Behavioral Modeling of Persian Instagram Users to detect Bots

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Abstract
Bots are user accounts in social media which are controlled by computer programs. Similar to many other things, they are used for both good and evil purposes. One nefarious use-case for them is to spread misinformation or biased data in the networks. There are many pieces of research being performed based on social media data and their results validity is extremely threatened by the harmful data bots spread. Consequently, effective methods and tools are required for detecting bots and then removing misleading data spread by the bots. In the present research, a method for detecting Instagram bots is proposed. There is no data set including samples of Instagram bots and genuine accounts, thus the current research has begun with gathering such a data set with respect to generality concerns such that it includes 1,000 data points in each group. The main approach is supervised machine learning and classic models are preferred compared to deep neural networks. The final model is evaluated using multiple methods starting with 10-fold cross-validation. After that, confidence in classification studies and is followed by feature importance analysis and feature behavior against the target probability computed by the model. In the end, an experiment is designed to measure the models effectiveness in an operational environment. Finally, it is strongly concluded that the model performs very well in all evaluation experiments.

Introduction
Before web usages become widespread, there were rather simple methods for communication among people, including letter, telephone, and fax. After this time, tools such as email and video chat platforms, such as Skype, appeared. These platforms were only capable of a peer to peer data transmission which was also limited by acceptable data types at the beginning of the era.

This generation was obsoleted by Social Networks; a new platform had brought novel facilities for information sharing and connectivity. The data shared by users were preserved and the relationship’s networks were explicitly defined and accessible, thus a large amount of data, representing people’s activities, was stored. This data is commonly referred to as The Big Data.

With the big data, new opportunities have appeared for solving problems with no exact solutions. Most of these problems were coming from social science creating a new field of study known as Computational Social Science. Multiple issues are threatening the validity of research results in this field among which data pollution is a major threat. One of the resources for this problem is an entity known as Bot.

Bots are user accounts controlled by a computer program aimed at gathering or spreading data. Although they might be used for good purposes, a large number of them are used for evil goals. Accordingly, providing tools for detecting such accounts and canceling their effects is extremely required. In this research, an effective solution is suggested for this problem which has achieved great scores from multiple evaluation metrics.

Here, Instagram is the target social media. Recently, it has become common among people from all around the world. Persian speaking users have a large community in this media such that analyzing their data provides valuable answers to important questions.

Literature Review
Bot detection is a well-known problem in computational social science. In this section, the most important researches in this field are reviewed. They are divided into three categories, corresponding to the approach they have adopted. Each category is described below:

The first category includes: (Chu et al. 2012), (Gao et al. 2015), (Gong, Frank, and Mittal 2014), (Carminati, Ferrari, and Viviani 2014), (Danezis and Mittal 2009), (Yu et al. 2008b), (Yu et al. 2008a), (Cross and Jain 1983), (Murphy, Weiss, and Jordan 2013), (Mohaisen, Yun, and Kim 2010), (Leskovec et al. 2008), (Viswanath et al. 2010), (Mehrotra, Sarreddy, and Singh 2016) and (Jia, Wang, and Gong 2017), (Zhang et al. 2016). In mentioned researches, the main approach is using network structures; as a result, their job includes mostly graph-based methods. The major weakness of this researches is their poor results compared to the last category.

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In the second category: researches such as [Jiang et al.
2013], (Yang et al. 2014), (Wang et al. 2013), (Subrahman-
ian et al. 2016) and (Gilani, Kochmar, and Crowcroft
2017) are found. Their research mostly relies on crowd-sourcing.
Threatening user’s privacy is the most important challenge in
researches in this section.

In the last category researchers such as: (Chu et al. 2012),
(Subrahmanian et al. 2016), (Yang et al. 2014), (Lee, Eoff,
and Caverlee 2011), (Dickerson, Kagan, and Subrah-
manian 2014), (Davis et al. 2016), (Varol et al. 2017), (Alar-
ifi, Alsalem, and Al-Salman 2016), (Kantepe and Ganiz
2017), (Jia, Wang, and Gong 2017), (Mehrotra, Sarreddy,
and Singh 2016), (Gilani, Kochmar, and Crowcroft 2017),
(Cai, Li, and Zeng 2017) and (Chavoshi, Hamooni, and
Mueen 2016) are included. Above mentioned researches have adopted a supervised learning approach toward this
problem. Compared to the other categories, researches in
this one have achieved highers scores.

The Data set
There is no data set of bots and genuine accounts except one
which was introduced in (Akyon and Esat Kalfaoglu 2019)
which does not include any Persian user account. As a result,
a new data set suitable for present research’s goals should
have been gathered.

