Towards Automatic Identification of X(formerly Twitter) Opinion Leaders by Means of Stylistic and Behavioral Features

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Introduction

In the digital age, online communities have burgeoned, proliferating countless messages that encapsulate the diverse sentiments, ideas, needs, and beliefs of internet denizens. Among these users, Opinion Leaders, possessing the prowess to wield persuasive influence over others. Opinion Leaders have the unique capacity to sway individual attitudes and behaviors with regularity.

This work presents an empirical investigation into the problem of Opinion Leader identification within X. Our proposed methodology posits that Opinion Leaders can be discerned by scrutinizing their communication patterns through the prism of distinctive stylistic and behavioral features.

We asked us the question: It is possible to automatically identify Opinion Leaders among the members of a social networking community?

Related Work

In the context of X, certain methodologies[2, 3] leverage a modified rendition of the Page Rank algorithm, adeptly capitalizing on the inherent following-followers structure that characterizes this particular social network.

Numerous web apps aimed to gauge influence in X. Most focused on public profile metrics. Yet, recent changes in X's API policies have halted many of these tools.

Web Tool	Access	Status	Public Profile Attributes	Behavioural Attributes	Stylistic Attributes
retweetrank.com	free	offline	✓	X	X
klout.com	free	offline	✓	X	X
twitalyzer.com	pay	offline	✓	✓	X
brandwatch.com	pay	online	✓	X	X
twitonomy.com	pay	online	✓	✓	X
kred.com	free	offline	✓	X	X

Table 1. Web Tools Comparison

Methodology

The notion of identifying Opinion Leaders in X through communication patterns and distinctive stylistic and behavioral attributes originates from Ramirez de la Rosa's work[4]. Her study introduces a framework comprising thirty-two features[a], nine stylistic(**S**) and twenty-three behavioral features(**B**).

i)The data contained within the user's public profile, encompassing their self-description and public statistics[b].

ii)The user's posts, which refer to the tweets authored by the user[c].

Dataset

A 2014 RepLab[1] user database containing 2,434 user profiles, each with a minimum of 1,000 followers and their 600 latest tweets was used. RepLab researchers manually classified these profiles as Opinion Leaders or Non Opinion Leaders. From this pool, the top 250 profiles with the most mentions were selected to identify users with substantial interactions. Subsequently, the text content of all 600 tweets from each of these profiles underwent preprocessing, analysis, and tagging based on the mentioned behavioral and stylistic attributes.

[a] The features marked with ∗were excluded from the training process due to recent changes in X's API.

[b] Usernames at Profile Description (**B**), Hashtags at Profile Description (**B**), URLs at Profile Description (**B**), Self-mentions at Profile Description (**B**), Tenure (**B**), Number of Tweets (**B**), Number of Followings (**B**), Number of Followers (**B**), ∗Number of Media Shared (**B**), Number of Favorites (**B**), Following per Followers (**B**), Followers per Following (**B**), ∗Tweets per Follower (**B**), Tweets per Month (**B**), ∗Media per Month (**B**), ∗User's Category (**B**)

[c] URLs Employed (**B**), Number of Hashtags (**B**), Direct Messages (**B**), Words per Post (**S**), Words' Size (**S**), User Name Length (**S**), Vocabulary Richness (**S**), Number of Hapax (**S**), ∗Number of Retweets (**B**), ∗Number of Favorites (**B**), Characters per Tweet (**S**), ∗Special Symbols (**S**), Size of User Mentions (**S**), Size of Hashtags (**S**), ∗Update Frecuency (**B**), ∗Update Frecuency SD (**B**)

Classification Model

In our experimental setup, we chose to train six distinct learning algorithms, namely Naive Bayes, Logistic Regression, K Neighbors, Support Vector Machine, Random Forest, and Gradient Boosting.

To ensure optimal model performance, we conducted a comprehensive grid search for hyperparameter tuning. Subsequently, we evaluated the models using a dedicated test set and identified the algorithm that gained the highest accuracy score.

	Naive Bayes	Logistic Regression	K Neighbors	SVM	Random Forest	Gradient Boosting
Accuracy	52%	71%	69%	55%	82%	80%

Table 2. Learning Algorithms Accuracy Score

Best Model Hyperparameter Tuning

We aim to enhance the selected model predictive capabilities and its overall effectiveness by hyperparameter tuning. After Grid Search and Cross Valudation conducted, these are the best Hyperparameters found:

Best accuracy on test data: 0.735

Bootstrap	Max Depth	n Estimators
False	10	200

Table 3. Best Hyperparameters

Evaluation of the model on the test set:

	Precision	Recall	F1-Score	Support
0	0.87	0.78	0.82	50
1	0.75	0.85	0.80	39
accuracy			0.81	89
macro avg	0.81	0.81	0.81	89
weighted avg	0.82	0.81	0.81	89

Table 4. Classification Report

In the confusion matrix, Figure 1, we can observe that the model exhibits relatively high precision for both classes. Demonstrating a reasonably balanced performance with favorable precision, recall, and F1-score values.

