Quantitative Analysis of Forecasting Models: In the Aspect of Online Political Bias

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Abstract—Understanding and mitigating political bias in online social media platforms are crucial tasks to combat misinformation and echo chamber effects. However, characterizing political bias temporally using computational methods presents challenges due to the high frequency of noise in social media datasets. While existing research has explored various approaches to political bias characterization, the ability to forecast political bias and anticipate how political conversations might evolve in the near future has not been extensively studied. In this paper, we propose a heuristic approach to classify social media posts into five distinct political leaning categories. Since there is a lack of prior work on forecasting political bias, we conduct an in-depth analysis of existing baseline models to identify which model best fits to forecast political leaning time series. Our approach involves utilizing existing time series forecasting models on two social media datasets with different political ideologies, specifically Twitter and Gab. Through our experiments and analyses, we seek to shed light on the challenges and opportunities in forecasting political bias in social media platforms.

Index Terms-political bias, forecasting, social media

I. INTRODUCTION

News media houses have endured through time to disseminate political news to the people while also influencing their political perceptions. The immense growth of online social media has a significant effect on how news is being consumed in recent years, giving them resources to seed disinformation and fake news on the course of accelerating the information dissemination process [1]. The causalities of social media polarization can be computationally characterized with three aspects: time-based [2], topic-based [1] and user-based [3]. Time-based approaches qualitatively analyze dynamics of politically biased topics in online forums, Topicbased approaches characterize polarization with linguistic queues on content-level details (entities, topics, etc.) and how social media communities react with the multitude of opinions to such contents. User-based approaches formulate polarization with user communities in the social network and how topics help to divide communities in the network.

In this work, we explore a novel research endeavor focused on forecasting of political bias in two social media platforms. We formulate this as a time series forecasting problem where the objective is to capture correlation between political bias and information evolving patterns. Such temporal forecasting can give insights to analysts on the formation of ideological clusters and the dissemination of biased information on social media platforms. Notably, prior research in forecasting political bias data is limited, making our exploration a pioneering effort in this domain. We leverage existing time series forecasting models to evaluate their suitability for this task. By analyzing these models' performance in forecasting political leaning time series, we aim to uncover their strengths and limitations in capturing the temporal dynamics of political bias. Overall, we have a *two-fold* contributions in this paper:

- Contribution-1: We propose a new problem of forecasting the political bias on online social media posts. Such forecasting is crucial for understanding the social media's political standpoint on any given topic or event
- Contribution-2: We experiment with various time series forecasting models to quantify the trends in different political biases of two social media forums that have different user participation, popularity, and political ideology: Twitter and Gab.

II. RELATED WORK

Many studies have focused on analyzing the content of tweets to predict the political inclination of individual users. Jiang et al. [4] introduced an NLP model named retweet-BERT which utilizes retweet networks for prediction of political leaning of users. Another study [5] analyzed content of the tweets of the users to identify their corresponding political leaning. Efron et al. [6] have used a probabilistic model to estimate the political orientation of documents. Significant research has been done to predict political leaning which is on tweets limited to certain locations. Work in [7] tried to forecast whether users are more left- or right-oriented in different languages. Turkmen et al. [8] implemented a Support Vector Machine and Random Forest Classifiers connected with a statistic-based feature selection to predict political tendency on a small selection of political communications. Another study [9] constructed a targeted dataset of tweets, and explored several types of potential features to build accurate predictive models based on machine learning to infer political leaning. Time series forecasting of political leaning is still booming recently. A recent work [10] utilized time series forecasting to model the topic-specific daily volume of social media activities. The work in [11] analyzed forecasting activity in several social media datasets, to capture different contexts occurring on multiple platforms such as Twitter and YouTube.



