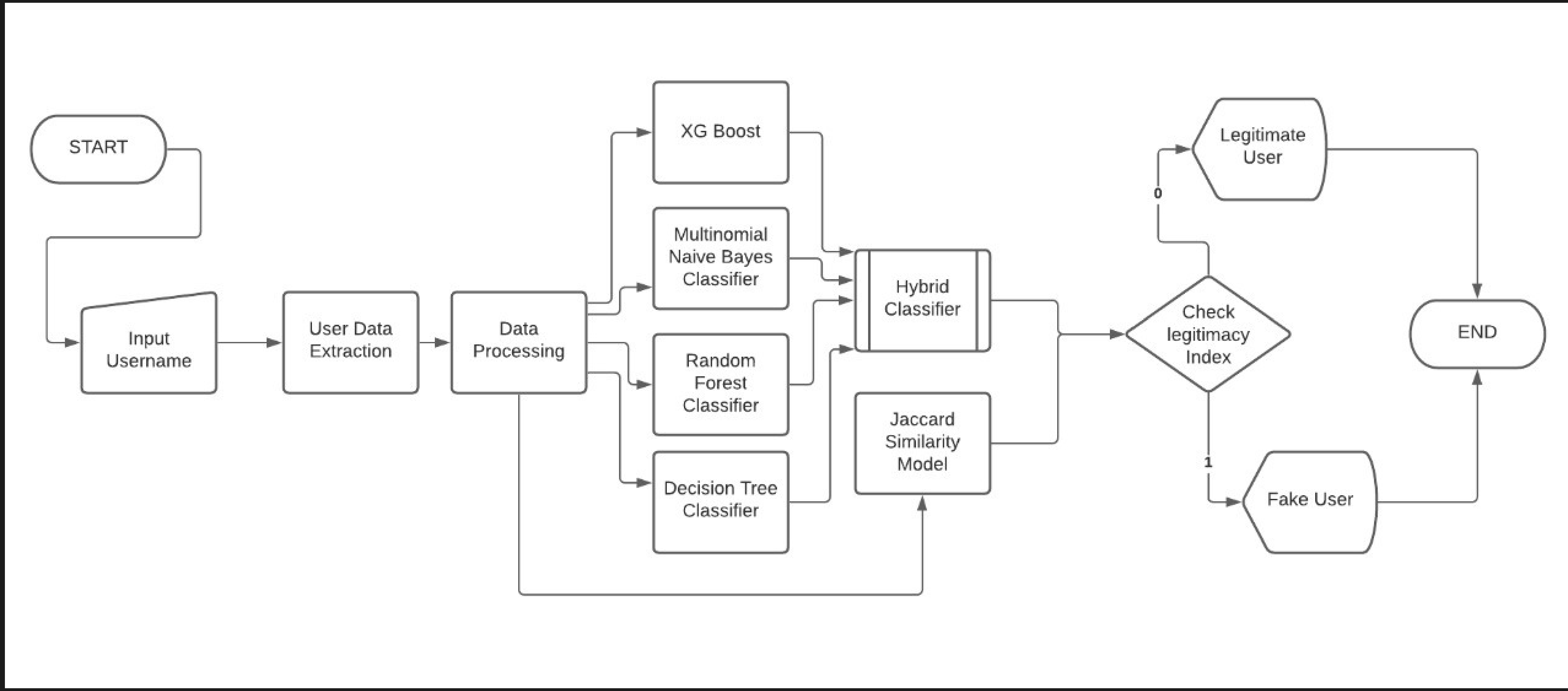

FIGURE 1: CLASSIFYING USER ACCOUNTS AS FAKE OR LEGITIMATE

Bot Detection

Data Collection

Data.csv

id	id_str	screen_na	location	descriptior	url	followers_	friends_co	listed_cou	created_at	favourites_	verified	statuses_c	lang	status	default_pr	default_pr	has_exten	name	bot
