Provision a generalizable approach to the ranking of credible Twitter users

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Abstract

The abundance of information shared on social networks presents valuable opportunities, such as timely news coverage and user needs forecasting. However, the lack of oversight facilitates the spread of fake content across various fields. Therefore, evaluating user credibility is crucial for responsible social media usage. This paper proposes a topic-based user ranking system on Twitter. The system leverages machine learning algorithms to prioritize user credibility based on specific topics and introduces new features for comprehensive evaluation. Finally, users are rated with 5 models of machine learning, Linear Regression (LR), Support Vector Regression (SVR), k-nearest neighbors (KNN), Random Forest (RF) and Decision Tree (DT) that, DT has achieved the highest accuracy of 82%. This approach offers a generalizable solution for various user credibility assessment needs.
Keywords: credibility assessment, social media

1. Introduction

Online social networks (OSNs) generate information very quickly, and Twitter is one of the most popular one, generating 350,000 messages per minute (Erl et al., 2016), and the huge and growing volume of data has increased the importance of Twitter. However, recent research suggests Twitter is a breeding ground for rumors and scams. The ease of disseminating false content can damage individuals, organizations, and their services. Consequently, evaluating information sources, including user credibility, is essential before utilizing Twitter for various purposes, both personal and professional.

User credibility is positively correlated with content credibility. Reputable users strive to publish valid content (Morris et al., 2012; Abbasimehr et al., 2020). Therefore, this research focuses on user credibility assessment. (Morris et al.,2012; Abbasimehr et al.,2020) for this reason, this article evaluates the user's credibility. Most research in the field of social evaluation focuses on politics and natural disasters, but since it is possible to spread false content on all subjects, the scope of this research is very wide (Pir mohammadiani et al.,2023). The primary contribution of this paper is a novel approach for ranking Twitter users to achieve diverse goals. The system incorporates 41 features, including 15 novel ones, and utilizes five machine learning models (Linear Regression, Support Vector Regression, k-Nearest Neighbors, Random Forest, and Decision Tree) for user evaluation. The Decision Tree model achieved the highest accuracy, reaching 82%. The remainder of this paper is structured as follows: Section 2 explores related work on social media credibility evaluation. Section 3 provides an overview of the proposed methodology. Section 4 evaluates the system's performance. Section 5 discusses the obtained results, and Section 6 concludes the paper.

2. Background

Supervised machine learning methods offer a prevalent approach for evaluating user credibility in social networks. These methods can achieve accurate results with appropriate datasets, powerful features, and simple online implementation. This research adopts this approach wide (Pir mohammadiani et al.,2017). In Table 1, the details of these articles are examined. Most of these articles did not pay attention to feature selection, while according to Pasi et al. (2020), features are not of equal importance and they classified, therefore, between the two valid components they cannot differentiate. Also, some articles evaluate credibility in general, while some of them pay attention to the subject of users' activity, this is because users can only get credit for certain topics, so articles that focus on user activity are better than other articles. Our proposed system selects the best features using machine learning methods, and finally teaches the model on specific topics with user ratings in Google Scholar (GS), and our output is user credibility rating.

Table 1 Comparison of Previous Studies Using Supervised Machine Learning Methods

Authors	Topic	Social media	Methods	Features	Goal
Saikaew & Noyunsan (2015)	×	Facebook	Support vector machines (SVM)	8	Content classification
Gupta et al. (2018)	✓	Facebook	Naive Bayes (NB) , SVM , RF, Logistic regression	152	Content classification
Afify et al (2019)	×	Facebook	SVM	10	Content ranking and user classification
Devi & Karthika (2019)	✓	Twitter	NB , SVM , RF	40	Content classification
Setiawan et al. (2020)	✓	Twitter & Facebook	SVM ، DT, Logistic regression	Twitter: 49 Facebook:54	Content classification
Son et al. (2020)	✓	Twitter	Logistic regression	3	Content classification
Evans et al. (2021)	✓	Twitter	KNN، DT،RF	55	Content classification

3. Proposed system

The proposed system consists of two datasets, GS and Twitter, which are shown in Figure 1. The GS database was used to generate tags (estimate the actual ranking of each user in each topic) to evaluate models and Twitter metadata was used to predict rankings. Time is important in this system; each time window has its own value because the valid user must be valid in all windows or its validity will increase over time (Dehghan et al. 2024, Abu-Salih et al. 2019; Embar et al. 2015).

