Predicting Factuality of Facebook Posts

Shota Yasunaga, Justin Lauw, Madison Hobbs

Overview

- ***Motivation***
- Data Exploration & Insights
- Pre-Processing
- Results
- Conclusion

Motivation

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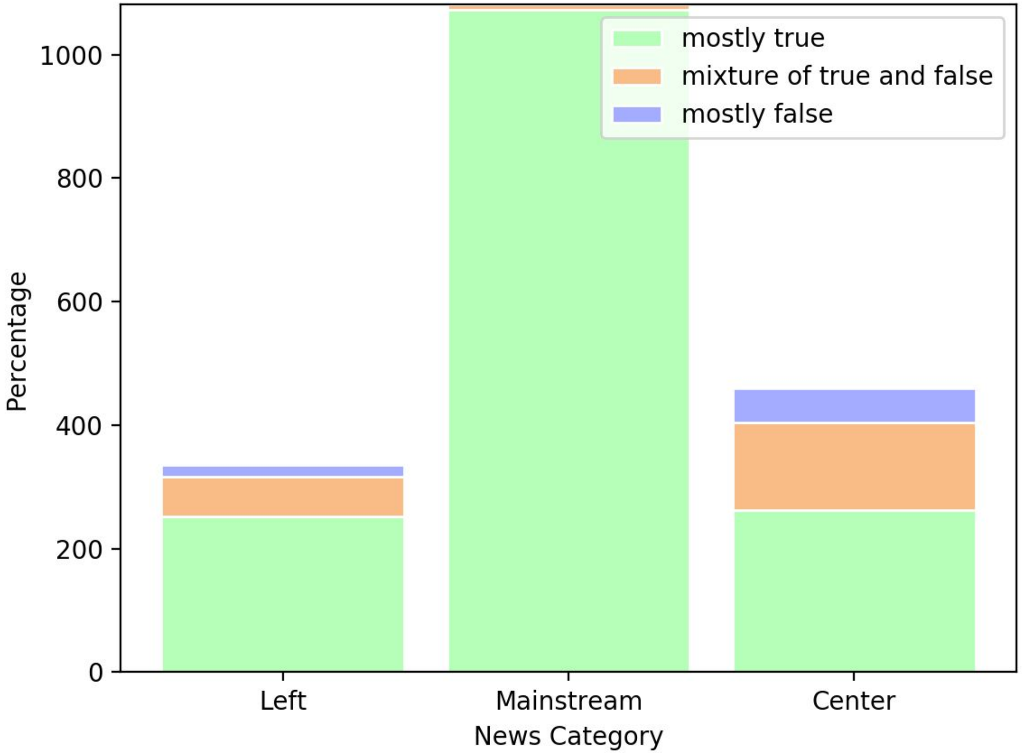
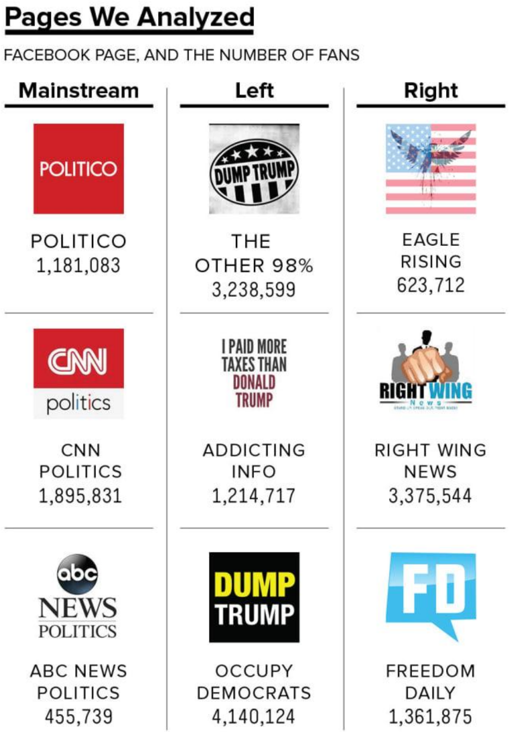
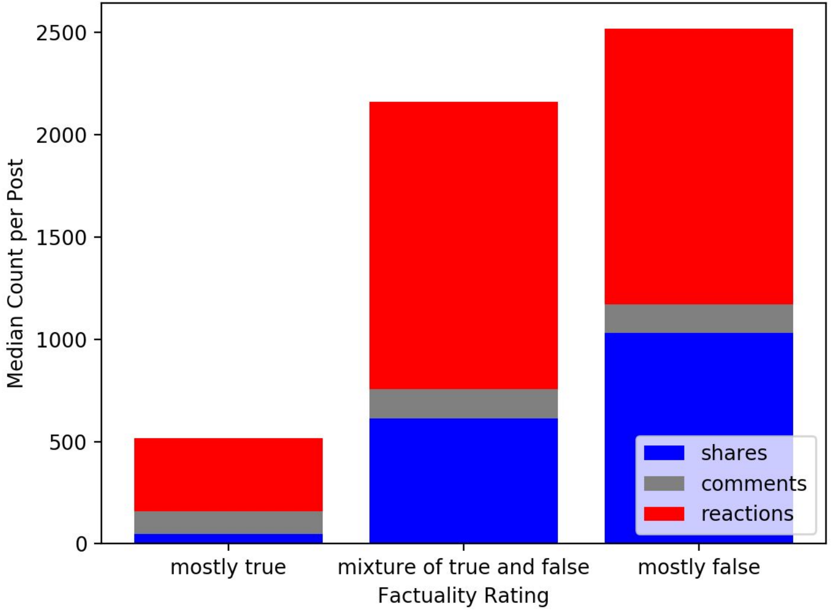
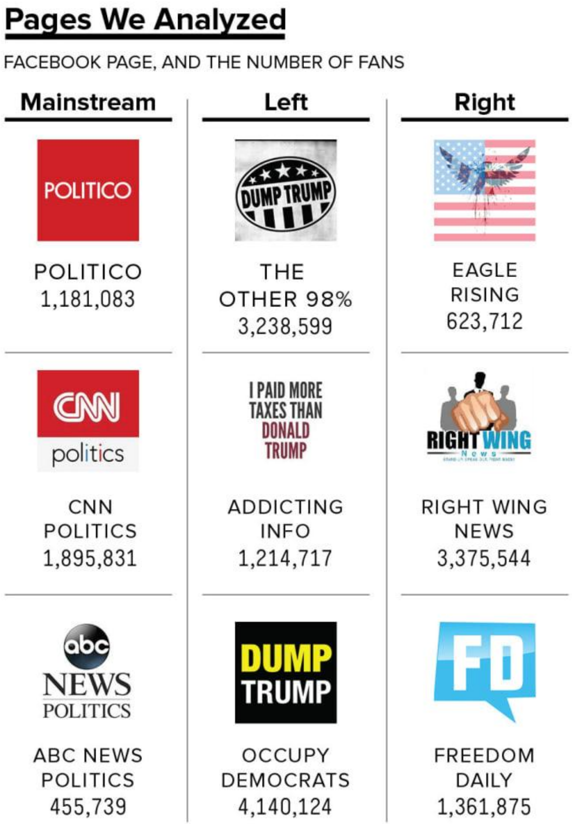
Mainstream news is mostly true
Dataset is unbalanced