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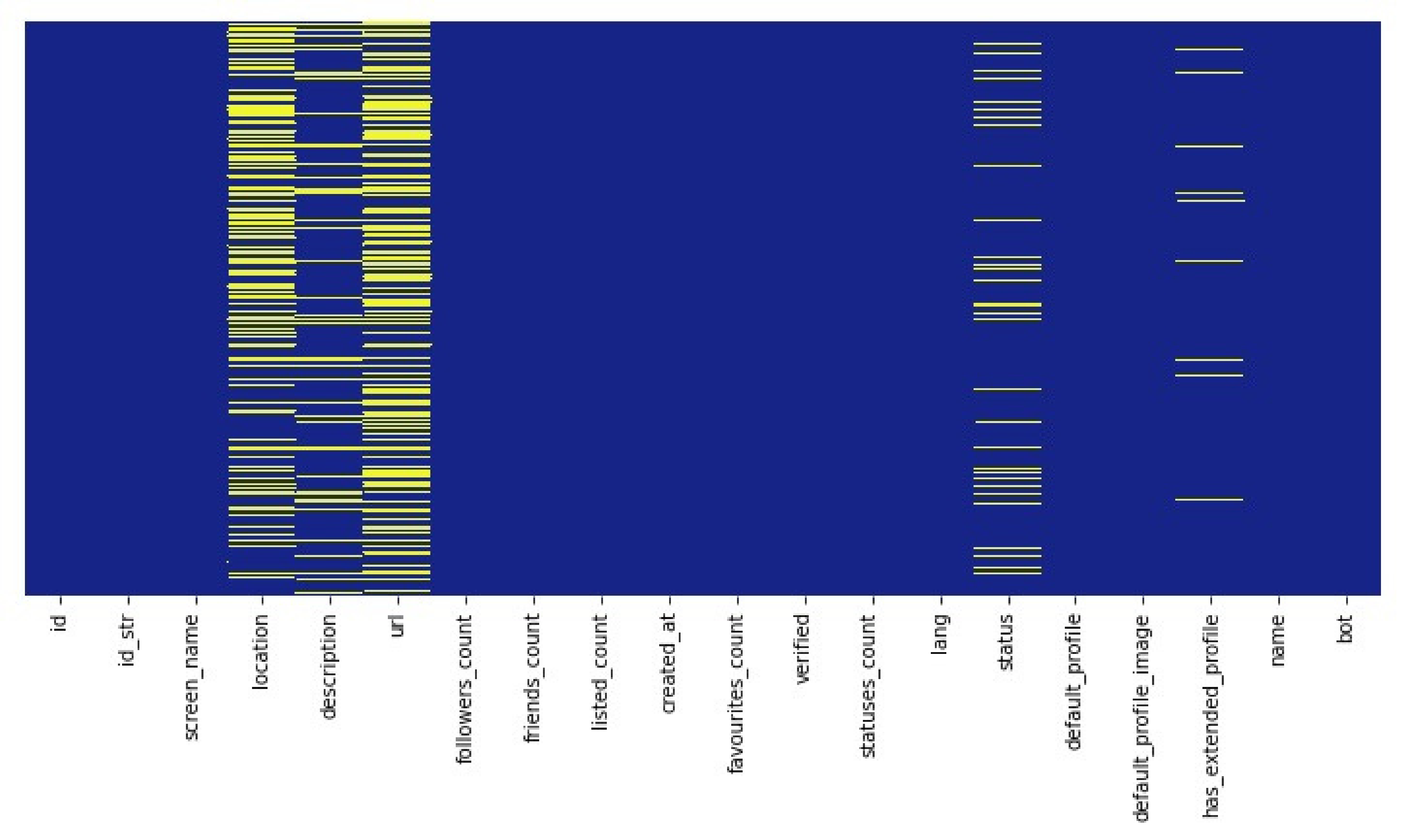
Data Preprocessing

Technologies used:

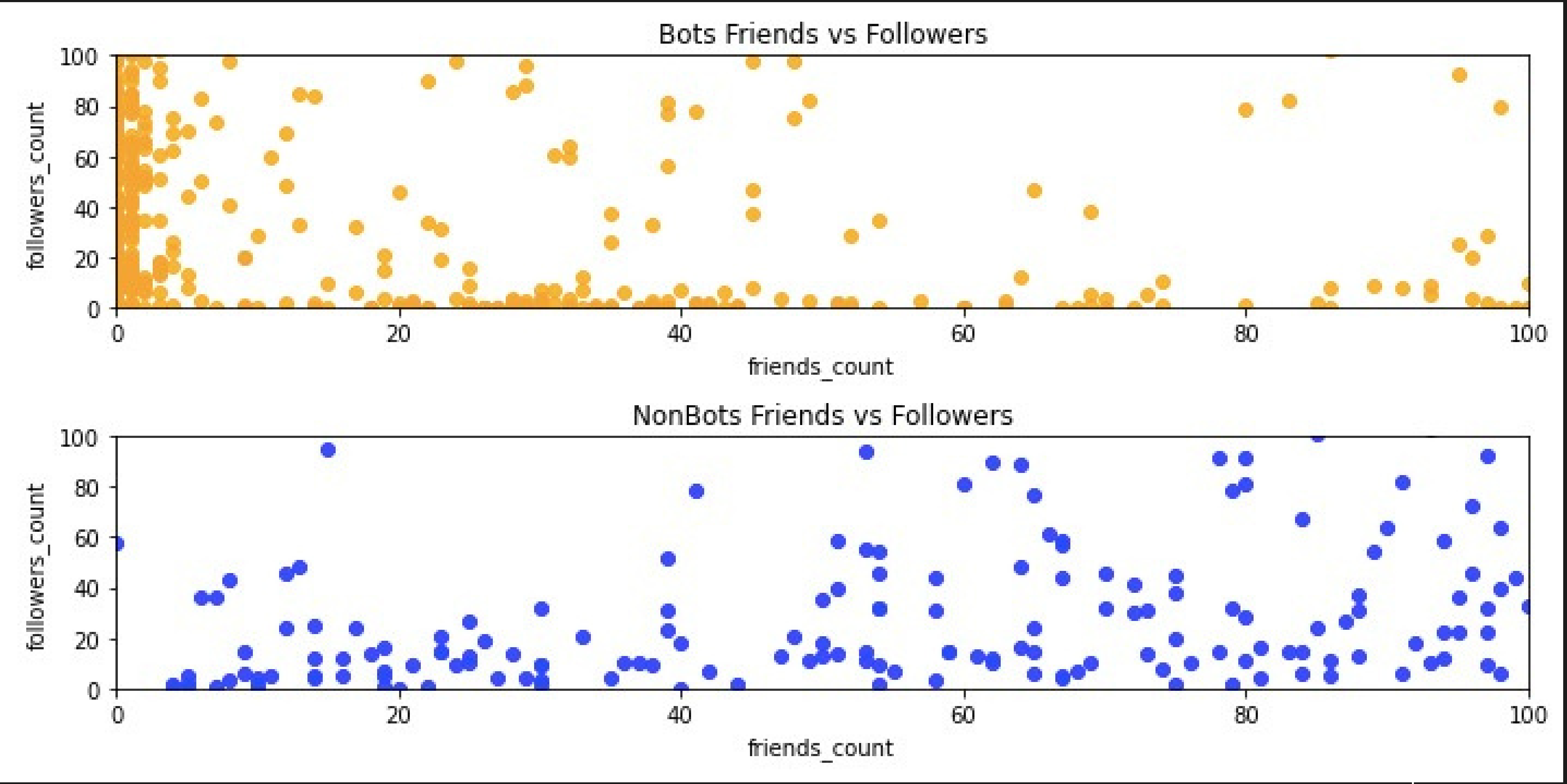
-Twitter API
-Tweepy library
-get_user() method
-Anaconda
-Jupyter Notebook
-Python3 Libraries

