VIRAL TEXT ANALYSIS

Predicting Information Propagation in Machine Learning Communities

01 WHY DO WE CARE?

Why does information propagation matter?

02 DATA

What’s our data?
Where does it come from?

03 METHODS

How do we interpret this data?

04 FINDINGS

What was discovered?

05 Recommendations

What next?

06 CONCLUSION

Closing thoughts, questions

01

WHY DO WE CARE?

Why does information propagation matter?

01

WHY DO WE CARE?

A better model of text propagation means a better understanding of:

- How companies build brands or attract customers
- How research gets attention, citations, and funding
- How ideas spread across cultures or teams
- How misinformation spreads

02 DATA

What’s our data? Where does it come from?

02

What's our data?
Where does it come from?

- Scraped text data from Twitter users connected to ML researchers
- Accounts between 1000 and 50000 followers
- Predicting 'Retweets' as our goal

02

OUR DATA IN 3 NUMBERS:

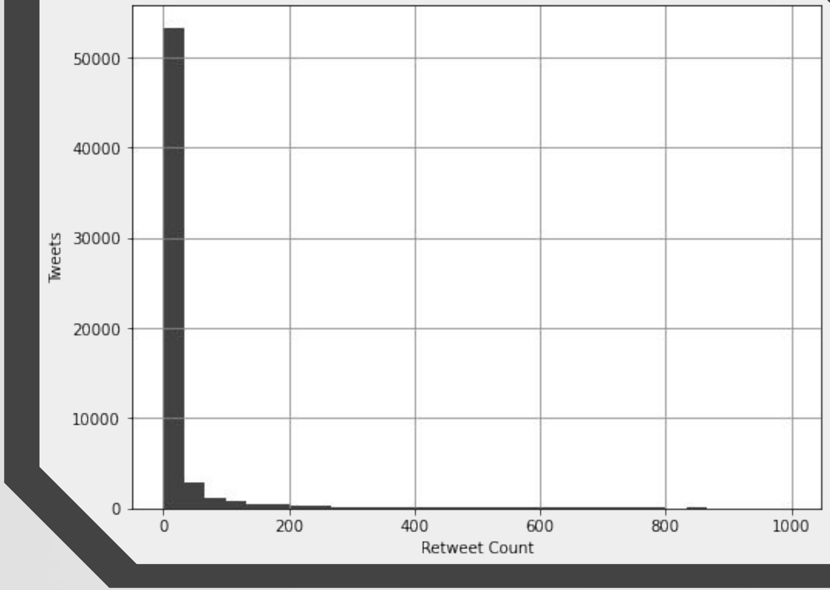
63000 Tweets Analyzed

1524 Different Users

2 Machine Learning Clusters

What is our data?