False Posts are Popular





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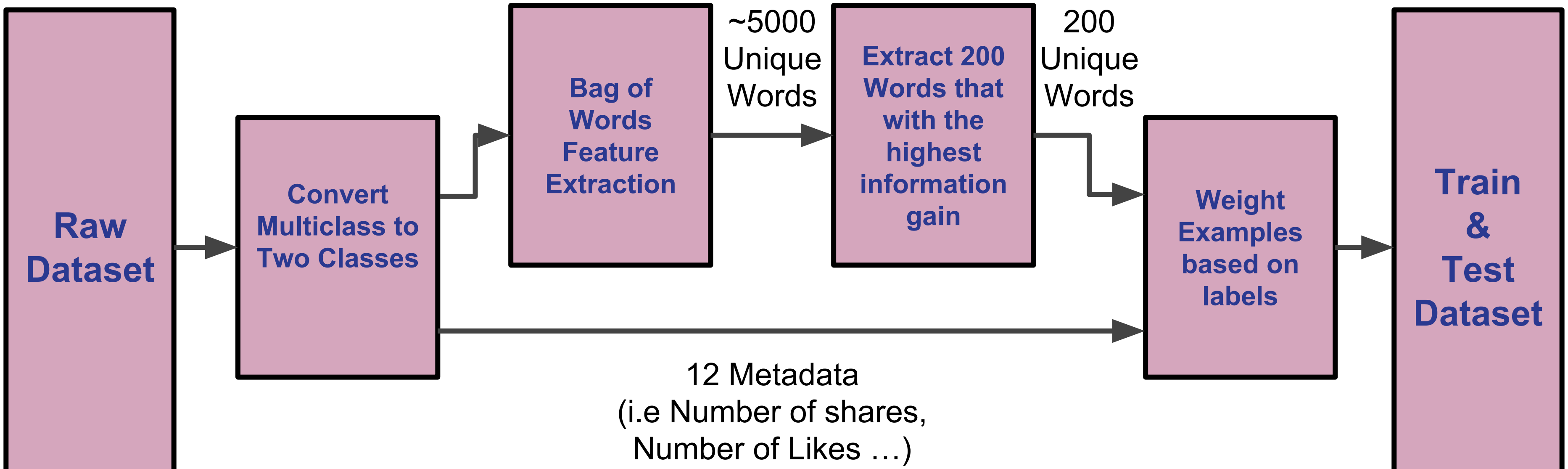
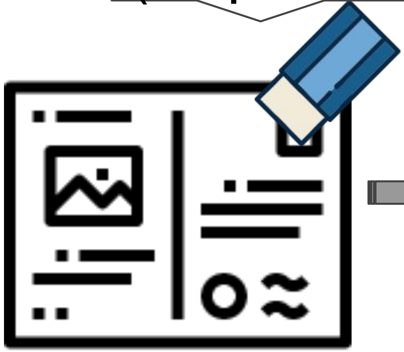
Data Preprocessing (Feature Selection)

