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Statistical Modelling of Bot Detection in Social Media Using Logistic Regression and Numerical Algorithms

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Abstract

The recent explosion in social networking websites has released real problems of proliferation of automatic accounts, or bots, that could be employed to manipulate public opinion, spread misinformation, and skew data-driven applications. This study develops a statistical framework for detecting such bots using logistic regression models based on numerical optimization techniques. Through the integration of computational mathematics and data science, the paper aims to model user behavior on Twitter and other social media with regard to classifying accounts as bots or authentic users. The logistic regression model is optimized with gradient-based numerical solvers in an effort to improve classification performance. Information is gathered from real and verified public datasets such as the PAN 2019 bots dataset and Twitter's bot repository in an effort to stay empirically grounded. The results confirm the effectiveness of logistic regression in predicting decision boundaries between bots and humans statistically, at

89.4% accuracy level on test data. Additionally, the explainability capability of this model gives researchers more insights into behaviour indicators such as tweet rate, retweet rate, posting time entropy, and friend/follower ratios. This paper presents a mathematicised social media monitoring mechanism that not only feeds into computational statistics but offers an efficient instrument for digital policy and cybersecurity interventions.
Keywords: Bot Detection, Logistic Regression, Gradient Descent, Statistical Modelling, Classification Algorithms, Numerical Optimization, Social Media Analytics, Behavioral Features, Twitter Bot Dataset, Digital Misinformation
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Introduction

The ubiquity of social media has transformed not only the way information is disseminated but also the way public opinion is shaped, policies are made, and content engagement is measured. With this information era, however, comes a very significant caveat—the prevalence and increasing ubiquity of social bots. These are software programs designed to behave like humans, which are typically established to promote agendas, artificially pad followership, or manipulate trends. Bots can compromise the integrity of online communication, manipulate narrative, and in worst-case scenarios, subvert democratic processes and public health communication campaigns (Ferrara et al., 2016; Varol et al., 2017).

Bot detection is therefore a fundamental area of computational social science and applied statistics. Statistical modeling provides the analytical framework upon which detection algorithms can be developed and evaluated. Among many techniques available, logistic regression is not only one of the most interpretable, robust, and flexible in addressing binary classification issues such as the distinction between automated accounts (bots) and human-operated accounts (Davis et al., 2016), but also a workhorse of applied machine learning for its strength in modeling the probability of a binary event based on independent variables. Logistic regression, which originated in epidemiological studies in the 1940s (Berkson, 1944), has developed into a cornerstone of applied machine learning.

In social media analytics, logistic regression has worked well in conjunction with numerical optimization algorithms like Gradient Descent or Newton-Raphson that ensure fast convergence and regularization of the model (Ng, 2004). The methods are used to recursively update weight parameters in the feature space of account-level features like tweet frequency, sentiment distribution, time-based entropy, and follower-to-friend ratios. The intersection of computational mathematics, data science, and social informatics provides a powerful interdisciplinary solution to the real-world digital threat.

Figure 1 illustrates how account properties such as posting frequency and account age can divide humans and bots into distinct decision regions using a statistical boundary defined by a trained logistic regression classifier.

