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Bot-MGAT: A Transfer Learning Model Based on a Multi-View Graph Attention Network to Detect Social Bots

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Abstract: Twitter, as a popular social network, has been targeted by different bot attacks. Detecting social bots is a challenging task, due to their evolving capacity to avoid detection. Extensive research efforts have proposed different techniques and approaches to solving this problem. Due to the scarcity of recently updated labeled data, the performance of detection systems degrades when exposed to a new dataset. Therefore, semi-supervised learning (SSL) techniques can improve performance, using both labeled and unlabeled examples. In this paper, we propose a framework based on the multi-view graph attention mechanism using a transfer learning (TL) approach, to predict social bots. We called the framework 'Bot-MGAT', which stands for bot multi-view graph attention network. The framework used both labeled and unlabeled data. We used profile features to reduce the overheads of the feature engineering. We executed our experiments on a recent benchmark dataset that included representative samples of social bots with graph structural information and profile features only. We applied cross-validation to avoid uncertainty in the model's performance. Bot-MGAT was evaluated using graph SSL techniques: single graph attention networks (GAT), graph convolutional networks (GCN), and relational graph convolutional networks (RGCN). We compared Bot-MGAT to related work in the field of bot detection. The results of Bot-MGAT with TL outperformed, with an accuracy score of 97.8%, an F1 score of 0.9842, and an MCC score of 0.9481.

Keywords: semi-supervised learning; transfer learning; GNN; prediction; bot detection; Twitter

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1. Introduction

Despite the early recognition of social bots on Twitter, and the good performance of different bot detection techniques that have been proposed in the literature [1–3], detection performance drops when they are tested on new data [4,5], for two main reasons. The first reason is that labeled data play an important role in supervised learning (SL) performance. Thus, the majority of proposed work in bot detection has been performed in this manner, using human annotation to label Twitter accounts as humans or bots [6,7]. SL techniques are based on labeled data for training and testing the learning model. Therefore, the issue of obtaining labeled data that contain representative samples of different generations of bots, for this problem, is a very challenging task in terms of time, cost, and effort. In fact, obtaining labeled data for real-world problems, such as bot detection, is one of the limitations associated with SL techniques [8]. The second reason is that bots adapt their behavior and features very quickly to avoid being detected by artificial intelligence and Chatbot advancements [6,9]. For this reason, learning models fail to detect new updated versions of bot accounts, and show a significant drop in performance.

Consequently, semi-supervised learning (SSL) techniques aim to mitigate this limitation in SL, by using both labeled and unlabeled data to build learning models for classification problems [10]. Both graph and non-graph SSL have been implemented to enhance classification or to obtain more hidden information that unlabeled data can reveal [11]. The common techniques of SSL that have been proposed in the literature vary in their mechanisms. For example, there are graph neural network (GNN) techniques that have been shown to be successful in several domains, such as graph convolutional networks (GCN) and graph attention networks (GAT). Additionally, there are SSL wrapper techniques, such as self-training (another name is self-labeling or pseudo-labeling) and co-training. Furthermore, there are generative model techniques, where the focus is on generating data using labeled data such as generative adversarial networks (GAN). In our case, we focused on graph SSL techniques, in particular GAT, as we aimed to work out the hidden relationships between nodes of a trending hashtag, to be able to predict the label of a given node. Non-graph techniques cannot reveal such information, due to the absence of graph structural information.

In this paper, we address the issue of labeled data for the bot detection problem, to enhance performance using related labeled and unlabeled data within a graph attention network mechanism by using the transfer learning (TL) approach. We aimed to combine the success of GNN and TL approaches, to overcome the issue of the scarcity of data for the bot detection problem, and to enhance classification. Our framework, Bot-MGAT, was designed based on multi-view graph attention networks, to distinguish the importance of different nodes within the neighborhood using node representations to predict the label. GAT has efficiency in operating, and can be applied to different degrees of nodes, in contrast to GCN, where nodes have equal or pre-defined weights. Bot-MGAT uses profile features only, as they have been shown to be effective in detecting social bots [12]. Our model evaluation was compared using baseline models and cross-domain evaluation. The success of this classification task will save the effort and tedium of manual labeling for learning models. Additionally, it will improve the detection of bots, as it will accelerate the labeling process, to obtain large amounts of data for models that require large volumes of data to improve prediction. Additionally, using a deep learning attention mechanism is more efficient for applying node representation learning, and discovering hidden link information in embedding space that a regular classifier fails to detect.

Our work's contributions were as follows:

- We proposed a framework based on the transfer learning model, using the multi-view graph attention mechanism to enhance bot detection on Twitter;
- We built our model using two different types of links: friendship and interaction;
- We used profile features only, to predict labels and apply cross-validation, in order to estimate accuracy and avoid uncertainty in the model performance;
- We performed a cross-domain evaluation of Bot-MGAT performance, by training the model using a diverse dataset, and testing the model using two other datasets that were not used in training.

The rest of this paper is organized as follows: the review of the literature is presented in Section 2; in Section 3, we present background details; Section 4 discusses the materials and methods; Section 5 discusses the results of the proposed framework; Section 6 highlights the challenges that remain in this domain, and considers future directions for research efforts that aim to address this problem.

2. Related Work

In this section, we briefly review the related literature on graph neural networks as an SSL technique, and related bot detection work that has been recently proposed in the literature. In addition, we discuss and highlight the remaining issues relating to the detection of social bots on Twitter.

2.1. Graph Neural Networks

Deep learning has demonstrated successful performance in recent years in different domains. Research efforts have proven the powerfulness of this machine-learning approach to extracting complex patterns from massive amounts of irregular data [13]. Therefore, using these machine-learning techniques to analyze graphs has been frequently proposed in recent years. The objective of this task was to overcome the challenges that remain in applying traditional deep learning to graphs [14]. These challenges included the irregular structures of graphs, the heterogeneity and diversity of graphs, and large-scale graphs.

Graph neural networks (GNNs) were promoted after the success of neural networks and their ability to learn to extract latent representation from complex relations and interactions of a given network. GNNs are categorized into: recurrent graph neural networks (RGNNs), convolutional graph neural networks (CGNNs), graph auto-encoders (GAEs) and spatial–temporal graph neural networks (STGNNs) [15]. GNNs can graph structured data to perform tasks such as node classification, link prediction, and graph classification. Therefore, GNNs can be trained in a semi-supervised manner by using the labeled nodes to classify the unlabeled ones in the graph [16].

