Topic Model & Text Generation

An investigation into **conspiracy theories**, by Adrian Chapman

Inspiration

The 2020 election illustrated the importance of conspiracy theories and their power to shape public opinion, voting decisions, and choices relevant to public health and safety:

- COVID-19
- Election Fraud
- Q Anon supporting congressmen

6x

On twitter, false news travels 6 times faster than true stories

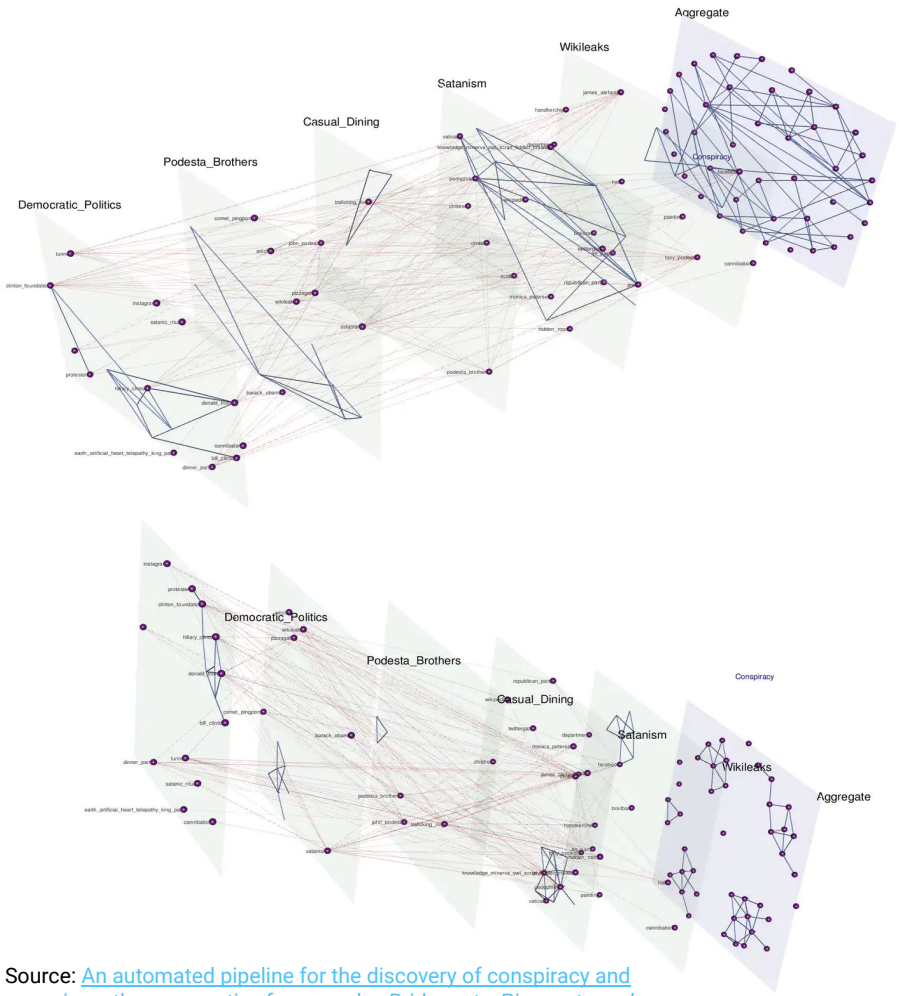
Source: https://news.mit.edu/2018/study-twitter-false-news-travels-faster-true-stories-0308


/the
social
dilemma

Problem Statement

To explore the relationship between Conspiracy Theory, misinformation, and AI through:

1. A demonstration of a text generation application (GPT2) fine tuned on conspiracy theories
2. Topic modeling (BERT) on popular conspiracy theories
3. A review of research in NLP and conspiracy theory



