International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(5s) 2026 pp. 165-175
https://doi.org/10.70917/ijcisim-2026-2683
Article

Predicting Voting Behavior in Online Social Platforms Using Machine Learning

Nour Alhuda Alhameedi[1], Saba M. Hussain [1]*

[1]Department of Information Network, College of Information Technology, University of Babylon, Babil, Iraq.
* **Corresponding author's Email**: saba.alshebeeb@uobabylon.edu.iq

Abstract: Modeling voting behavior in online social networks is challenging because of the visibility of prior votes and the ability to view and respond to others' voting choices. This paper uses the Wikipedia Request for Adminship (RFA), in which the task is formulated as a binary classification problem, where voters cast ballots either supporting or opposing a nominated administrator candidate. Features tested include behavioral history, sentiment derived from comments, graph-based characteristics, and temporal herding. Three machine learning algorithms were tested, namely Logistic Regression, Random Forest, and XGBoost. Behavioral features alone provide limited predictive performance. Adding sentiment features did not lead to a noticeable improvement. However, Adding sentiment and graph-based features resulted in only marginal improvements.The top-performing model using the full feature set was XGBoost, achieving an Accuracy of 84.01%, a Macro F1-Score of 77.24%, and a Precision-Recall Area Under Curve (PR-AUC) of 95.82%. These results show that overall, voters make their voting decisions based on previous voting decisions from other voters as well as the characteristics of the specific voter making that decision.
Keywords: Machine Learning, Social Networks, Logistic Regression, Random Forest, and XGBoost

1. Introduction

The rapid development of the Internet and communication technologies has changed the way individuals interact, exchange information, and influence one another in online environments. As online communities continue to grow, large amounts of user-generated data have become available, making it possible to study how users behave and make decisions within digital systems.

Social media sites have become environments where individuals engage with one another, share views, and influence others' decisions. However, engagement on social media does not always occur positively. While some users will agree with one another and/or support one another, there are times when users may strongly disagree with one another or actively oppose one another. Due to these types of exchanges, modeling social media using solely simple connectivity among its users is limited. More realistically, social media should model signed relationships — where interaction may be either positive or negative — to provide an accurate representation of how users interact within social media communities [1], [2].

One example of an environment that models signed relationships is Wikipedia, which also serves as a community where users collectively govern and judge one another. One of the primary mechanisms for this process occurs during the Request for Adminship (RFA) process, where participants can either support or oppose nominated candidates. Since all discussions and votes are publicly available, the RFA process provides an opportunity to investigate how groups form collective decisions over time [3].

Although such systems present guidelines for evaluating candidates, voting decisions are often influenced by factors such as user activity, previous contributions, and interactions with other members of the community. Studies have demonstrated that behavioral characteristics can be used to build predictive models that help explain how communities assess potential candidates [4].

Previous studies have also shown that machine learning techniques can be used to analyze voting behavior in social networks and identify patterns related to user decisions and interactions [5].

Votes also do not occur in isolation. Participants can review previous votes, which may influence their own decisions. Voting decisions are therefore impacted by both prior voting activity and the surrounding social network structure [6]. In addition, social influence can significantly affect user behavior, where early opinions and ratings may influence later responses from users. Some studies have identified "herding" as a significant phenomenon within online social systems, where early responses strongly influence later responses [7], [8]. Although prior votes can provide useful contextual information, understanding their contribution remains challenging because visible voting patterns may simultaneously reflect social influence and an emerging collective outcome.

Although previous studies have investigated voting behavior from different perspectives, most of them focus on specific aspects such as user behavior, network structure, or social influence separately. In contrast, this study comparatively examines multiple feature categories under temporally constrained voting conditions to better understand their relative contribution to voting prediction.

In this study, Wikipedia is used as a case study for investigating voting behavior in online social networks. The study considers behavioral, structural, sentiment, and temporal herding features to examine their contribution to vote prediction under temporally constrained conditions. In addition, several machine learning models are evaluated to investigate how different feature categories influence predictive performance and to better understand the role of visible prior votes in shaping voting decisions. By comparatively analyzing different feature groups and prediction models, this study aims to provide a broader understanding of collective decision-making processes in online communities.