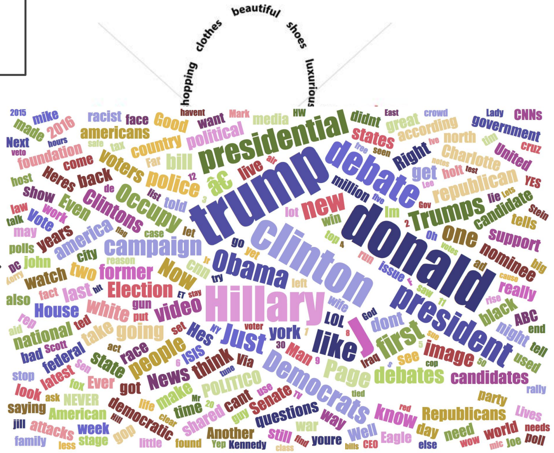


Feature Setup

, . an, a, in
(stop words)



Removed Punctuation
stop words

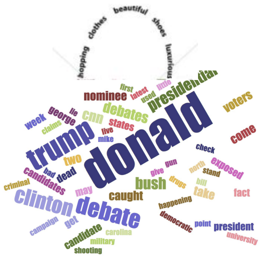


Bag of words

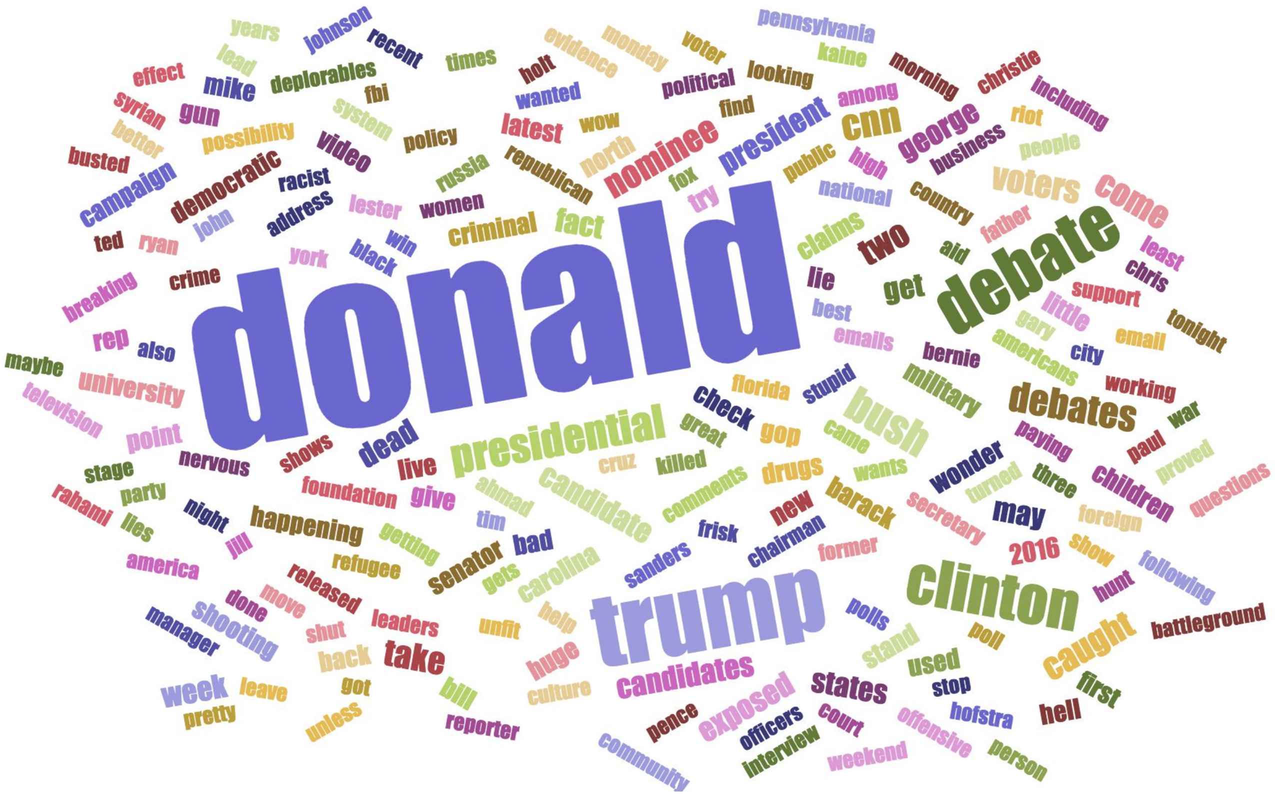
Choose 200 words based on entropy

Meta Data

+



Feature Importance (1st order information gain)



Depends on frequency of appearance

Alternative: 200 most common words, but choosing features this way performs better

Class Weights & Preprocessing

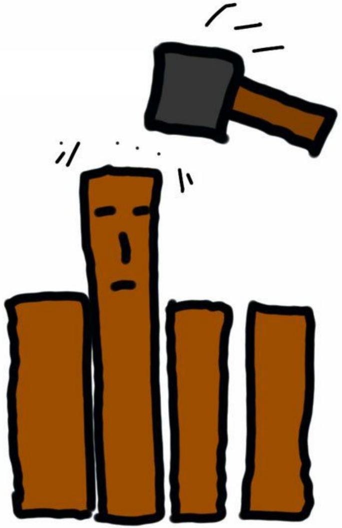
5 1

Mostly true

Mostly false
Mixture of true/false

Class weights

Feature Normalization



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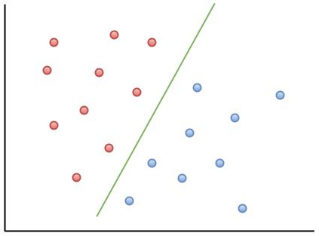
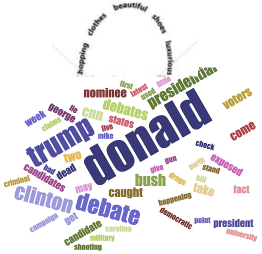
Experimental Process