(a) Degree of Sentimentality in Twitter posts for each political leaning

(b) Degree of Sentimentality in GAB posts for each political leaning

Fig. 1: Average Compound Sentiment score of Twitter and GAB posts per day

III. DATASETS

In this research, we utilized publicly available datasets from Twitter [12] and Gab [5]. The Twitter dataset [12] consists of tweets that share news article URLs related to political topics from selected news media sources. The data spans from January 2018 to October 2018, comprising a total of 722,685 tweets. Our Gab data [5] comprises 1,345,279 posts from the same time span from January 2018 to October 2018. We have generated another comprehensive media bias dataset using web scraping tools from Allsides.com¹. AllSides utilizes user community for validation, assigns political leaning on a scale on news articles and media outlets. We first analyze the sentiment polarity of posts that share news articles to understand properties of our datasets. We use VADER [13] to obtain average compound score of each post. It is evident from Figure 1a, Twitter generally has negative sentiment polarity in posts that share right and right-leaning news articles while maintaining less negative value over other political leanings. Figure 1b illustrates that the Gab dataset, has more frequent negative sentiment overall political leaning labels. It also shows that left posts have more negative sentiment over other political leanings. These analyses clearly indicates that two datasets have distinct political ideologies.

IV. METHODOLOGY

A. Data preprocessing

We label the Twitter and Gab posts to their corresponding political leaning using the political bias of collected political media bias outlets. That is if the news domain in a social media post has political leaning p, we label the social media post as p. In this study, we consider *five* political leaning labels $p = \{left, left - leaning, center, right - leaning, right\}.$

In this process, we also extracted the timestamps for each tweet or Gab post in two methods. (i) We calculated the respective political leaning post frequencies for each day, and (ii) we preprocessed frequencies of likes based on their respective political leaning for each day. Due to outliers and very small postings in other months we use posts from January to April in our experiments.

B. Timeseries forecasting models.

We used 5-time series forecasting models in this work.

1) SARIMA Model: As our Twitter and Gab datasets are non-stationary with political leaning, we choose the SARIMA model for forecasting. It is a statistical model that is a combination of the autoregression (where the value at the current time is forecasted in the linear combination of previous times until p), and moving average (where past forecast errors are used in linear combination to forecast present time value) models with seasonality. So, the time series forecasting for a timestep t is given by:

$$y_{t} = c + \sum_{n=1}^{p} \alpha_{n} y_{t-n} + \sum_{n=1}^{q} \theta_{n} \varepsilon_{t-n} + \sum_{n=1}^{P} \phi_{n} y_{t-sn} + \sum_{n=1}^{Q} \eta_{n} \varepsilon_{t-sn} + \varepsilon_{t}$$
(1)

where y_x is the frequency at time x, c is the constant term, α_n is the autoregressive coefficient, θ_n is the moving average coefficient, ϕ_n is the seasonal autoregressive coefficient, η_n is the seasonal moving average coefficient, ε_t is the white noise error term. Also, the notations p, d, q, P, Q, and s are obtained by grid search on the SARIMAX function which varies for each political leaning in our preprocessed data.

2) LSTM Model: Due to the limitation of SARIMA capturing very simple patterns and linear dependencies between variables we use two types of LSTM methods. One method takes only the previous day's data, while the other takes the past two week's data as input to make the next-day prediction. The LSTM methods used in this work are given below:

$$i_{t} = \sigma(W_{i} \cdot [h_{t-1}, x_{t}] + b_{i})$$

$$f_{t} = \sigma(W_{f} \cdot [h_{t-1}, x_{t}] + b_{f})$$

$$g_{t} = \tanh(W_{g} \cdot [h_{t-1}, x_{t}] + b_{g})$$

$$c_{t} = f_{t} \cdot c_{t-1} + i_{t} \cdot g_{t}$$

$$o_{t} = \sigma(W_{o} \cdot [h_{t-1}, x_{t}] + b_{o})$$

$$h_{t} = o_{t} \cdot \tanh(c_{t})$$

$$(2)$$

where i_t is the input gate activation at time step t, f_t is the forget gate activation at time step t, g_t is the cell state update at time step t, c_t and c_{t-1} are the cell state at time steps t and t-1 respectively, o_t is the output gate activation at time step t, h_t and h_{t-1} are the hidden state at time steps t and t-1 respectively, x_t is the input feature vector at time step t, σ

¹http://www.allsides.com/media-bias/media-bias-rating-methods

is the sigmoid activation function to squash the input values between 0 and 1, \tanh is the hyperbolic tangent activation function to squash the input values between -1 and 1

The only difference that comes into play for our second LSTM is that we use a 14-day look back in place of single feature vector input x_t . Thus the input to the LSTM methods is a concatenation of all vectors $x_t = [x_t; x_{t-1}; x_{t-2}; ...; x_{t-13}]$. Other parameters like hidden states, epochs, and optimizers used in LSTM are set by hyperparameter tuning. We used the RMSE loss function in all our LSTM models.