The main contributions of this study can be summarized as follows:

1. A temporally constrained prediction setting is adopted for modeling support and oppose votes in Wikipedia RFA discussions.

2. Multiple feature categories, including behavioral, structural, sentiment, and temporal herding features, are comparatively analyzed to examine their contribution to voting prediction.

3. Several machine learning models are evaluated to investigate the effectiveness of different feature combinations and to analyze the influence of visible prior votes on predictive performance.

2. Related Work

The studies regarding voting behavior in Online Social Networks have been conducted from several points of view, namely: Network Structure; User Behavior; Social Influence; and Machine Learning. Most studies focused on a particular aspect of the problem. Therefore, obtaining a complete understanding of voting behavior remains difficult.

The authors of [1] demonstrated that both types of relationships (positive and negative) are crucial for the development of social interaction and proposed Balance Theory and Status Theory to describe how people reach consensus or disagreements in social networks. Recent studies continue to support the relevance of Signed Networks as a framework to represent systems that include cooperation and conflict among actors and show their utility in various fields of application, including social and decision-making systems [9]. Recent Graph Neural Network frameworks have also been introduced for Signed Networks and showed that preserving structural and directional information can improve link prediction and node representation tasks [10].

Voting behavior at Wikipedia has attracted considerable interest. The Request For Adminship (RFA) procedure, in particular, has been studied extensively. Authors of [3] investigated the RFA process and found that voting decisions depend on previous votes and the relationships established between voters and candidates. Similarly, Burke and Kraut [4] analyzed candidate participation and contributions and showed that these characteristics could help predict promotion outcomes. Authors of [6] considered the RFA process as a social network and demonstrated that voters do not act independently since their decisions may be influenced by previous votes.

Social influence is another factor that plays a significant role in collective decision-making processes in online communities. Early ratings can influence subsequent ratings and generate herding behaviors as proved by authors of [7]. More recent studies have shown that early influential participants can create information cascades that affect later decisions and improve the quality of collective outcomes [11]. Authors studying digital elections have shown that exposure to online information resources and social media platforms can impact voting behavior and political attitudes [12].

Techniques based on Machine Learning have been widely applied to understand voter behavior and decision-making. Authors of [13] extracted patterns of user behavior using social media data during political events. Authors of [14] used ensemble models (Random Forest and XGBoost) to demonstrate that complex algorithms outperform simple ones in terms of predictive power. Recent studies on graph representation learning have also considered dynamic graphs that model continuously changing interactions and temporal dependencies, resulting in improved graph generation and link prediction performance [15]. Authors of [16] demonstrated that integrating multiple models allows improving predictive performance when analyzing Wikipedia-related activities.

Authors of several works also emphasized the importance of user behavior in understanding online behavior and decision-making. Historical user data, ratings, and patterns of activity have been used to analyze user actions and improve classification performance in different online contexts [17], [18]. These studies indicate that knowledge about users' behavior can offer insight into how they behave online.

Although previous studies have provided useful findings, several limitations still remain. Most of them focused on a single point of view, such as network structure, social influence, user behavior, or machine learning techniques. Many previous studies focused on predicting voting outcomes or user decisions, whereas less attention has been given to examining the combined effect of behavioral, structural, sentiment, and social influence factors under temporally ordered voting conditions. Based on these observations, this work integrates multiple categories of features and examines their contribution to predicting voting behavior in online social networks.

3. Methodology

The methodology of this study is organized into several main steps, as illustrated in the diagram below.