1

Data Exploration

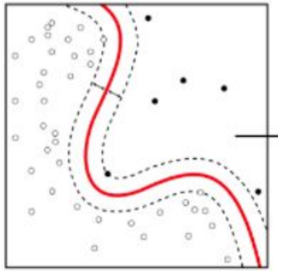
2





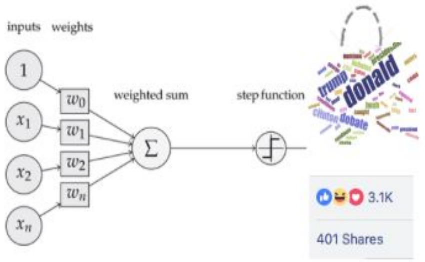
Linear SVC with bag of words
4 classes
2 classes

3



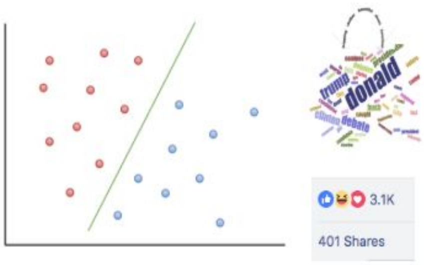
Polynomial SVC with meta data
4 classes

4



Perceptron with both
2 classes

5



Linear SVC with both
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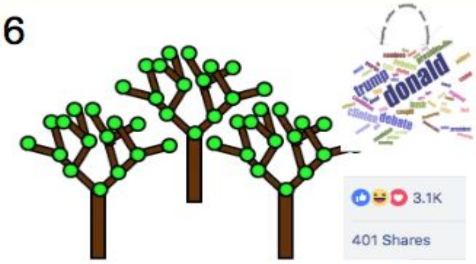
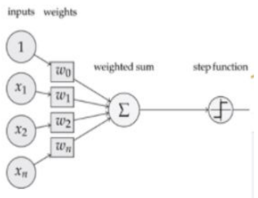
6



Random Forest
2 classes



Perceptron (high bias)

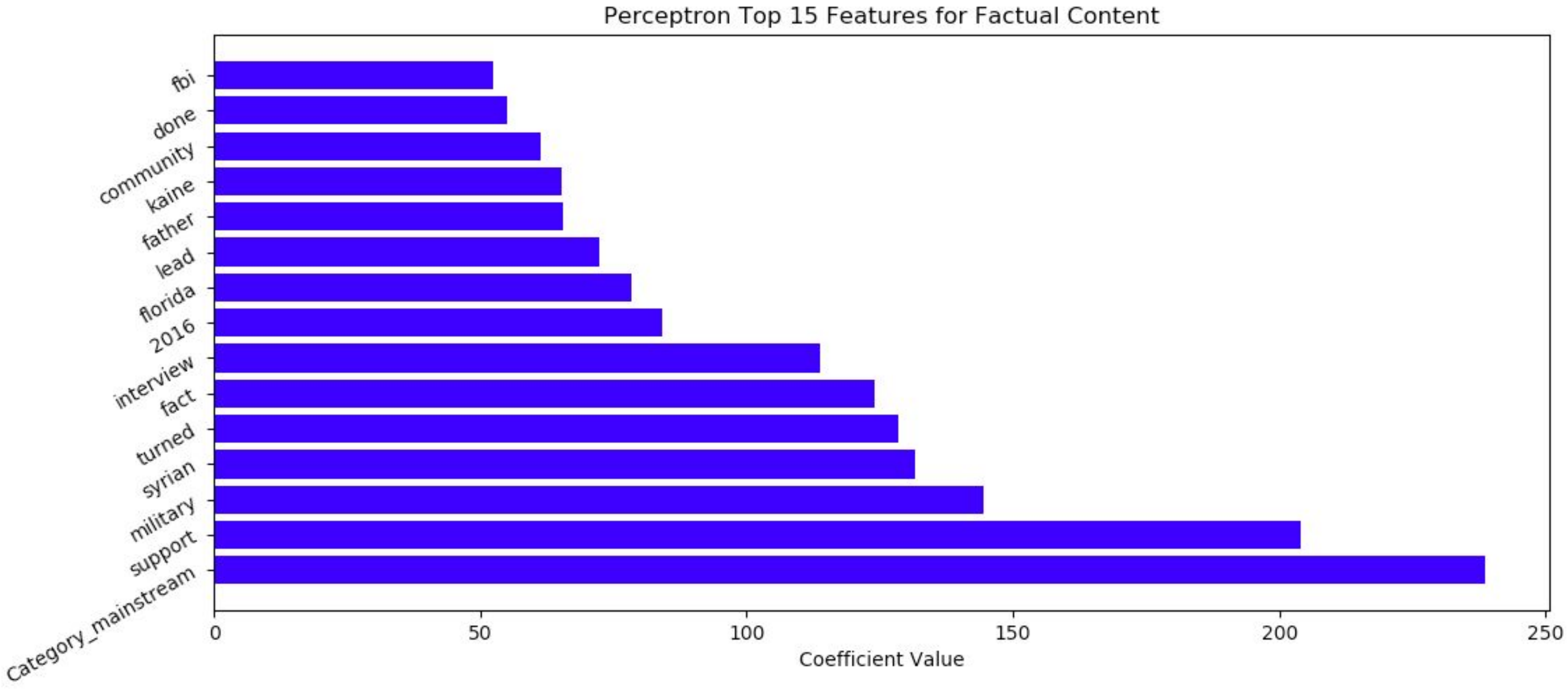
	Actually Negative	Actually positive
Predicted Negative	TN = 34	FN = 24
Predicted Positive	FP = 33	TP = 285