Spatially based GNN models such as GAT are preferred, as they maintain efficiency, generalizability, and flexibility of implementation compared to spectral models. This is because spatial models can handle multi-source graph inputs, in contrast to spectral models that only handle undirected graphs [15]. In addition, spatial models are more scalable, as they perform graph convolutions locally on individual nodes, and share weights across different locations and structures. GAT models as a spatial model are considered a GCN model with an attention mechanism, and have achieved good performance in the literature [17]. This has encouraged research to expand this model into multi-view perspectives, where different views of data are integrated [18,19].

Recent studies have proposed using GCNNs to enhance bot detection using relational graph convolution networks (BotRGCN) [20] and GCNNs for spam bot detection [21]. In [20], the authors aimed to construct a heterogeneous graph of Twitter, and to apply relational GCN to detect bot communities. In [21], the authors deployed graph convolutional neural networks to a well-known spam bot dataset that outperformed previous methods with regard to the results. Hence, the issue with previous datasets is that they were easily detected and did not include recent generations of bots.

2.2. Bot Detection

Social bots differ in their behavior patterns, based on their goals. Thus, common approaches proposed in the literature to detect social bots, using SL, include feature-based, network or graph-based, and crowdsourcing approaches [6,22]. In the feature-based approach, machine learning algorithms are applied, to identify social bot accounts based on selected features. In the graph-based approach, an understanding of social network information, through links and edges of relationships between accounts, is applied to detect activity. In the crowdsourcing approach, human expert ability is utilized to identify, evaluate, and determine the behavior of social bots. Table 1 summarizes the strengths and limitations for each of the bot detection approaches in SL.

Accordingly, researchers have been looking for techniques other than SL, that might improve the classification task of social bot detection. A recent work was proposed by [23], using the GAN method and long short-term memory (LSTM), to detect bots based on textual content. Their goal was to detect the behavioral patterns of bot samples for a given classifier, by improving true positive rates and reducing false negatives. Feng, et al., proposed a self-learning framework (SATAR) for Twitter bot detection, where the framework adapted itself by pre-training a massive number of users [24]. They aimed to solve the issue of failing to adapt to new generations of Twitter bots. They constructed their framework based on tweet semantics, profile properties, and neighbors' networks; the strength of this work lay in considering these three aspects for bot detection, as the experimental results conveyed.

Table 1. Supervised learning approaches' strengths and limitations.

Detection Approach	Strengths	Limitations
Feature-Based	Good overall performance, as the literature reported [6]; Easy to implement when trained data are available, especially as some literature works provide their code for testing [7]; Commonly used, enabling combination of techniques and avoidance of pitfalls and mistakes reported in previous work [25];	Bias to trained datasets (including representative samples), performs less well with new data [26]; Available datasets do not include the full list of features, due to user privacy issues; therefore, not all features are available for testing and analyzing [27]; Some techniques are based on assumptions which lack wide application [22]; Using the accuracy rate is not enough to evaluate the performance of the proposed work [28].
Graph-Based	Helpful when detecting influence ranking [29]. Using visualization mapping to more easily identify influence/rank [29]; Understanding links/behavior patterns; Detecting communities based on similarities/dissimilarities [30].	Computational cost, as a social network's size is usually large [31]; Simulation of behavior of a network can be sensitive to chosen scalability measurements [32].
Crowdsourcing	Humans are more able to distinguish differences in the Turing test [33]; Good with a small amount of data; Useful to build a ground-truth baseline [34].	Needs an expert; Lack of an automation tool to make the task easier [35]; Inconsistent quality, as there are cyborg accounts [36]; Workload- and time-consuming for large datasets [34].

3. Background

In this section, we model our problem, and provide details about graph attention networks, multi-view graph attention networks, and transfer learning.

3.1. Problem Definition

We let G be a graph defined as $G = (V,\ E)$, where V was a set of nodes of size N; each node represented a Twitter account, and E was the adjacency matrix. Nodes of the graph were described using the feature matrix $\boldsymbol{X} = \{x_i\}_{i=1}^{N}$ of dimension $N \times F$, where F was the number of features in total for each node, and each row was the feature vector of node i. Each account was associated with a set of numerical features, Nu, and categorical features, C. Therefore, $x_i = \{Nu_i,\ C_i\}$ for $i = 0,\ 1,\ 2,\ 3, \ldots,\ N$.

The relationships among the different nodes were presented in the adjacency matrix E of size $N \times N$, where $e_{ij} \in \{0,\ 1\}$ indicated whether there was an edge (relationship) between node i and j. The diagonal elements of this matrix were the self-loop edges of the nodes (an edge from the node to itself). As our graph was undirected, the adjacency matrix was symmetric, and hence $e_{ij} = e_{ji}$.

Labels of the nodes were included in the label vector l of size N, where $l_i \in \{0,\ 1\}$ was the ground truth of node i, to indicate if this node was a human account (0) or a bot account (1).

The Twitter bot detection problem was modeled as a binary classification task under the semi-supervised learning schema shown in Figure 1. This was because we had a large dataset, but only a few nodes were labeled. Here, we found a function $f : (Nu_i,\ C_i\ ,\ E) \to l'_i$ that mapped each feature vector of a node to its true label, such that the predicted label l' was close to the ground truth l for maximum prediction accuracy (or minimum prediction error).

