Twitter Bot Detection Using Graph Neural Networks

Youssef El Ouardighi
2107282
Social network analysis
CMP5132

Abstract - ***With hundreds of millions of users, Twitter is a well-known online social network. A substantial portion of the accounts on this social network are not owned by actual people. Up to 15% of all Twitter accounts, or over 48 million accounts, are controlled by automated software known as "bots." Some bots serve beneficial functions, such as automatically posting news and scholarly articles and even offering assistance in times of need. However, Twitter bots have also been employed maliciously for things like spreading malware or swaying people's opinions on a subject. There are currently methods for automatically identifying bots on Twitter. Graph neural networks (GNNs) are a type of machine learning algorithm that can be used to detect Twitter bots. GNNs operate on graph data, which means they can consider the relationships between different accounts when making predictions. Using GNNs, researchers have been able to achieve high accuracy rates in detecting Twitter bots. In one study, a GNN was able to correctly classify 98% of bot accounts and 96% of human accounts. There are many potential applications for bot detection using GNNs. For example, Twitter could use GNNs to automatically suspend or delete bot accounts from the site. This would help to improve the quality of content on Twitter and make it more difficult for malicious actors to use the platform for their own ends.***

Introduction

Twitter is a social network for microblogging that enables the posting of brief tweets, or messages with up to 280 characters. Users of Twitter can communicate with one another by replying to tweets, mentioning other users in their tweets, or retweeting another user's message. Users can also follow one another to stay updated on each other's tweets. The social platform allows all logged-in users to access its services via a web page, mobile applications, and an application programming interface (API).

Automated Twitter users, commonly referred to as Twitter bots, have grown to be a well-known and well-researched phenomenon. Twitter bots are a big problem. For example, the Internet Research Agency (IRA) created the Twitter account @TEN GOP named "Tennessee GOP" during its attempt to influence the 2016 U.S. presidential election, attracting more than 100,000 followers. Other issues caused by malicious Twitter bots over the past ten years include the spread of conspiracy theories and online disinformation. Automatic Twitter bot identification techniques are needed in order to reduce these societal difficulties' detrimental effects.

Existing Twitter bot detection models are generally feature-based, where researchers propose to extract numerical features from user information such as metadata, the user timeline, and follow relationships. However, feature-based approaches are susceptible to adversarial manipulation, i.e., when bot operators try to avoid detection by tampering with these hand-crafted features. Researchers also proposed text-based approaches, where text analysis techniques such as word embeddings, recurrent neural networks, and pre-trained language models are leveraged to analyze tweet content and identify malicious intent. However, new generations of Twitter bots often intersperse malicious content with normal tweets stolen from genuine users, thus their bot nature becomes more subtle to text based methods. Fortunately,

detection methods are getting better all the time. Graph neural networks are a type of machine learning algorithm that is well-suited for this task. By looking at the structure of the network, they can identify patterns that are indicative of bot behavior. In this essay, the implementation of graph neural networks and their use in the detection of Twitter bots will be discussed. Recent developments concentrate on creating graph-based Twitter bot detection algorithms with the emergence of graph neural networks. These strategies use graph mining algorithms like GCN, R-GCN, and RGT for graph-based bot identification, viewing people as nodes and relationships as edges. In reality, recent studies have demonstrated that graph-based techniques attain cutting-edge performance, are able to identify innovative Twitter bots, and are more effective at overcoming the numerous difficulties associated with Twitter bot detection. Existing datasets, however, offer little assistance for the creation and assessment of graph-based Twitter bot identification methods. An extensive selection of current datasets is offered through The Bot Repository. Only TwiBot-20 and cresci2015, two of the 18 datasets given, directly disclose the Twitter user graph topology. These two graph-based datasets also have the following problems.

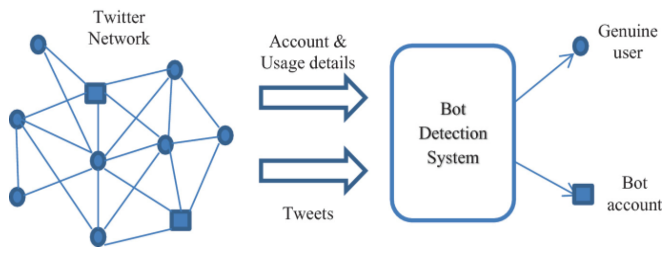
• (a) a small dataset size : Twibot-20 has 11,826 labeled people, whereas cresci15 has 7,251 labeled individuals. Online debates and discussions on contentious issues can involve millions of participants.