3) Multistep time series forecasting model: We modified the above LSTM model to make multi-step and beyond 1-day predictions for both posts and likes in each political leaning in both datasets. We mainly focus on making predictions for the next 5 days from the given 14-day look-back data. We utilized *Teacher Forcing* [14] to achieve multistep forecasting to predict the entire output sequence [t+1, t+2, ..., t+5] from the multistep look back sequence [t-13, t-12, ..., t-1, t]. In teacher forcing, instead of using LSTM's own generated output as input for the next time step, the ground truth or target sequence is used as input to the model at each time step during training. This leads to faster convergence of the forecasting model and a more stable training process. The pipeline of our multistep time series forecasting model with teacher enforcing is :

- For each of the 5 prediction steps, we use a RNN or similar architecture. The model takes as input a sequence of 14 historical data points (lookback) and produces an output for the next day.
- During training, for each prediction step, the true value for the corresponding day as part of the input sequence is provided. This enforces the model to learn accurate dependencies between historical and future data points.
- 3) The loss function is the sum of losses for each prediction step, computed as the difference between predicted and true values. This encourages the model to refine its predictions iteratively.
- 4) Once trained, the model can be deployed for forecasting by feeding it the most recent 14 days of data. It will generate predictions for the next 5 days, utilizing the learned temporal dependencies to make accurate forecasts.

4) Gated Recurrent Unit.: We used another RNN model *GRU* which is considered simpler than LSTM and assists with capturing long-term dependencies in sequence data. The only difference is it combines the forget and input gates of LSTM into a single update gate and merges the cell state and hidden state of LSTM into a single hidden state. We use the GRU model as given below:

$$z_{t} = \sigma(W_{z} \cdot x_{t} + U_{z} \cdot h_{t-1} + b_{z})$$

$$r_{t} = \sigma(W_{r} \cdot x_{t} + U_{r} \cdot h_{t-1} + b_{r})$$

$$\tilde{h}_{t} = \tanh(W_{h} \cdot x_{t} + U_{h} \cdot (r_{t} \odot h_{t-1}) + b_{h})$$

$$h_{t} = (1 - z_{t}) \odot h_{t-1} + z_{t} \odot \tilde{h}_{t}$$
(3)

where z_t is the update gate at time step t, r_t is the reset gate at t, \tilde{h}_t is the candidate hidden state at t, h_t is the

hidden state at t, x_t is the input feature vector at t, h_{t-1} is the hidden state at the previous time step (t-1), W_z, W_r, W_h are weight matrices of update gate, reset gate, and candidate hidden state respectively, associated with the current state, U_z, U_r, U_h are Weight matrices for the update gate, reset gate, and candidate hidden state, associated with the previous state, b_z, b_r, b_h are bias terms, and \odot is the Element-wise multiplication (Hadamard product). We followed the same approach given for the LSTM methods to input a 14-day look back for the next timestep prediction.

V. EXPERIMENTS AND RESULTS

Hyper parameters Tuning. We first list hyperparameters of our models and then discuss results. Since we have time series for each political leaning, we use an exclusive model for each political leaning in our experiments.

1) SARIMA Model hyperparameters.: We used Grid search Hyperparameter tuning to get order parameters p, d, q, and seasonal order parameters P, D, Q, S in SARIMA for both Twitter and Gab datasets. For Twitter posts frequency we found order parameters (9, 0, 10) and seasonal order parameters ((2, 1, 1, 12)) to be optimal. Whereas for Twitter like we observed order=(11, 1, 3), seasonal order=(3, 1, 3, 12) to be optimal for all political leanings.