Algorithm :

- Identifying missing values and imbalance in data.
- Feature extraction
- Feature engineering
- Discarding unwanted attributes



Heatmap of training data


Bots Friends vs Followers
followers_count
friends_count
0
20
40
60
80
100
NonBots Friends vs Followers
followers_count
friends_count
0
20
40
60
80
100

Features used for training the machine learning model :

- Screen name
- Name
- Description
- Status
- Verified
- Followers_count
- Friends_count
- Statuses_count
- Listed_Count

Cleaning of Data

Attributes containing strings and tweets extracted from the user accounts needed to be cleaned.

Steps performed for cleaning -

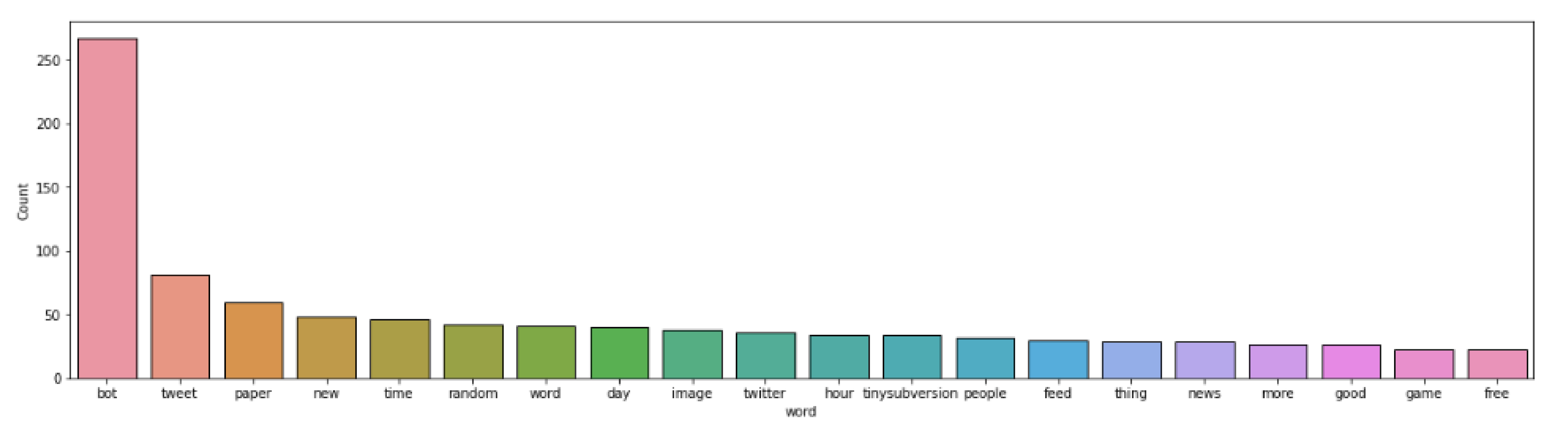
- Removing links, @mentions and two & less letter words
- Lemmatization
- Tokenization
- Stop word removal
- Conversion to lowercase

Atributes like status, name, screen name and description were converted into binary attributes.