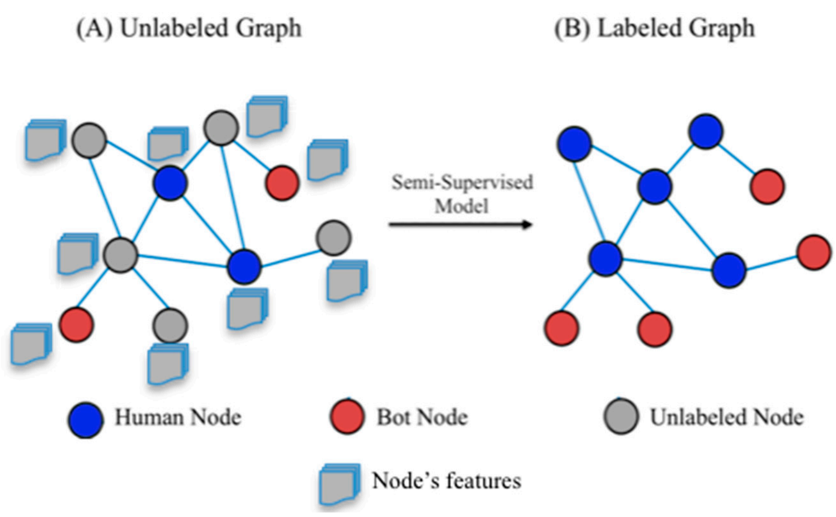


Figure 1. Semi-supervised learning uses nodes' embedding to predict the node class. Both labeled and unlabeled nodes are used in SSL.

3.2. Graph Attention Network

Graph attention networks (GATs) are a type of graph neural network in which the edges of the graph are weighted differently, to indicate the importance of nodes with respect to other nodes. The weighting is performed through a self-attention mechanism [37]. Initially, the node representations (node embeddings) are the raw features $\boldsymbol{h}^{\mathbf{0}} = \boldsymbol{X}^T$ with a size $N \times F$. Then, a series of linear transformations can be applied through weight matrix multiplication, as follows in Equation (1):

$$\boldsymbol{h}^{(l)} = \sigma\left(\boldsymbol{W}^{(l)} \times \boldsymbol{h}^{(\boldsymbol{l}-\mathbf{1})} + b^{(l)}\right) \tag{1}$$

where $\boldsymbol{W}^{(l)}$ is the weight matrix of the l^{th} linear layer, with a size of $F' \times F$. Consider F as the number of inputs of the l^{th} layer, and F' as the number of outputs of the l^{th} layer. $b^{(l)}$ is the additive bias vector of the l^{th} layer, and of size F'. The activation function to add non-linearity is $\sigma(.)$. The linear layer can be applied separately for numerical features Nu_i and categorical features C_i of each node.

To calculate the weight of each edge (including the self-loops), we used Equation (2):

$$e_{ij} = a\left(\boldsymbol{W} \times h_i^{(l-1)}, \boldsymbol{W} \times h_j^{(l-1)}\right) \tag{2}$$

where $a(\ .\ )$ was the self-attention mechanism. These weights were not normalized, and therefore a Softmax function was utilized for normalization, as in Equation (3):

$$\alpha_{ij} = \text{softmax}\left(e_{ij}\right) = \frac{\exp\left(LeakyReLU\left(e_{ij}\right)\right)}{\sum_{k \in \mathcal{N}_i} \exp\left(LeakyReLU\left(e_{ij}\right)\right)} \tag{3}$$

where α_{ij} was the attention coefficient; $\mathcal{N}_i$ represented the neighbors of node i; LeakyReLU was an activation function, defined as follows in Equation (4):

$$LeakyReLU\,(x) = \begin{cases} x, & x \geq 0 \\ \mu \times x, & otherwise \end{cases} \tag{4}$$

where μ was the negative slope.

The attention mechanism was performed by concatenating the representation of node i and node j (after linear transformation), and multiplying this by a learnable weighting vector z of size $2F'$. The result was passed through the LeakyReLU function. Thus, the attention coefficient in Equation (3) could be re-written as shown in Equation (5):

$$\alpha_{ij} = \frac{\exp\left(LeakyReLU\left(z^T \times \left[\boldsymbol{W} \times h_i^{(l-1)} || \boldsymbol{W} \times h_j^{(l-1)}\right]\right)\right)}{\sum_{k \in \mathcal{N}_i} \exp\left(LeakyReLU\left(z^T \times \left[\boldsymbol{W} \times h_i^{(l-1)} || \boldsymbol{W} \times h_k^{(l-1)}\right]\right)\right)} \tag{5}$$

where $(\ .\ )^T$ represented the transpose operator and $||$ was the concatenation operator.

In [38], the authors discovered that the implementation of the GAT had a static attention nature. The reason for this was the application of the $\boldsymbol{W}$ and z^T in the above equation sequentially. The authors fixed this by altering the operations, in which multiplication by $\boldsymbol{W}$ was performed after concatenating the nodes' representations, a LeakyReLU was applied, and multiplication by z^T was carried out as a final step. This is shown in Equation (6):

$$\alpha_{ij} = \frac{\exp\left(z^T \times LeakyReLU\left(\boldsymbol{W} \times \left[h_i^{(l-1)} || h_j^{(l-1)}\right]\right)\right)}{\sum_{k \in \mathcal{N}_i} \exp\left(z^T \times LeakyReLU\left(\boldsymbol{W} \times \left[h_i^{(l-1)} || h_k^{(l-1)}\right]\right)\right)} \tag{6}$$

This is called modified GAT (or GATv2), and we used it in our framework.

To obtain the final node representations h', we included the learned attention coefficients when aggregating the representations of the neighbors, as in Equation (7):

$$h_i' = \sigma\left(\alpha_{ii} \times \boldsymbol{W}^{(l)} \times h_i^{(l-1)}\right) + \sigma\left(\sum_{j \in \mathcal{N}_i} \alpha_{ij} \times \boldsymbol{W}^{(l)} \times h_j^{(l-1)}\right) \tag{7}$$

The first term was for the self-loops, and the second term was the weighted sum of the neighbors' representations. These final representations could be utilized for different prediction tasks. In our work, we decided to use the single-head attention mechanism.