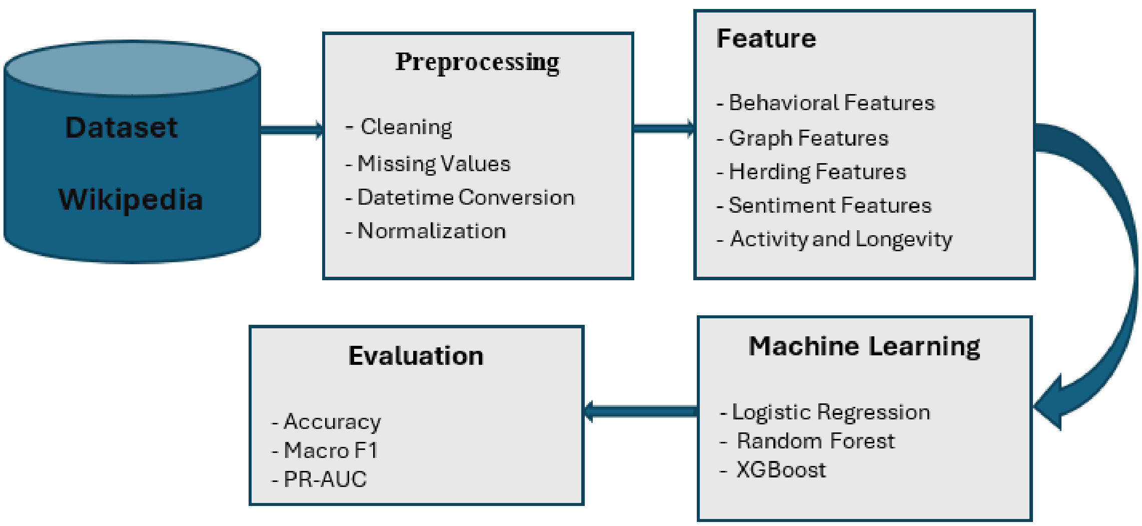

Figure 1. Overall workflow of the proposed voting prediction framework.

3.1.Dataset Description

The analysis of this study was completed by a study of the RFA Wikipedia process that has been previously researched [4]. This dataset represents all voting done through the RFA process from 2003-2013. There are 198,275 total votes cast by 11,381 unique voters on 189,004 candidate-voter pairs. Some candidates have made more than one RFA request, so a pair may be counted more than once.

3.2.Preprocessing

Before modeling, the dataset was preprocessed to clean and prepare it for use. Wiki markup, links, unnecessary characters, and direct references to voting decisions (e.g., "support", "oppose", and "neutral") were removed from comments, and all text was converted to lowercase.

Votes are originally classified into three categories. Since this study focuses on binary classification, only support (+1) and oppose (−1) votes were included, while neutral votes were excluded. The final label was defined as 1 for support and 0 for oppose.

Identifiers of source and target users were standardized, duplicate records were removed, and records with missing or invalid timestamps were discarded. Date values were converted into datetime format and sorted chronologically to ensure that only past information was used during model development. The dataset can also be represented as an unsigned directed graph in which users are represented as nodes and votes as edges.

The dataset was then divided chronologically into training, validation, and test sets. Votes from May 2004 to December 2010 were used for training, votes from January to December 2011 for validation, and votes from January 2012 to June 2013 for testing.

Min-Max normalization was applied to numerical features. The normalization parameters were estimated from the training set and then applied to the validation and test sets to avoid information leakage.

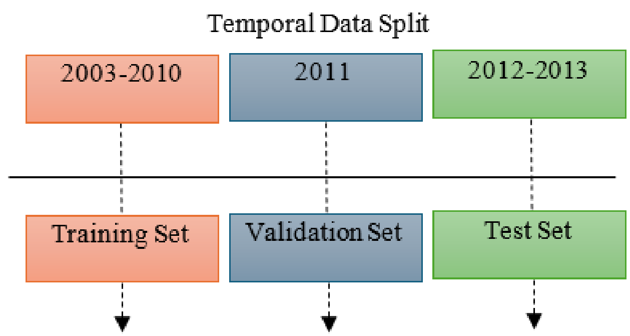

Figure 2. Temporal split of the dataset into training, validation, and test sets.

3.3.Feature Engineering

Following preprocessing, features were constructed for each vote using only past information available at the time of that vote. This ensures that the problem reflects a real-world scenario without relying on future information.