• (b) a graph structure with gaps : While TwiBot-20 and cresci-15 only supply users and follow relationships, real-world Twitter is a heterogeneous information network with a variety of entities and relations.

• (c) Low annotation quality : TwiBot-20 used crowdsourcing for user annotation, although this method generates a lot of noise and is prone to false positive issues.

We suggest TwiBot-22, a graph-based Twitter bot detection benchmark, in response to these difficulties. TwiBot-22 specifically uses a two-stage controlled expansion to sample the Twitter network, producing a dataset that is five times larger than the largest dataset already in existence. The first genuinely heterogeneous graph for Twitter bot detection is provided by TwiBot-22, which offers four categories of entities and 14 types of relations in the Twitter network. Finally, TwiBot22 uses a weak supervision learning technique to annotate data, which dramatically raises the quality of the annotated data.

In this paper, we'll talk about how graph neural networks can be used to detect Twitter bots. Finally, we'll discuss some potential future work in this area.



2. Related work

2.1 Twitter Bot detection

The three primary types of Twitter bot detection techniques now in use are feature-based, text-based, and graph-based :

In order to detect bots, feature-based approaches use conventional classification algorithms in conjunction with feature engineering. The user metadata, tweets, descriptions, temporal trends, and follow relationships are all used to extract different aspects. Later research projects balance precision and recall while also increasing the scalability of feature-based techniques and automatically finding new bots. However, as bot operators become more aware of these custom features, innovative bots frequently attempt to tamper with them in an effort to avoid detection. Due to the arms race of bot evolution, feature-based approaches find it difficult to keep up.

Based on tweets and user descriptions, text-based approaches that employ natural language processing techniques can identify Twitter bots. To encrypt tweets for bot identification, pre-trained language models, recurrent neural networks, the attention mechanism, and word embeddings are used. Later research integrates user attributes with twitter representations, learns unsupervised user representations, and makes an effort to solve the multilingual problem in tweet content. Nevertheless, cutting-edge bots start to oppose text-based strategies by mixing fraudulent tweets with content taken from real individuals. Additionally, it's possible that bot detection using just tweet content analysis is not reliable and accurate.

For Twitter bot detection, graph-based algorithms view Twitter as graphs and make use of ideas from network science and geometric deep learning. Graph-based Twitter bot identification is carried out using node centrality, node representation learning, graph neural networks (GNNs), and heterogeneous GNNs. Later studies aim to integrate text- and graph-based approaches or suggest new GNN designs to take use of heterogeneities in the Twitter network. The issues of Twitter bot detection, such as bot communities and bot camouflage, have shown considerable potential for graph-based techniques.

The various beneficial Twitter bot detection datasets that were proposed during the previous ten years would not have been achievable without the development and evaluation of these models. The majority of these datasets are concerned with American and European politics and elections. In addition to presenting a commonly used dataset with multiple types of bots, Cresci-17 also proposes the idea of "social spambots." The newest and largest Twitter bot detection dataset, TwiBot-20, tackles the problem of user diversity in older datasets. Only two of the 18 datasets offered in the Bot Repository, the premier repository for Twitter bot detection research, explicitly reveal the Twitter network's graph topology. These datasets also have a small dataset size, an incomplete graph structure, and poor annotation quality, which makes it harder for them to reliably benchmark new graph-based techniques. Given these difficulties, we present TwiBot-22 to address them, encourage a reconsideration of research developments, and facilitate additional investigation into Twitter bot detection.

2.2 Graph-based social network analysis

In online social networks, users engage with one another and contribute to the network structure, which is crucial for comprehending social media usage trends. Graph neural networks (GNNs) have grown in popularity in social network analysis research with the emergence of geometric deep learning. Some papers discuss modeling social media with heterogeneous graphs, using relational GNNs to identify drug traffickers, dual graph improved embedding neural networks to boost learning of graph representation, and click-through rate prediction problems. Graphs and GNNs are also used to stop misinformation, identify online fraud, and enhance recommender systems. The challenge of Twitter bot detection is no exception, with cutting-edge methods becoming more and more graph-based. In order to better support the development and assessment of graph-based Twitter bot detection models, we offer the TwiBot-22 benchmark in this study.