3.3. Multi-View Graph Attention Networks

A multi-view graph is a relational graph that consists of different relationships among the nodes (or, technically, multiple graphs with the same nodes, but different edges). This inspired [39] to extend the graph convolutional networks (GCNs) to relational graph convolutional networks (RGCNs), to consider them. Let $\mathcal{R}$ be the number of relations. In regard to Twitter, relationships can include following/follower, tweet/retweet, replies/mentions, or any interaction. The updated node representation was modified to include the relations, as indicated in Equation (8):

$$h_i' = \sigma\left(\boldsymbol{W}_0^{(l)} \times\ h_i^{(l-1)}\right) + \sigma\left(\sum_{r \epsilon \mathcal{R}} \sum_{j \in \mathcal{N}_i^r} \frac{1}{\mathcal{N}_i^r} \times \boldsymbol{W}_r^{(l)} \times h_j^{(l-1)}\right) \tag{8}$$

where $\mathcal{N}_i^r$ represented the neighbors of node i with respect to relation r. $\boldsymbol{W}_0^{(l)}$ was the relation-independent weight matrix for the self-loop edges to include node i representation. This equation summed the nodes' representations across all relations, to obtain the final nodes' representations. As can be seen, RGCN—which was modeled using Equation (8)—did not consider the importance of the neighbors among the relations. We propose our framework, a multi-view graph attention network which was adopted from [18], and combines both GAT and RGCN. The new model calculated the relation-wise attention coefficients for ranking the influence of the neighbors among different interactions (relationships). We simply modified Equation (8) to define the view-specific node representation as follows:

$$h_{i,r}' = \sigma\left(\alpha_{ii}^r \times\ h_{i,r}^{(l-1)}\right) + \sigma\left(\sum_{j \in \mathcal{N}_i^r} \alpha_{ij}^r \times \boldsymbol{W}_r^{(l)} \times\ h_j^{(l-1)}\right) \tag{9}$$

The relation-specific attention coefficient in Equation (9) was described by α_{ij}^{r}. This time, the attention for the self-loop term was relation-specific. The reason for this was because every node had a different set of neighbors in each relation. The formula for calculating α_{ij}^{r} is shown in Equation (10):

$$\alpha_{ij}^{r} = \frac{\exp\left(z_r^T \times LeakyReLU\left(\mathbf{W}_r \times \left[h_{i,r}^{(l-1)}||h_{j,r}^{(l-1)}\right]\right)\right)}{\sum_{k\in\mathcal{N}_i^r}\exp\left(z_r^T \times LeakyReLU\left(\mathbf{W}_r \times \left[h_{i,r}^{(l-1)}||h_{k}^{(l-1)}\right]\right)\right)} \tag{10}$$

Finally, we aggregated the nodes' representations across the different views by using a weighted sum with parameter β (number between 0 and 1). This differed from the approach used in [18], as we did not want to add overhead to the training of the model. Additionally, because we had datasets with different types of relations (edges), we decided to combine them into two views only ($\mathcal{R} = 2$), where a view contained a set of the edges, and the rest were in the other view. This was done for each dataset. Thus, the aggregation across the views is shown in Equation (11):

$$h_i^{final} = \beta \times h'_{i,r_1} + (1-\beta) \times h'_{i,r_2} \tag{11}$$

where r_1 and r_2 were the two views ($\mathcal{R} = \{r_1, r_2\}$). The model was trained by optimizing the loss function, using the Adam optimizer. We used the binary cross-entropy loss function, as we had only two classes (human and bot):

$$Loss = \sum_{i\in\varphi}\left[-l_i \times \log\left(l_i'\right) - (1-l_i) \times \log\left(1-l_i'\right)\right] \tag{12}$$

We considered only a portion of the labeled samples for calculating the training loss, as indicated by φ.

3.4. Transfer Learning (TL)

Transfer learning is one of the machine learning tools that leverage knowledge (features, weights, etc.) from previously trained models to train newer models. It aims to solve the issue of insufficient training data for a learning model [40]. There are three categories of TL. Inductive transfer learning occurs when the labels are available only in the target domain, and are missing in the source. Both source and target tasks are related but different. Unsupervised transfer learning is another category of TL, in which no labels exist in both source and target domains. A transductive transfer learning technique is applied when source labels are available but target labels are missing [41].

In our scenario, there were similarities between the source and target tasks, in that both were Twitter datasets. The difference was that the source dataset was built on friendship links (i.e., account A followed account B), while the target dataset was built on interaction links. In this setting, the source domain had a lot of labeled data, while the target domain had none. Therefore, we adopted the transductive TL in our work, as shown in Figure 2. We trained our model using TwiBot-20 (source), which has different types of bots, to transfer as much knowledge as possible, so as to distinguish between bots and human classes in new data (target). We used this approach to make our model more generalized for bot detection, especially with the growth of sophisticated bots that are able to avoid being detected. The results of our model in Section 5 emphasize that our model outperformed previous models, and that it had the ability to predict unlabeled data classes, successfully using the transfer learning approach.

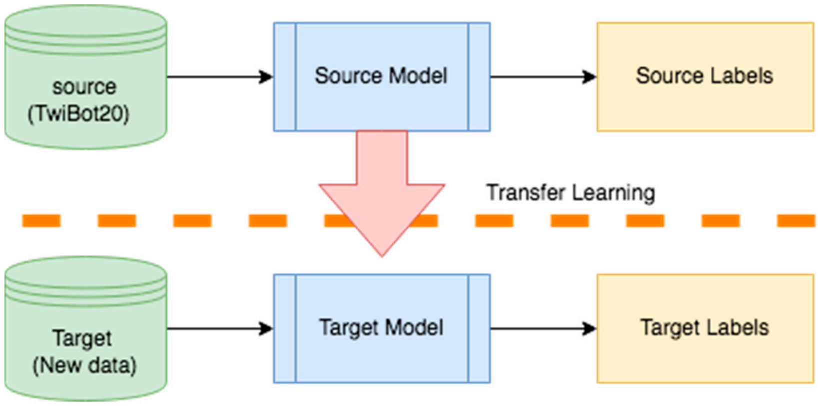


Figure 2. Illustration of transfer learning in our case scenario. Twibot20 was used as a source to train our model, Bot-MGAT, and to train target data that were new and unlabeled, to predict the labels.

4. Methodology

In this section, we provide details of the used datasets and preprocessing steps. We then discuss the selected features and environmental setup for the experiments. Then, we provide the required details of our proposed framework and parameter settings.

4.1. Data and Preprocessing

For our experiments, we used a recent benchmark dataset TwiBot20 [42] that included samples from the Twittersphere to train our model. The authors of TwiBot-20 divided users into four interest domains: politics; business; entertainment; and sports. For each user, TwiBot-20 contains the tweets, profile properties, and neighborhood information of a Twitter user. This dataset includes 229,573 Twitter users, 33,488,192 tweets, and 455,958 following relationship links.