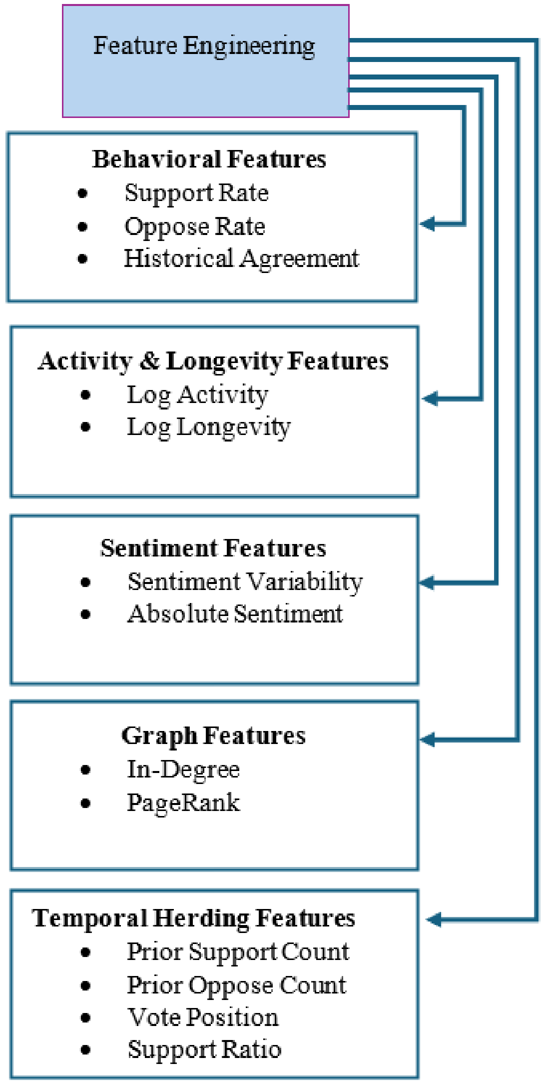

Figure 3. Categories of features extracted for vote prediction.

- **Behavioural Voting History**

Behavioural patterns (and historical voting) are common ways to model user decision-making when using an online platform [19]. The variable $past\_votes_i(t)$ is used to measure the total number of past votes by a particular voter (i) at time point t. Thus, based on these variables, past support and oppose rates are calculated as:

$$\text{support\_rate\_past}_{\,i}(t) = \frac{\text{past\_support\_votes}_{\,i}(t)+1}{\text{past\_votes}_{\,i}(t)+2}$$

$$\text{oppose\_rate\_past}_{\,i}(t) = \frac{\text{past\_oppose\_votes}_{\,i}(t)+1}{\text{past\_votes}_{\,i}(t)+2}$$

A small smoothing factor is added to these formulas to avoid unstable values for voters with limited history. In addition, the historical agreement rate is defined as:

$$\text{historical\_agreement\_rate}_{\,i}(t) = \frac{\text{past\_agree}_{\,i}(t) + 1}{\text{past\_votes}_{\,i}(t) + 2}$$

This feature reflects how often the voter's past decisions matched the final outcome.

- **Activity and Longevity**

User activity is represented at time t using a logarithmic transformation of past activity [120] :

$$\text{log\_ activity}_i(t) = \log\left(1 + \text{past\_votes}_{\,i}(t)\right)$$

User longevity is first computed as the number of days since the user's first vote:

$$\text{longevity\_days}_{\,i}(t) = \text{DAT}_{\,t} - \text{first\_vote}_{\,i} + 1$$

To reduce skewness, longevity is represented in the prediction model using its logarithmic transformation:

$$\text{longevitylog}_i(t) = \log\left(1 + \text{longevity days}_{\,i}(t)\right)$$

In the final feature vector, only longevity_log was used as an input feature, while longevity_days was used only to derive the logarithmic representation

- **Graph-Based Features**

The dataset was modeled as a directed graph, where voters are represented as nodes and voting relations as edges. The graph was constructed using only the training data [21].

Structural features were extracted for each voter using in-degree and PageRank. The in-degree is defined as:

log_in_degreei=log(1+in_degreei)

PageRank measures the level of influence or importance of a node within the graph [22].