5-fold CV tuned with f1 score

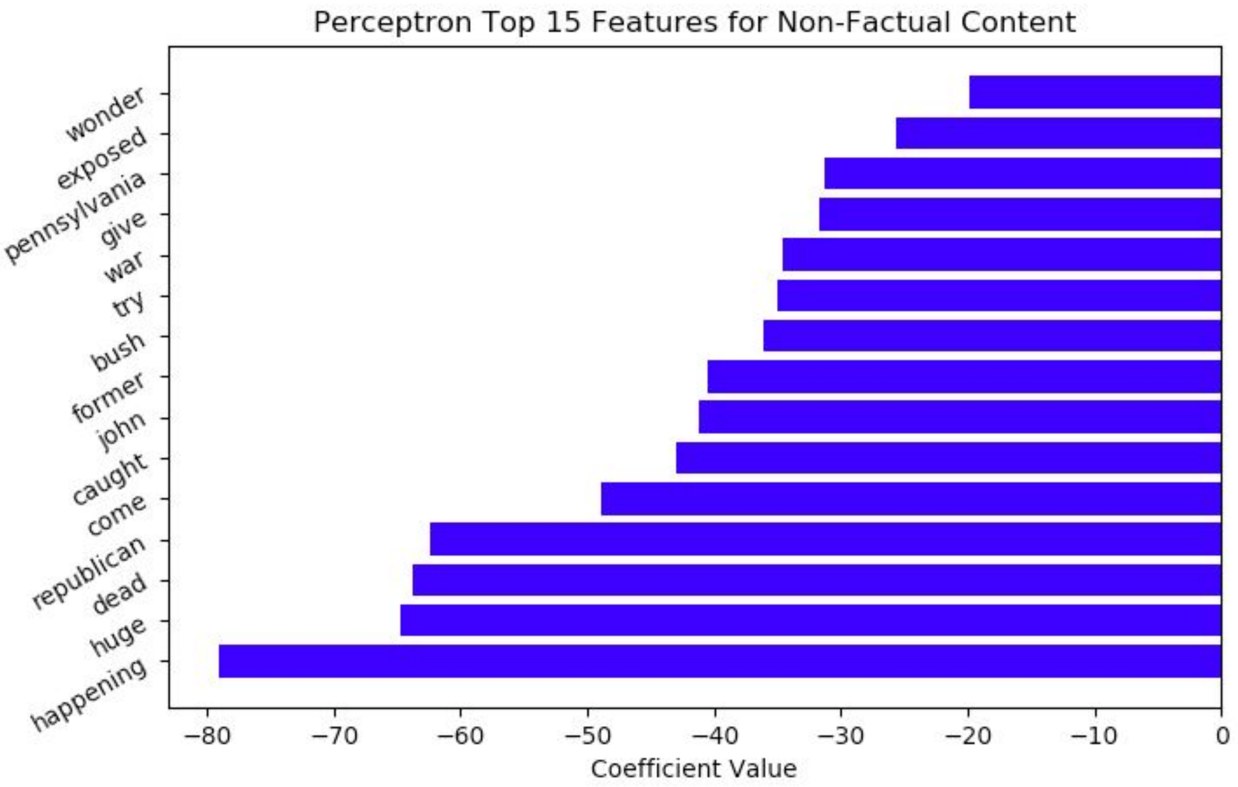
Training f1 score: 0.868
Test f1 score: 0.853

Training accuracy score: 0.867
Test accuracy score: 0.848

Perceptron Feature Importance



Perceptron Feature Importance



"Not Mostly Factual Content"	"Mostly Factual Content"
Popularity: 1. num_reactions 7. num_shares News Source: 2. Category_right 5. Category_left Negative Words: 8. war 14. lies 15. least 19. bad 25. hell Race-based: 13. Black	Popularity: 1. num_likes 3. num_angrys 4. num_loves 5. num_hahas 6. num_sads 20. num_wows News Source: 2. Category_mainstream Negative Words: 18. stop Positive Words: 9. support 15. fact 21. community

Linear SVC

(slightly lower bias)