TwiBot20 includes 38 features for profile metadata. These features are called the user's metadata, as they represent the profile information. We extracted 18 profile features in addition to the account label, either as a human user or bot, from three files, Train/Test/dev. These profile features are shown in Table 2. The total number of labeled accounts that the three files had was 11,826. According to the data, 55.7% of the samples consisted of bot accounts, and 45.3% were human. Figure 3 depicts the distribution classes of bots and humans in the TwiBot-20 data.

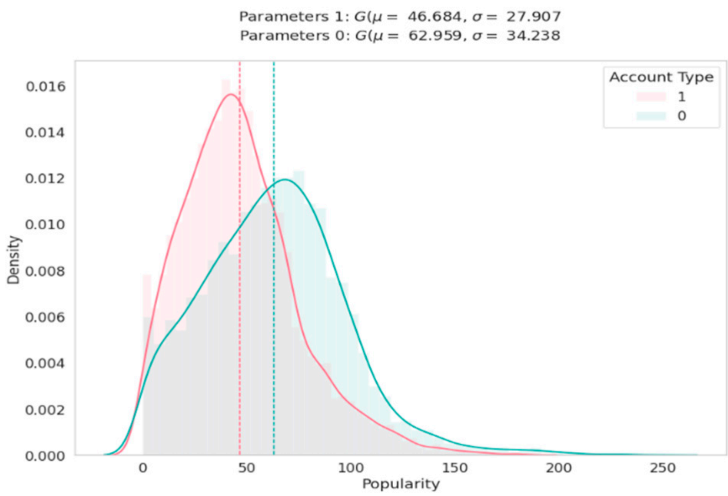


Figure 3. Distribution of the popularity of bots (class = 1) and humans (class = 0) in TwiBot-20.

Table 2. List of extracted profile features and their description.

#	Feature	Type	Description	Selected *
1	ID	Numerical	Unique identifier for the user account (64-bit).	
2	Follower count	Numerical	The number of users who are following this user account.	✓
3	Favorites count	Numerical	The number of tweets a user has liked since the account creation date.	✓
4	Statuses count	Numerical	Total number of tweets and retweets issued by the user.	✓
5	Friends count	Numerical	Total number of accounts this user is following.	✓
6	Age in days	Numerical	The total number of days since the account was created until the day of retrieving the data.	✓
7	Screen name length	Numerical	Total number of digits in the screen name.	✓
8	Listed count	Numerical	The number of public lists of which this user is a member.	
9	Protected	Boolean	True if the user has chosen to protect their tweets.	
10	Verified	Boolean	Indication that the user has a verified account.	✓
11	Profile image	Boolean		
12	Default profile	Boolean	TRUE that the user has not altered the theme or background of their profile.	✓
13	Default profile image	Boolean	TRUE that the user has not uploaded a profile image and the default image is used.	✓
14	Profile background image	Boolean	True if the user has changed the background image.	
15	Geo enabled	Boolean	TRUE if the current user attaches geographic data when tweeting or retweeting.	✓
16	Lang	String	The language that Twitter detects for a user account; if no language is detected (undefined).	
17	Location	String	An optional value where the user has defined their location in their account profile.	
18	Description	String	An optional value where user writes a description on their profile.	

* The final selected profile features in our model shown with (✓).

To test our model, we used two different hashtag datasets from NodeXL [43,44]. The first dataset was for a climate hashtag, "#actonclimate", and we refer to it as "climate hashtag". This dataset had a total of 5664 nodes and 15,651 edges. The second dataset was constructed based on the keywords "#IStandWithPutin" OR "#IStandWithRussia" OR "#StandWithRussia" OR "#NaziUkraine". This dataset contains 4941 nodes, and 6944 links. We refer to this dataset as "Russian hashtag". For both datasets, we extracted the profile features shown in Table 2, in addition to the links of interaction to build the graphs for the attention mechanism. Table 3 provides the summary statistics of the used datasets.

Table 3. Summary statistics for the used datasets.

Dataset	Released	Nodes	Edges
Twibot20	May 2021	229,573	455,958
Climate hashtag	April 2022	5664	15,651
Russia hashtag	May 2022	4941	6944

For data preprocessing, we deleted the IDs and lang features for better processing, as the lang value was null for all the records. We thus worked with 16 out of the 18 features in Table 2. To avoid any encoding process, we tried to deal with features in terms of numerical value. Therefore, we considered the screen name length instead of the screen name character encoding. Furthermore, the Boolean and string features were converted to 0 and 1 to indicate the changing of default status. In addition, the created date string was used to calculate the account age in days. The labels in the account type represented humans with zero and bot accounts with one.

4.2. Selected Features

Many proposed works in the literature addressed feature selection to train learning models. However, the number of selected features varied from 1000 [4] to much less [3,12]. In our experiments, we aimed to focus on using fewer features to enhance the efficiency and interpretability of our learning model. This will assure lower complexity costs when used in an online manner. In addition, recent studies [12,45,46] have shown that profile features are predictive enough to detect social bots. Therefore, we used profile numerical features, and we considered the availability of a value for a certain feature such as description, to eliminate any encoding process. Thus, if a user filled in the description field or location, we considered this as 1; otherwise, it would be 0; we employed a similar treatment for a number of other features, so as to avoid any language processing costs. Our final selected features are shown in the last column in Table 2.

4.3. Environmental Setup

In our work, all our experiments were undertaken on a workstation with a processor model Intel core i7-1087 = CPU with a RAM of 32 GB and NVIDIA GeForce RTX 3070 Max-Q GPU with 6 GB of VRAM. All the machine-learning models were built using python Scikit-learn library. All the graph-learning models were implemented using PyTorch geometric (PyG) (https://pytorch-geometric.readthedocs.io/en/latest/index.html accessed on 1 September 2021).

4.4. Proposed Framework

Our proposed framework model architecture utilized the transfer learning approach, as Figure 4 demonstrates. In this framework, there are two learning phases. The first phase is called "Source Training Phase". The model is trained to use multi-view graph attention networks on a partially labeled dataset. Once the model is trained, phase two starts. This phase is called "Target Training Phase". In this phase, another dataset, that is totally unlabeled, is tested, to predict the classes for data points using the trained model from the first phase. The output of this phase is labels for the new data that are unlabeled. Consequently, an evaluation process takes place to evaluate the output predictions, after applying a machine-learning classifier to ensure that the model can distinguish between classes.

