



Fact or Fake News: Developing a Fact Checking Algorithm

Prepared by Group #5

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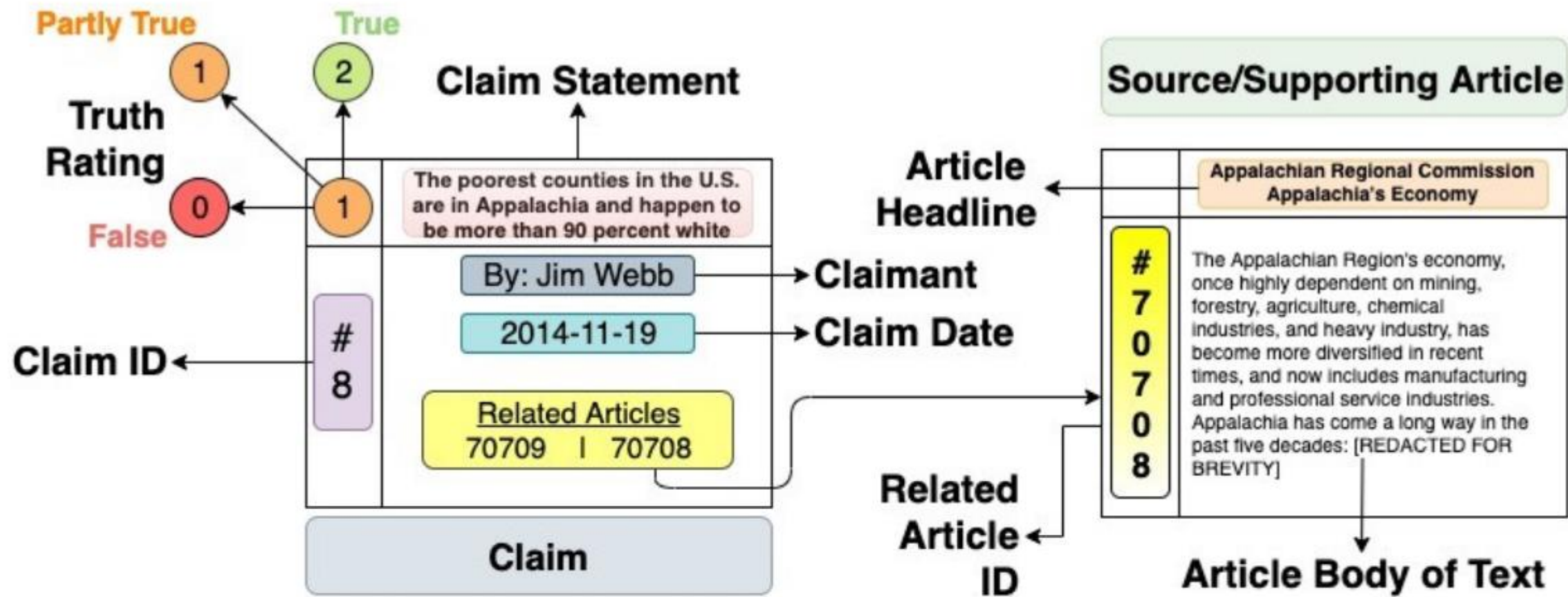
INTRODUCTION

Total Facebook Engagements for Top 20 Election Stories



ENGAGEMENT REFERS TO THE TOTAL NUMBER OF SHARES, REACTIONS, AND COMMENTS FOR A PIECE OF CONTENT ON FACEBOOK SOURCE: FACEBOOK DATA VIA BUZZSUMO