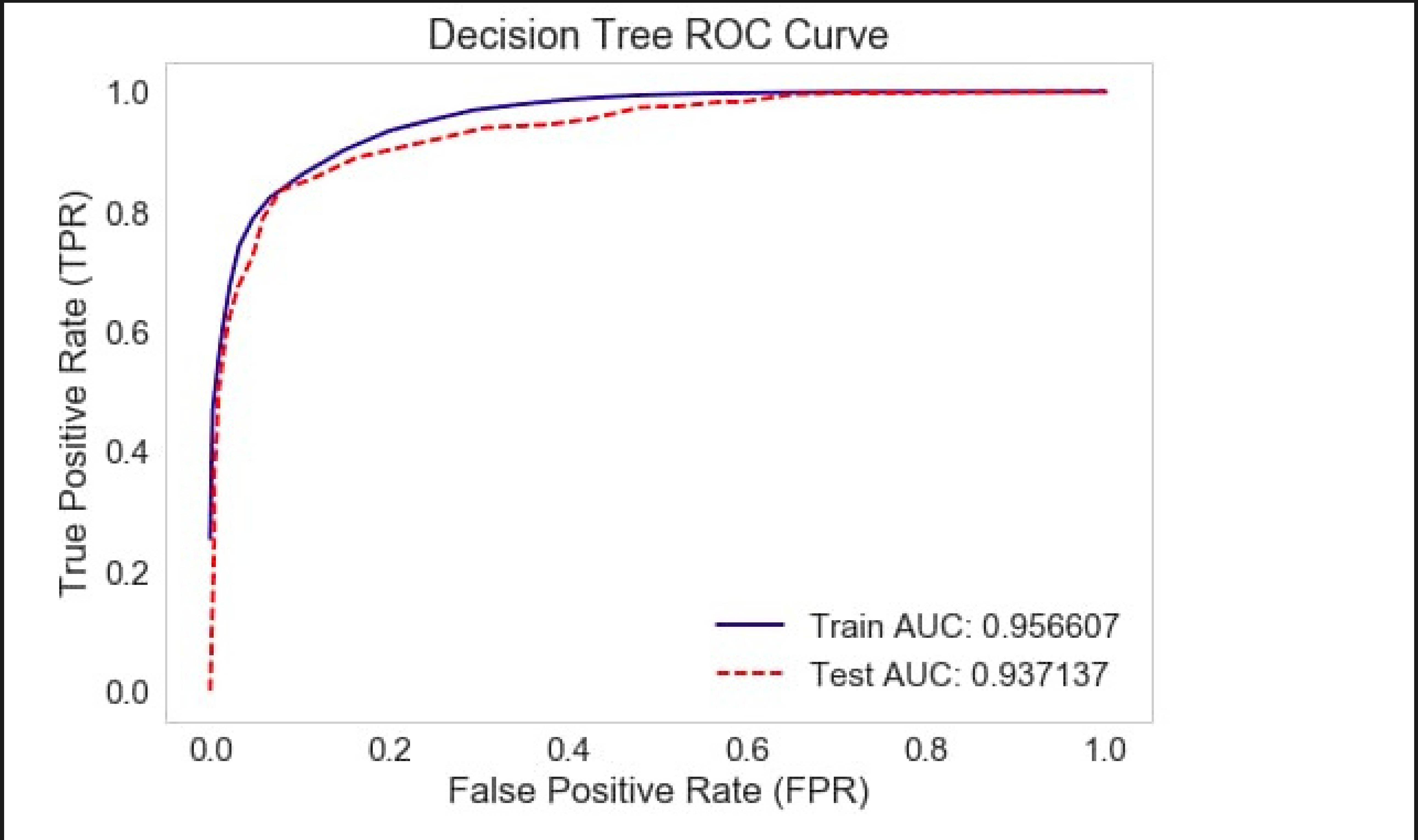
For this a bag of words was created using 50 most frequent words from each attribute.