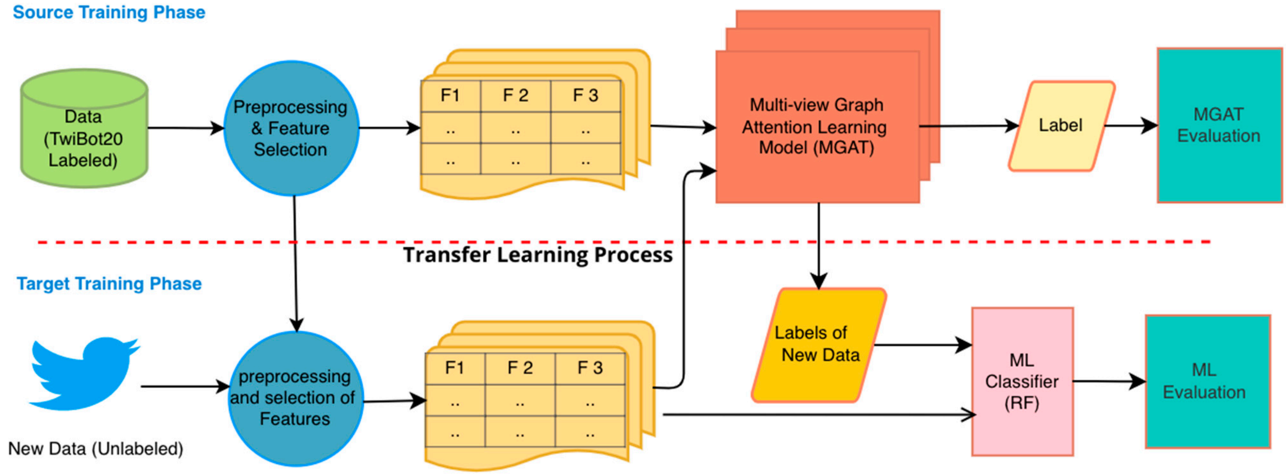


Figure 4. Bot-MGAT model architecture using the transfer learning approach.

Accordingly, we used TwiBot-20 as the input for the source domain model. We extracted the features into multi-view perspectives. These views can provide a different view of the data, for example (following, followers, mentions...etc.). In our case, as Figure 5 depicts, we used the edges' views that represented the following links (i.e., friendship) and interaction graphs. We implemented a linear layer to transform the input features into sufficient higher-level expressive representation for every node, as shown in Section 3.2. An importance weight was calculated using the attention mechanism for every node and its neighboring nodes. We applied an activation function (LeakyReLU) to maintain non-linearity. We used only one message-passing layer in each view, to avoid over-smoothing, which could occur when we had cascaded message-passing layers. This was because it would result in nodes with the same representations, and this would make the classification process more difficult.

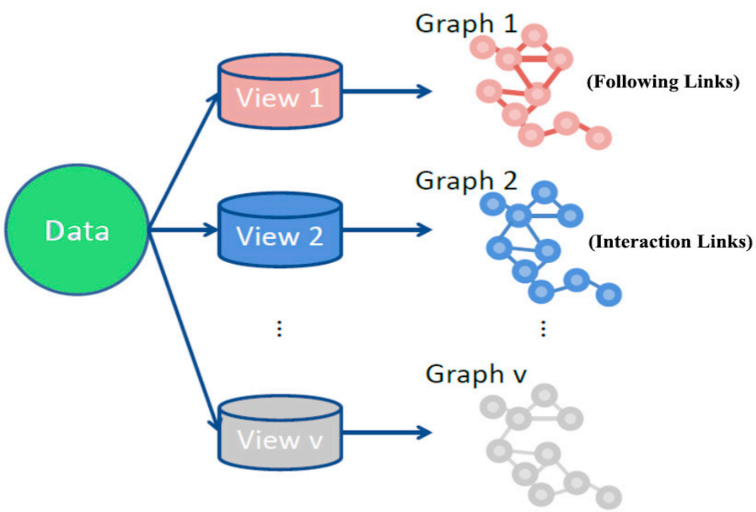


Figure 5. Multi-view perspectives in Bot-MGAT.

We used a weighted sum with parameter β to aggregate the representations from the different views of our graph. Although this parameter can be learnable through a linear layer or an attention layer, we decided to use a fixed value to reduce the complexity of the model. In Table 4, we present Bot-MGAT's parameters.

Table 4. Bot-MGAT parameters.

Parameter	Value
Activation function	Leaky ReLU
Learning rate	0.001
Optimizer	Adam
Epoch	100
Dropout	0.5
Weight decay	0.00003
Message passing layers	2
Folds	10
Embedding size	128
β	0.001

Once the model was trained on TwiBot-20, we transferred the learning by utilizing the model with target data, namely unlabeled "climate hashtag". We applied the same steps for preprocessing and feature selection. Then, we applied the MGAT model to predict the label for every node in the target data. Once we obtained the labels, we evaluated the labeling process using a machine-learning classifier. We chose random forest (RF), as it performs well in this classification problem, as shown in different studies [12,47].

We used the "Russian hashtag" dataset, which was not used in the training or testing phases, to validate our model. We applied the same steps and model to verify our results. We evaluated our model using three different evaluation metrics: accuracy, F1 score, and MCC. The accuracy aimed to evaluate the model correctness. The F1 score and Matthews correlation coefficient (MCC) were used as more balanced evaluation metrics for the binary classification task. Bot-MGAT's performance is shown in Section 5. We summarized the steps in Algorithm 1.