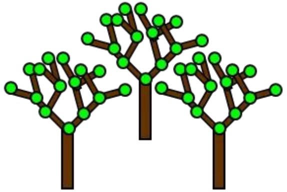
Training F1: 0.873

Test F1: 0.842

Training accuracy: 0.857

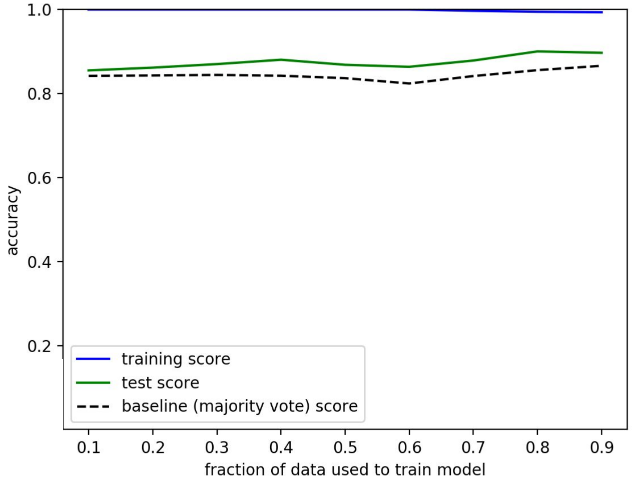
Test accuracy: 0.822

	Actually Negative	Actually positive
Predicted Negative	TN = 28	FN = 30
Predicted Positive	FP = 17	TP = 301



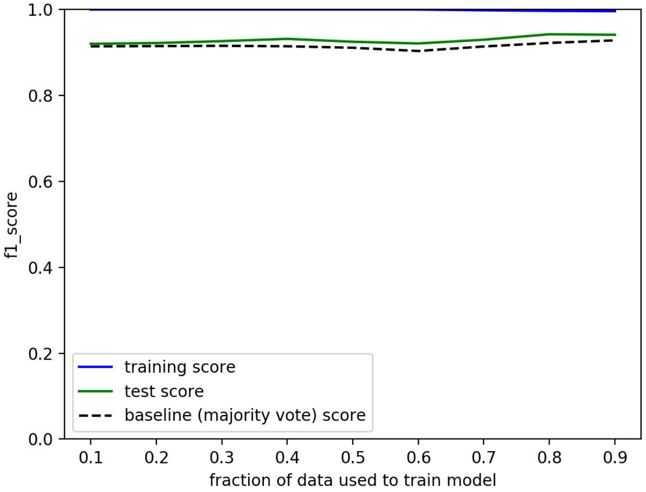
Random Forest

(high variance)