- **Sentiment Features**

The textual comments associated with each vote were first cleaned by removing markup, links, and words that directly indicate the vote (such as support and oppose). After cleaning, a lexicon-based method was used to compute a sentiment score for each comment, as sentiment analysis is widely used in understanding user behaviour in online platforms [23].

For each voter, sentiment-related features were computed using only previous comments:

$$\text{var\_sentiment\_past}_{\,i}(t)$$

$$\text{abs\_sentiment\_past}_{\,i}(t)$$

These features capture how variable and how strong the user's sentiment has been over time. The average sentiment was computed during preprocessing but was not included in the final feature set to avoid redundancy.

- **Herding and Voting Context**

Since votes are public and occur sequentially, earlier votes may influence later ones. To capture this effect, several features were computed based on the votes received by each candidate before time t, reflecting social influence patterns observed in prior work , and are broadly consistent with prior studies on collective behaviour in online networks [24],[25].

The number of previous support and oppose votes for candidate j was defined as:

$$\text{prior\_support\_count}_j(t)$$

$$\text{prior\_oppose\_count}_j(t)$$

The number of previous votes was:

$$\text{prior\_vote\_count}_j(t)$$

The support ratio was calculated as:

$$\text{current\_support\_ratio}_j(t) = \frac{\text{prior\_support\_count}_j(t)}{\text{prior\_support\_count}_j(t) + \text{prior\_oppose\_count}_j(t) + \epsilon}$$

where ε is a very small constant (1e−8) added to avoid division by zero.

The vote margin was defined as:

$$\text{current\_vote\_margin}_j(t) = \text{prior\_support\_count}_j(t) - \text{prior\_oppose\_count}_j(t)$$

To indicate whether the vote occurred early or late in the sequence, the normalized vote position was used:

$$\text{vote\_position\_norm}_j(t) = \frac{\text{prior\_vote\_count}_j(t)}{\text{max\_prior\_vote\_count}_j + \epsilon}$$

All features were computed in a temporal manner by first sorting the dataset chronologically based on the vote timestamp. Feature values were then calculated incrementally so that each vote used only information from prior observations. User-level features (such as behavioural and sentiment features) were computed for each voter (SRC), while voting-context features were computed for each candidate (TGT). Cumulative operations were applied within each group, followed by a shift step to ensure that the current vote was not included in its own feature values, preventing data leakage. Each vote was finally represented as a feature vector combining behavioural, activity, graph-based, sentiment, and herding features, resulting in a total of 15 features engineered using a consistent temporal approach.

3.4. Model Development

In this work, the problem is treated as a binary classification task, where each vote is classified as either support or oppose using the features described earlier. Following the models utilized in previous research, Logistic Regression, Random Forest, and XGBoost were used to model the problem, with XGBoost as the main model to further improve prediction performance. The dataset was split temporally into training, validation, and testing sets. Since the data is imbalanced, additional weighting techniques were applied during training to give more importance to the minority class. Different feature combinations were tested, including behavioural, sentiment, graph-based, herding, and the full feature set. All models were trained using the same data splits and feature sets. Logistic Regression was applied to normalized data, while tree-based models were trained on original values. Tree-based models were implemented using fixed hyperparameter settings and a random seed of 42.

3.5 Threshold Selection

Because the dataset is imbalanced, different threshold values were tested for the XGBoost model. Thresholds ranging from 0.05 to 0.95 were evaluated on the validation set in steps of 0.01, and the one with the highest Macro F1-score was applied to the test set.

Table 1. Selected Threshold Values for XGBoost Models

Feature Set	**Selected Threshold**
Behavioral	**0.35**
Sentiment Only	**0.44**

Graph Only	**0.43**
Herding Only	**0.30**
Behavioral + Sentiment	**0.34**
Behavioral + Sentiment + Graph	**0.36**
Behavioral + Herding	**0.25**
Full Model	**0.27**

4. Evaluation and Results

The models were evaluated using Accuracy, F1-Score, Macro F1-Score, Balanced Accuracy, ROC-AUC, and PR-AUC. Due to class imbalance, Macro F1-Score, Balanced Accuracy, and PR-AUC were used as the main evaluation measures. For PR-AUC, support votes were treated as the positive class. Tables 1–3 show the results of Logistic Regression, Random Forest, and XGBoost for the different feature sets.