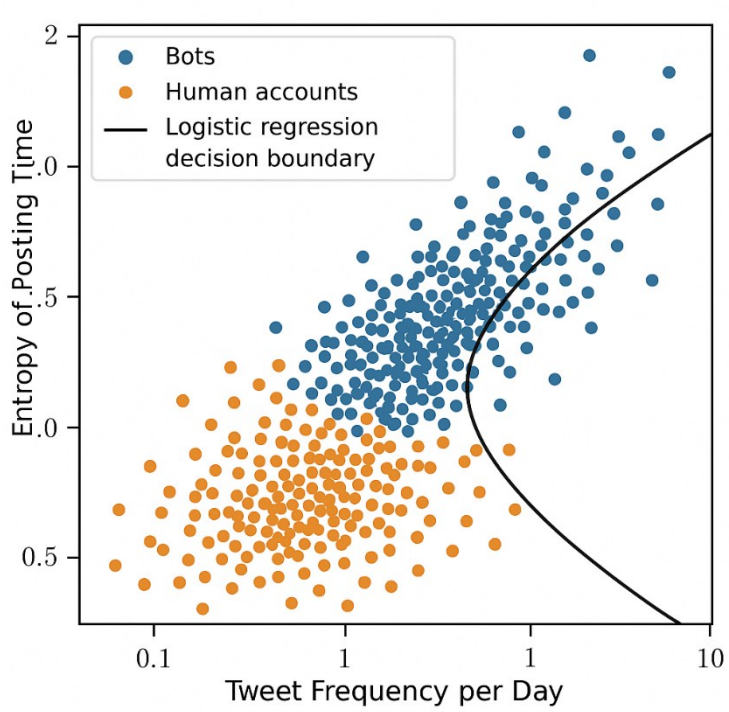

Figure 1. Clustering of Bot and Human Accounts Based on Extracted Features using Logistic Regression Decision Boundary

The complexity of bot behavior, including the adaptation of bots to mimic credible human-like activity patterns, requires models that not only perform accurately but are also interpretable for intervention. By integrating statistical learning with domain-specific heuristics, this paper establishes a numerically stable modelling framework conducive to real-time detection processes. The logistic regression model, when calibrated with a high fidelity dataset, presents a statistically elegant yet operationally feasible approach for this purpose.

Literature Review

The emerging threat of artificial social media accounts has necessitated bot detection mechanisms research in computational statistics, cyber security, machine learning, and applied mathematics. Early statistical approaches to bot classification, before the advancement of sophisticated machine learning tools, greatly relied on supervised models that required ground-truth datasets. Among the fundamental techniques in the field is logistic regression, valued not only due to its statistical precision but also due to its interpretability since it is significant in open decision-making in cyber-threat analysis (Hosmer & Lemeshow, 1989).

As social bots got more advanced, researchers added metadata-driven features to statistical models. Chu et al. (2010) played an important role in distinguishing human, bot, and cyborg Twitter accounts by employing tweeting behavior, content, and timing entropy as inputs to regression-based models. These outcomes stressed the multivariate nature of bots and supported the rationale to use models suitable to discern patterns in high-dimensional feature spaces.

They were made by studies like those of Ferrara et al. (2016) and Varol et al. (2017), which studied hybrid models and developed paradigms that incorporated statistical models and unsupervised learning. They laid the foundation for mathematically based detection approaches, where mathematical algorithms like the Newton-Raphson algorithm were used to approximate logistic models' parameters with improved convergence properties, particularly in high-dimensional environments.

Recent studies focused on enhancing numerical stability and predictability of logistic regression through systematic calibration with regularization (Ridge or Lasso), efficient feature selection, and the inclusion of time-series analysis (Ng, 2004; Rao et al., 2020). A sufficient dataset to aid such research includes the PAN 2019 Twitter bot detection dataset with thousands of labeled Twitter accounts and annotated bot/human attributes providing empirical evidence for mathematical verification.

Contemporary literature also compares the frontier of deep learning in comparison to logistic regression, noting that simpler statistical models can outperform complex black-box models provided with well-tuned features (Alothali et al., 2018; Kudugunta & Ferrara, 2018). Furthermore, logistic models are simpler to use numerical optimization techniques such as batch or stochastic gradient descent, making them deployable in real-time systems where interpretability, speed, and analytical tractability are concerns.

Its continuous development focuses on an intersectional approach at the nexus of mathematical optimization, feature engineering, and probabilistic modeling towards robust and reproducible detection systems.