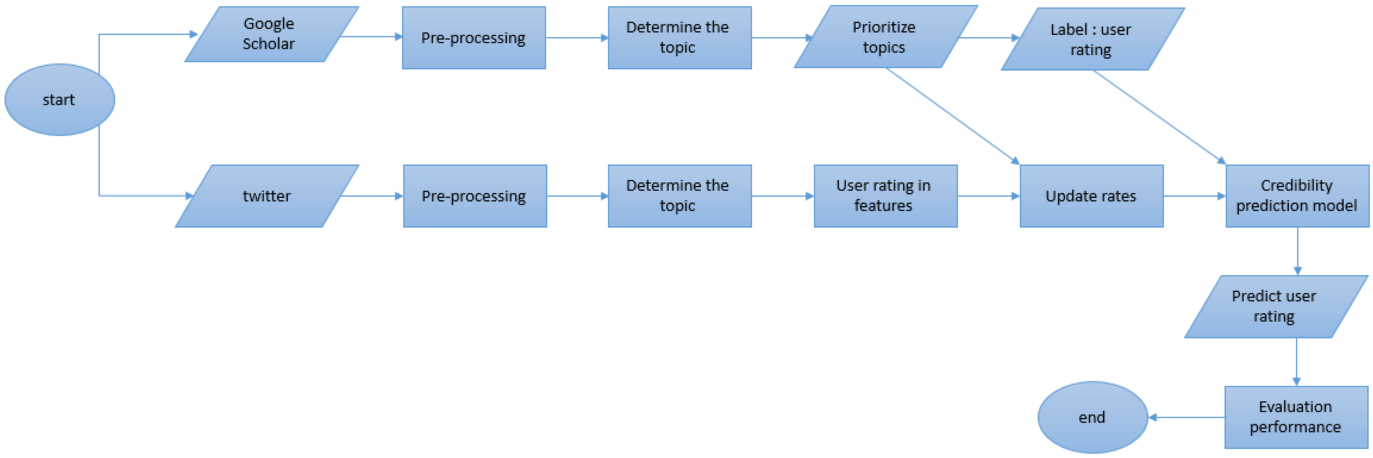

Figure 1 Proposed system of user credit rating

3.1 Data collection

Information is collected from fifty users who have Google and Twitter accounts and are active in the field of machine learning.

3.2 Pre-processing

In both sources, non-English content is removed, GS's user articles are deleted if they do not have an abstract, and for Twitter metadata, only users who have tweeted in both years and wish to reply to users, to continue Research is selected so the number of selected users is reduced to 33.

3.3 Determine the topic

Machine learning can be divided into different sub-topics (z), By teaching Bertopic algorithm on the abstract of articles, 3 sub-topics were found, finally, with this model, the activity of users on Twitter was determined by examining their content (Tweets, Replies, Bio).

3.4 User rating in features

Twitter has many features to determine the user's credibility, some of these general features, such as the number of followers and a number of other specialized features that have a unique range for each sub-topic, such as the number of retweets. The features are divided into three levels: profile, tweet, and reply. Most previous articles did not examine the reply level features. You can see these features in Table 2. Finally, we get the user rank in each feature is gotten.

Table 2 Twitter features

Level	Features	New Features	General

			Features
profile	Profile image, number of followers, following, interests, number of lists, bio length, Bio polarity, total number of tweets by age, follower growth compared to following, user popularity, account age	Post-processing bio length, important bio words, bio specialization, bio subjectivity	9
tweet	Tweets, links, links other than social networks, unique content, content transparency, polarity, subjectivity, likes, retweets, mentions, hashtags, order in sending tweets, number of sub-topics, spelling mistakes	Retweet to tweet, number of specialized content relative to total tweets, level of expertise, useful words, quotes, long tweets	1
reply	Specialized answers, polarity	Number of answers, level of expertise, useful words, subjectivity, likes	1

This system is used for several purposes, so, some of sub-topics have the preference for others and we prioritize them using the parameters α, β, δ, which are limited between zero and one. Based on these parameters, we update the user rank in specialized features $RT_{f,i,U,Z}$ for each sub-topic according to Equation 1.

$$RT_{f,i,U,0}= RT_{f,i,U,0}\times \alpha,\ RT_{f,i,U,1}= RT_{f,i,U,1}\times \beta\ ,\ RT_{f,i,U,2}= RT_{f,i,U,2}\times \delta\ ,\ RT_{f,i,U,3}= RT_{f,i,U,3}\times \theta \qquad (1)$$

3.5 label

In order to teach our 5 models, we need to estimate the actual rank of each user that, we calculate these rankings using the citation of the articles of each sub-topic (C_Z) , H-index (H_U) in GS, weight of years (y) and prioritization of sub-topics according to equations 2 and 3.

$$RG_{U,z} = \frac{\sum_{j=0}^{\mathrm{len}(as_{U,z})} Cjz}{\sum_{i=0}^{2} y[i]} \qquad (2)$$

$$RG'_U = H_U \times (\alpha \times RG_{U,0} + \beta \times RG_{U,1} + \delta \times RG_{U,2} + \theta \times RG_{U,3}) \qquad (3)$$

4. Results and analysis

Our experiments used a comparison of training data versus data testing, with a composition of 70:30.

Which we evaluated with feature selection methods and after applying the feature engineering process with 5 models (LR, KNN, SVR, DT, RF). The DT model achieved the highest accuracy of 82% and the KNN the lowest accuracy of 0.48. Table 3 summarizes the evaluation results.

Table 3 Model analysis

Models	Number of features	RMSE	MAE	MSE	Accuracy
LR	7	0.88	0.83	0.78	49%
SVR	8	0.74	0.53	0.55	64%
KNN	27	0.89	0.83	0.79	48%
DT	29	0.13	0.12	0.02	82%
RF	2	0.18	0.14	0.03	80%

5. Conclusion

In this article, we propose a subject-based credit rating system suitable for multiple purposes, which ranks users according to topic prioritization, the proposed system uses 41 features, including 15 new features at three levels (profile, tweet, and reply), and DT achieved the highest accuracy of 82% with only 29 features. The conducted experiments to evaluate this approach validate the applicability and effectiveness of determining credible users based on the organization's objectives. In the future, the importance of each feature and level in credit evaluation should be examined.

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