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Protest Event Analysis: A New Method Based on Twitter's User Behaviors

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Protest Event Analysis is important for government officials and social scientists. Here we present a new method for predicting protest events and identifying indicators of protests and violence by monitoring the content generated on Twitter. By identifying these indicators, protests and the possibility of violence can be predicted and controlled more accurately. Twitter user behaviors such as opinion share and event log share are used as indicators and this study presents a new method based on a Bayesian logistic regression algorithm for predicting protests and violence using Twitter user behaviors. According to the proposed method, users' event log share behaviors which include the rate of tweets containing date and time information is the reliable indicator for identifying protests. Users' opinion share behaviors which include hate-anger tweet rates is also best for identifying violence in protests.

A dataset which consists of tweets that are generated on protests in the Black Lives Matter (BLM) movement after the death of George Floyd is used in the evaluation of the proposed method. According to information published on acleddata.com, protests and violence have been reported in various cities on specific dates. The dataset contains 1414 protest events and 3078 non-protest events from 460 cities in 37 U.S. states. Protest events in the BLM movement between May 28 and June 30 among which 285 were violent and 1129 were peaceful. Our proposed method is tested on this dataset and the occurrence of protests is predicted with 85% precision. It is also possible to predict violence in protests with 85% precision with our method on this dataset. This study provides a successful method to predict small and large-scale protests, different from the existing literature focusing on large-scale protests.

KEYWORDS: Protest Prediction, Social Behavior, Social Media, Bayesian Logistic Regression, Machine Learning.

1. Introduction

Protest Event Analysis (PEA) is important for government officials and social scientists because of protests' economic and national security risks [19]. Social protest is one of the protests in which citizens express their opinions and dissatisfactions. The occurrence of a protest may have different economic reasons (high unemployment rate, poverty, and rising food prices), political reasons (absence of democracy and freedom, and political corruption), and social reasons (social injustice and police violence) [3, 6].

A protest event means that a group of people gathers at a specific time and place and declares their objection [27]. If these protests are not predicted, there can be instability in the country. With the emergence of social networks as new tools for social movements, protests are organized and announced using these networks [13]. Social networks led to expanding democracy and liberation and showed what happened in the country [7, 25]. The data spread in social networks such as Twitter is rapid and decentralized, making the updated information available in real-time [37]. Tweets are responsive to real-world events and analyze various events, from festivals to disasters [41, 32]. For these reasons, it is possible to identify the reasons for the occurrence of protests through data published on social networks such as Twitter [15].

The Black Lives Matter (BLM) movement attracted the attention of people and the media in 2020 [23]. Injustice against African Americans has a long history, and several topics about factors of dissatisfaction were discussed [21]. These massive protests started with the death of George Floyd on May 25, 2020, and lasted for months [8]. In this paper, the data obtained from Twitter showed that the protests and the occurrence of violence in these protests could be forecast based on the users' behaviors on Twitter.

The masses take collective action (peaceful or violent), such as protests, to achieve their demands [31]. Predicting the protest and identifying the possibility of violence is crucial for government officials. People use these social networks to generate massive data and organize these protests. The generated data is like a gold mine to detect protests [35]. This article uses Twitter open data to assess the likelihood of protests and violence and identify their indicators. The findings of this study can be useful for government officials because by using the proposed method and monitoring early indicators, they can predict the occurrence of protests and the violence in them.

This paper proposes a protest prediction model based on the Bayesian logistic regression and uses Twitter users' behaviors such as Event Log Share, Information Share, and Opinion Share. Both the day of the protest and the probability of violence in the protest is predicted by our proposed method. In addition, there is a way to select a feature to predict and specify protest indicators based on the users' behaviors on Twitter. Although we focus on Twitter in this study, the proposed method can also be generalized to other social networks. Another primary goal of the research is to simultaneously provide an applicable method to small and large-scale events.

Firstly, the aim of this study is to predict whether a protest occurs on a given day or not. Secondly, the aim is to predict whether violence occurs in the protest or not. Thirdly, indicators that warn of protests and violence are identified.

The contributions of this paper can be summarized as follows:

- Forecasting protest events using Twitter users' behaviors. A new method for predicting protests is presented using the Bayesian logistic regression approach and user behaviors.
- Providing a Bayesian logistic regression algorithm to predict protests and identify early indicators to monitor social networks.
- Providing a way to select a feature to predict protests based on Twitter users' behaviors. Twitter users' behaviors (EventLogShare, InformationShare, and OpinionShare) are presented as features for predicting protests and protest type.
- Predicting violent protests using Twitter user's behaviors. In most work, protests are predicted, but the probability of violent protests is not investigated.
- Identifying the most important early indicators of violence in social protests. The most worrying feature of the protests is the probability of violence. This paper identifies the most important indicators that specify the probability of violent protests.