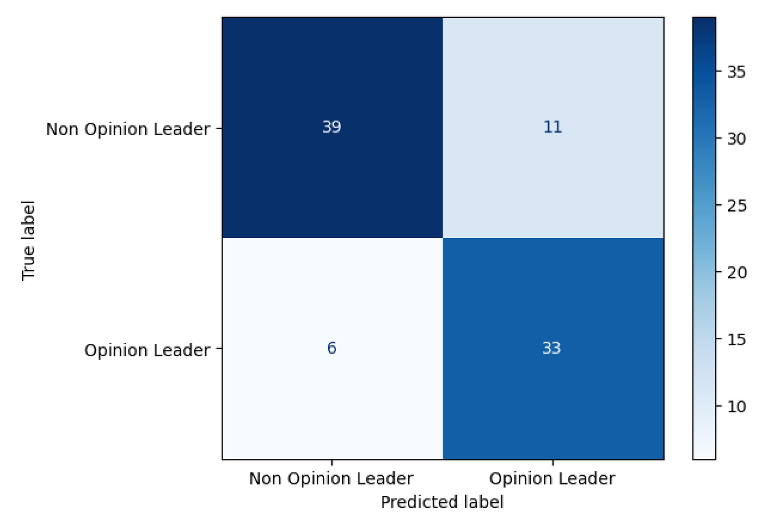
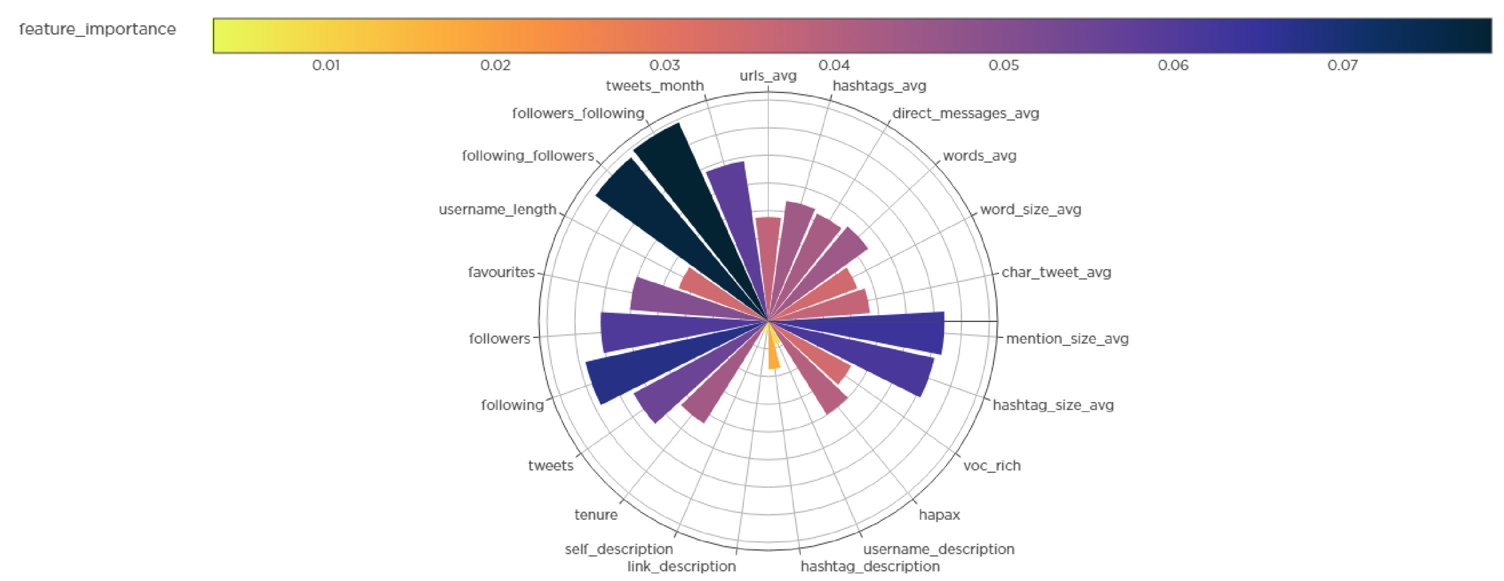


Figure 1. Random Forest Confusion Matrix

Feature Importance

As noted in Figure 2, certain features stand out in shaping predictive outcomes. Notably, the *Followers per Following* and *Following per Followers* ratio hold a pivotal role reflecting the network dynamics between users. *Mention Size Average* feature offers insights into communication patterns and their impact, while *Tweets per Month* encapsulates the temporal dimension of user interactions.