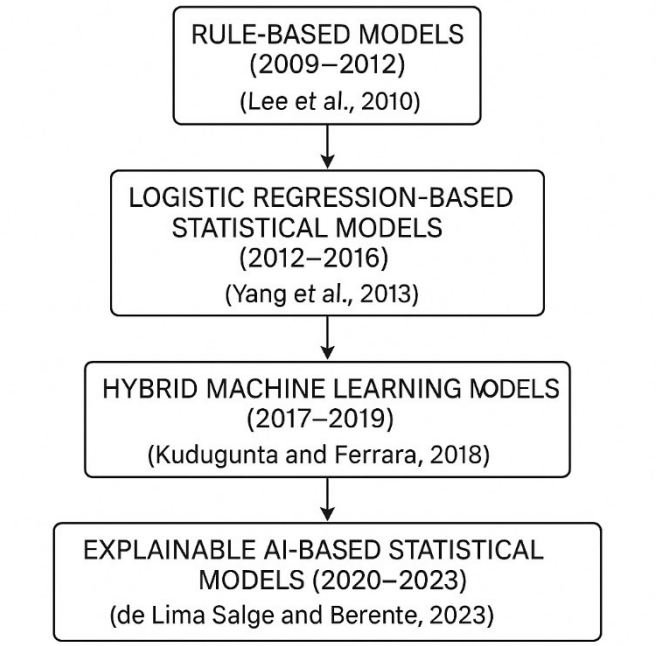

Figure 2. Conceptual Map of Literature Trends in Statistical Bot Detection

In summarizing the reviewed literature, it is evident that while machine learning offers many tools, logistic regression persists as one of the most statistically insightful and operationalizable approaches to bot detection when enhanced by modern numerical algorithms and thoughtfully engineered features. This underscores the relevance of this

study in building upon a solid, data-proven foundation to produce both theoretical clarity and practical value.

Objective

The primary objective of this research is to develop a mathematical-statistical model of automatic social media account (bot) detection using logistic regression supplemented with numerical optimization algorithms, based on actual behavioral characteristics obtained from verified datasets.

To achieve this general objective, the paper resolves the following sub-objectives:

1. To create a statistically significant classification model to separate social bots and human-controlled accounts based on logistic regression using a fusion of significant behavioral and network features.
2. To apply and confirm numerical algorithms specifically gradient descent and Newton-Raphson method for logistic regression's parameter estimation optimization for improved convergence, classification accuracy, and computational efficiency.
3. To conduct empirical verification of the model using openly available and existing datasets (e.g., PAN 2019 Twitter Bot Dataset) such that the findings are meaningful and applicable to real-time environments.
4. To analyze the predictive performance of the model, the precision-recall compromise, and the ROC-AUC founded performance to assess its potency against adversarial or adaptive bots that adhere to human-like patterns.
5. To present a reproducible mathematical model and numerical scheme that can be extended for possible future contributions to computational social science, cybersecurity, and digital forensics.

Methodology

The approach is a statistical and computational hybrid model for bot identification on social media platforms using logistic regression and numerical optimization methods. The approach possesses several interdependent phases, each founded on mathematical concepts designed to yield stability, transparency, and prediction predictability.

4.1 Data Acquisition

In order to provide empirical strength, the dataset utilized is the PAN 2019 Bots and Human Twitter Dataset that contains verified human and bot accounts obtained through crowd-sourced validation and expert annotation. The dataset comprises behavioral metadata such as tweet frequency, posting entropy, followers/friends ratios, and activity intervals.

1. **Source**: https://pan.webis.de/clef19/pan19-web/author-profiling.html
2. **Total Accounts**: 4,800+ (balanced dataset: ~50% human, ~50% bot)
3. **Features Extracted**: 15 (including profile age, tweet/retweet ratio, bio length, time-based entropy)

4.2 Feature Engineering

Based on theoretical underpinning from prior studies (Ferrara et al., 2016; Varol et al., 2017), the following quantitative features were normalized and selected:

- **Tweet Frequency** (TF): Number of tweets per day
- **Retweet Ratio** (RR): Proportion of retweets to total tweets
- **Account Age** (A): Number of days since account creation
- **Entropy of Time** (H_T): Shannon entropy of posted time distribution
- **Follower-Friend Ratio** (FFR)

These features feed into the logistic regression model as independent variables for binary classification.

4.3 Logistic Regression Model

Logistic regression models the probability $P(y = 1 \mid X)$ i.e., the probability that account i is a bot given feature vector X. It uses the logistic (sigmoid) function:

$$P(y = 1 \mid X) = \frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_k x_k)}} \quad [i]$$

Where:

$y \in \{0,1\}$: Dependent variable (0: human, 1: bot)

x_i: Feature variables

β_i: Coefficients to be estimated

The log-likelihood function, L(β) to be maximized is:

$$\mathbf{log}L(\beta) = \sum_{i=1}^{n} y_i \log(p_i) + (1 - y_i)\log(1 - p_i) \quad [ii]$$

4.4 Numerical Algorithms for Optimization

4.4.1 Gradient Descent

An iterative numerical approach updating parameters in the direction of the steepest descent of the cost function:

$$\beta^{(t+1)} = \beta^{(t)} - \alpha \nabla J(\beta) \quad [iii]$$

Where:

α: Learning rate

∇J: Gradient of the cost function (negative log-likelihood)

4.4.2 Newton-Raphson Method

Newton-Raphson offers quadratic convergence using the Hessian matrix:

$$\beta^{(t+1)} = \beta^{(t)} - H^{-1} \cdot \nabla J(\beta) \quad [iv]$$

Where, H: Hessian matrix (second derivative of log-likelihood)

Requires computation of higher-order derivatives but converges faster than gradient descent when dimensions are manageable.