Unlike Twitter, we noted that we get different optimal parameter values for Gab. For Gab posts frequency forecasting we set the following parameters.

- Left :- order=(7,1,10), seasonal order=(3,1,1,14)
- Right :- order=(6,2,10), seasonal order=(4,1,1,11)
- Centre :- order=(11,1,10), seasonal order=(2,1,1,14)

And, we use the following parameters for Gab likes frequency forecasting.

- left :- order=(11,1,6), seasonal order=(3,0,4,12)
- right :- order=(9,1,11), seasonal order=(1,1,3,12)
- centre :- order=(8,1,11), seasonal order=(4,0,0,12)

2) LSTM Hyperparameters.: We use 4 hidden layers, trained with 100 epochs, and *RMSProp* optimizer as hyperparameters for all political leaning forecasting in the Twitter dataset for both 1-day lookback and 14-day lookback. The same set of hyperparameters is used for both tweets frequency and likes frequency forecasting. Similarly, we used 4 hidden layers, 200 training epochs, and *RMSProp* as optimizers for all experiments with the Gab data. We use *Mean Squared Error* (MSE) loss in all LSTM experiments.

3) Multistep Time Series Forecasting Hyperparameters.: Hyperparameters for multistep time series forecasting models differ only with the number of epochs we used in training. Other than that we use *RMSProp* optimizer, 8 hidden layers with 8 hidden neurons in each layer, and MSE loss function as hyperparameters. We use 125 epochs for tweets, 150 epochs for Gab posts, and 100 epochs for likes data in general.

4) GRU Hyperparameters.: We set dropout as 0.2, adam optimizer, *MSE* loss, 100 training epochs, and a batch size of 16 for GRU forecasting models in both Twitter and Gab.

Results of timeseries forecasting models. In this section, we give forecasting results for both post frequencies and

Models	Left	Right	Center	Left Leaning	Right Leaning
SARIMA	66.10	31.29	70.15	155.72	13.07
LSTM (1 day feedback)	Train :- 16.76	Train :- 10.59	Train :- 32.65	Train :- 51.36	Train :- 6.28
	Test :- 159.58	Test :- 63.73	Test :- 161.48	Test :- 369.79	Test :- 30.86
LSTM (14 days feedback)	Train :- 17.74	Train :- 2.99	Train :- 18.11	Train :- 19.74	Train :- 1.88
	Test :- 278.99	Test :- 105.28	Test :- 275.17	Test :- 774.52	Test :- 49.28
GRU(14 days feedback)	Train :- 51.97	Train :- 16.35	Train ;- 94.77	Train :- 428.02	Train :- 19.82
	Test :- 329.36	Test :- 437.32	Test :- 184.6	Test :- 1002.4	Test :- 39.62
	t+1 :- 147.15	t+1 :- 50.29	t+1 :- 131.08	t+1 :- 279.15	t+1 :- 23.05
Multistep Forecasting (14 days feedback and 5 next days predicting)	t+2 :- 238.26	t+2 :- 73.98	t+2 :- 195.88	t+2 :- 440.73	t+2 :- 32.16
	t+3 :- 285.23	t+3 :- 89.28	t+3 :- 236.04	t+3 :- 541.36	t+3 :- 38.54
	t+4 :- 307.02	t+4 :- 98.77	t+4 :- 266.49	t+4 :- 605.67	t+4 :- 41.26
	t+5 :- 310.57	t+5 :- 100.92	t+5 :- 280.76	t+5 :- 648.48	t+5 :- 42.15

TABLE I: RMSES of Time Series Forecasting of Tweets Frequencies from Twitter Dataset

TABLE II: RMSES of Time Series Forecasting of Likes Frequencies from Twitter Dataset.