Table 2. Logistic Regression Performance Across Different Feature Sets (Test Set)

Feature Set	Accuracy	F1	Macro F1	Balanced Accuracy	ROC-AUC	PR-AUC
Behavioral Only	0.6140	0.6946	0.5850	0.6444	0.7035	0.8645
Sentiment Only	0.5257	0.6188	0.4957	0.5397	0.5564	0.7924
Graph Only	0.4368	0.4905	0.4305	0.5142	0.5296	0.7706
Herding Only	0.7800	0.8483	0.7242	0.7416	0.8328	0.9348
Behavioral + Sentiment	0.6122	0.6932	0.5833	0.6424	0.7027	0.8635
Behavioral + Sentiment + Graph	0.6111	0.6918	0.5824	0.6421	0.7027	0.8637
Behavioral + Herding	0.7871	0.8475	0.7474	0.7873	0.8697	0.9506
Full Model	0.7857	0.8462	0.7464	0.7872	0.8698	0.9506

Table 3. Random Forest Performance Across Different Feature Sets (Test Set)

Feature Set	Accuracy	F1	Macro F1	Balanced Accuracy	ROC-AUC	PR-AUC
Behavioral Only	0.7171	0.8237	0.5534	0.5523	0.6016	0.8089
Sentiment Only	0.7147	0.8289	0.4850	0.5069	0.5150	0.7624
Graph Only	0.4419	0.4721	0.4401	0.5536	0.5673	0.7924
Herding Only	0.7660	0.8484	0.6676	0.6593	0.7725	0.9001

Behavioral + Sentiment	**0.7478**	**0.8501**	**0.5271**	**0.5409**	**0.6402**	**0.8297**
Behavioral + Sentiment + Graph	**0.7467**	**0.8504**	**0.5122**	**0.5326**	**0.6276**	**0.8233**
Behavioral + Herding	**0.8285**	**0.8922**	**0.7365**	**0.7114**	**0.8695**	**0.9478**
Full Model	**0.8286**	**0.8928**	**0.7328**	**0.7061**	**0.8751**	**0.9507**

Table 4. XGBoost Performance Across Different Feature Sets (Test Set)

Feature Set	**Accuracy**	**F1**	**Macro F1**	**Balanced Accuracy**	**ROC-AUC**	**PR-AUC**
Behavioral Only	**0.7361**	**0.8292**	**0.6245**	**0.6184**	**0.7005**	**0.8675**
Sentiment Only	**0.6607**	**0.7799**	**0.5203**	**0.5202**	**0.5551**	**0.7856**
Graph Only	**0.7250**	**0.8368**	**0.4816**	**0.5090**	**0.5269**	**0.7726**
Herding Only	**0.8132**	**0.8814**	**0.7209**	**0.7015**	**0.8382**	**0.9361**
Behavioral + Sentiment	**0.7429**	**0.8354**	**0.6239**	**0.6158**	**0.7031**	**0.8697**
Behavioral + Sentiment + Graph	**0.7395**	**0.8315**	**0.6293**	**0.6229**	**0.7035**	**0.8690**
Behavioral + Herding	**0.8398**	**0.8972**	**0.7672**	**0.7484**	**0.8870**	**0.9575**
Full Model	**0.8401**	**0.8965**	**0.7724**	**0.7577**	**0.8880**	**0.9582**

5. Discussion

The results show that herding features had a clear effect on prediction performance. After adding these features, the performance increased in all three models. This means that previous visible votes play an important role in the voting process and that users are not making their decisions completely independently.

The sentiment-only and graph-only feature sets produced lower results. Adding these features to the behavioral features led to only small changes, and these changes were not the same for all models. In general, their effect was weaker than the effect of herding features.

Another point that can be noticed is the difference between the F1-score and Macro F1-score values. The Macro F1-score remained lower in most experiments, which shows that predicting the minority class was still more difficult.