The rest of this paper is structured as follows. Sections 2 and 3 discuss related works and datasets. In

Section 4, Bayesian Logistic Regression is examined. This section also discusses the proposed method. In Sections 5 and 6, the model is applied for forecasting protests and protest type and concludes with results and discussion.

2. Related Works

This section discusses recent literature on developing models to forecast protests. Compton et al. [11] predicted civil unrest events in Latin America using a logistic regression classifier and tweets containing data about time, date, and location. Zhao et al. [42] used an unsupervised approach (Dynamic Query Expansion) to forecast protests. Ramakrishnan et al. [34] forecast follow-up civil unrest in Latin America using an ensemble method. Muthiah et al. [29] used a key phrase learning and probabilistic soft logic to forecast protests in 10 countries in Latin America. Cadena et al. [9] used activity cascades (follower and mention plus retweet) and logistic regression to forecast protests in Brazil. Hoegh et al. [22] use a Bayesian decision theoretical framework for releasing alerts about protests in Brazil, Mexico, and Argentina. Goode et al. [18] use tweet volume as the data source to present a differential game theoretic approach to characterize the cost of participation.

Korkmaz et al. [24] use Lasso and multi-source models to predict anti-government protests in Latin American countries. Agrawal and Sureka [1] use event-related tweets to predict immigration-related protests. Qiao and Chen [33] use Hidden Markov Model to predict the opposition protests in Southeast Asia. Alsaedi et al. [2] uses temporal, spatial, and textual features to predict a riot in a small and large protest event.

Bahrami et al. [4] compare machine learning algorithms to predict protests against banning citizens of seven Muslim countries. Ertugrul et al. [14] used a neural network approach to forecast protests to the Charlottesville rally in 2017. Tuke et al. [39] used an empirical Bayesian approach to forecast protests in Australia. Bakerman et al. [5] used dynamic logistic regression to forecast the probability of protests in Latin American countries. Zhao et al. [43] predict civil unrest using a novel feature learning model based on fused-overlapping group Lasso and an Nth-order strong hierarchy from multiple data sources with different geographical levels (country, state, and city level). Timonda et al. [38] used Google Trends to forecast protests.

In previous studies, small and large-scale protests have not been examined simultaneously. Some research studied large-scale protests [22, 28, 34] and small-scale protests [38]. In studies on protest prediction, other specifications of the protest, such as the type of event (violent or peaceful) have not attracted the attention of researchers. The Twitter users' behaviors have not been taken into account to predict the protest, and the spatial information about tweets [2, 11], keywords appearing in tweets [9, 29], economic conditions [22], and social conditions [4] were considered in the protest prediction. Protests are essential in real-time and have a different essence than text classification data; it is challenging and limiting to provide PEA methods from this point of view. In conclusion, we believe early indicators of protests are more critical than the forecasting model's accuracy. The current research works still need more accuracy and robustness. Feature selection models are limited, and identifying early indicators of protest still needs more attention.

Our work can be differentiated from the above studies in the following ways. This paper is the first work we are aware of identifying early indicators of protest and violent events. Finding out which features should be actively monitored as key indicators of protests may be important for government officials. We detect violent events, which is a significant subset of protest events. Further, we represent a new protest detection method capable of simultaneously capturing large-scale and small-scale protests. Some previous works have provided models for only one protest event [4], while in this study, there are 4492 day-location pairs in the data set, which is one of the strengths of the research.

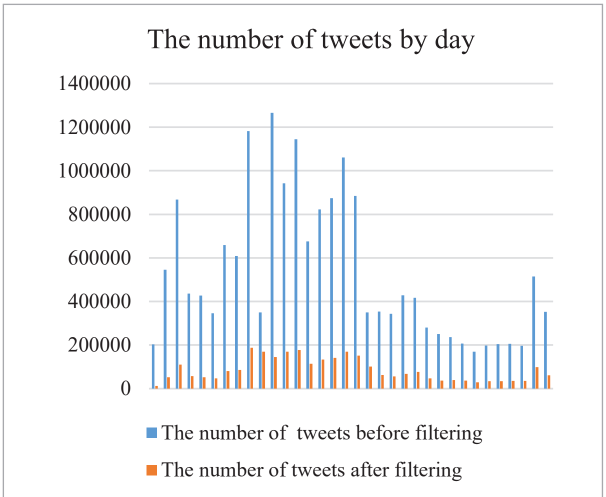
3. Data Description

Two datasets about the BLM movement are combined to create the dataset used in this paper. Twitter corpus of the Black Lives Matter movement in Giorgi's paper [17] and the ground-truth data obtained from the website of acleddata.com on the occurrence of protest events during the movement. This dataset contains 41.8 million tweets collected from ten million users and BLM movement tweets from 2013 to 2020. Tweets in this dataset are published as tweet ID, and then the contents of the tweets are downloaded with Twitter APIs. 19,388,309 tweets are used in this paper because the information published on the acleddata.com[1] website is about the movement after the death of George Floyd in 2020 and the website data contains events from May 28 to June 30. The following two filters are applied to the downloaded tweets:

- The location field of the tweet's bio information contains the name of cities.
- The presence of hashtags BlackLivesMatter, AllLivesMatter, and BlueLivesMatter in a tweet

After the filtering operation, the initial 19,388,309 tweets are reduced to 2,908,634 tweets in the final dataset. The final dataset contains tweets in 34 days between May 28 and June 30 and each tweet has the city information in its location field Fig 1 shows the number of tweets per day before and after applying the filters. The datasets generated during the current study are available from the corresponding author upon reasonable request.

Figure 1
The number of tweets by day



One of the most challenging steps is to obtain information about the event and protest type. Table 1 provides a record of the data expected on the acleddata.com website.

1 https://acleddata.com/data-export-tool/

Table 1
The information is available in the acleddata.com dataset

Item	Description
Event ID	5129
Event date	30.05.2020
Sub event type	Peaceful protest
City	Charlottesville
Notes	On May 30, 2020, about 1,000 people marched in a protest in Charlottesville (Virginia) in support of the Black Lives Matter movement and against police brutality and the death of George Floyd. [size=about 1,000]

Table 1 shows that the website data provides the event ID, event date, event type, location, and event description. In addition to the type of event, information on the size of the protest and the number of participants is also provided. Then the information about the occurrence of protests is added to final dataset tweets with spatial information about cities using the website data, if there is a protest on the specified day and place, the protest column will be equal to one, and if no protest occurs, it will be equal to zero. If this type of protest is violent, the column of the type of protest will be equal to one, and if it is peaceful, the column will be equal to zero.

The last step to obtain the dataset is the extraction of user behavior features. For all the tweets in a certain date and location, user behavior features are obtained by the methods presented in Section 4, and they are added to the dataset. The state in which the city is located is also added to the data. The structure of the dataset after filtering and feature selection is presented in Table 2. The final cleaned dataset contains 1414 protest events and 3078 non-protest events from 460 cities in 37 states. A non-protest event means that no protest took place on that day and location. Protest events include 1414 protests in the BLM movement between May 28 and June 30, among which 285 were violent and 1129 were peaceful.

Tables 3 and 4 give the observed number of protest events and non-protest events for the state and city. Table 3 shows the states in which the most frequent protests occurred. The state of North Carolina is ranked

Table 2
The final dataset

Features	Sub features	Sample	Description
Event ID	ID Number	5129	Unique ID for each protest
Date Information	Date	30.05.2020	Date of protest
	Month	May	Month of protest
	Day	Saturday	Day of protest
Event Location	City	Charlottesville	City of protest
	State	North Carolina	State of protest
Number of tweets in the date and location	Number Of Tweets	1978	Total number of tweets in Charlottesville on May 30
The ratio of Tweets containing EventLogShare Behavior	Date Info	0.03	Date tweets to total tweets ratio
	Time Info	0.1	Time tweets to total tweets ratio
	Place Info	0.129	Spatial tweets to total tweets ratio
The ratio of Tweets containing Opinion Share Behavior	Sad	0.291	Sad tweets to total tweets ratio
	Happy	0.198	Happy tweets to total tweets ratio
	Hate-anger	0.185	Hate and anger tweets to total tweets ratio
The ratio of Tweets containing General Information Behavior	Neutral	0.326	Neutral tweets to total tweets ratio
Event Information	Event Type	1	0: Non-protest events; 1: Protest
Protest Information	Protest Type	0	0: Peaceful; 1: Violent

Table 3
The states with the most frequent protests

States	Protest events	Non-protest events
North Carolina	116	216
Ohio	93	168
Illinois	90	171
Florida	80	209
Pennsylvania	72	146
Tennessee	61	70
California	66	190

first with 116 protests. One hundred sixteen protests occurred in eleven cities of North Carolina in 34 days.

Table 4 shows cities in which the most frequent protests occurred. Portland is ranked first with 33 protests. In Portland, protests are held every day except for one day. Of these, 20 were violent protests, and 13 were peaceful.