Positive class
Since there was no sample for the Instagram bot, a simpli-
fying assumption was made: Since all harmful bots possess
fake identities, gathering a set of fake accounts, will result
in having a set of Instagram accounts which could be con-
sidered a superset for Instagram bots. The same assumption
has been made before in (Cresci et al. 2017) when preparing
a data set of twitter bots that were used for developing the
famous bot detection tool Botometer in (Varol et al. 2017)
afterwords. Furthermore, to satisfy generalization consider-
ations, five fake account providers for Instagram were re-
ferred to and 1000 fake accounts where ordered.

Negative class
To have a set of genuine Instagram accounts, data from So-
cial Networks laboratory is used. A data set of nearly all
Persian Instagram accounts is gathered in this labora-
tory concerning the user’s privacy. A random sample of size
1000 from this data was taken to represent genuine accounts.
Since most user accounts in each social media belong to real
humans, thus a random sample will provide a set of accounts
including a large portion of genuine accounts.

In this data set, six features are used which are described in table 1.

Behavioral Modeling
Behavior on Instagram has three forms: 1) to share a post,
2) to comment beneath a post and 3) to like a post or a com-
ment; the three forms are referred to as behavioral prop-
ties. According to Instagram’s structure, tracks of only the

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Table 1: Features introduced in the data set.

| No | Feature name          |
|----|-----------------------|
| 1  | username length       |
| 2  | full name length      |
| 3  | biography length      |
| 4  | followers count       |
| 5  | followings count      |
| 6  | Posts creation times  |

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Table 2: Statistical measure used for modeling posts sharing times.

| No | Statistical Measure |
|----|---------------------|
| 1  | Min                 |
| 2  | Max                 |
| 3  | Mean                |
| 4  | Median              |
| 5  | Std                 |
| 6  | Skewness            |
| 7  | Kurtosis            |
| 8  | Entropy             |

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Effectiveness of Behavioral Modeling
To test how effective this form of modeling is, a simple clas-
sifier is used, which is Gaussian Naive Bayes in this case,
as a baseline. During two different experiments, one all fea-
tures and then only basic features (all feature minus statisti-
cal measures defining behavioral properties) are fed to the
classifier. In each experiment, the classifier is evaluated us-
ing 10-fold cross-validation. To check for the statistical sig-
nificance of the reported results, the above-mentioned ex-
periments are performed 1000 times which results in having
1,000 values for each of the measures per model. In each
iteration (every single experiment of all 1,000), observations
are shuffled 100 times to avoid bias. For 10-fold cross-
validation, observations are shuffled again which sums up to
101 times random shuffling the data. It should be mentioned
that the data is normalized using Z-standardization before
being fed to the model. The final results for this evaluation
are represented in table 3.

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Figures 1 to 4 illustrate distributions for metric values.
Table 3: Behavioral modeling evaluation results.

| No | Measure | Basic Features | All features | p-value |
|----|---------|----------------|--------------|---------|
| 1  | Accuracy| 0.63 +/- 0.03  | 0.81 +/- 0.01| 0.00    |
| 2  | Precision| 0.61 +/- 0.05  | 0.99 +/- 0.00| 0.00    |
| 3  | Recall  | 0.90 +/- 0.08  | 0.65 +/- 0.02| 1.00    |
| 4  | F-1     | 0.71 +/- 0.03  | 0.78 +/- 0.01| 0.00    |

Figure 1: Distribution of accuracy values for both models. The darker curve (left) represents the model trained on all features and the lighter (right) has only used basic features.

Figure 2: Distribution of precision values for both models. The darker curve (left) represents the model trained on all features and the lighter (right) has only used basic features.

Figure 3: Distribution of recall values for both models. The darker curve (right) represents the model trained on all features and the lighter (left) has only used basic features.

Figure 4: Distribution of F-1 values for both models. The darker curve (left) represents the model trained on all features and the lighter (right) has only used basic features.

Furthermore, the last column, depicts the result of a statistical test evaluating the null hypothesis which says the measure for both states are equal against the alternative hypothesis saying numbers in the right column are greater than the left column in a one-tailed test. As is illustrated in the right-most column, for all measures except the recall, the null hypothesis is strongly rejected in favor of the alternative hypothesis. To make certain that the experiment meets central limit theorem’s criteria:

- Observations for the test are picked randomly.
- Sample size is equal to 40, as a result, it is:
  - less that 10% of the population.
  - greater than 30 (in order to support skewness in the data).