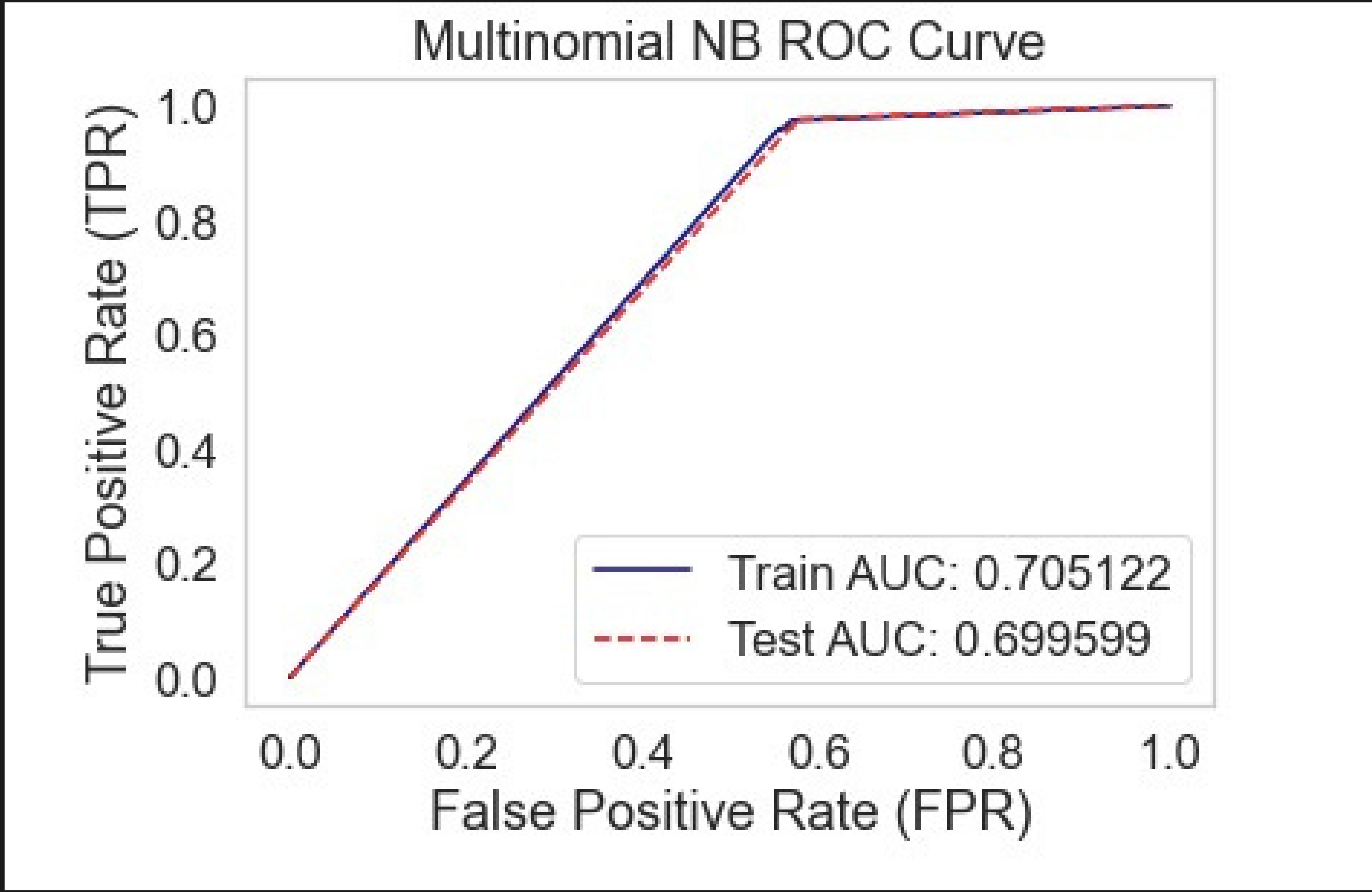
If the given attributes contained words from the bag of words, they were labelled as 1 otherwise 0.