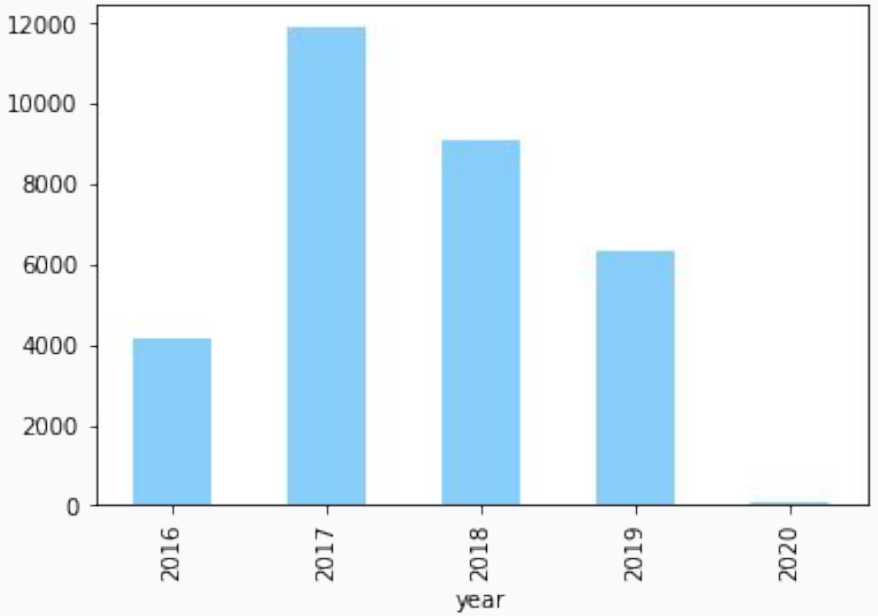
Source: [An automated pipeline for the discovery of conspiracy and conspiracy theory narrative frameworks: Bridgegate, Pizzagate and storytelling on the web]

Research is also exploring how AI can help us differentiate conspiracy theory from true conspiracy by studying structural differences between the two narrative frameworks

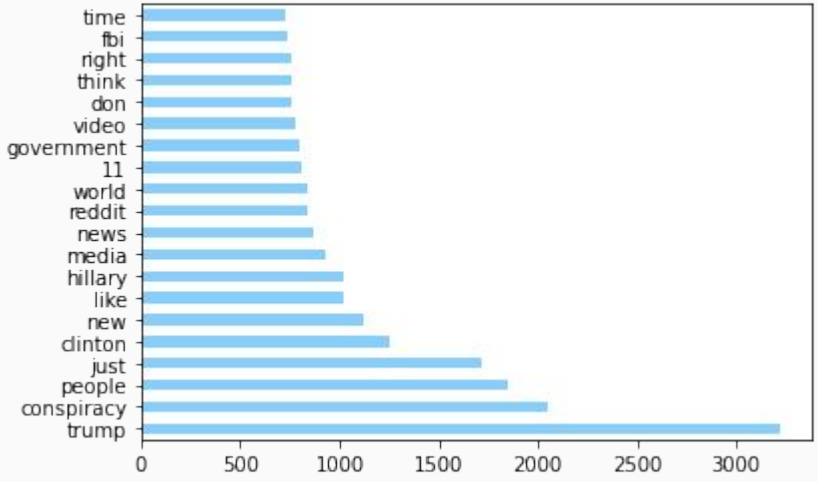
Data & EDA

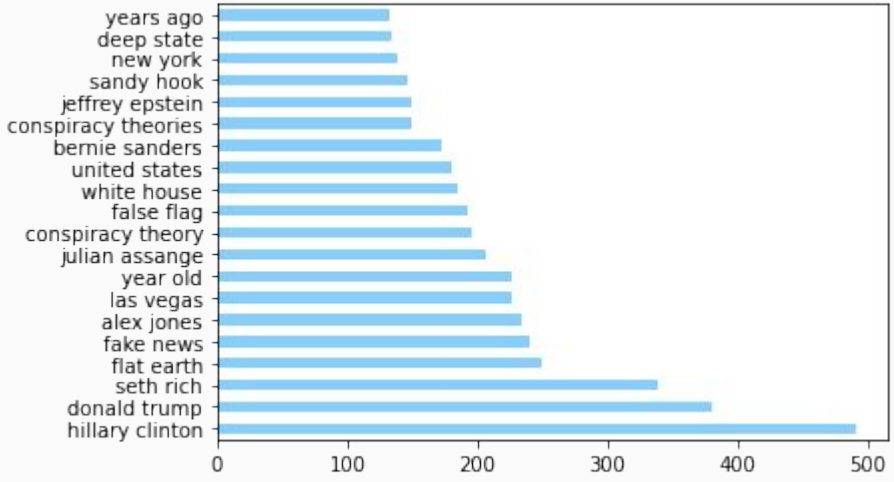
Data

- 30k post titles from r/conspiracy
- At least 50 comments
- From 2016-2019
- Minimal cleaning/preprocessing