Training f1 score: 0.998
Test f1 score: 0.868
Best CV f1 score: 0.872

Training accuracy: 0.995
Test accuracy: 0.894

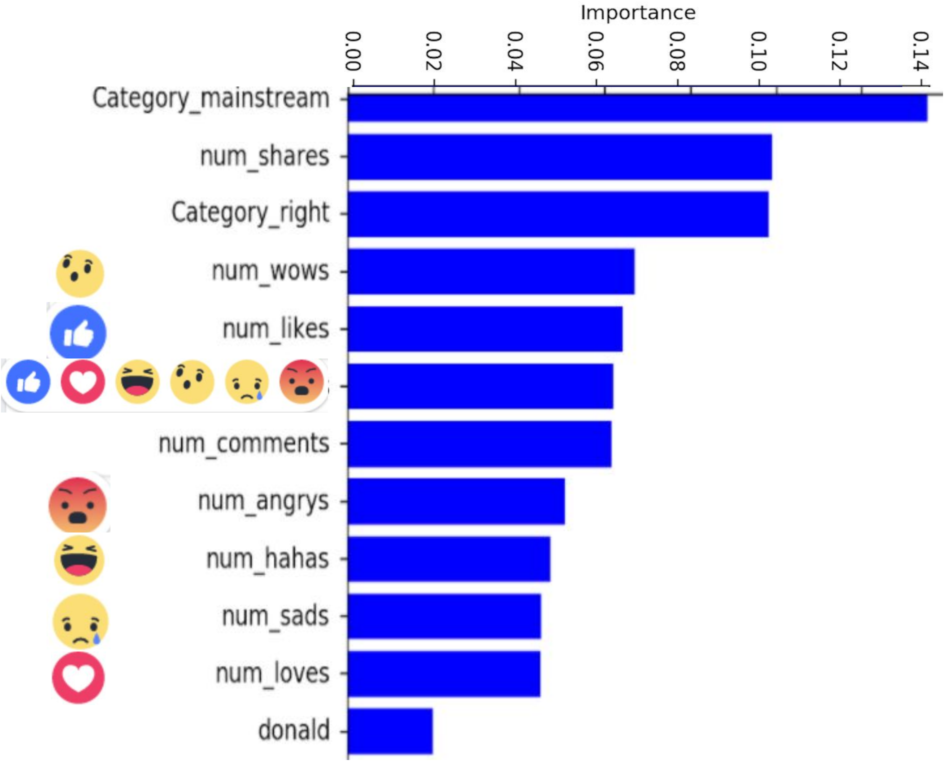


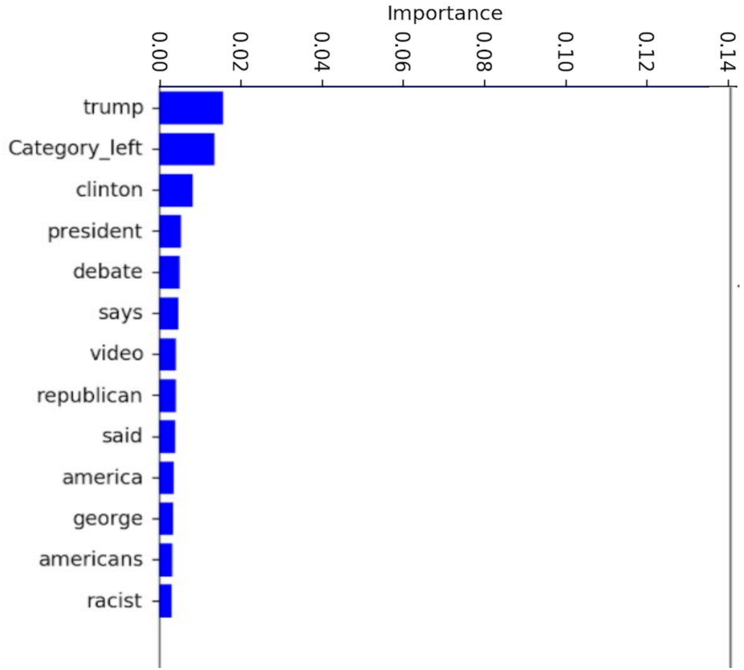
	Actually Negative	Actually positive
Predicted Negative	TN = 28	FN = 30
Predicted Positive	FP = 17	TP = 301

5-fold CV tuned with f1 score

```
bootstrap = True,
min_samples_leaf = 1,
n_estimators =  400,
max_features = 'sqrt',
min_samples_split = 5,
max_depth = 100
```

Random Forest Insights ~ Feature Importance





Random Forest - Metadata Only

5-fold CV tuned with f1 score

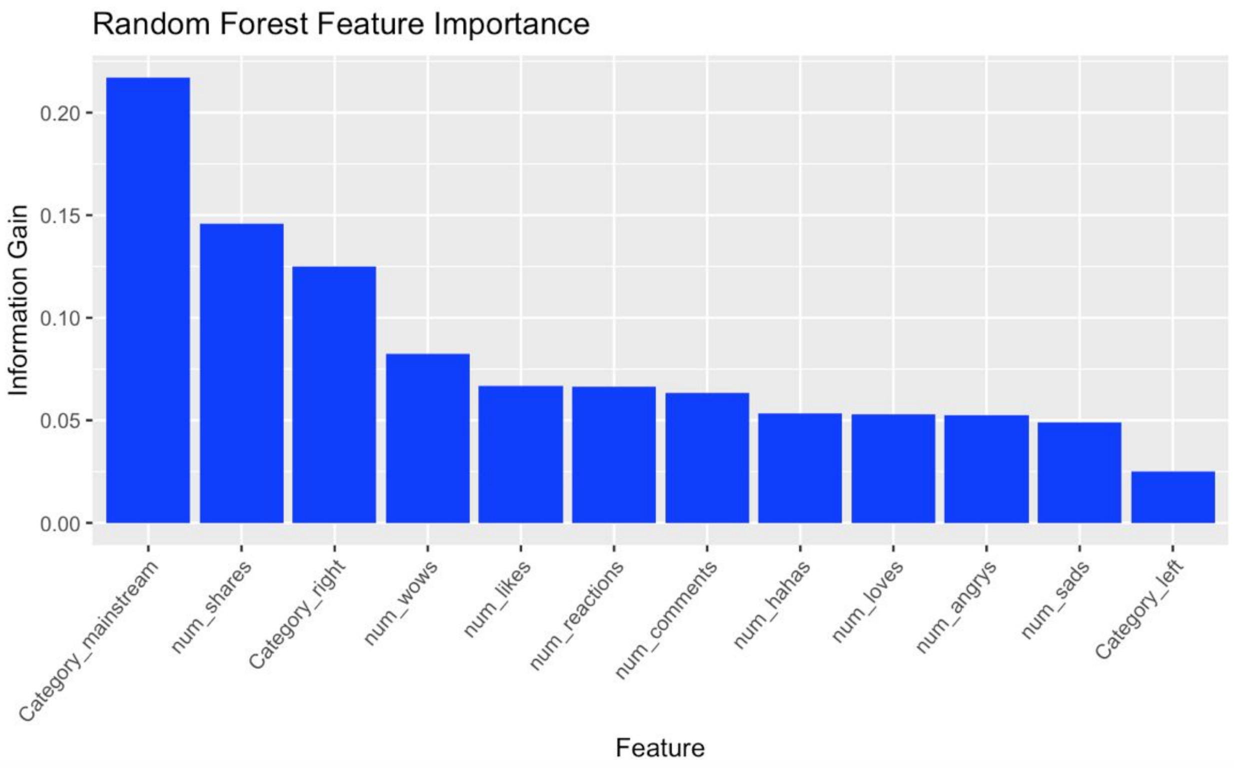
```
bootstrap = True,
min_samples_leaf = 1,
n_estimators =  1600,
max_features = 'sqrt',
min_samples_split = 10,
max_depth = None)
```

Training f1 score: 0.975
Test f1 score: 0.872
Best CV f1 score: 0.856

Training accuracy: 0.973
Test accuracy: 0.872

	Actually Negative	Actually positive
Predicted Negative	TN = 41	FN = 17
Predicted Positive	FP = 31	TP = 287