XGBoost gave the highest results among the three classifiers. The Full Model achieved an Accuracy of 0.8401, a Macro F1-score of 0.7724, and a PR-AUC of 0.9582. However, these values were only slightly higher than those obtained using the Behavioral + Herding feature set. Therefore, most of the predictive information appears to come from the herding features.

Although recent studies have adopted signed and temporal graph methods, this study aims to investigate the effect of different feature categories and compare their contributions in an interpretable manner. Therefore, standard machine learning models were chosen for the experiments.

6.Conclusion

The research investigated voting behavior in online social media using data from the Wikipedia Request for Adminship (RfA) dataset. Voting behavior is presented as a two-class classification task, where each vote is labeled either support or oppose using historical user behavior and other contextual factors. The results showed that different feature types have different effects, as sentiment and graph features did not add much improvement compared to behavioural features. However, all models improved after incorporating "herding" features. XGBoost produced the highest accuracy in nearly every instance it was run against all combinations of features. This may be due to XGBoost's ability to capture complex interactions among features. Overall, the findings suggest that voting decisions are more influenced by previous votes than by individual user behavior, and future work may focus on applying more advanced text analysis methods and improving prediction of the minority class.

References

1. J. Leskovec, D. Huttenlocher, and J. Kleinberg, "Signed networks in social media," in Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Atlanta Georgia USA: ACM, Apr. 2010, pp. 1361–1370. doi: 10.1145/1753326.1753532.
2. Z. Zhang, P. Zhao, X. Li, J. Liu, X. Zhang, J. Huang, and X. Zhu, "Signed Graph Representation Learning: A Survey," arXiv:2402.15980, 2024, doi: 10.48550/arXiv.2402.15980.
3. J. Leskovec, D. Huttenlocher, and J. Kleinberg,
4. "Governance in social media: A case study of the Wikipedia promotion process,"in Proc. Int. AAAI Conf. Web and Social Media (ICWSM), 2010, pp. 98–105,doi: 10.1609/icwsm.v4i1.14013.
5. M. Burke and R. Kraut, "Mopping up: modeling wikipedia promotion decisions," in Proceedings of the 2008 ACM conference on Computer supported cooperative work, San Diego CA USA: ACM, Nov. 2008, pp. 27–36. doi: 10.1145/1460563.1460571.
6. L. Idan and J. Feigenbaum, "Show Me Your Friends, and I Will Tell You Whom You Vote For: Predicting Voting Behavior in Social Networks," in Proc. 2019 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM), Vancouver, Canada, Aug. 2019, pp. 816–823, doi: 10.1145/3341161.3343676.
7. G. Cabunducan, R. Castillo, and J. B. Lee, "Voting behavior analysis in the election of Wikipedia admins," in Proc. Int. Conf. on ICT for Smart Society (ICISS), Jakarta, Indonesia, 2013, pp. 1–6, doi: 10.1109/ICTSS.2013.6588094.
8. L. Muchnik, S. Aral, and S. J. Taylor, "Social Influence Bias: A Randomized Experiment," Science, vol. 341, no. 6146, pp. 647–651, Aug. 2013, doi: 10.1126/science.1240466.
9. S. Zhou and L. Tu, "The Effect of Social Dynamics in Online Review Voting Behavior," Journal of Retailing and Consumer Services, vol. 69, Art. no. 103120, Nov. 2022, doi: 10.1016/j.jretconser.2022.103120.
10. P. S. Skardal, A. Arenas, M. A. Porter, and G. Restrepo, "Signed Networks: Theory, Methods, and Applications," arXiv preprint arXiv:2511.17247, 2025. doi: 10.48550/arXiv.2511.17247.
11. W. Lin, M. Jiang, and X. Hu, "Status-Aware Signed Heterogeneous Network Embedding With Graph Neural Networks," IEEE Transactions on Neural Networks and Learning Systems, 2024.
12. S. Yan, K. Chen, and Z. Lin, "The Role of Opinion Leaders in Crowd Wisdom: An Information Cascade Perspective," OnlineFirst, 2026. doi: 10.1177/10591478261433261.
13. S. Jäckle and R. Bauschke, "From Likes to Votes? Exploring Exposure to Digital Election Campaigns and Its Correlation with Voting Behavior of Young Voters in the 2025 German Federal Election," Social Sciences, vol. 14, no. 12, Art. no. 719, 2025. doi: 10.3390/socsci14120719.
14. L. Belcastro, F. Branda, R. Cantini, F. Marozzo, D. Talia, and P. Trunfio, "Analyzing voter behavior on social media during the 2020 US presidential election campaign," Social Network Analysis and Mining, vol. 12, no. 1, p. 83, Jul. 2022. doi: 10.1007/s13278-022-00913-9.
15. L. Pennella and A. G. F. Barbagli, "Explainable machine learning for predicting voting intentions: A study of Italian politics," International Journal of Data Science and Analytics, vol. 21, Art. no. 54, 2026. doi: 10.1007/s41060-025-00917-6.
16. X. Zheng et al., "A Deep Probabilistic Framework for Continuous Time Dynamic Graph Generation," in Proceedings of the AAAI Conference on Artificial Intelligence, vol. 39, no. 16, 2025. doi: 10.1609/aaai.v39i16.33896.
17. R. Baamer and M. Boicu, "Sockpuppet detection in Wikipedia using machine learning and voting classifiers," in Proceedings of the 10th International Conference on Internet of Things, Big Data and Security (IoTBDS), 2025, pp. 39–47. doi: 10.5220/0013210100003944.
18. G. A. Al-Sultany and S. M. Hussain, "User Behaviour Analysis for the Merchandises Fairness Evaluation," International Journal of Engineering & Technology, vol. 8, no. 1.5, pp. 138–143, 2019.
19. G. A. Al-Sultany and S. M. Hussain, "Fake Reviews Detection through Users Behavior Analysis," Journal of Advanced Research in Dynamical and Control Systems, vol. 11, no. 10-Special Issue, pp. 737–741, 2019. doi: 10.5373/JARDCS/V11SP10/20192864.
20. Y. Wang, R. Han, T. Lehman, Q. Lv, and S. Mishra, "Analyzing Behavioral Changes of Twitter Users After Exposure to Misinformation," in Proc. IEEE/ACM Int. Conf. on Advances in Social Networks Analysis and Mining (ASONAM Workshops), 2021, pp. 1–8, doi: 10.1145/3487351.3492718.