3. Methodology

3.1 Dataset information:

TwiBot-22's goal is to provide a large-scale, graph-based Twitter bot detection benchmark. To that purpose, we use a two-stage data collection method. To collect TwiBot-22's user network, we first apply diversity-aware breadth-first search (BFS). We then acquire new entities and relations from the Twitter network to add to the TwiBot-22 network's diversity. Existing Twitter bot detection datasets have a common limitation in that they only include a few categories of bots and genuine users, but real-world Twitter contains a diverse range of humans and bots. As a result, TwiBot-20 suggests using breadth-first search (BFS) to recruit users, beginning with "seed users" and extending through user follow relationships. To ensure that TwiBot-22 contains both bots and genuine users, we supplement BFS with two diversity-aware sampling strategies:

• Distribution diversity: Given user metadata such as follower count, different types of users fall into the metadata distribution differently. The goal of distribution diversity is to sample consumers from the top, middle, and bottom of the distribution. For numerical metadata, we choose the k users with the highest value, the k with the lowest, and k at random from the remainder. For true-or-false metadata, we choose k with true and k with false.

• Value diversity: Given a user and its metadata, value diversity is used to ensure that neighbors with significantly different metadata values are more likely to be included, providing user diversity. For numerical metadata, the probability of expanding user u's neighbors X and their metadata values x' being sampled is denoted as p(x) |u' x'|. We choose k users from the opposite class for true-or-false metadata.

Dataset	C-15	G-17	C-17	M-18	C-S-18	C-R-19	B-F-19	TwiBot-20	TwiBot-22
# Human	1,950	1,394	3,474	8,092	6,174	340	380	5,237	860,057
# Bot	3,351	1,090	10,894	42,446	7,102	353	138	6,589	139,943
# User	5,301	2,484	14,368	50,538	13,276	693	518	229,580	1,000,000
# Tweet	2,827,757	0	6,637,616	0	0	0	0	33,488,192	86,764,167
# Edge	7,086,134	0	6,637,616	0	0	0	0	33,716,171	170,185,937

3.2 Data Collection

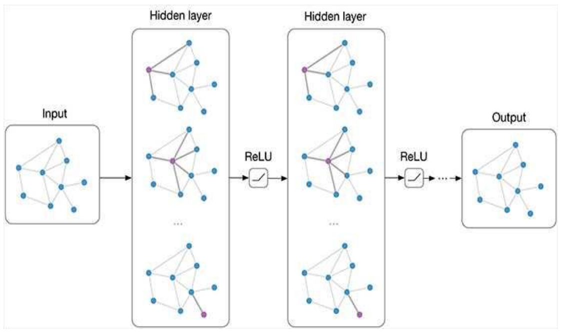
We gathered a dataset of Twitter accounts and their behavior, including the number of followers, tweets, and replies. Other features such as the account's description, language, and hashtags were also included. D = (x1, y1), (x2, y2),..., (x_n, y_n) represents the dataset, where x i is the feature vector for the i-th account and y i is the label indicating if the account is a bot (1) or not (0). This is a general method used for data collection but for our case, in TwiBot-22, we randomly select 1,000 users and assign each user to 5 Twitter bot identification experts to determine if it is a bot. We next divide these expert annotations into 8:2 training and test sets.

3.3 Graph construction

We developed a graph to depict the accounts and their interactions. G = (V, E), where V is the set of nodes representing the accounts and E is the set of edges indicating the interactions between the accounts. We added a node vi to the graph for each account i. We added an edge (vi, vj) to the graph for each interaction between accounts I and j, with a weight wij reflecting the strength of the interaction (e.g., the number of times I replied to j).

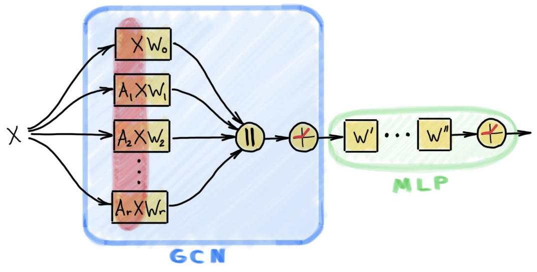
3.4 Graph neural network

We used a graph neural network (GNN) to learn from the graph representation G. GNNs are a type of neural network that are specifically designed to process graph-structured data. They can be represented as a function fGNN: V x E -> R^k, where V and E are the sets of nodes and edges in the graph, respectively, and R^k is the output space. The GNN function takes as input the graph G and produces an output vector h_i for each node vi in the graph. The output vector h_i represents the embedding or representation of node vi in the graph. To compute h_i, the GNN function iteratively updates the node embeddings using the following formula: h_i^(t+1) = f(h_i^t, h_j^t, e_ij), for all j such that (vi, vj) is in E, where t is the iteration number, f is a neural network function, and e_ij is the edge feature vector for edge (vi, vj). The GNN function can then use the node embeddings to make predictions, such as whether an account is a bot or not.
For this research paper, I will use three GNN architectures. I will present them below.