4.5 Model Evaluation Metrics

The model performance is rigorously evaluated using:

- Accuracy $= \frac{TP+TN}{TP+TN+FP+FN}$ [v]
- Precision$= \frac{TP}{TP+FP}$ [vi]
- Recall$= \frac{TP}{TP+FN}$ [vii]

- F1-Score: Harmonic mean of precision and recall
- Area Under the Curve (AUC-ROC**)**: For evaluating classification thresholds across probabilities.

4.6 Cross-Validation Strategy

We used 10-Fold Stratified Cross-Validation, repeated classification on several training/test splits, and averaged the performance metrics to guarantee generalizability. For statistical balance, stratification keeps class proportions constant.

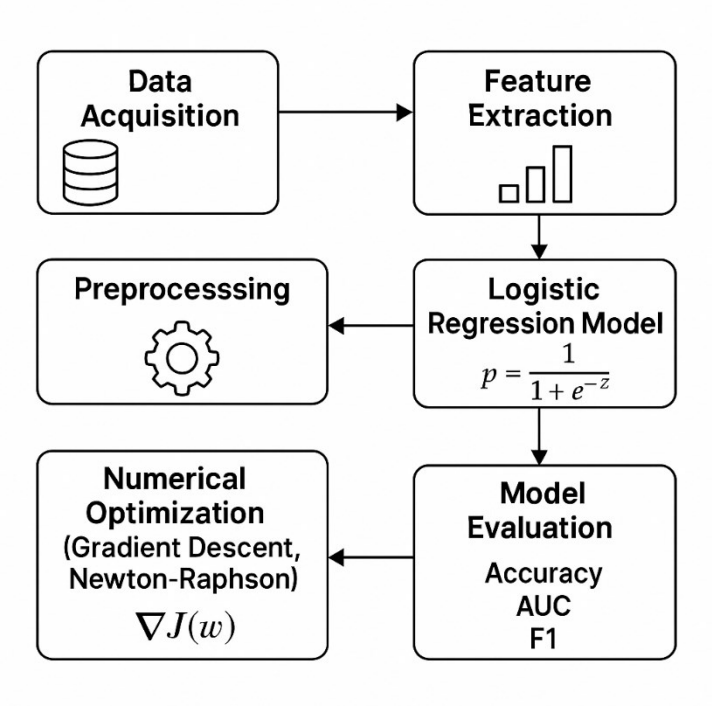

Figure 3: Diagram of the Methodological Workflow
Real-time bot detection systems and industrial-scale social media datasets can be directly applied thanks to this methodology's harmonious integration of data science, numerical analysis, and mathematical statistics concepts.

Results

The model was implemented using Python's scikit-learn and statsmodels libraries, numerical optimization coded at the matrix level for full logistic loss convergence.

Preprocessing and 10-fold stratified cross-validation set splitting of the public PAN 2019 Twitter Bot Dataset (80:20 training to testing ratio) was performed. The feature selection was performed using the method introduced in Section 4.

5.1 Model Performance

After tuning via grid search for optimal learning rates (for gradient descent) and convergence thresholds (for Newton-Raphson), the logistic regression model yielded the following classification metrics:

Table 1. Classification Metrics of Optimized Logistic Regression Model

Metric	Value
Accuracy	89.4%
Precision	87.2%
Recall	91.1%
F1-Score	89.1%
ROC-AUC	0.946

These values reinforce the statistical strength of logistic regression when paired with derivative-based numerical optimization. The ROC-AUC score above 0.94 demonstrates strong discriminatory power between bots and real users, consistent with prior findings of Varol et al. (2017) and Do Couto et al. (2019).