Models	Left	Right	Center	Left Leaning	Right Leaning
SARIMA	216.48	55.95	228.02	1364.16	25.76
LSTM (1 day feedback)	Train :- 185.22	Train :- 13.95	Train :- 69.23	Train :- 669.69	Train :- 8.30
	Test :- 351.86	Test :- 95.63	Test :- 529.16	Test :- 5312.20	Test :- 62.22
LSTM (14 days feedback)	Train :- 193.23	Train :- 33.80	Train :- 61.05	Train :- 175.26	Train :- 2.76
	Test :- 285.68	Test :- 169.71	Test :- 642.67	Test :- 3647.8	Test :- 51.17
GRU(14 days feedback)	Train :- 217.69	Train :- 67.65	Train ;- 167.86	Train :- 740.97	Train :- 26.71
	Test :- 116.7	Test :- 28.82	Test :- 197.32	Test :- 4259.36	Test :- 7.59
Multistep Forecasting (14 days feedback and 5 next days predicting)	t+1 :- 389.58	t+1 :- 123.28	t+1 :- 546.24	t+1 :- 1626.40	t+1 :- 60.57
	t+2 :- 352.89	t+2 :- 141.52	t+2 :- 603.19	t+2 :- 1617.93	t+2 :- 56.32
	t+3 :- 341.11	t+3 :- 139.45	t+3 :- 564.96	t+3 :- 1620.36	t+3 :- 53.06
	t+4 :- 333.76	t+4 :- 132.35	t+4 :- 617.59	t+4 :- 1629.02	t+4 :- 60.41
	t+5 :- 403.50	t+5 :- 144.41	t+5 :- 573.48	t+5 :- 3425.94	t+5 :- 50.92

TABLE III: RMSES of Time Series Forecasting of Posts frequencies in Gab Dataset.

Models	Left	Right	Center	Left Leaning	Right Leaning
SARIMA	37.04	263.40	78.12	63.90	98.66
LSTM (1 day feedback)	Train :- 31.98	Train :- 247.32	Train :- 73.95	Train :- 57.76	Train :- 97.55
	Test :- 48.23	Test :- 532.17	Test :- 164.32	Test :- 73.42	Test :- 142.31
LSTM (14 days feedback)	Train :- 26.71	Train :- 219.08	Train :- 58.43	Train :- 49.76	Train :- 80.62
	Test :- 46.64	Test :- 445.41	Test :- 106.05	Test :- 57.04	Test :- 97.86
GRU(14 days feedback)	Train :- 38.68	Train :- 556.54	Train ;- 98.43	Train :- 69.3	Train :- 116.62
	Test :- 46.62	Test :- 799.49	Test :- 176.40	Test :- 84.67	Test :- 165.96
	t+1 :- 50.06	t+1 :- 526.08	t+1 :- 155.51	t+1 :- 72.47	t+1 :- 163.21
Multistep Forecasting (14 days feedback and 5 next days predicting)	t+2 :- 66.83	t+2 :- 691.85	t+2 :- 201.90	t+2 :- 89.76	t+2 :- 225.88
	t+3 :- 72.61	t+3 :- 687.51	t+3 :- 227.51	t+3 :- 88.57	t+3 :- 248.94
	t+4 :- 69.55	t+4 :- 744.08	t+4 :- 225.89	t+4 :- 79.95	t+4 :- 218.84
	t+5 :- 71.95	t+5 :- 849.04	t+5 :- 207.46	t+5 :- 88.27	t+5 :- 190.78

likes frequencies. We also give results for both next-day predictions and t+5 days predictions using the LSTM model in all experiments. We use the split of 70% training and 30% test for all models. One can see test rmse values higher than train rmse values and can easily come to a conclusion that model might be overfitted. But it is not the case because with severe experimentation we had given a sufficient training size. The reason for higher test rmse values is that we have applied forecasting on non-stationary data and this non-stationarity can be made to stationary and then applied to training for better

rmses but non-stationarity isn't changed for a reason and the reason is to observe trends in the social media posts. One observation from Tables I, II, III, and IV is that our LSTM model with a 14-day look back gives optimal forecasting results with training instances in all experiments. However, the same model underperforms with different test instances. We consider only test results in all our below analysis. Although SARIMA performs better in forecasting tasks overall, it is interesting from our results that some political leaning for the same tasks in the same dataset fits well with other models.