From this experiment, it is clearly understood that behavioral modeling is effective in distinguishing bots and genuine accounts on Instagram, and this result is statistically significant.

**Training the candidate models**

**Features management**

In all machine learning studies, the quality of features must be examined before feeding the data to the model. In the present research, this job is done in two phases: 1) Calculating the importance of each feature 2) calculating the correlation between each pair of features.

After the two above-mentioned phases, redundant and highly correlated features (except one of them), also known as redundant features, are removed in order to reduce model complexity and training time. The remaining features are introduced in the table.

**Finding candidate models**

Deep learning models have achieved astonishing results in the AI community, however, studies such as (Dacrema, 2023).
Table 4: Remaining features after removing non-related and redundant features

| No | Feature name           |
|----|------------------------|
| 1  | Max                    |
| 2  | Std                    |
| 3  | Skewness               |
| 4  | Entropy                |
| 5  | following count        |
| 6  | full name length       |
| 7  | biography length       |

Cremonesi, and Jannach 2019, have shown that in many cases, fine-tuned classic machine learning algorithms (such as KNN, etc.) can achieve good performance even compared to deep learning methods. Furthermore, due to the complex structure of deep methods, a large amount of training data is required for them to achieve a high performance, which is not present in this study. Accordingly, classic machine learning methods are preferred over deep learning methods in current research.

Among classic methods, some are selected for further analysis including KNN, Decision Tree, SVM, Random Forest, and AdaBoost. This set, includes a spectrum of classic machine learning methods, from simple to complex. It is assumed that they can achieve good performance when using optimal hyperparameters.

Fine-tuning the models

In order to fine-tune the models, a portion of the data should be taken as the test set. A random sample including 30% of all observations is selected for this process. A different sample is used for fine-tuning each model. In this research, sci-kit learn is used for implementing the solution, as a result, hyper-parameters names are compatible with sci-kit learn the terminology. Final results in this phase are reported through tables 5 to 9.

Table 5: Optimal hyper-parameter values for KNN

| Name       | Value       |
|------------|-------------|
| Algorithm  | Ball Tree   |
| Leave size | 10          |
| K          | 5           |
| Distance   | Manhattan   |
| Weights    | Distance    |

Table 6: Optimal hyper-parameter values for Decision Tree

| Name          | Value  |
|---------------|--------|
| Criterion     | Gini-index |
| Max depth     | 10     |
| Min samples leaf | 2      |
| Min impurity split | 3      |
| Splitter      | Random |

Table 7: Optimal hyper-parameter values for SVM

| Name                        | Value       |
|-----------------------------|-------------|
| C                           | 3           |
| Kernel                      | Polynomial  |
| degree                      | 5           |
| coef0                       | 1.5         |
| shrinking                   | True        |
| probabilistic approximations| True        |

Table 8: Optimal hyper-parameter values for Random Forest

| Name                      | Value  |
|---------------------------|--------|
| Criterion                 | Entropy|
| Max depth                 | None   |
| Max features              | 5      |
| Min samples split         | 3      |
| n estimators              | 20     |

Table 9: Optimal hyper-parameter values for AdaBoost

| Name          | Value  |
|---------------|--------|
| Algorithm     | SAMME  |
| Learning rate | 1.0    |
| n estimators  | 50     |

Train and evaluate

When optimal hyper-parameters are determined, fine-tuned models should be trained with enough data. For each model, the whole data is shuffled, a random sample including 70% of observations is selected for training models and the rest is preserved for the test. In addition to test data, the models are evaluated using 10-fold cross-validation, however, reported values for all metrics are from cross-validation except for the area under the ROC curve which is computed using the test data. In this table, the greatest values are written in bold. The evaluation results are illustrated in 10.

According to the results, the AdaBoost has achieved the highest scores. Compared to the baseline model, this model has achieved a better score in metrics such as accuracy, recall, and f-1 but has got a lower score in precision.

AdaBoost further analysis

Classification confidence

To examine how confident the AdaBoost is when it makes decisions about observations, probabilities of being a bot computed by the model for the test data are computed.