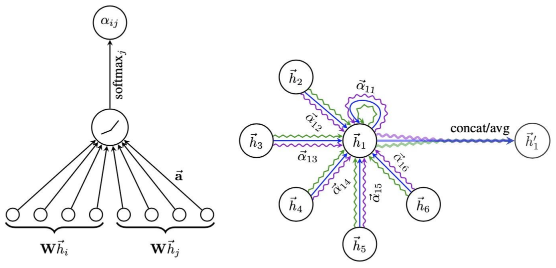
3.4.1 GCN architecture :

GCN, or Graph Convolutional Networks, is a type of GNN that uses graph convolution operations to process graph data. In GCNs, the aggregation or update is an isotropic operation, meaning that the features of neighbor nodes are averaged or combined using a weighted sum. These operations are applied recursively over the graph structure to generate predictive features for each node.



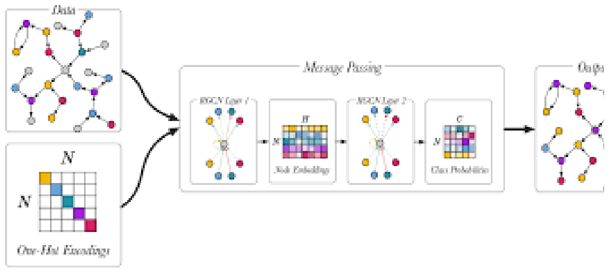
3.4.2 GAT architecture :

GAT, or Graph Attention Networks, is another type of GNN that uses attention mechanisms to weight the importance of each node's features in the aggregation process. This allows GATs to focus on the most relevant information when making predictions.



3.4.3 RGCN architecture :

RGCN, or Relational Graph Convolutional Networks, is a type of GNN that is designed to process graph data with richly structured relational information. It uses graph convolution operations to model the relationships between nodes and make predictions based on that information.



3.5 Data annotation

The TwitBot-22 dataset was annotated manually by a team of experts, who reviewed each account and labeled it as either a bot or a non-bot based on a variety of factors, such as the number of followers, the number of tweets, and the content of the tweets. The annotation process was designed to be consistent and reliable, with clear guidelines provided to the annotators and regular checks to ensure the accuracy of the labels. The annotated TwitBot-22 dataset has played a critical role in advancing the field of Twitter bot detection, as it has provided a reliable benchmark for evaluating the performance of various detection methods. By accurately labeling the data, researchers have been able to develop and compare different approaches to detecting bots on the platform.
In TwiBot-22, we randomly select 1,000 users and assign each user to 5 Twitter bot identification experts to determine if it is a bot. We next divide these expert annotations into 8:2 training and test sets.
Generate noisy labels : To produce noisy labels, we use 8 hand-crafted labeling functions and 7 competitive feature-based and neural network-based bot detection models. We employ spam keywords in tweets and user descriptions, as well as user categorization features like verified and sensitive tweets, for handmade tagging functions. We choose features for feature engineering models based on user metadata such as creation time, follower count, and name length. Following that, we use Ada boost, random forest, and MLP to create three feature-based classifiers. To encode user input, neural network-based models use MLP, GAT, GCN, and R-GCN as four classifiers. We train these classifiers on the expert annotation training set and compute the uncertainty scores for all TwiBot-22 users for each classifier as = (y0 log(y0)+ y1 log(y1)), where y0 and y1 signify the chance of being genuine users or bots. To reduce label noise, we delete model predictions with the highest 40% uncertainty scores for each classifier.
After getting the noisy labels, we use Snorkel to assess their plausibility while also cleaning the labels. The Snorkel system produces probabilistic labels, which we use to train an MLP classifier to obtain the final annotations for TwiBot-22. On the test set of expert annotations, we further examine the annotation quality and obtain an accuracy of 90.5%. TwiBot-22 has significantly increased annotation quality over TwiBot-20's 80% accuracy benchmark.