Table 4
The cities with the most frequent protests

Cities	Protest events	Non-protest events
Portland	33	1
Richmond	28	6
Seattle	27	7
Detroit	25	9
Louisville	25	9
Oakland	25	9
Phoenix	25	9
Chicago	24	10
Columbus	24	10

4. The Proposed Prediction Method Based on User Behaviors

The proposed method consisted of five phases: (1) data preparation, (2) classification of raw data, (3) identify user behaviors, (4) setup of day-location pairs and features, and (5) evaluation of Bayesian Logistic Regression (BLR) algorithm and report prediction results and indicators (Figure 2). An overview of the proposed method is shown in Figure 2. This figure shows how to predict protest events and protest types based on user's behavior.

The first step extracts the required data from the Twitter social network. Other social network texts than Twitter could also be used. In the second step, the extracted data are saved in JSON format. JSON's files are heavy and intertwined and contain much information. In this step, the extra information is deleted, and the data are pre-processed and cleaned. Information on the day and place of the protest is extracted and stored.

Raw tweets obtained from Twitter are processed in the third step, and the Twitter users' behaviors are identified. User behavior can be classified into three groups. Wang et al. [34] ranked the users' behaviors on social networks in events such as Occupy Wall Street. The paper classified users' behaviors in social networks during protests, claiming that the users' behaviors in social networks during the Wall Street protests are as follows: Event log sharing (Event Log Share), sharing general information about the event (General Info Share), sharing opinions about the event (Opinion Share), and call for action. Wang et al. [40] believe that when an event such as a social protest occurs, users try to show one of the above-mentioned social behaviors on social networks.

Event log sharing (ELS): The event log sharing behavior of the users is widely observed in a social protest. One of the users' main behaviors on Twitter in street protests is that users try to share spatial, temporal, and logistic event logs. Through this content creation; users try to share the event log information. Three groups of tweets describe this behavior:

- Time information: Tweets containing time information such as protest hour.[2]

2 Example: RT @angelxxelyse: A rally/protest is scheduled Friday (tomorrow) 5 p.m. at Peter's Park in the South End Boston. Please consider attending...

- Date information: Tweets containing date information.[3]
- Spatial information: Tweets containing information such as the name of the street or square where the protest occurs.[4]

We use Stanford NLP's SUTime to identify tweets with time and date information [10]. A list of places collected from the Internet is used to identify tweets with spatial information.

Opinion Share (OS): For each event, users share opinions about that event. These opinions can be positive[5] and negative (sadness and hatred[6]) about the event. The third case is the sharing of neutral views about the event.

General Information Share (GIS): General information sharing is another behavior expressed by users of social networks, particularly Twitter, in protest events. The main aim of these tweets is to share general information about the events. These tweets post the news of the event and have a neutral tone.

In order to determine whether tweets contain OS and GIS behaviors, a deep learning classification algorithm is used. A combined deep learning algorithm is used to identify OS behaviors and GIS behavior. Three groups of emotions that are considered for OS behavior are happiness, sadness and anger-hatred. Neutral emotions are also considered for GIS behavior. We use "multi-channel" combinations of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) units to classify tweets into one of the four emotional classes (sad, happy, hate-anger, and neutral) [26]. Other categories such as linguistic features and public outreach ignored in this paper. These are rare tweets.

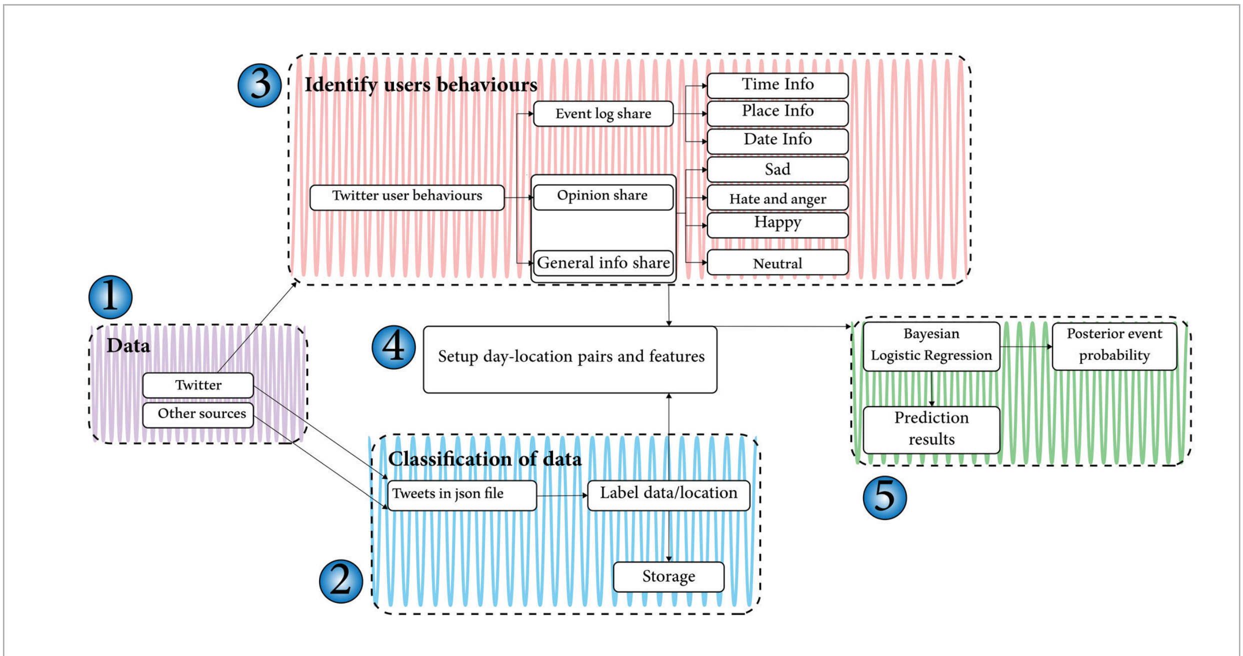
3 Example: RT @HeadOverFeels: On June 6th join the #DoctorWhoBlackout! We're supporting #BlackLivesMatter with this livetweet of THE GHOST MONUMENT a...,https://t.co/6zqPO3gIve