In this figure, the curve on the left (the darker) depicts the distribution of probabilities for being a bot computed for genuine accounts in the test data. The curve on the right (the lighter one) shows the same probabilities for genuine accounts in the test data. Ideally, both curves should have been located away from each other, however, the figure shows the opposite. Consequently, it is understood that despite its high accuracy, the model is not much confident about the decisions it makes.
Table 10: Classification Results

| The model | Accuracy | Precision | Recall | F-1 | ROC AUC |
|-----------|----------|-----------|--------|-----|---------|
| KNN       | 0.92     | 0.95      | 0.90   | 0.92| 0.97    |
| Decision Tree | 0.92    | 0.93      | 0.91   | 0.92| 0.94    |
| SVM       | 0.93     | 0.94      | 0.94   | 0.94| 0.96    |
| Random Forest | 0.95   | 0.94      | 0.94   | 0.95| 0.99    |
| AdaBoost  | 0.95     | 0.95      | 0.95   | 0.95| 0.99    |

Features’ importance and relations

One way to analyze decisions made by a model is to compute the importance of each feature in the classification process (recall some features were removed in the feature management phase, thus Gini importance is computed for remaining features by the model). One method for computing the importance values, is gini importance which is described in (Louppe et al. 2013). The Gini importance values for all features which are used in the data are computed and reported in figure 6.

According to this figure, Max is the most effective feature in the classification process. It is followed by following count, standard deviation, entropy and three others. Among the four most important features, three are behavioral features. This is another proof of the effectiveness of behavioral features.

The last step toward investigating the AdaBoost is to analyze relations between every single feature’s values and the probability of being a bot which is computed by the model. This is done by using Partial Dependency Plots (PDPs); these plots are illustrated in figures 7 to 10. Since the rest of the features have rather no observable relation with the probability of being a bot, their corresponding PDPs are not presented.

Final experiment - I

A final experiment is designed to investigate the practical effectiveness of the AdaBoost. This experiment includes the following steps:

- A random sample of size 5000 is selected from social networks lab’s data
- All observations from the sample are fed to the AdaBoost and the probability of being a bot is computed for all of them.
- Observations are sorted in decreasing order of probabilities and 50 first accounts were selected for hand-check.

The results of this experiment are briefly illustrated in table 12 and are comprehensively described here. Among these fifty accounts:

- Ten were not found. This might have been due to username change and/or account removal.
- Ten accounts were similar to genuine accounts. This experiment is based on observing profile pictures, the similarity between the profile picture and other posted pictures, etc. It is clear that in this step, decisions are made based on the user’s content. Since content-related features
are absent in the data set, such a phenomenon is likely to be observed.

- Thirty accounts looked like genuine accounts. Decisions in the step are made on a similar basis as the previous step. Recalling that content-related features are absent, this observation shows that behavioral features are in tight relation with content features.
accounts. To investigate the classifier in this fashion, an experiment was designed. This experiment includes five iterations. In each iteration, accounts belonging to one of the visited Instagram service providers are hold out plus an equal number of genuine accounts altogether as test data, and the model (AdaBoost with optimum hyper-parameters) is trained on rest of data. The results of this experiment are reported in Table 13.

Table 13: Results of the class by class evaluation.

| Measures | Itr 1 | Itr 2 | Itr 3 | Itr 4 | Itr 5 |
|----------|------|------|------|------|------|
| Accuracy | 0.98 | 0.98 | 0.96 | 0.95 | 0.97 |
| Precision| 0.98 | 0.98 | 0.96 | 0.95 | 0.97 |
| Recall   | 0.98 | 0.98 | 0.96 | 0.95 | 0.97 |
| F-1      | 0.98 | 0.98 | 0.96 | 0.95 | 0.97 |

In Table 13, each column includes same values for all metrics. Although this observation seems strange, it is similar to results in Table 12 so the results are reasonable in this setting.

Furthermore, in all iterations, except for iteration 4, all metrics’ values are greater than 0.95 which was achieved in 10-fold cross-validation (as reported in Table 10). Such an increase in evaluation metrics might be observed due to the following reasons:

- Usually, evaluation metrics achieve higher scores with test data.
- In this experiment, data is re-sampled with replacement to provide an equal size for both classes. Extra observation gathered in this way, might have improved classification’s quality.

Results

In this research, a new data set including samples of bots and genuine Instagram accounts are gathered concerning generality concerns. Behavioral modeling is introduced as an effective technique for modeling Instagram users’ data concerned with the bot detection problem. Classic machine learning algorithms are used for classification and are fine-tuned to have their performance boosted. It is shown that fine-tuned classic machine learning models perform well in the current study. Boosting, as an ensemble method has proved to be more effective compared to simpler methods. AdaBoost, which has achieved the best performance among all studied methods. Creation times of most recent posts (which is introduced as the Max in the data set) are proved to be the most important feature in classification which has a negative linear relationship with the probability of being a bot computed by the classifier.

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