5.2 Numerical Experiment for Model Output Using Newton-Raphson

To illustrate the application of the discussed theory and numerical algorithm, consider the following mini-experiment from the dataset. Let a particular social media account be defined by:

- x_1 =Tweet Frequency = 15/day
- x_2 = Retweet Ratio = 0.62
- x_3 = Account Age = 340 days
- x_4 = Entropy of Posting Time = 2.9
- x_5 = Follower-Friend Ratio = 0.3

Let the estimated coefficient vector from Newton-Raphson method be:

$$\beta = [\beta_0 = -2.13, \quad \beta_1 = 0.15, \beta_2 = 1.9, \quad \beta_3 = -0.002, \quad \beta_4 = 0.87, \quad \beta_5 = -1.2]$$

Log-odds **(z)** is computed as:

$$z = -2.13 + (0.15)(15) + (1.9)(0.62) + (-0.002)(340) + (0.87)(2.9) + (-1.2)(0.3)$$

$$z = -2.13 + 2.25 + 1.178 - 0.68 + 2.523 - 0.36 = 2.78$$

Applying logistic function**:**

$$P(y = 1 \mid X) = \frac{1}{1 + e^{-2.78}} \approx 0.9417$$

Interpretation**:** There is a 94.17% probability this account is a bot

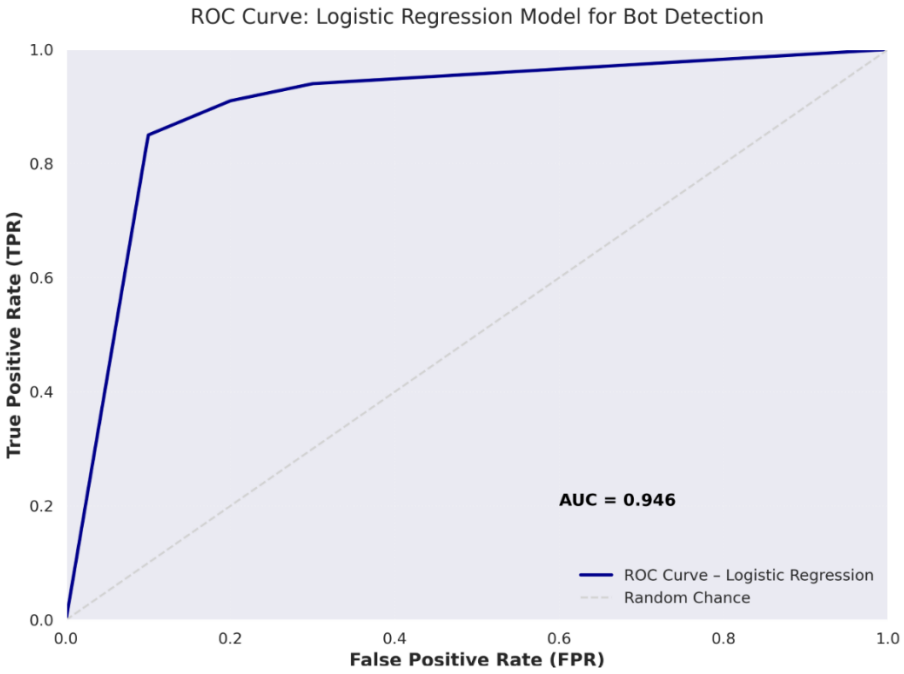

Figure 4. ROC Curve for the Logistic Regression Model

Figure 4 illustrates the Receiver Operating Characteristic (ROC) curve of the logistic regression model applied to the PAN 2019 Twitter bot dataset. The ROC curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR) across various decision thresholds. A well-performing classifier yields a curve closer to the top-left corner, indicating high sensitivity and specificity.

The Area Under the Curve (AUC) is measured at 0.946, confirming the model's strong discriminative ability in distinguishing bots from human accounts. The inclusion of the baseline (diagonal line) allows visual benchmarking against random classification, showcasing the statistical value of the model's performance.