4 Example: RT @MrAndyNgo: Antifa groups in Portland, Ore. have announced a 6 p.m. gathering at Laurelhurst Park. This is a middle class residential ne...

5 Example: RT @HealthworksFit: #BlackLivesMatter. We stand in solidarity with the Black community near and far against systemic racism and injustice....,https://t.co/cdedP2V4eP

6 Example: Don't let these mothafuckas fool you https://t.co/DoUW6SV9Tb

Figure 2
Overview of the presented method



In the fourth step, the day and place pairs that are obtained in the second step the extracted features that are obtained in the third step are combined to create the dataset whose structure is given in Table 2.

In the fifth step, Bayesian Logistic Regression (BLR) algorithm was used to calculate prediction accuracy and the indicator identification of events. Along with the model's accuracy, it is essential to interpret the results obtained in the presented model. High precision and interpretable results for identifying protest and violence are one of the most important advantages of using the BLR algorithm. This algorithm determined the necessary early indicators of protests and violence with high precision. It is vital to identify the features that should be monitored to identify the protest and the probability of violence. The prediction results show the model's accuracy, and the posterior probability determines the best indicator for monitoring events.

We define a Bernoulli random number for the probability of protest occurrence (Y_{ij}) [30]. Y_{ij} is the probability of a protest event occurring on a specific day (i) and city (j). If Y_{ij} is equal to 1 the protest event will occur, and it will not happen if Y_{ij} is equal to 0. This is also applicable to the protest type prediction.

$$\Pr(Y_{ij} = 1) = p$$
$$p = 1 - \Pr(Y_{ij} = 0) = 1 - q \tag{1}$$

The probability mass function f of Bernoulli distribution over possible n outcomes can be expressed as:

$$f(n; p) = p * n + (1 - p)(1 - n) \; for \; n \in \{0,1\} \tag{2}$$

The Bernoulli distribution is a discrete distribution having two possible outcomes labeled by n=0 and n=1 in which n=1 ("protest event") occurs with probability p, and n=0 ("no event") occurs with probability, $q = 1 - p$ where $0 < p < 1$.

The Bayesian approach can completely master prior knowledge with strong robustness [16]. By increasing the number of samples, this algorithm can fit the posterior distribution of the objective function [36].

An event X is described by a set of features. Based on Bayes theorem, the conditional probability of whether a given event is a protest event or not can be computed as follows:

$$P(Y_{ij}|X) = \frac{P(X|Y_{ij})P(Y_{ij})}{P(X)} \tag{3}$$

In what follows, we use the logistic link function:

$$P(Y_{ij}|X) = \frac{e^{(\alpha+\beta_i x_i)}}{1+e^{(\alpha+\beta_i x_i)}} \quad (4)$$

Which has the following probability mass function:

$$\mathrm{P}(\mathrm{Y_{ij}}|\mathrm{X}) = \frac{1}{1+\mathrm{e}^{-(\alpha+\beta_i x_i)}} = \frac{1}{1+e^{-(logit)}} \quad (5)$$

$$P(Y_{ij}|X) = \frac{1}{1+e^{-(\alpha+\sum_{i=0}^{8}\beta_i x_i)}} \quad (6)$$

The interpretation formula is as follows:

$$\begin{aligned} Logit = \alpha + \beta_0 * (Number\ Of\ Tweet) + \\ \beta_1 * (Day) + \beta_2 * (Date\ Info) + \\ \beta_3 * (Time\ Info) + \beta_4 * (Place\ Info) + \\ \beta_5 * (Sad) + \beta_6 * (Happy) + \\ \beta_7 * (Hate\ and\ anger) + \\ \beta_8 * (Neutral) \end{aligned} \quad (7)$$