PROBLEM IDENTIFICATION

Leaders Prize
Creating the next generation of technology innovators

1

Effectiveness

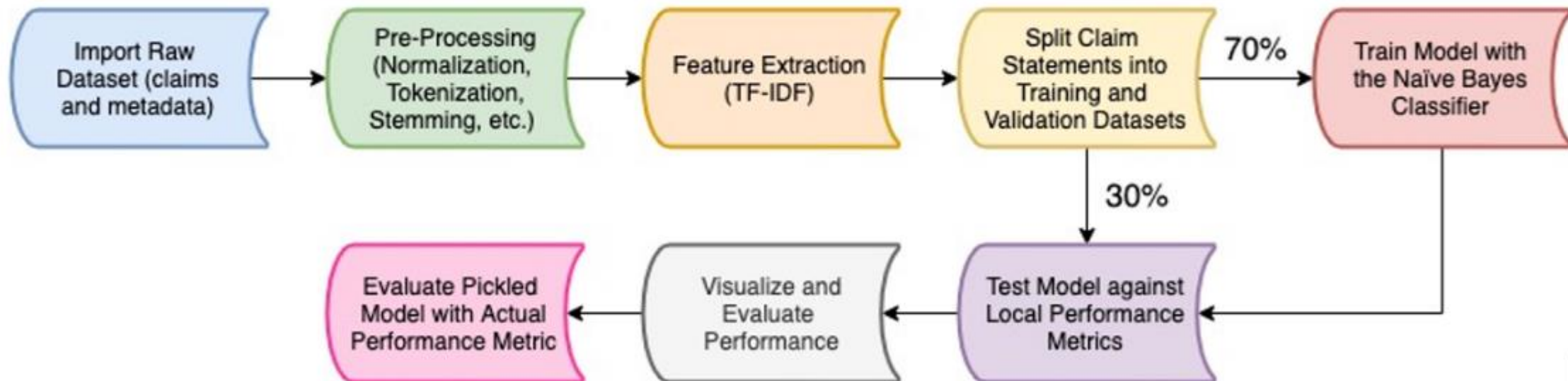
Robust and high accuracy as measured by the