02



Distribution of Retweet Count

Most content is not viral –
Most has 0-1 retweets

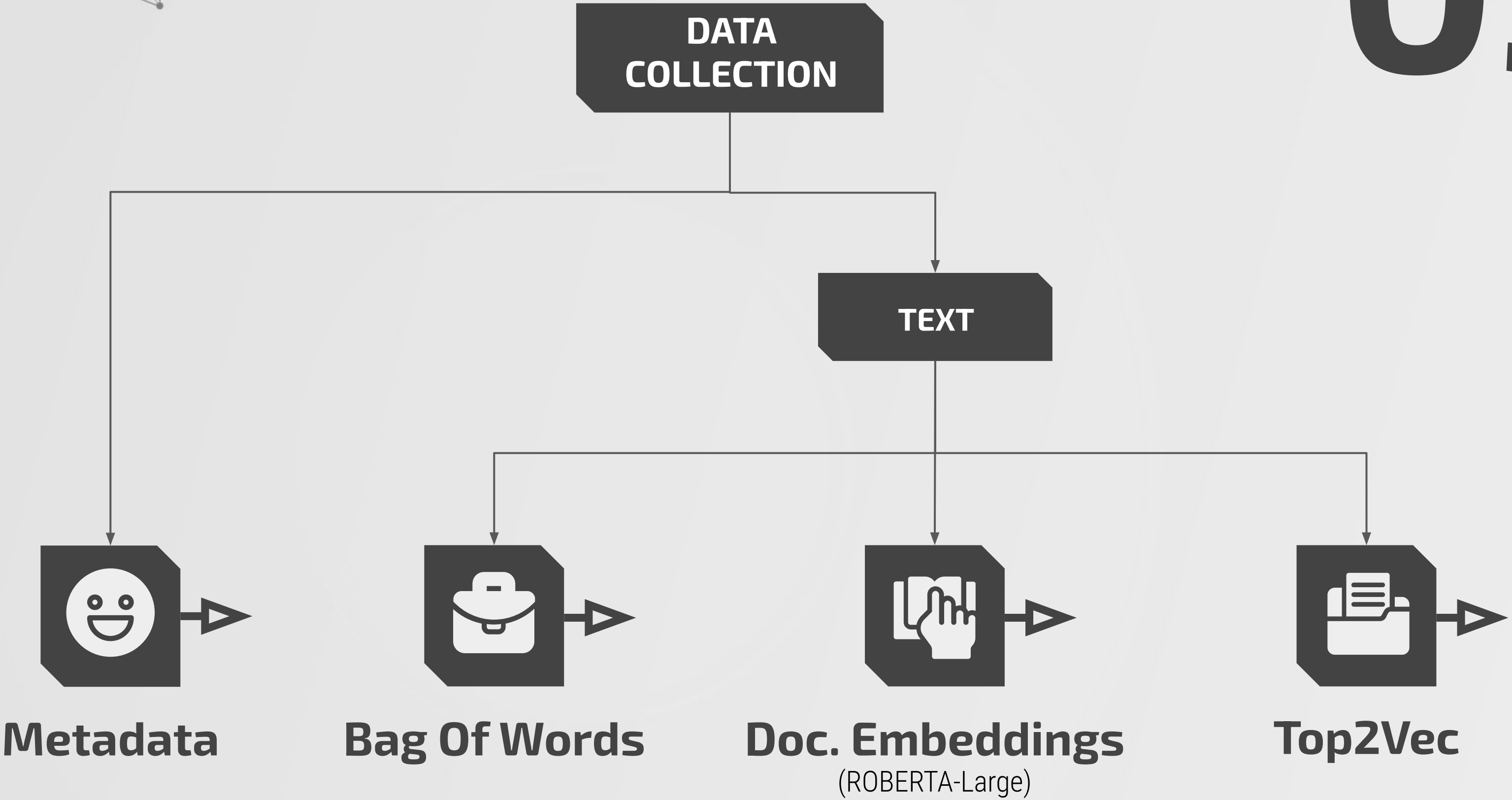
03

METHODS

How do we interpret our data?

HOW DO WE INTERPRET OUR DATA?