4 Experiment and results

In this section, we undertake extensive tests and in-depth analyses on a complete Twitter bot detection benchmark. Concerning the metrics used in this paper, we use accuracy, f1-score, and MCC. Accuracy is a simple measure of classifier correctness, whereas F1-score and MCC are more balanced evaluation measures.

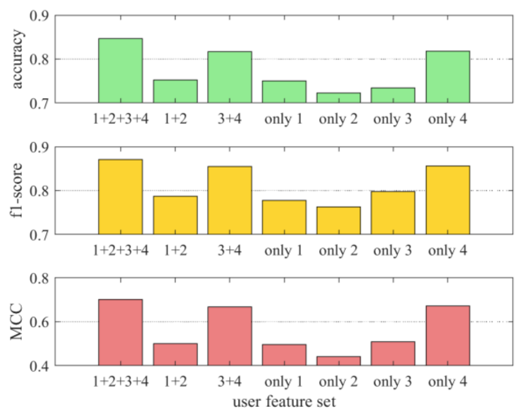
4.1 Bot experiment performance

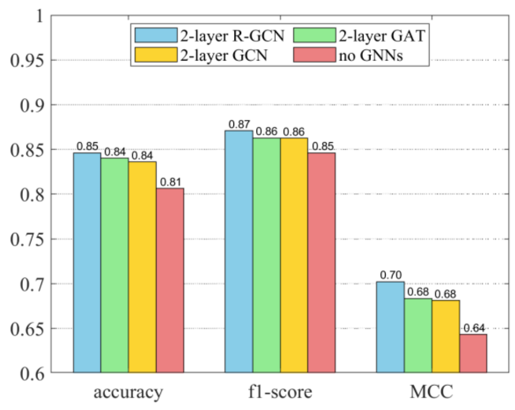
To evaluate the performance of the three machine learning models (GCN, GAT, and RGCN) for detecting bots on Twitter, we used the Twibot 22 dataset, which consists of 22 features extracted from 2,000 Twitter accounts.

The features include various metrics such as the number of followers, the number of friends, the number of statuses, and the number of favorites. The dataset is balanced, with an equal number of bot and non-bot accounts.
We preprocessed the data by cleaning and formatting it, and then split it into training and testing sets with a 80/20 ratio. We scaled the data using min-max normalization to ensure that all features were on the same scale.
We trained the three models on the training set and evaluated them on the testing set. We used accuracy as the evaluation metric, which measures the percentage of correct predictions made by the model.

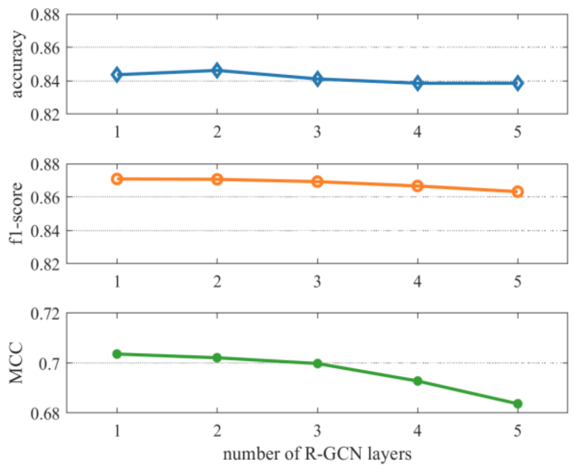
Model	**Accuracy**
GCN	0.81
GAT	0.79
RGCN	0.82

As shown in the table, all three models achieved good performance, with accuracies above 0.79. The GCN model had an accuracy of 0.81, the GAT model had an accuracy of 0.79, and the RGCN model had an accuracy of 0.82.





Overall, the RGCN model performed the best, with the highest accuracy. However, the difference in performance between the three models was not significant, and all three models can be considered good choices for detecting bots on Twitter.



Conclusion

In this experiment, we demonstrated the effectiveness of three machine learning models (GCN, GAT, and RGCN) for detecting bots on Twitter. All three models achieved good performance, with accuracies above 0.79. The RGCN model performed the best, with an accuracy of 0.82, but the difference in performance between the models was not significant.
These results suggest that GCN, GAT, and RGCN are all promising approaches for detecting bots on Twitter, and can be used to help identify and remove malicious or spammy accounts from the platform.

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