weighted average of the precision and sensitivity of the predictions of truth ratings for each claim

2

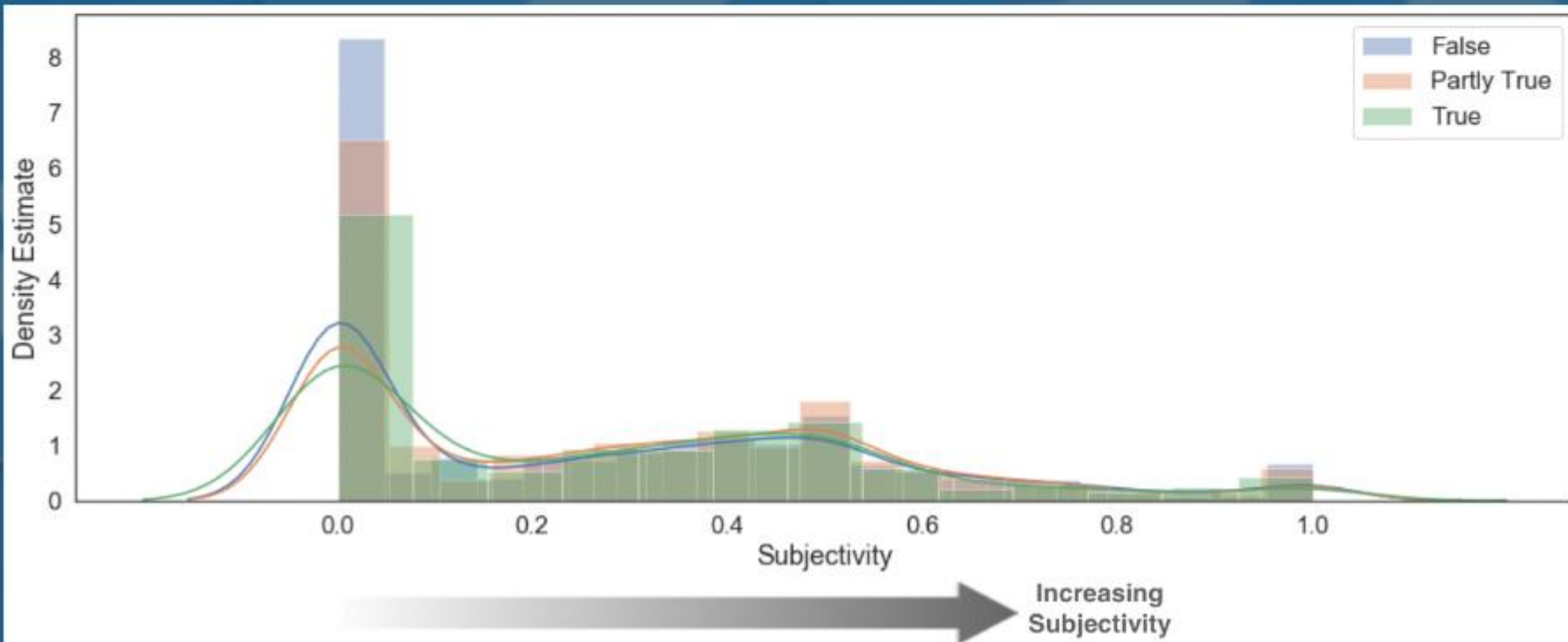
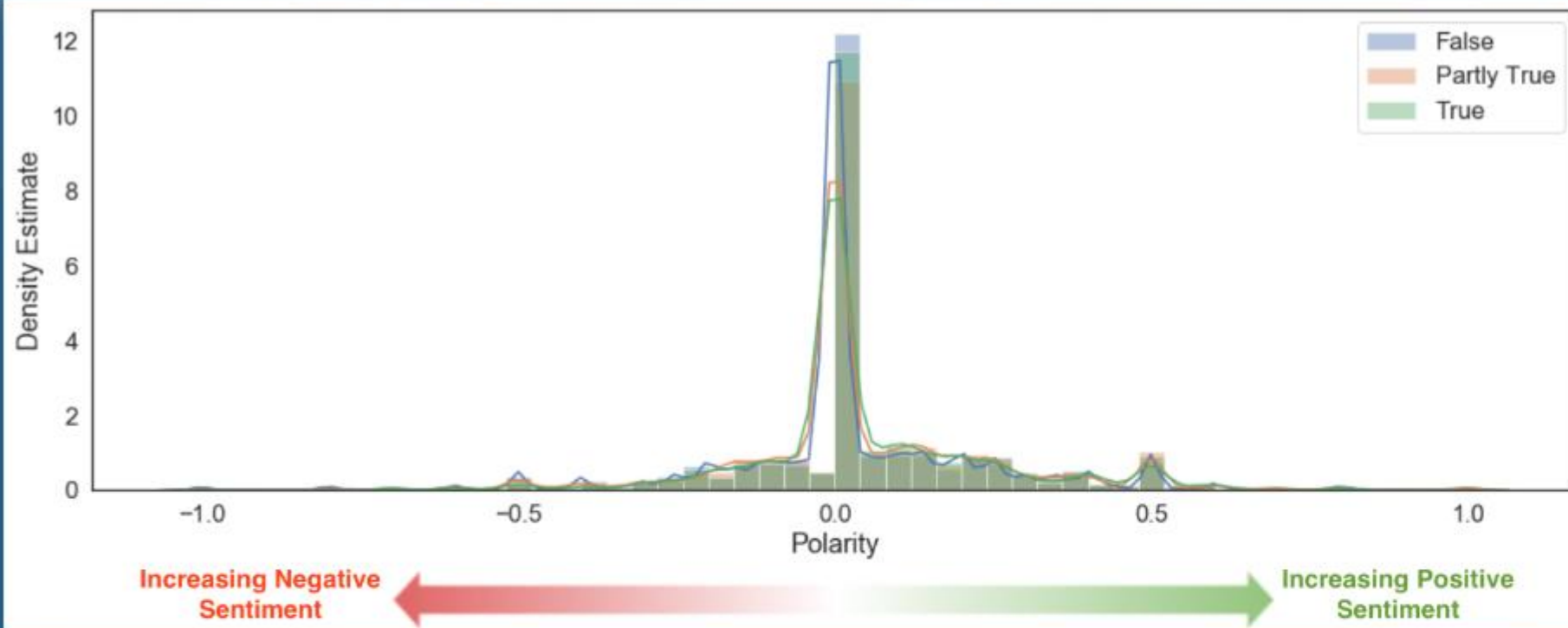
Efficiency