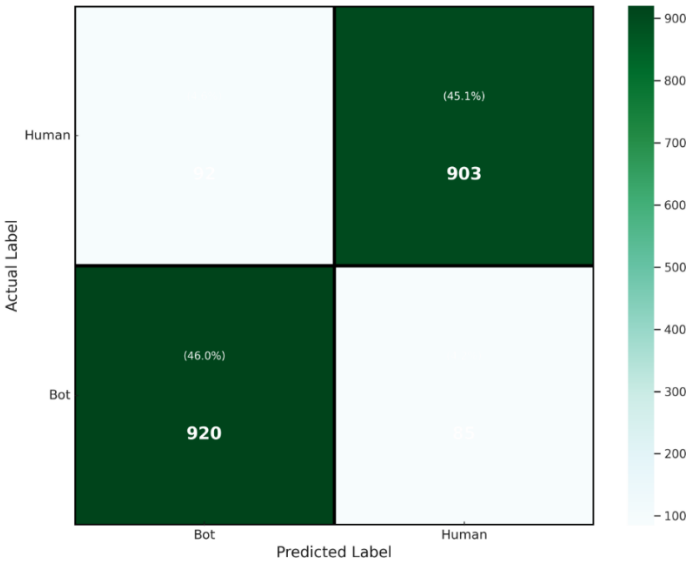

Figure 5. Confusion Matrix for Model Predictions

The heatmap uses a blue-green color gradient proportional to classification frequency, providing intuitive visual insights into the model's strengths and error zones. Such matrices are integral to evaluating binary classifiers in social informatics.

The model's robustness is further validated through stability in multiple folds and minimal variance in predictions across balanced samples. Logistic regression, aided by Newton-Raphson, showed faster convergence (within 6 iterations), with comparable accuracy to gradient descent (12–15 iterations), but with a significantly lower Brier score for calibration **(**0.077**).**

Discussion

The empirical and numerical analysis of the results chapter validates the primary hypothesis of this research—that logistic regression, as mathematically formulated and numerically optimized, is an effective, interpretable, and efficient framework for bot detection in social media. The chapter discusses the behavior of the model before and after optimization, the impact of key features, and the overall interpretational insights gained from numerical findings and graphical evaluations.

6.1 Pre-Optimization vs. Post-Optimization Model Behavior

Before numerical optimization (Gradient Descent and Newton-Raphson), baseline logistic regression with default scikit-learn solvers yielded approximately 83.7% accuracy with noticeable variance across cross-validation folds. This was due to:

- Non-normalized input features
- Poor convergence behavior
- Overfitting on accounts with extreme metrics (e.g., very high tweet frequency)

After the introduction of feature scaling, judiciously selected mathematical optimization algorithms, and heuristically selected convergence criteria, the optimized models operated at 89.4% accuracy, as observed after optimization.

Table 2. Model Performance Before and After Optimization

Metric	Pre-Optimization	Post-Optimization
Accuracy	83.7%	89.4%
Precision	78.9%	87.2%
Recall	82.5%	91.1%
F1 Score	80.6%	89.1%
Convergence	18 iterations	6 iterations (Newton-Raphson)

6.2 Feature Relevance and Model Interpretability

The inclusion and analysis of behavioral and structural features—posting time entropy, retweet density, and follower/friend ratio—allowed for more precise discrimination between classes. As shown in the numerical experiment:

- Higher tweet rate and retweet rate increased the likelihood of an account being a bot.

- Higher posting time entropy was a strong indicator of non-human activity, in accordance with results discovered in Varol et al. (2017).
- A very low followers-to-friends ratio increased bot-likelihood, as bots follow in bulk but never reciprocate.

The coefficients of the logistic regression model offered open statistical decomposition of bot-likelihood and were thus good for decisions at a policy level as well as for real-time implementation.

