Finding Qs: Profiling QAnon Supporters on Parler

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Supplementary materials

Robustness checks

We check the robustness of our machine learning approach by repeating the analysis with alternative classifiers. For this purpose, we fit three additional classifiers: (1) A LASSO model to assess the relative gain of considering nonlinearites. (2) A random forest model as a common, out-of-the-box alternative to our XGBoost classifier. (3) A neural network with the same neural architecture search as in earlier works for user profiling (e. g., predicting verified status on Twitter (Paul et al. 2019)).

The training of the above classifiers was conducted as follows. We again trained separate classifiers for each of the three feature sets as well as a classifier for the combined set of all features. Moreover, we again trained each classifier using 10-fold cross-validation in combination with grid search.

Tbl. 1 shows the prediction performance for different feature sets and machine learning classifiers. Overall, we find that XGBoost performs best, as documented by the highest ROC AUC. This justifies why we selected this classifier for our main analysis. However, more importantly, all of the other classifiers reach a similar performance. For example, the random forest classifier using all features achieves a ROC AUC of 0.75, while the corresponding XGBoost model is only marginally better with a ROC AUC of 0.76. Similar patterns are observed for user features (0.73 vs. 0.74), linguistic features (0.62 vs. 0.61), and content features (0.69 vs. 0.67). Here, the ordering of the different feature sets remains the same (i. e., user features have the largest predictive power, followed by content features). The neural network reaches similar performance levels. Of note, all of the ROC AUC are substantially better than a random guess with a ROC AUC of 0.50. The improvement is also statistically significant (with $p < 0.01$ for all feature sets and classifiers). These findings confirm that machine learning can discriminate QAnon from non-QAnon supporters across different classifiers. This contributes to the robustness of our findings for RQ3, thus establishing that the different feature sets lend discriminatory power in order to distinguish QAnon vs. non-QAnon supporters.

As expected, we observe a lower performance for the LASSO due to its linear structure (i. e., a ROC AUC of 0.69 when using all feature sets). This allows us to assess the relative gain due to considering classifiers that capture nonlinearities, thus highlighting its overall relevance.

Input	**XGBoost**	**LASSO**	**RF**	**NN**
User features	**0.74*****	0.61***	0.73***	0.72***
Linguistic features	**0.62*****	0.55***	0.61***	0.60***
Content features	**0.69*****	0.68***	0.67***	0.65***
All features	**0.76*****	0.69***	0.75***	0.68***

p-values are obtained using the Mann–Whitney U-test (Mason and Graham 2002): $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
Best value per feature (= row) in bold

Table 1: Performance of discriminating QAnon supporters vs. non-QAnon supporters based on user, linguistic, and content features. Here, we report the ROC AUC for different classifiers: XGBoost, LASSO, random forest (RF), and a neural network (NN) to confirm the robustness of our findings.

Hyperparameter tuning

For the training of the classifiers reported in the main paper we use 10-fold cross-validation in combination with a grid search. Overall, we use the following 5 classifiers:

1. **XGBoost**: Here, we vary the learning rate (*LearningRate*), the maximum tree depth (*MaxTreeDepth*), the subsample ratio of training instances (*Subsample*), the subsample ratio of variables to construct each tree (*ColSample*), and the number of boosting iterations (*Nrounds*). The corresponding tuning range for each parameter is reported in Tbl. 2.
2. **LASSO** was tuned using a custom grid for λ (i. e., 100 equally spaced values from 0.001 to 1000).
3. **Random forest** (RF) use grid varying the number of variables to split at each node (*Mtry*) and the splitting rule (*Splitrule*). Again, the corresponding tuning range for each parameter is shown in Tbl. 2.

4. **NN (literature)**. We used state-of-the-art network consistent with prior literature (Paul et al. 2019). Here, we used an additional validation set, a batch size of 32, and early stopping. Consistent with (Paul et al. 2019), we further used ReLU activation functions and Adam for optimization. We set the number of hidden layers to 3 and the number of neurons to 100, 30, 10, respectively, as in (Paul et al. 2019). This was done to obtain results where the network architecture is comparable to earlier research. The network was implement in Keras.
5. **NN (custom)**. We implemented a customized neural network, where, instead, all parameters (i. e., number of layers, number of neurons per layer, dropout, batch size, etc.) were manually tuned. The network was again implement in Keras. However, this led to overall similar results to the NN (literature). Hence, we omitted NN (custom) for brevity.

Classifier	**Hyperparameter**	**Tuning range**
XGBoost	*LearningRate*	[0.3, 0.4]
	MaxTreeDepth	[1, 2, 3, 4, 5]
	Subsample	[0.5, 0.625, 0.75, 0.875, 1]
	ColSample	[0.6, 0.8]
	Nrouds	[50, 100, 150, 200, 250]
RF	*Mtry*	[2, 46, ..., 354, 399]
	Splitrule	[“Gini”, “Extratrees”]

Table 2: Tuning range for XGBoost and random forest (RF) hyperparameters.

Supplementary tables

Overview of collected variables

Variable	**#Total**	**Per user**
Followers	279,298,787	437
Followees	194,442,610	304
Posts	157,849,243	247
Comments	42,321,848	66
Impressions (posts)	25,675,925,576	40,190
Upvotes (posts)	256,789,008	402
Upvotes (comments)	102,436,423	160
Downvotes (comments)	3,854,418	6

Table 3: Overview of the variables. Reported are the cumulative counts across all users (#Total) and the mean values per user (per user).

The following list of keywords was used to identify QAnon-supporters (adapted from (Sharma, Ferrara, and Liu 2022)):

anons	anon
qanons	qanon
q	thegreatawakening
greatawakening	wwg1wga
wgaworldwide	qarmy
obamagate	pizzagate
savethechildren	saveourchildren
taketheoath	deep state
deepstate	deepstatecoup
deepstatecabal	deepstateexposed
plandemic	scamdemic
sheepnomore	adrenochrome
thestorm	followthewhiterabbit
downtherabbithole	thesepeoplearesick
wearethenewsnow	pizzagateisreal
thestormisuponus	newworldorder
darktolight	clintonbodycount

Table 4: List of keywords used to identify QAnon supporters (adapted from (Sharma, Ferrara, and Liu 2022)).

References

Mason, S. J.; and Graham, N. E. 2002. Areas beneath the relative operating characteristics (ROC) and relative operating levels (ROL) curves: Statistical significance and interpretation. *Quarterly Journal of the Royal Meteorological Society* 128(584): 2145–2166.

Paul, I.; Khattar, A.; Chopra, S.; Kumaraguru, P.; and Gupta, M. 2019. What sets verified users apart? Insights, analysis and prediction of verified users on Twitter. In *WebSci*.

Sharma, K.; Ferrara, E.; and Liu, Y. 2022. Characterizing online engagement with disinformation and conspiracies in the 2020 U.S. Presidential Election. In *ICWSM*.