Experimental Results

For our experiments we resorted to an online tweets dataset from Kaggle[a]. After filtering for users with at least 50 tweets, we preprocessed the text. We obtained user profile data from X API, computed the feature matrix, and employed our pre-trained model to classify 492 users.

Non Opinion Leader	480
Opinion Leader	12

Table 5. Users Classification

Feature Comparison

Figure 3 illustrates the feature means and the distance between both classes in the tested dataset. Certain features, like *Favourites*, *Followers*, *Followers per Following*, and *Following*, show low importance for both classes, implying limited discriminative power. Conversely, *Tenure*, *Characters per Post*, and *Words per Post* seems to have more importance for both classes, suggesting their strong influence on identifying users.

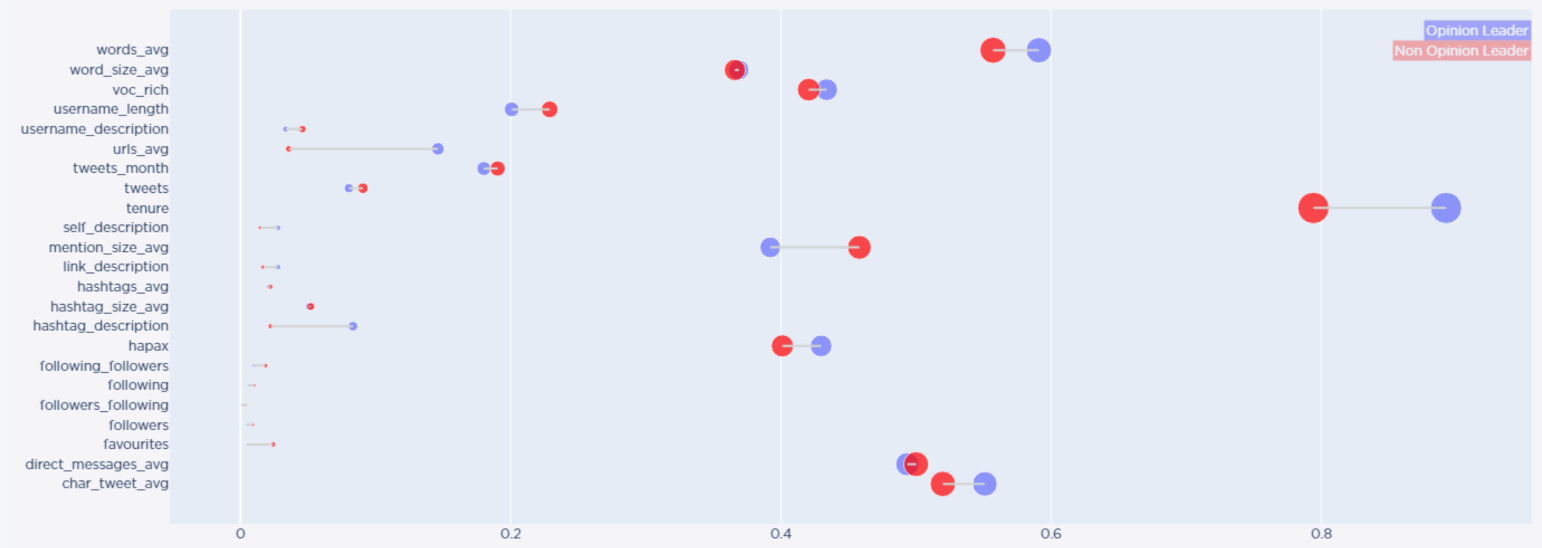


Figure 3. Feature Means Test Dataset

Conclusion and Future Work

The experiments confirm that the proposed features effectively can help to distinguish between Opinion Leaders and Non Opinion Leaders within a social network community. These features, rooted in writing styles and posting behaviors, align with the initial intuition proposed by professor Ramirez de la Rosa regarding influential user characteristics. The data supports the relevance of these features for classifying Opinion Leaders.

Future work will focus on improving the accuracy and robustness of Opinion Leader identification. This will involve incorporating the previously mentioned features and integrating metrics derived from user interaction graphs. Additionally, the development of a web application for identifying influential X users using stylistic, beahavioural and relationship-based attributes will be pursued.

References

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[a] Because of recent changes in the X API that restrict post access, we were unable to conduct experiments involving current users and their timelines. Dataset can be found here: https://www.kaggle.com/datasets/kazanova/sentiment140/