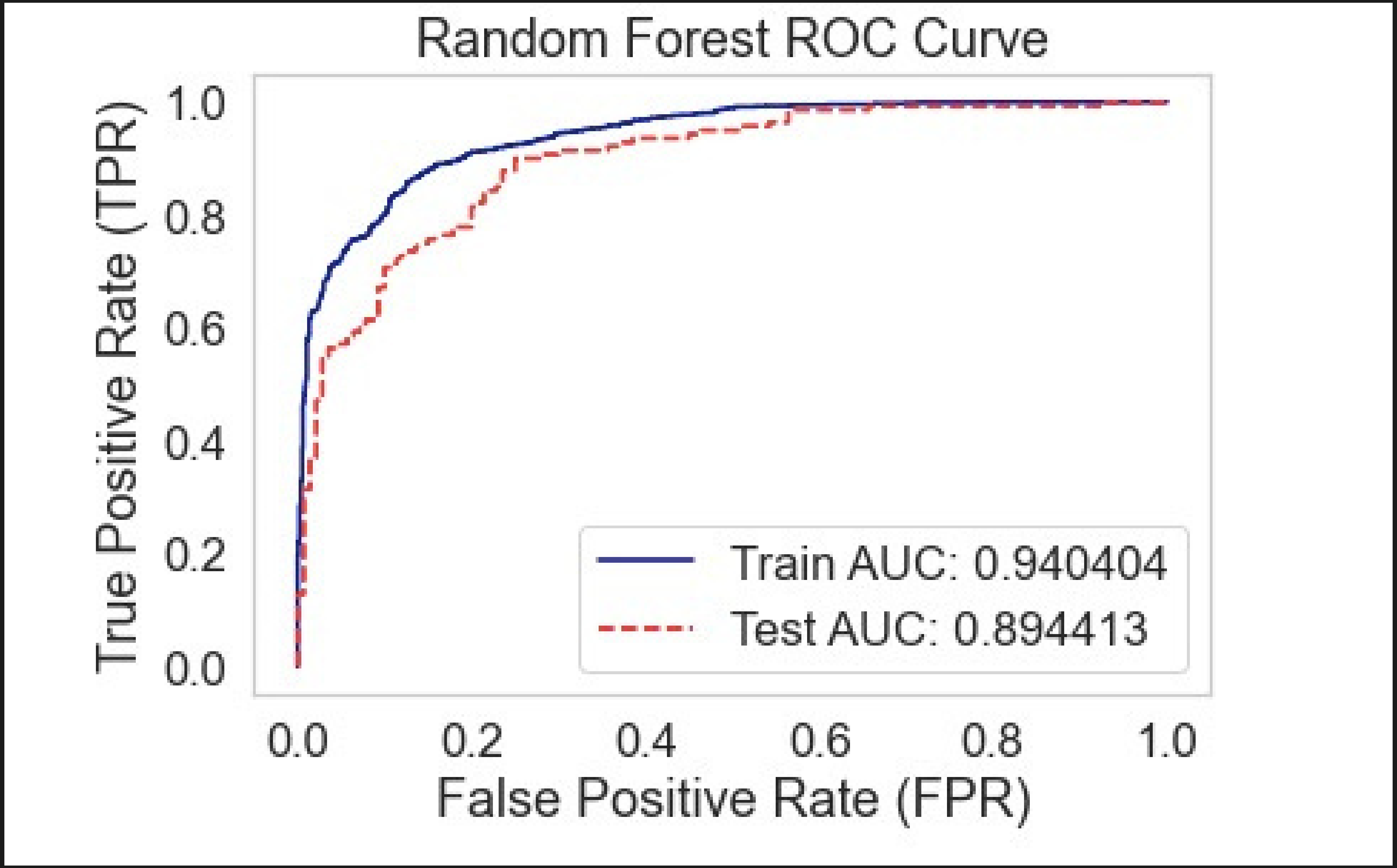
The below figure contains the 20 most frequent words found in description of bot accounts from the training dataset.