Algorithm 1 Bot-MGAT with TL

Input : *Source data:* TwiBot-20 dataset with $Nu_i^{twi},\ C_i^{twi}, l_i^{twi}, E^{twi},\ i = 1, 2, 3, \ldots, N$
Target data: unlabeled data of different hashtags with $Nu_j^{un},\ C_j^{un},\ E^{un},\ j = 1, 2, 3, \ldots, J\ (unlabelled\ data\ size)$

Output : Node labels for the unlabeled data l_j^{un}

Train Phase:

1. $model \leftarrow$ Initialize parameters $(\boldsymbol{W}, b)$
2. **For** $epoch$ in $epochs$:
3. **For** i in N:
4. $l_i^{twi'} \leftarrow model\left(Nu_i^{twi},\ C_i^{twi}, E^{twi}\right)$ using Equations (1) and (9)–(11)
5. End **For**
6. $loss \leftarrow BCE(L^{twi'},\ L^{twi})$ using Equation (12)
7. Calculate the gradients$(\nabla loss_{\boldsymbol{W}},\ \nabla loss_b)$
8. Update the parameters through back propagation
9. $\boldsymbol{W} \leftarrow \boldsymbol{W} - \nabla loss_{\boldsymbol{W}}$
10. $b \leftarrow b - \nabla loss_b$
11. End **For**
12. Save $model$

Prediction Phase:

13. For j in J:
14. $l_j^{un} \leftarrow model(Nu_j^{un},\ C_j^{un},\ E^{un})$
15. End **For**
16. Train a random forest model on $l_j^{un}, Nu_j^{un},\ C_j^{un},\ for\ j = 1, 2, 3, \ldots, J$
17. Record performance

5. Results

In this section, we discuss the performance results of Bot-MGAT in two states: with and without the TL approach. We highlight the performance by addressing evaluation metrics such as accuracy, MCC, and F1. We compare our performance to baselines, including works that addressed the bot detection problem.

5.1. Bot-MGAT without TL

As an initial step, we used TwiBot-20 to train and test Bot-MGAT without the TL phase. We used the profile features mentioned in Section 4.2. We compared our model with other graph neural networks models, namely GCN, GAT, and RGCN, as shown in Table 5. We chose these models as they were close to our model's implementation, and remained in the domain of GNN. For example, RGCN is an application of a relational graph convolutional network for link prediction and classification. We tested a simple GCN, to find the difference between the base model and the RGCN model. Based on the results, RGCN performed better than GCN, and (0.01) better than GAT. This highlighted the reported performance in the literature of RGCN [20]. For GAT, a single attention graph network was applied, with a single view of the dataset. We applied cross validation (10 folds) for all models, to ensure confidence that there was no over-fitting issue in the trained models.

Table 5. Bot-MGAT without TL compared to other GNN models.

Model	Accuracy	F1 Score	MCC
GCN	0.7469	0.7790	0.4867
GAT	0.7962	0.8399	0.6185
RGCN	0.8069	0.8470	0.6371
Bot-MGAT$_{no_TL}$	0.8098	0.8485	0.6491

Bot-MGAT without TL outperformed the other GNN models slightly, with an accuracy score of 80.98%, an F1 score of 0.8485, and an MCC of 0.6491. This indicated that there was scope for improvement in Bot-MGAT with TL. In addition, GAT and RGCN both showed similar performance to Bot-MGAT in terms of accuracy and F1 scores: they achieved a score of 79.62% and 80.69%, respectively, for accuracy, and 0.8399 and 0.8470, respectively, for F1. This highlighted the hidden information that attention mechanism models aim to reveal.

5.2. Bot-MGAT with TL

Our objective was to use node representations to predict the label of a given node by applying the attention mechanism with a multi-view of trained data. As an initial step, we used an available tool [48] to label both datasets "climate hashtag" and "Russian hashtag", using Botometer API (https://botometer.osome.iu.edu/ accessed on 12 May 2022). This tool has been used in the literature [49,50]. The labeling process used a complete automation probability (CAP) score, with a threshold of 75%, in order to determine that the account label was a bot if it was higher than the threshold. After the labeling process was completed, we applied cross-validation (10 folds) and the random forest (RF) classifier to the climate hashtag and Russian hashtag, as shown in Table 6. We chose RF, as mentioned previously; it performed well with the bot detection problem.

Table 6. RF results for all datasets, after using Botometer for both hashtags, compared to TwiBot-20.

Dataset	Nodes	Accuracy	F1 Score	MCC
TwiBot-20	11,826	0.8015	0.8371	0.5810
Climate hashtag	5664	0.7691	0.64361	0.4582
Russian hashtag	4941	0.7106	0.7581	0.4045

The labeling results in Table 6, after using Botometer, show that the Russian hashtag results were convenient and better, compared to the climate hashtag. This was due to the issue of imbalance that is common in this problem. In the Russian hashtag, there were 2807 accounts labeled as bots out of the total; for the climate hashtag, there were fewer accounts labeled as bots. The results, compared to TwiBot-20, were obviously poor and average, in terms of F1 score. Twibot-20 was able to maintain a good F1 score of 0.8371 among both hashtags. This was due to the sophisticated bots' design, in order to avoid being detected [7]. Therefore, TL was useful in our case, especially as both the source and target datasets were Twitter data, and they had a similar task: the detection of bots.

Consequently, we trained Bot-MGAT with TwiBot-20, as it was a recent diverse dataset that was available for experimentation. In addition, it covered different domains of both humans and bots, which increased the probability of detecting different types of bot account when tested on a specific domain. After the training phase, we tested the model, using the climate hashtag dataset. Table 7 shows the results of our framework comparison using TL compared to not using TL.

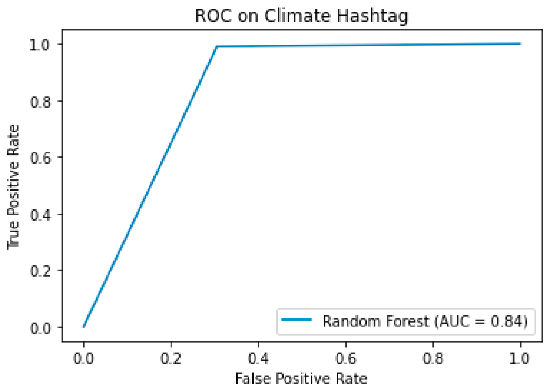
Table 7. Bot-MGAT performance with TL and without TL.