In the Bernoulli distribution, the theta parameter is important and it is calculated using alpha and beta parameters as follows.

$$\theta = logistic(\alpha + \beta_i x_i) \quad (8)$$

Alpha and beta parameters with normal distribution were used to estimate the theta parameter to generate the BLR algorithm. Based on Bayesian logic, the numbers in the data have been randomly selected, starting with the stated parameters. Bayes uses a distribution to express these numbers. The BLR algorithm is employed to identify protest indicators and violence indicators. Also, the prediction model is created by this algorithm.

5. Results

A combination of features is considered to achieve the best protest prediction model. We considered five models, as follows:

1. EventLogShare only: This model only uses the EventLogShare (Time Info, Place Info, and Date Info) features (Group I).
2. OpinionShare only: This model only uses the OpinionShare (sad, happy, hate-anger) features (Group II).
3. GeneralInforShare only: This model only uses the GeneralInforShare (neutral) feature (Group III).
4. EventLogShare + OpinionShare + GeneralInforShare: This model uses all user behavior features of tweets in Twitter (Group IV).
5. EventLogShare + OpinionShare + GeneralInforShare + Number of Tweets + Day: This model uses all user behaviors on Twitter plus the number of indicative tweets and the protest day information (Group V).

Each model is used to predict the protest and the possibility of violence in the protest. The following section reports the obtained accuracy precision, recall, and F1 measure results.

A Spearman's rank-order correlation method is used to examine the strength of the relationship between features and outcomes (event type and protest type). Besides user behavior features, the month and day of the protests have also been collected. Because there is information about only two months in our data, only the day parameter has been considered. In addition, the number of tweets per day has been used as a feature in models. Correlation results for features are also presented in the next section.

5.1. Protest Events

We first tested the strength of the relationship between features (the protest day, the number of tweets, Date Info, Time Info, Place Info, sad, happy, hate-anger, and neutral) and outcomes (event type and protest type). A Spearman's rank-order correlation was run to determine the relationship between features and outcomes. There was a moderate, positive correlation between Time Info and protest events, which is statistically significant (r = 0.52, p = 6.87 × 10-261). There is a moderate, positive correlation between Date Info and protest events, which is statistically significant (r = 0.44, p = 2.77 × 10-195). There is a weak, positive correlation between the protest day features and protest events. There is a weak, positive correlation between the number of tweets and protest events.

The performance results of the models for the protest event classification are given in Table 5. According to Table 5, the best combination of features belongs to user behavior besides the number of informative tweets and the protest day. In this combination, the accuracy is 92%, the precision is 85%, the recall is 87%, and the F1 is 86%. The performance of the triple users' behavior model is very close to that best model. EventLogShare behavior has been more successful in

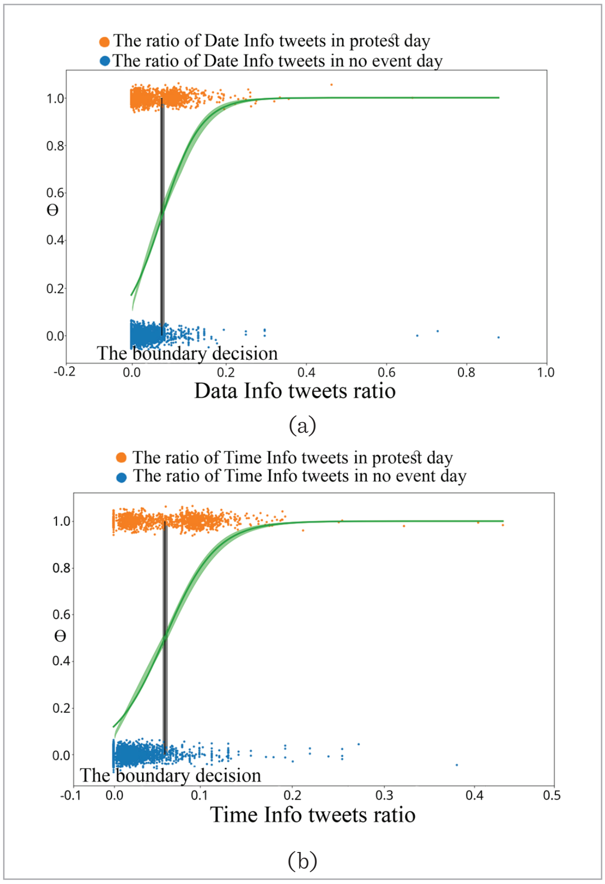
Table 5
Protest event classification accuracy, precision, recall, and F1 score

Features Groups	Accuracy	Precision	Recall	F1
Group I	0.88	0.84	0.86	0.85
Group II	0.55	0.68	0.52	0.60
Group III	0.69	0.50	0.35	0.41
Group IV	0.91	0.83	0.89	0.86
Group V	0.92	0.85	0.87	0.86

predicting the protest day among the users' behavior. We omitted the confusion matrix table for comparing the five models for brevity.