Random Forest - Metadata Only



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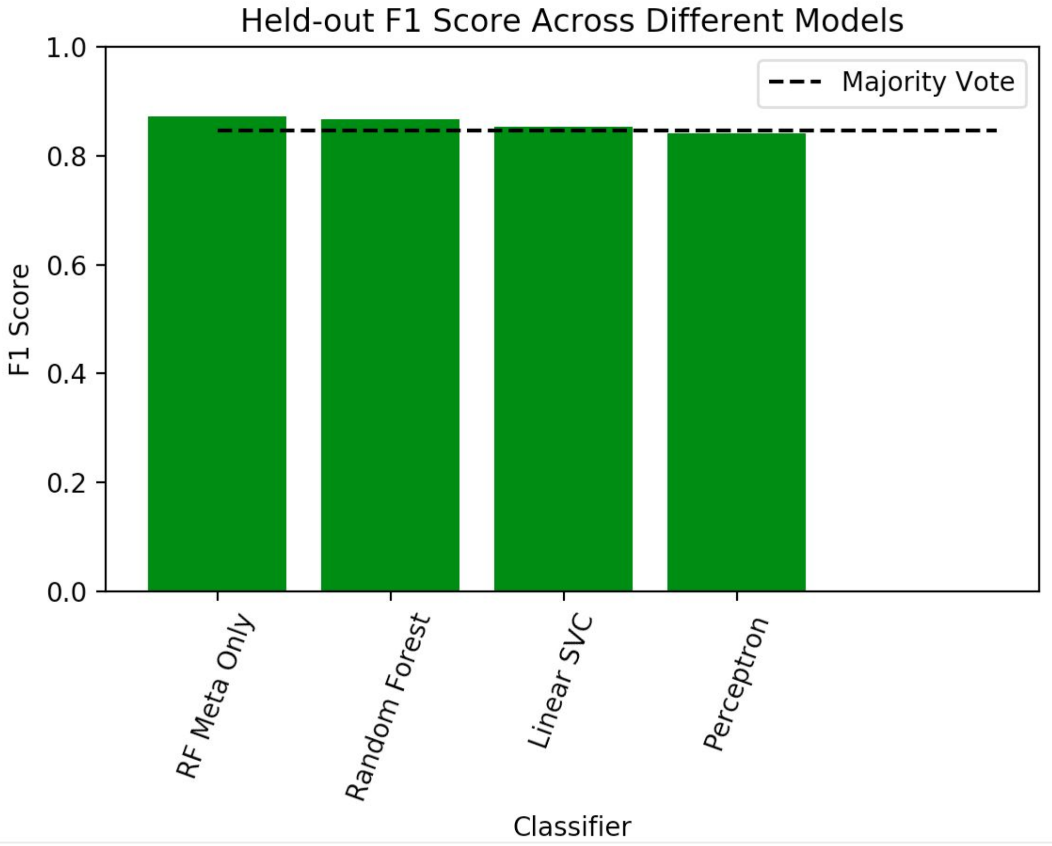
Discussion

- High Bias Models > High Variance Models
- Meta-data > Bag of Words
  - Probably because factuality detection based on words is a lot more complicated than what we can do with 2000 examples
- Popularity & Source's Political Leaning are Most Important Predictors



Limitations	Mitigation
Unbalanced Data	Get more examples of far left and far right posts
No stemming used in bag of words	Use stemming
5-fold CV	Multiple trials of 10-fold CV
Only used some ML models	Try other models
Small data set (<2000 posts)	Get more data
Restricted time-frame: seven weekdays (9/19 - 9/23 and 9/26 - 9/27 2016)	Gather posts from wider time range
Buzzfeed source/labeling factuality and news source category	Label posts ourselves or get unbiased panel

Future Work

- Perfect a broader model trained on more representative data
  - Equal number of left, right, and mainstream posts
  - Wider time frame or sampled across multiple time frames
- Leverage the full capacity of NLTK
- More exhaustive model search
  - Finer CV grid and mutliple runs of tuning
- Focus on specificity (we don’t want to true to be classified as false)
- Predict more than two classes
- Predict percentage of factual content in a news post
- Multilayer Perceptron
- Naive Bayes
- Metadata with KNN

Questions?

How did Buzzfeed select the posts?

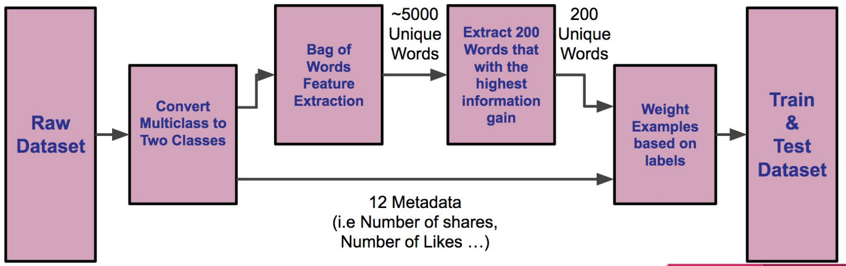
What train-test split was used?

Why not return to poly and rbf SVC?

How did you choose those machine learning modells over others?

Did you use stratified sampling?

Data Preprocessing



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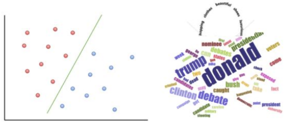

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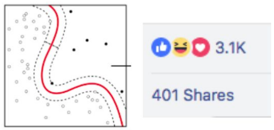

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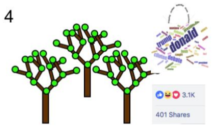

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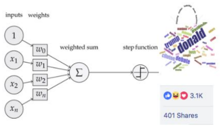

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2 classes

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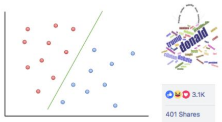

Linear SVC with both
2 classes