Approach	Datasets	Accuracy	F1 Score	MCC	AUC
Bot-MGAT$_{no_TL}$	TwiBot-20	0.8098	0.8485	0.6491	0.79
Bot-MGAT$_{TL}$	Climate hashtag	0.9558	0.9739	0.8334	0.84
	Russian hashtag	0.9780	0.9842	0.9481	0.98

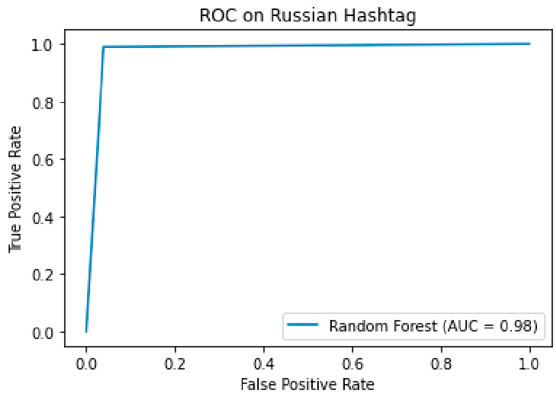
Bot-MGAT with TL, using the Twibot-20 and climate hashtag datasets, outperformed the results of the other models, with a 15% improvement in accuracy, a 13% increase in F1 score, and an 18% increase in MCC. This indicated the ability of our model to distinguish the properties of each view of data with a completely unseen dataset used for testing. This showed the efficiency and flexibility of GAT-based models that outperformed in the literature [18,37,51,52].

We used the Russian hashtag dataset, which was not used in training or testing, to validate our model. We applied the same experiment that we performed with the climate hashtag dataset. The results are shown in Table 7. It outperformed the model without TL, demonstrating a score of 0.9780 for accuracy, 0.9842 for F1 score, and 0.9481 for MCC. This emphasized the effectiveness of TL in the bot detection problem. This incorporated the fact that GAT models are capable of obtaining hidden representations of each node in the graph, using self-attention and neighboring nodes embedding for the classification task.

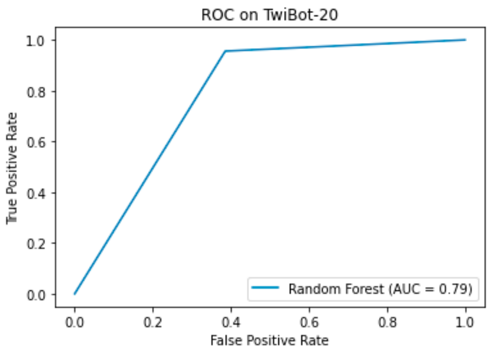
Figure 6 provides the results for BotMGAT with TL receiver operating characteristics (ROC) and area under the receiver operating characteristic curve (AUC) for Twibot20, the climate hashtag, and the Russian hashtag. The reason for the high AUC (0.98) in the Russian hashtag was the number of bots involved. Unlike TwiBot-20 (AUC = 0.79), which was created based on the different interests of the users, and the climate dataset (AUC = 0.84), which was created based on the influence of the climate change hashtag, it seems that modern bots mostly interact with political topics.



(**a**)



(**b**)



(**c**)

Figure 6. (**a**) The climate hashtag area under the curve (AUC) using Bot-MGAT$_{TL}$ was 0.84. (**b**) The Russian hashtag area under the curve (AUC) using Bot-MGAT$_{TL}$ was 0.98; this highlighted the number of bots that were in the Russian hashtag compared to the climate change hashtag. (**c**) The Twibot20 area under the curve (AUC) was 0.79.

5.3. Comparison with Baselines

Table 8 shows that the performance of our model, Bot-MGAT with TL, outperformed other baseline works that aimed to detect social bots in Twitter. In BotRGCN [20], the proposed framework encoded different types of features (description, profile, tweet) into numeric features, to avoid feature engineering, to construct a heterogeneous graph of different types of edges between users in Twitter. The strength of this approach is that it focused on the following links of the graph to detect bots accounts. However, a recent study [53] found that bot accounts show a lower number of followers and friends with respect to humans. This contrasted with the fact that early generations of bots had a higher ratio of following rate [35]. In [21], an inductive representation learning was proposed, using GCNN to detect spam bots on Twitter. They used the same approach proposed by [54,55] to learn the embedding for nodes in the graph structure, using a neural network and propagation methods. They tested their model using early bot datasets that included fake accounts that proved to be easier to detect and distinguish from recent bots.

Table 8. Bot-MGAT performance compared to baselines.

REF#	Dataset	Approach	Accuracy	F1 Score	MCC
BotRGCN [20]	TwiBot-20	RGCN	0.8462	0.8707	0.7021
Alhosseini et al. [21]	Yang C et al. [56] 2013	GCNN	0.94	0.84	-
Bot-MGAT$_{no_TL}$	TwiBot-20		0.8098	0.8485	0.6491
Bot-MGAT$_{TL}$	TwiBot-20 + Climate hashtag	MGAT	0.9558	0.9739	0.8334
Bot-MGAT$_{TL}$	TwiBot-20 + Russian hashtag		0.9780	0.9842	0.9481

Bot-MGAT with TL outperformed other models because the graph attention mechanism with multi-view was able to reveal the hidden representations of nodes. Additionally, TL was the key player in enhancing the model, as shown in Table 8; using a training dataset that is recent, and rich in different domains of samples of bots, made it reliable to detect bot accounts in a specific domain (for example, a hashtag). It is clear, therefore, that semi-supervised graph neural network models with profile features can predict bot accounts with good performance.

6. Conclusions

The evolving nature of recent bot accounts makes bot detection a challenging task. Using traditional techniques has proved to perform poorly with new bot generations. In this paper, we propose the Bot-MGAT framework with a transfer learning approach based on the attention mechanism. The results show that our model outperformed other GNN models and baseline work, with an accuracy of 97.80%, an F1 score of 0.9842, and an MCC score of 0.9481. We evaluated our model using two different datasets that were not used in the training phase, and the results were the best reported.

Bot-MGAT with TL outperformed other models because the graph attention mechanism with multi-view was able to reveal the hidden representations of nodes. The results showed that our model was able to identify bot class very effectively, using profile features only, and the implementation of TL with a multi-view approach. In addition, this should reduce the effort and the tedious process of manual labeling, and highlight the sophisticated design of recent social bots that are able to avoid detection. For future work, we will test our model using additional views for graphs, and different parameters for the model.

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Data Availability Statement: We used public datasets for our experiments, as cited in Section 4.1, and have provided a reference to them in the list of references.

Conflicts of Interest: The authors declare no conflict of interest.

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