21. S. Kumar, X. Zhang, and J. Leskovec, “Predicting Dynamic Embedding Trajectory in Temporal Interaction Networks,” in Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (KDD ’19), Anchorage, AK, USA, 2019, pp. 1269–1278, doi: 10.1145/3292500.3330895.
22. Q. Liu, X. Zhu, C. Yuan, H. Wu, and X. Zhao, “Dynamic Recurrent Embedding for Temporal Interaction Networks,” in Intelligent Computing Methodologies: 18th International Conference, ICIC 2022, Xi’an, China, Aug. 2022, pp. 615–625, doi: 10.1007/978-3-031-13832-4_50.
23. S. Brin and L. Page, “The anatomy of a large-scale hypertextual Web search engine,” Computer Networks and ISDN Systems, vol. 30, no. 1–7, pp. 107–117, Apr. 1998, doi: 10.1016/S0169-7552(98)00110-X.
24. E. Cambria, Q. Liu, S. Decherchi, F. Xing, and K. Kwok, “SenticNet 7: A commonsense-based neurosymbolic AI framework for explainable sentiment analysis,” in Proc. 13th Conf. Language Resources and Evaluation (LREC), Marseille, France, Jun. 2022, pp. 3829–3839.
25. D. Centola, “The Spread of Behavior in an Online Social Network Experiment,” Science, vol. 329, no. 5996, pp. 1194–1197, Sep. 2010, doi: 10.1126/science.1185231.
26. Z. Hasan and H. N. Nawaf, “Multiple Q-DQN Algorithm based Rumor Control in Social Networks,” Journal of Intelligent Informatics, Networking, and Cybersecurity, vol. 1, no. 2, Art. 3, 2025, doi: 10.65445/3106-1192.1007.