Figure 3 shows no protest vs. protest (y = 0, y = 1). The S-shaped line is the mean value of theta parameter

Figure 3
The fitted sigmoid curve and the decision boundary for Time Info and Date Info



(θ). This line can be interpreted as the probability of a protest, given that we know the Time Info (a) and Date Info (b) tweets ratio. The boundary decision is represented as a vertical line. According to the boundary decision, the values of the TimeInfo tweets ratio to the left correspond to y = 0 (no protest), and the values to the right to y = 1 (protest). X vector has theta values that were described in equation 8.

The best combination of features is presented in Table 5. The best combination is used to identify the cut-off point for the ratio of Time Info tweets and Date Info tweets. The time and date tweets' cut-off points are 0.04 and 0.06, respectively. The rate of Date Info tweets greater than 6% of all tweets and Time Info tweets greater than 4% are crucial indicators for forecasting protests. Each point in Figure 4 shows the event in the city and the day. The total number of events is 4492, which includes 3078 no protest events and 1414 protest events, which are displayed in Figure 4 with 4492 points (1414 orange points and 3078 blue points). The ratio of Time Info tweets and Date Info tweets on protest and no protest day shows with orange and blue color, respectively.

5.2. Protest Types

Like the protest event, the violent event has also been studied similarly. There was a strong, positive correlation between the hate-anger tweets ratio and violent events, which was statistically significant (r = 0.62, p = 1.37 × 10-42). There was a moderate, negative correlation between the sad tweets ratio and violent events, which was statistically significant (r =-0.56, p = 2.5 × 10-36). Also, there was a moderate, negative correlation between happy tweets ratio and violent events.

Based on the results obtained from Table 6, the best combination of features belongs to user behavior besides the number of informative tweets and the protest day. In this combination, the accuracy is 92%, the precision is 85%, the recall is 87%, and the F1 is 86%. The performance of the triple users' behavior model is very close to that model. Among users' behaviors, OpinionShare behavior has been more successful in predicting violence. We omitted the confusion matrix table for comparing the five models for brevity.

Figure 4 shows no violence vs. violence (y = 0, y = 1). The S-shaped line is the mean value of θ. This line can be interpreted as the probability of violence, given that we know the hate-anger tweets ratio.

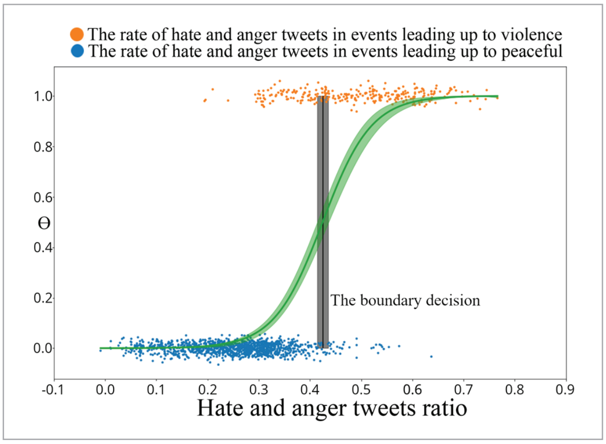
Table 6

Protest event classification accuracy, precision, recall, and F1 score

Features Groups	Accuracy	Precision	Recall	F1
Group I	0.79	0.50	0.50	0.45
Group II	0.90	0.82	0.87	0.84
Group III	0.71	0.50	0.50	0.41
Group IV	0.91	0.83	0.89	0.86
Group V	0.92	0.85	0.91	0.87

Figure 4

The fitted sigmoid curve and the decision boundary for hate-anger tweets ratio



Based on the boundary decision (vertical line), the values of hate-anger tweets ratio to the left correspond to y = 0 (no violence), and the values to the right to y = 1 (violence). Based on the extracted features, the proposed algorithm is implemented on five models, and the best combination for predicting protests and violence in protests is obtained. The triple Twitter users' behaviors besides the day and the number of informative tweets to predict the day of protest and violence provide the best model. The best combination is used to identify the cut-off point for the ratio of hate-anger tweets. The hate-anger tweets' cut-off points are 0.42. A rate of hate-anger tweets greater than 42% is an essential indicator for predicting the violence in protests. The ratio of hate-anger tweets on violence and no violence shows with orange and blue colors, respectively.