Must provide a robust output of the predictions of truth ratings for each claim in the shortest amount of time as possible.

DATA ANALYSIS

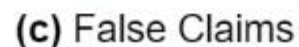


DATA VISUALIZATION

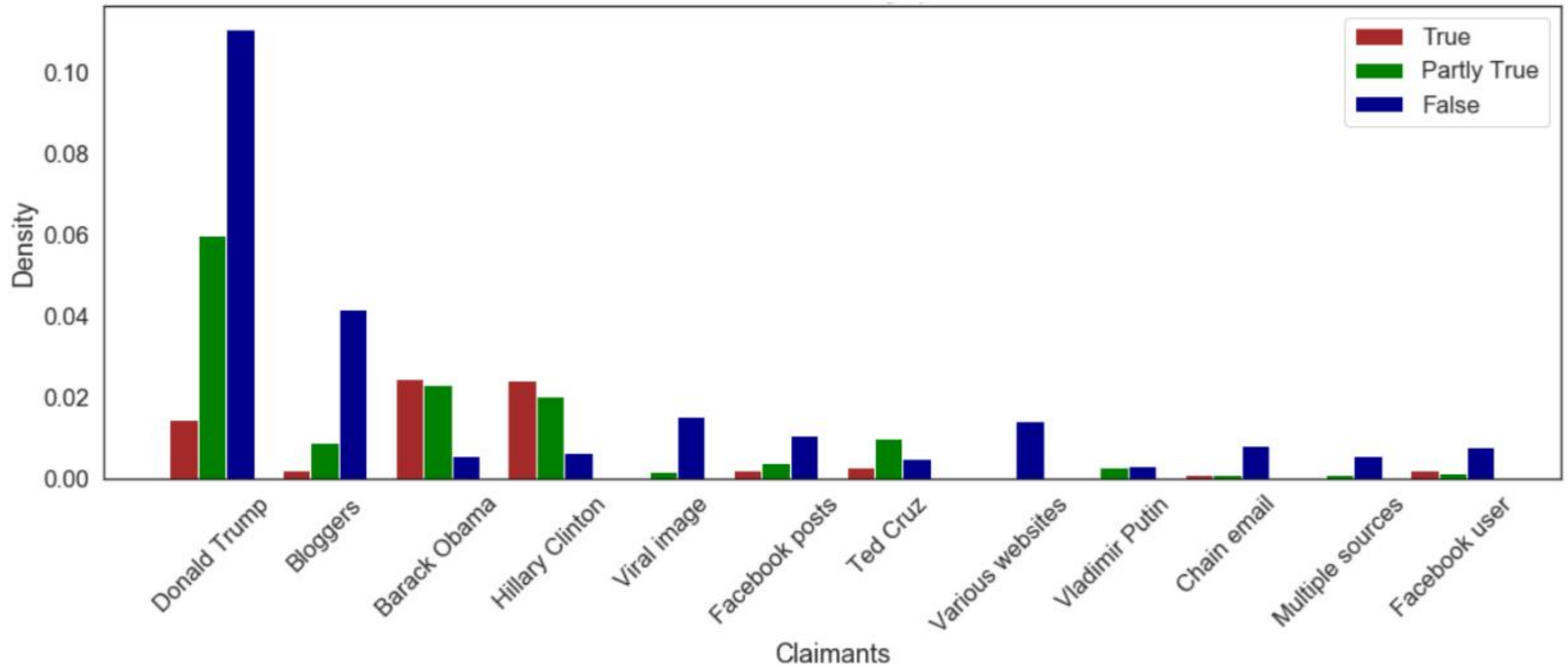


Application of current industry solutions for predicting polarity or subjectivity (eg. TextBlob) resulted in poor correlation with claim labels

4



The most frequently used words within each of the three truth rating categories are largely similar, suggesting that use of only word frequencies to train an ML classifier will result in poor classification of the claims



DATA VISUALIZATION

Correlation of the claimants data and the claim truth labels displays clear differences between the three types of claims, to the point of achieving near deterministic categorization for some of the claimants

ALGORITHM APPLICATION

Eight models were trained with different ML classifiers. The performance of each algorithm was evaluated using the F1-score. Bernoulli Naïve Bayes classifier was selected as the final model, as it yielded the best performance amongst those tested.

Table 1: Comparison of model performance against local performance metrics

ML Classifier	Training F1-Score	Validation F1-Score
Logistic Regression	60.66%	45.82%
Linear Discriminant Analysis <input type="checkbox"/>	61.89%	46.63%
Multinomial Naïve Bayes	55.03%	46.06%
Bernoulli Naïve Bayes	54.29%	47.36%
Support Vector Machine (linear kernel)	59.42%	45.35%
XGBoost	44.34%	43.98%
Random Forest	97.17%	43.96%
Decision Trees	99.88%	41.99%




ALGORITHM
EVALUATION

DataCup



Mickole Mulano 

Dashboard

Competitions 

Log out

EN 

Challenge

Prizes

Timeline

Rules

Data

Resources

Evaluation

Leaderboard

Teams

Submission

My Team

14	MICSII_NLP	0.506307
15	glia-team	0.502138
16	FoF	0.499765
17	hello-world	0.495999
18	ditto	0.495908
19	lululu	0.494268
20	Verse	0.490922
21	Master of Science	0.488436
22	MIE1624 Group 5	0.469259
23	MLAIR	0.461804
24	Akina	0.459159
25	MIE1624 Group7	0.453867
26	Veritas	0.43149

ALGORITHM
EVALUATION

channel

DISCUSSION



Using TF-IDF to create the feature set

Improves model efficiency may result in reduced model accuracy. Could use a more controlled but manual method such as Latent dirichlet allocation (LDA) for clustering



Use of related articles

Related articles would be critical in the cases where the training and validation datasets are from different general topics

Use of the stemming function to reduce word inflection

Does not take the meaning of the words into account. Lemmatization could be a better option



In case we have another

Lorem ipsum dolor sit amet, consectetur adipiscing elit.



DISCUSSION

Debunking false news and neutralizing false claims

Removal or insertion of claims that
correct false claims

Early detection of false news

First step and our objective



"Pre-bunking" to prevent false news

True information is preemptively
injected into social media before false
information is even created

Thank You!