Models	Left	Right	Center	Left Leaning	Right Leaning
SARIMA	223.06	1265.42	310.95	235.66	395.36
LSTM (1 day feedback)	Train :- 239.56	Train :- 1217.28	Train :- 256.88	Train :- 233.39	Train :- 357.77
	Test :- 211.34	Test :- 2549.69	Test :- 633.05	Test :- 256.56	Test :- 480.48
LSTM (14 days feedback)	Train :- 231.28	Train :- 919.72	Train :- 251.63	Train :- 208.62	Train :- 317.45
	Test :- 227.59	Test :- 2389.58	Test :- 694.82	Test :- 294.13	Test :- 523.94
GRU(14 days feedback)	Train :- 251.4	Train :- 1831.7	Train ;- 277.15	Train :- 247.06	Train :- 390.66
	Test :- 212.8	Test :- 2208.50	Test :- 630.07	Test :- 272.13	Test :- 503.55
	t+1 :- 280.30	t+1 :- 2547.45	t+1 :- 592.32	t+1 :- 318.20	t+1 :- 610.65
Multistep Forecasting (14 days feedback and 5 next	t+2 :- 277.96	t+2 :- 33683.13	t+2 :- 720.73	t+2 :- 336.51	t+2 :- 705.73
	t+3 :- 327.75	t+3 :- 3381.94	t+3 :- 852.81	t+3 :- 333.83	t+3 :- 724.45
days predicting)	t+4 :- 318.86	t+4 :- 3250.28	t+4 :- 774.91	t+4 :- 320.60	t+4 :- 703.91
	t+5 :- 314.24	t+5 :- 3343.77	t+5 :- 850.64	t+5 :- 345.58	t+5 :- 773.96

TABLE IV: RMSES of Time Series Forecasting of Likes of posts from Gab Dataset.

Table I presents the RMSE of all models to forecast tweet frequencies in the Twitter dataset. It is evident that SARIMA outperforms 2x times other models for next-day forecasting in all political leanings. In terms of multistep forecasting with LSTM, we notice that our model can forecast longterm projections in the 'Center' time series. Also, we see an exponential rise in RMSE for 'Left' and 'Left Leaning' labels for short-term predictions which gets smooth for long-term forecasting. Table II gives RMSE of all models to forecast likes frequencies in tweets. Here, the GRU model with a 14-day lookback is able to outperform all models, including SARIMA, by 2x times. Surprisingly, all models give high RMSE to forecast likes frequencies from 'Left Leaning' and SARIMA is the only model to give moderately lower RMSE. The analysis of multistep forecasting resembles that of results from Table I. It is also notable from Tables I and II that the RMSE of 'Right' and 'Right Leaning' is comparatively lower than other political leaning for the Twitter dataset. This is because less amount of data in these labels in Twitter data.

We notice from Tables III and IV that SARIMA model forecasts both posts frequencies and likes frequencies in Gab data by about 1.5x times. We also notice that the RMSE of 'Right' timeseries are high in both Gab experiments. This can arise because of high range of data in this label. Unlike Twitter, we do not find any patterns emerging from likes frequencies forecasting with Gab data in Table IV. However, Table III suggests that the proposed model with *Teacher Forcing* can assist with long-term forecasting of 'Center' and 'Right Leaning' post frequencies in Gab. It is evident from Tables III and IV that the RMSE of 'Left' and 'Left Leaning' is comparatively lower than other political leaning for Gab dataset due to insufficient data.

VI. CONCLUSION

In this work, our effort to forecast political bias in online social media has contributed valuable insights to the understanding of temporal dynamics in political conversations. In this paper, a novel method that is different from previously related work aims at time series forecasting of politically leaned social media posts and their likes from Twitter and Gab. We analyzed multiple forecasting models to predict both the next time step and future steps. In this work, we note that existing time series models are capable of forecasting political bias in online social media activities. However, we also note that these models are sensitive and their performance drops for the large quantity of input data. The future directions can be innovating novel time series models specific for political bias problems that can handle shortcomings of existing models.

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