6. Discussion

Today, with the free circulation of information and the increasing access of citizens to political information, political actions in various forms have risen, such as activities in citizen action groups, protests, and boycotts [12]. Each of these political actions can be accompanied by opinions in the online space, and the analysis of these opinions expressed by citizens in social networks and other sources can be of great value to researchers and decision-makers [20]. Content analysis is a field of study that automatically develops categories for the content people produce on social networks and assigns texts to categories. We believe that in PEA, the identification of early indicators is more important than the accuracy of classification to categories. Based on the finding of the BLR algorithm, ELS behavior is very important for predicting protest day. The rate of Time Info and Date Info tweets are a powerful indicator for predicting the protest day. Regarding violent events, OS behavior is also very useful. It is possible to predict the violence in protests by monitoring the rate of hate-anger tweets.

The content of tweets published by those who want to participate in protests is essential in real-time and has a different essence than the data of text classification, opinion mining, recommender systems, Etc. For this reason, we believe that identifying early indicators in the studies related to the prediction of the day of protest and violence in them is more important than the prediction accuracy as the success criteria of "hard" classification problems.

Interpretable research results are early indicators for system monitoring experts such as police staff. The value of the boundary decision is specified in the results (Time Info tweets rate = 0.04, Date Info tweets rate = 0.06, and hate-anger tweets rate = 0.42). The system monitoring experts can warn of upcoming protests and violence by monitoring this value. By monitoring hate-anger tweets, the police can learn about the increased likelihood of violence in protests. Preventing violence in protests by using the interpretable results extracted from the content of tweets published on Twitter is one of the most important contributions of this study. Predicting violence in protests can prevent many financial and human costs.

Korkmaz et al. [24] have mentioned economic reasons in Latin America as an early indicator of protests. Tuke et al. [39] have determined the role of weekdays and months, besides the number of informative tweets in a tropical country such as Australia, as an early indicator. Bakerman et al. [5] have identified specific keywords as the most important prediction indicator of protest day. Other works with machine learning algorithms and text mining approaches have been presented for predicting protests and have not presented an early indicator [1, 2, 4, 14, 18, 22, 33, 42].

The most crucial problem in protest identification studies is the lack of an open dataset. Because social network policies do not allow user content publication, there is no comprehensive data set. Many studies have unique datasets and have been collected by researchers. Thus, it is not easy to make comparisons between these studies. Most other papers reported an accuracy between 75% and 95%. The performance of this article includes accuracy (92%) and precision (85%) are more reliable and valuable because of the high number of protest events in the dataset and the identification of early indicators.

In previous studies, small and large-scale protests have not been examined simultaneously. Some studies studied large-scale protests [22, 28, 34] and some small-scale protests [38]. In the present study, small and large-scale protests were investigated, and the presented method was successful in both. One of the essential advantages of this research is providing a method for examining small and large-scale protests.

The proposed method was implemented in protests in small and big cities. This research detects both small and large scales protests successfully. Interpretable results are invaluable to the system expert. The indicators can be critical in predicting protests and violence.

There was no data on the exact hour of protests in BLM. In the JSON file, each tweet's hours, minutes, and seconds are known and can be used, but no information has been published about the exact hour of protests held in BLM. For this reason, it was impossible to implement the model based on the exact hour of the protests. The lack of similar studies with common datasets for accurate comparison is another limitation of this study. Regarding the Place Info, the lack of a complete list of streets, squares, and places in the United States of America made this indicator in our study unimportant. This list of places could make the impact of these types of tweets more effective in the model.

7. Conclusion and Future Works

In this work, we propose a detailed analysis of Twitter's open data to forecast future protests and violent events. The findings of this study showed a high correlation between the occurrence of protests and tweets, which indicates the reliability of Twitter as an indicator for predicting protest events and violence in them. Therefore, Twitter user behaviors on social media have become a useful source for capturing, understanding, and analyzing protest events.

We present a new method for predicting the day of protest and the possibility of violence during the protest using Twitter user behavior and the Bayesian Logistic Regression algorithm. The study dataset was obtained from the combination of the two open data and then based on the triple Twitter users' behaviors, the desired features were extracted from it. Based on the extracted features, the proposed algorithm was implemented on five models, and the best combination for predicting protests and violence in protests was obtained. The triple Twitter users' behaviors besides the day and the number of informative tweets to predict protests and violence in protests provide the best model. According to the results, the rate of tweets containing date and time information is the best indicator for identifying protests. Hate-anger tweet rates are also the best indicator of violence in protests.

In future work, we will develop the framework to estimate the size of the protest based on our dataset. The number of participants in a protest is as important as the probability of violence.

Statements and Declarations

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We declare that there is no conflict of interest.

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