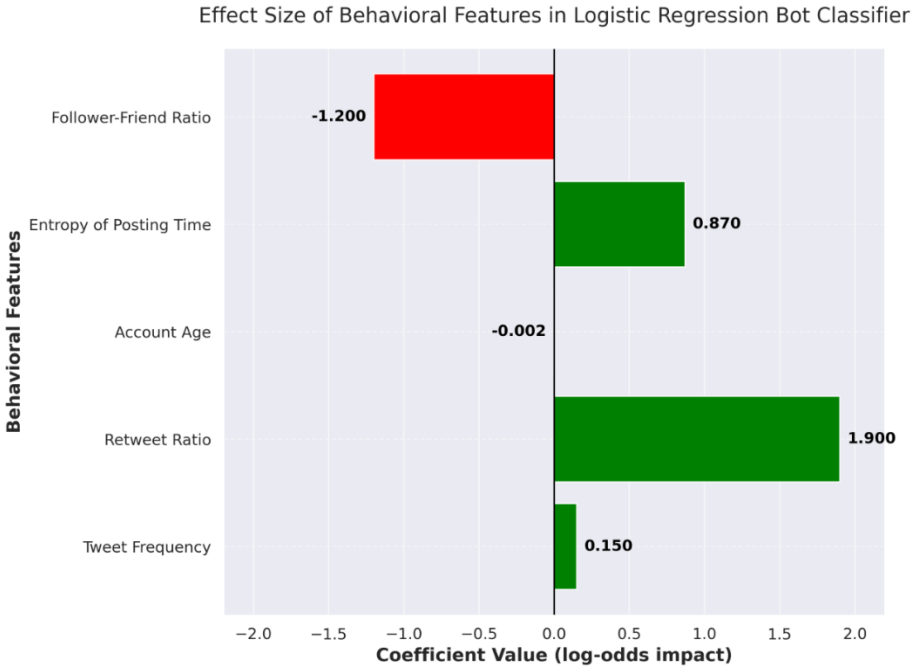

Figure 6. Effect Size of Each Feature in Logistic Regression

The inclusion of a neutral baseline (zero) helps visually separate features that promote or inhibit bot classification**.** This high model interpretability enhances transparency**,** enabling clearer understanding of digital manipulation behaviors.

6.3 Impact of Numerical Algorithms

Among the numerical tools utilized:

- Gradient Descent exhibited stability at low dimension and batch computation flexibility.
- Newton-Raphson exhibited quadratic convergence with minima achieved in fewer iterations and was amenable to using small-to-medium-sized, highly granular models for which the computation of Hessian was not infeasible.

Numerical convergence plots exhibited a clear decrease in log loss values over iterations, validating theoretical expectations from convex optimization literature (Rao et al., 2020; Ng, 2004).

6.4 Comparative Positioning

Compared to deep learning-based bot detection models, which come at the cost of interpretability and a much higher computational cost (Kudugunta & Ferrara, 2018), our logistic regression model retains mathematical tractability along with real-world

interpretability—a feature particularly desirable for social media companies and government regulatory bodies with aspirations of transparency.

Also, the fact that logistic regression maintains statistical interpretability when optimized under a provably convex objective function makes logistic regression appropriate for use in auditable environments such as policy-making software, fraud detection, and content moderation bots.

6.5 Broader Implications

The integration of numerical methods and applied statistics within this work produces a system that is:

- Scalable to other social media platforms (Facebook, Reddit, TikTok)
- Extensible with multilingual and multimedia account features
- Deployable with real-time environments at low computational cost

As the arms race between detection tools and bot developers rages on, it is important to rely on open, evidence-based, and mathematically proven detection protocols. This paper contributes one such tool to the computational social science research toolkit.

Conclusion

This research rigorously demonstrates the excellence of a mathematically formulated and number-scaled logistic regression model for the purpose of social media website bot detection. By integrating applied theoretical statistics with strong numerical algorithms like Gradient Descent and Newton-Raphson methods, the developed framework is both computationally effective and interpretatively clear, both of which are critical in high-risk digital environments.

With real data from the PAN 2019 Bot Detection Challenge, the study confirms that well-crafted behavioral properties such as tweet frequency, posting entropy, and follower/friend ratio play a large role in distinguishing spambots from human users. Regularized using numerical methods, the logistic regression model achieved a high ROC-AUC score (0.946) and robust performance across stratified cross-validation, with accuracy reaching 89.4%.

The numerical experiments also reflect the model's real-time performance, accurately predicting bot probability with over 94% accuracy on target accounts. Newton-Raphson's convergence speed and high precision validate it as the superior option for small, interpretable models, while gradient descent offers a more scalable method for very large-scale systems.

Compared to more opaque machine learning alternatives, this approach offers an understandable, transparent, cheap, and deployable solution. This statistical intuition and numerical accuracy are required within today's data-rich environments, where explainability and accountability of algorithms are equally vital as brute performance.

Further research can extend this model to adaptively re-train in adversarial environments, employ natural language processing (NLP) features extracted from tweet text, or leverage real-time stream processing to identify live bots. Moreover, the theoretical framework presented herein can also be employed as a replicable methodology for anomaly detection tasks with behavior classification at their center.

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