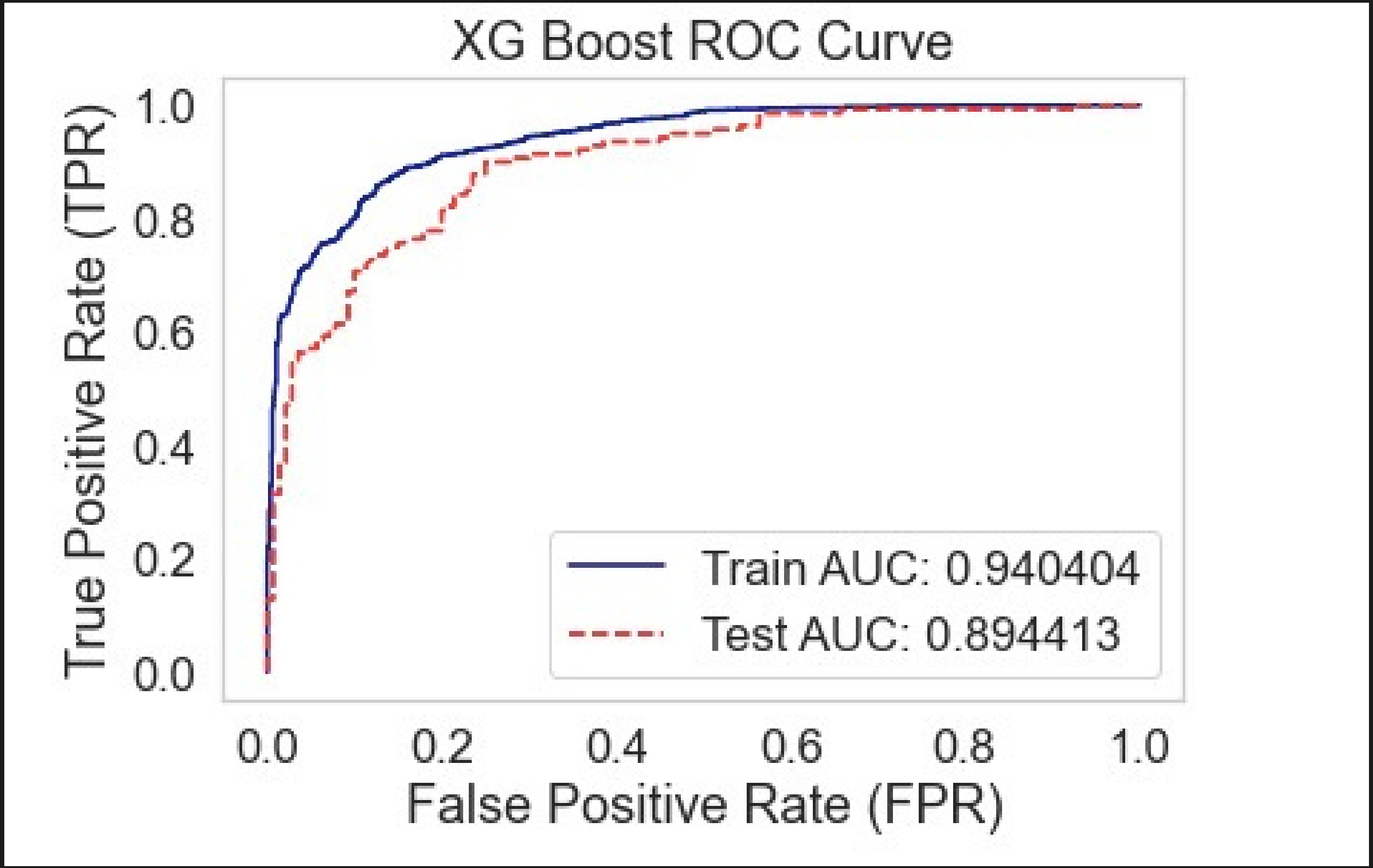


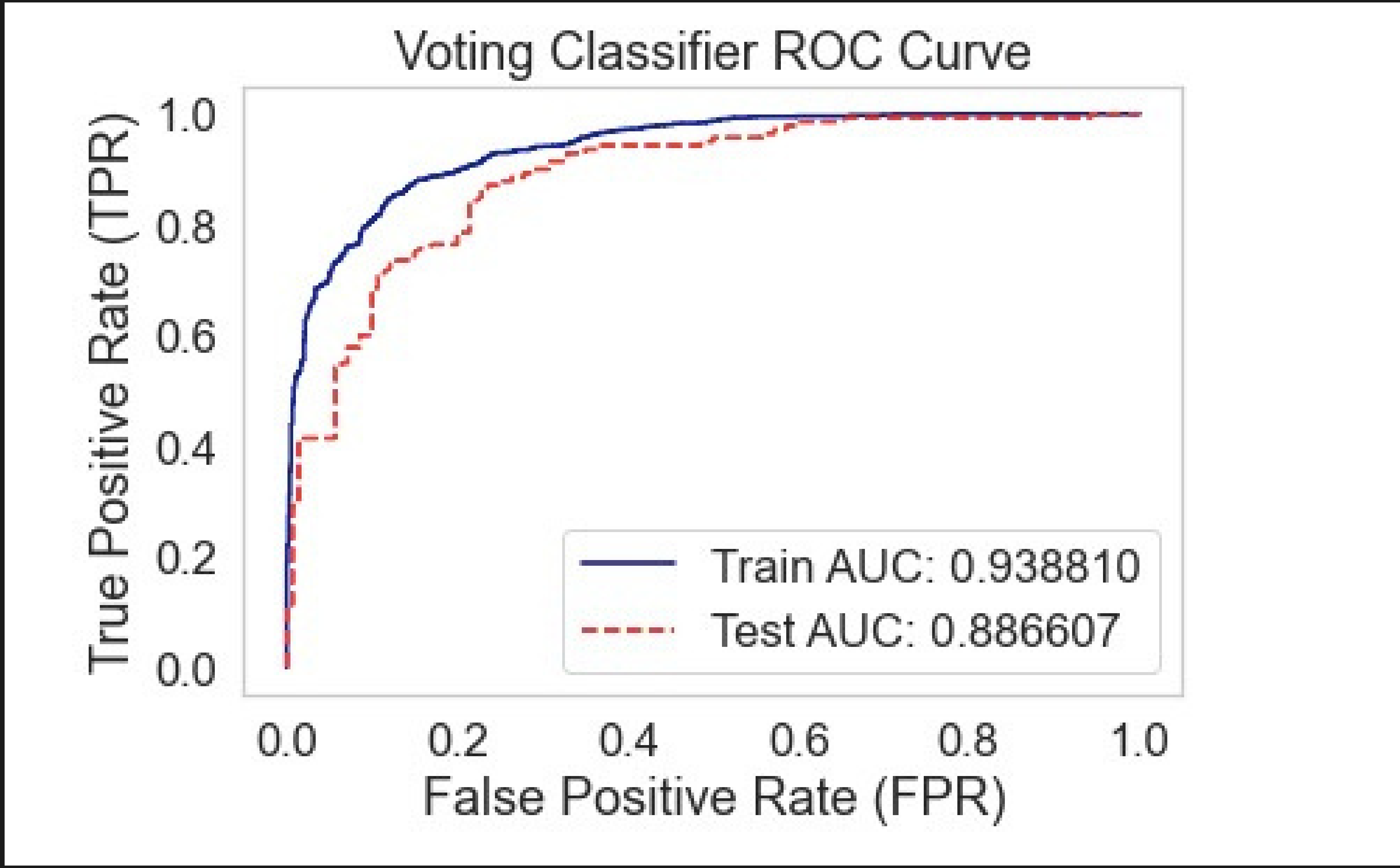
Implementation




Multinomial NB ROC Curve
True Positive Rate (TPR)
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate (FPR)
Train AUC: 0.705122
Test AUC: 0.699599