03



MACHINE LEARNING MODELS

03

Linear Regression
XGBoost
TabNet

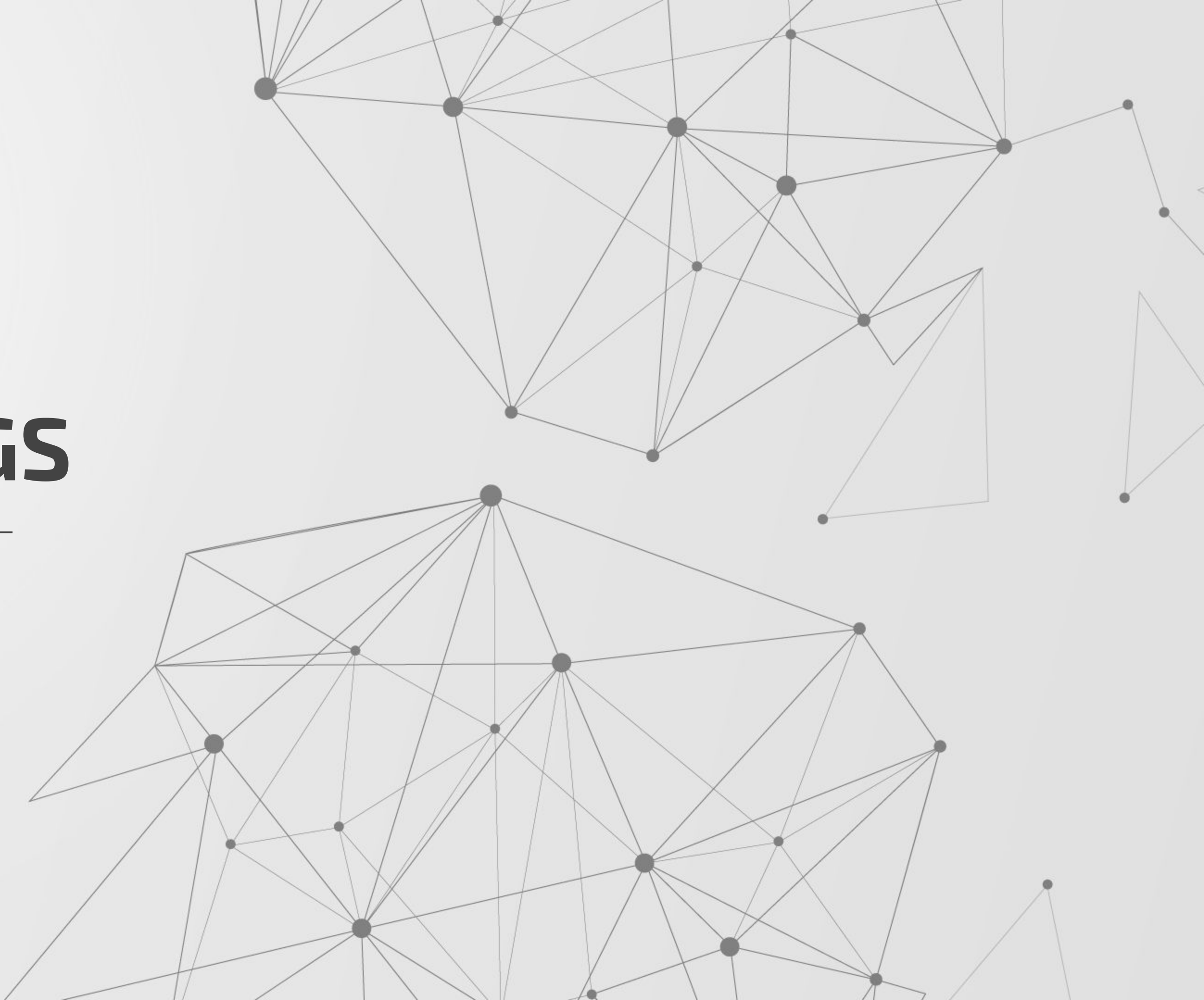
- Many algorithms tested (ask for details)
- Both Regression and classification

Random Forest
Deep Learning
1D CNN

04

FINDINGS

What was discovered?



What was discovered?

04

Viral Text is Different

There is a measurable difference between viral text and nonviral text - we could explain about 11% of variance (R2) using NLP

Viral Topics

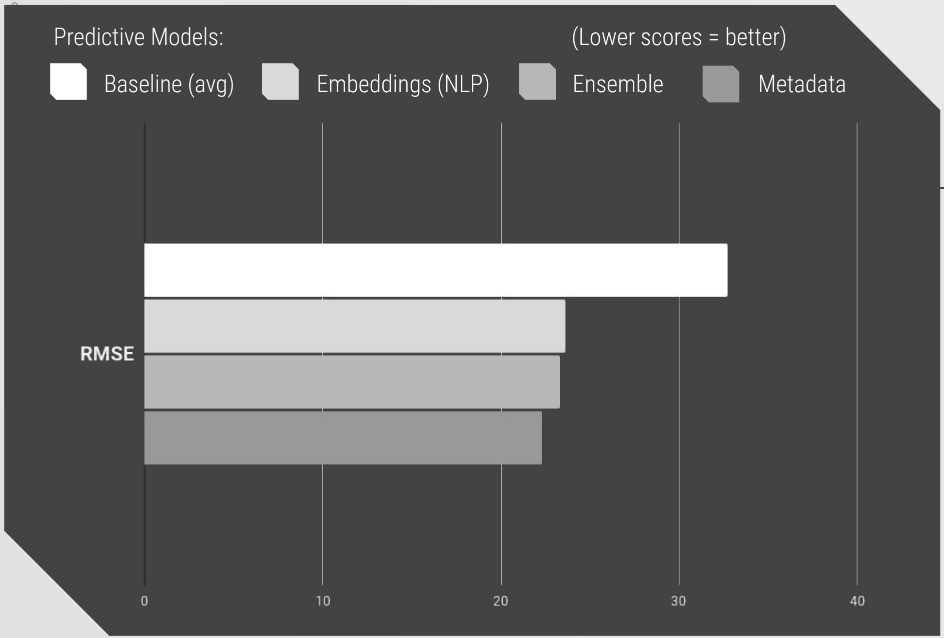
Some topics are clearly more viral, e.g. talking about OpenAI, or hiring phd candidates

