VIRAL TEXT ANALYSIS

Predicting Information Propagation for Machine Learning Communicators

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 research gets attention, citations, and funding
- How ideas spread across cultures or teams
- How misinformation spreads in academic circles
- How research crosses into commercial sectors

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

OUR DATA IN 3 NUMBERS:

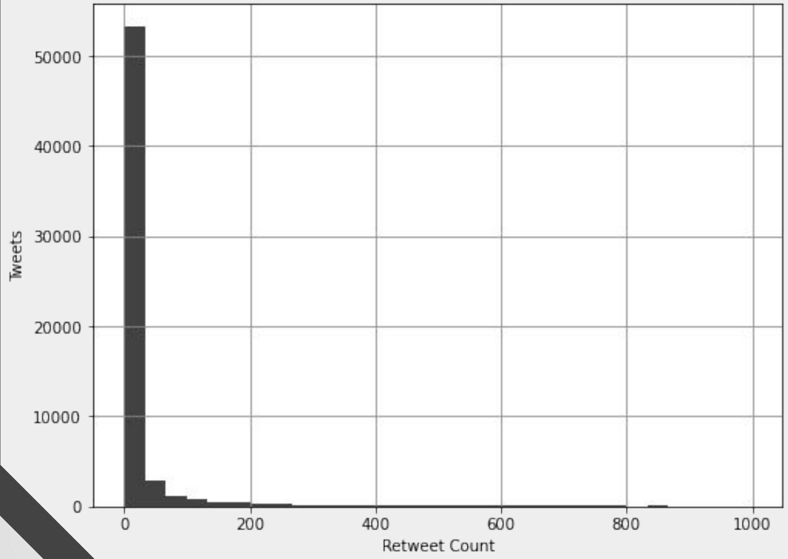
63000 — Tweets Analyzed

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

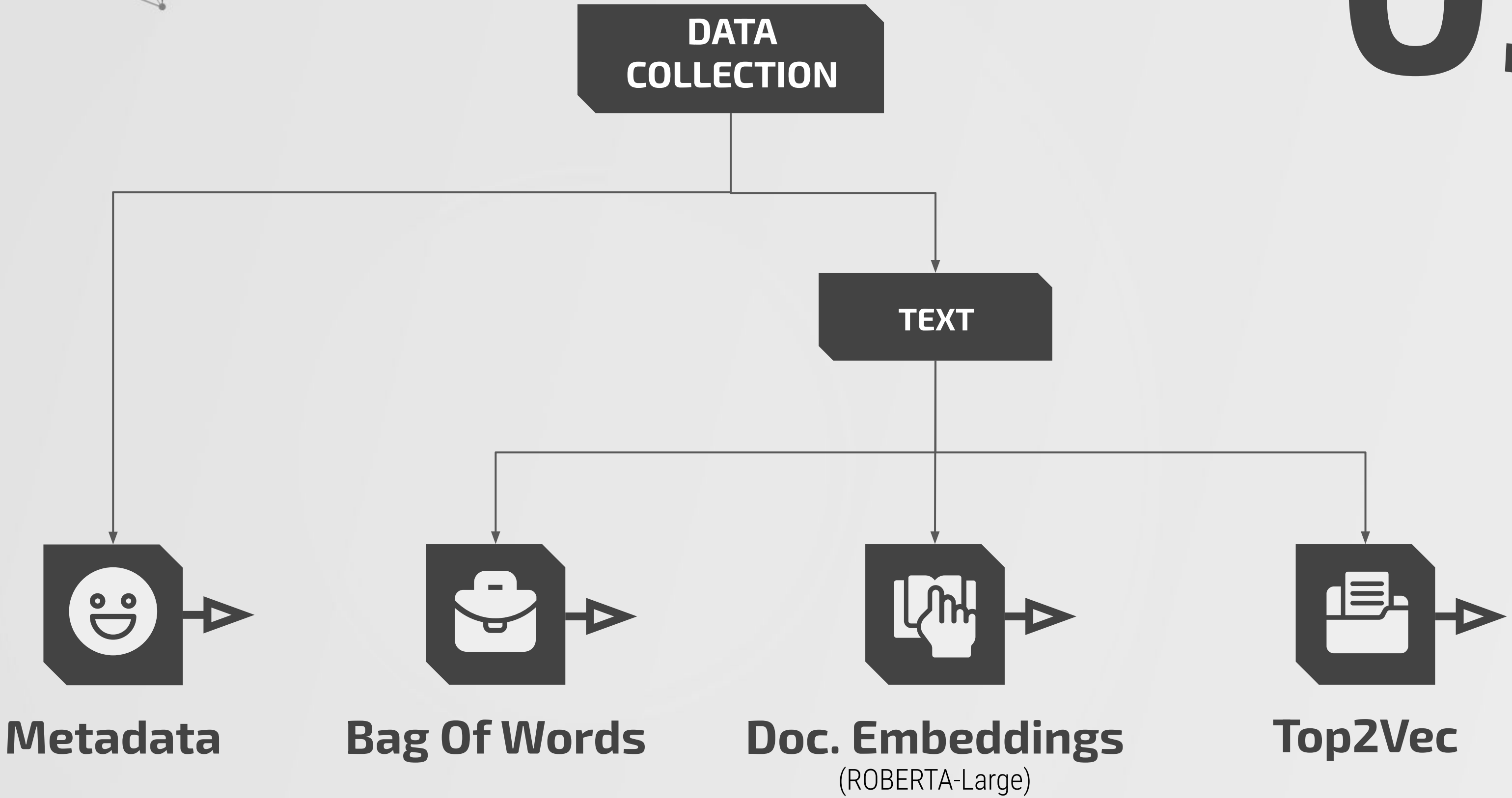
03

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)
- Regression and Classification

1D CNN → **Deep Learning** → **Random Forest**

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 explained about 11% of variance (R2) using NLP

Viral Topics

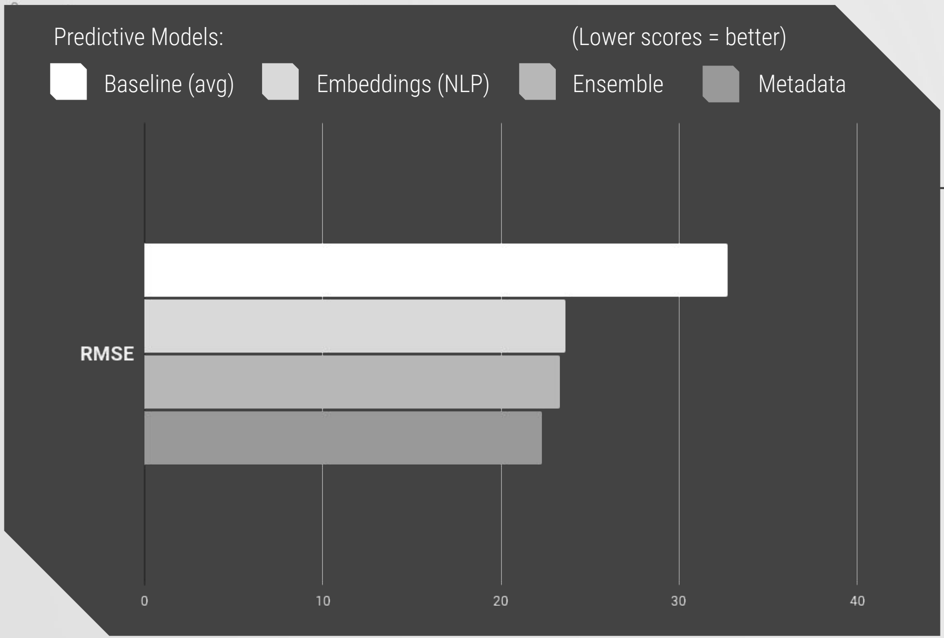
Some topics are clearly more viral, e.g. talking about OpenAI, or hiring phd candidates

Quantifiability

We can measure virality of specific features, 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

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 communications dashboard? Could the service be used to market itself?

Improve the Model

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

Reuse the Pipeline

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

06

CONCLUSIONS

In a nutshell…

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06

We were able to use machine learning to predict 26% of our viral tweets. That means we can begin to preemptively score academic findings for virality.

However virality may always be hard to predict – like predicting the stock market, if you find something that works, it might change the landscape and stop 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%