Random Forest ROC Curve
True Positive Rate (TPR)
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate (FPR)
Train AUC: 0.940404
Test AUC: 0.894413


XG Boost ROC Curve
True Positive Rate (TPR)
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate (FPR)
Train AUC: 0.940404
Test AUC: 0.894413



Voting Classifier ROC Curve
True Positive Rate (TPR)
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate (FPR)
Train AUC: 0.938810
Test AUC: 0.886607

Model	Training Accuracy	Testing Accuracy	Training Precision	Testing Precision	Training Data Recall	Testing Data Recall
Decision Tree Classifier	88.20%	87.85%	90.50%	91.10%	84.40%	83.60%
Multinomial NB Classifier	67.80%	69.70%	59.30%	62.50%	96.20%	97.10%
Random Forest Classifier	84.80%	84.40%	86.50%	87.60%	79.60%	79.80%
XGB Classifier	98.80%	83.50%	99.20%	84.50%	98.20%	82.10%
Hybrid Ensemble Model	92.30%	90.00%	91.10%	88.80%	92.70%	91.40%

Jaccard Similarity model

HERE, TO FIND SIMILARITY BETWEEN THE TWEETS, JACCARD SIMILARITY IS USED. IN THIS SIMILARITY TEST, THE EXPERIMENT DEPICTED THE JACCARD SIMILARITY SCORE BETWEEN THE 100 MOST RECENT TWEETS OF A GIV-EN TWITTER ACCOUNT. BEFORE THE SIMILARITY SCORE WAS COMPUTED, THE TWEETS MADE AVAILABLE FROM THE DATASET WERE IN THEIR RAW FORM AND HAD TO BE PREPROCESSED FIRST FOR EFFECTIVE USE. FURTHER, THE TOKENIZING OF THE TWEETS PERFORMED USING REGEXP TOKENIZER AND LEMMATIZED THE TWEETS USING WORDNET LEMMATIZER FROM NLTK LIBRARY. AFTER THIS, THE JACCARD SIMILARITY SCORE WAS COMPUTED. THE ACCURACY UP TO 93.2% IS ACHIEVED AFTER COMBINING THE RESULTS FROM BOTH THE HYBRID MODEL AND THE SIMILARITY MODEL.

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|}$$

Conclusion

- PRESENCE OF ARTIFICIAL BOT ACCOUNTS ON THE SOCIAL MEDIA PLATFORM POSE THREAT TO THE PRIVACY OF THE LEGITIMATE USERS.
- IN THE PROPOSED MODEL VARIOUS MACHINE LEARNING ALGORITHMS WERE USED AS WEAK LEARNERS TO MAKE A HYBRID MODEL THAT COULD SUCCESSFULLY CLASSIFY 90% OF THE ACCOUNTS USING THE PREPROCESSED TWITTER DATA.
- THE PROJECT ALSO CONSISTS OF CLASSIFICATION BASED ON JACCARD SIMILARITY MODEL WHICH USES RECENT TWEETS POSTED BY THE USERS.

The Research paper was published as a chapter in the following book.

Book Name - HANDBOOK OF RESEARCH ON DATA PREPROCESSING, ACTIVE LEARNING, AND COST PERCEPTIVE APPROACHES FOR RESOLVING DATA IMBALANCE.

Publication - IGI GLOBAL

LINK - https://www.igi-global.com/submission/book-project-chapters/?projectid=03dcf765-2e75-4bf4-9089-305370caa331

Future Work

SOME METHODS, SUCH AS GUIDED LEARNING APPROACHES, WERE EXTENSIVELY DISCUSSED IN THIS WORK. TO COMPREHEND, REINFORCE OR DISCOVER NEW RESULTS, SEVERAL APPROACHES REQUIRE MORE EXPLORATION. IT STIMULATES THE RESEARCH COMMUNITY TO DISCOVER NEW APPROACHES AND IM□PROVE EXISTING APPROACHES. THE ABOVE MODEL CAN BE UTILIZED FOR REAL TIME APPLICATIONS. WITH THE AWARENESS OF BOT ACCOUNTS AMONG USERS, IT WOULD BECOME CONVENIENT AND HIGHLY LUCRATIVE FOR PEOPLE AND ORGANIZATIONS TO DETECT THEM ON OSNS. IN FUTURE, THIS MODEL WILL BE COMPARED WITH OTHER AVAILABLE TECHNIQUES AND BY INCLUDING THE USAGE OF NETWORK INFORMATION OF USERS.

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