Quantifiability

Specific words/topics can be measured, e.g. ‘100daysofcode’ had 16% correlation (R) with retweets

What was discovered?

04



REGRESSION PERFORMANCE

- XGB on metadata remains more predictive than NLP
- Ensemble methods yet to improve performance

Classification Performance on Holdout Data

04

	Precision	Recall	F1-Score	Support
Not Viral	0.98	0.98	0.98	2520
Viral	.27	0.26	0.26	70
Accuracy			97%	2590

>50 retweets

05

RECOMMENDATIONS

What next?

What Next?

05

Process Integration

How might this fit in a marketing dashboard? Could the service be used to market itself?

Reuse the Pipeline

Can we predict citation counts of research papers based on their titles and abstracts? Etc.

Improve the Model

Collecting more data and improving on embeddings from newer large language models

06

CONCLUSIONS

In a nutshell…

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06

We were able to use machine learning to explain about 11% of what makes people share text

Virality may always be hard to predict – like predicting stock prices, if you find something that works, it changes the landscape and stops working!

THANKS!

Any questions?

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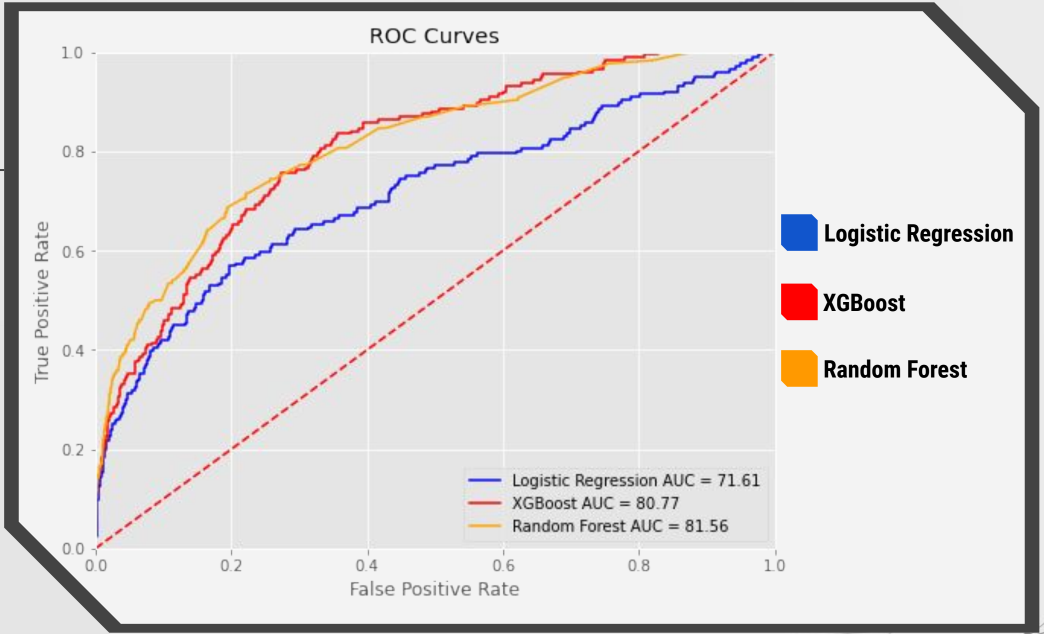
Technical Details

CLASSIFICATION PERFORMANCE

- Random Forest had the best F1 score at .31 on Val.
- Also the best Area Under the Curve at 82%


ROC Curves
True Positive Rate
False Positive Rate
Logistic Regression AUC = 71.61
XGBoost AUC = 80.77
Random Forest AUC = 81.56
🟦 Logistic Regression
🟥 XGBoost
🟧 Random Forest