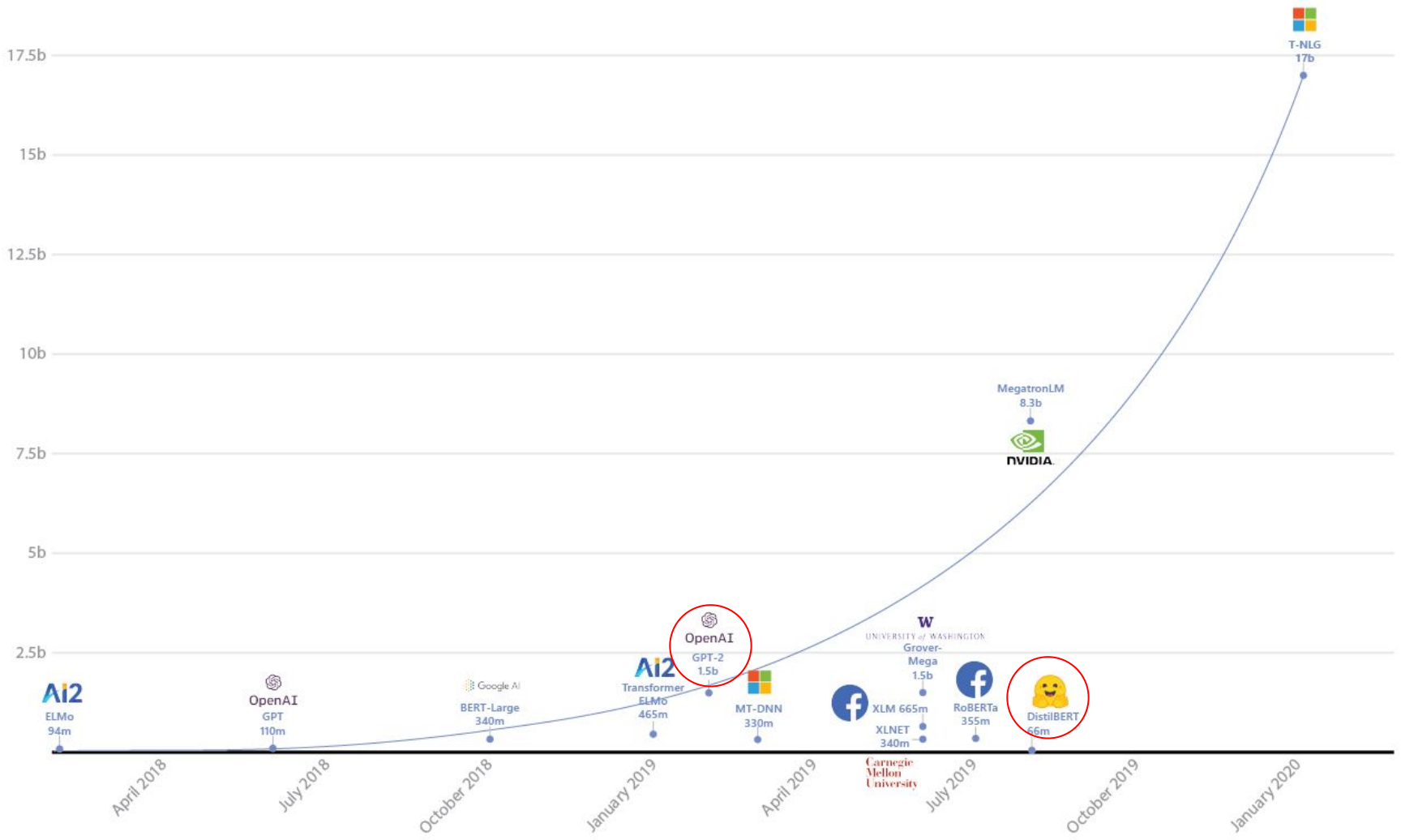


Most common words





Models

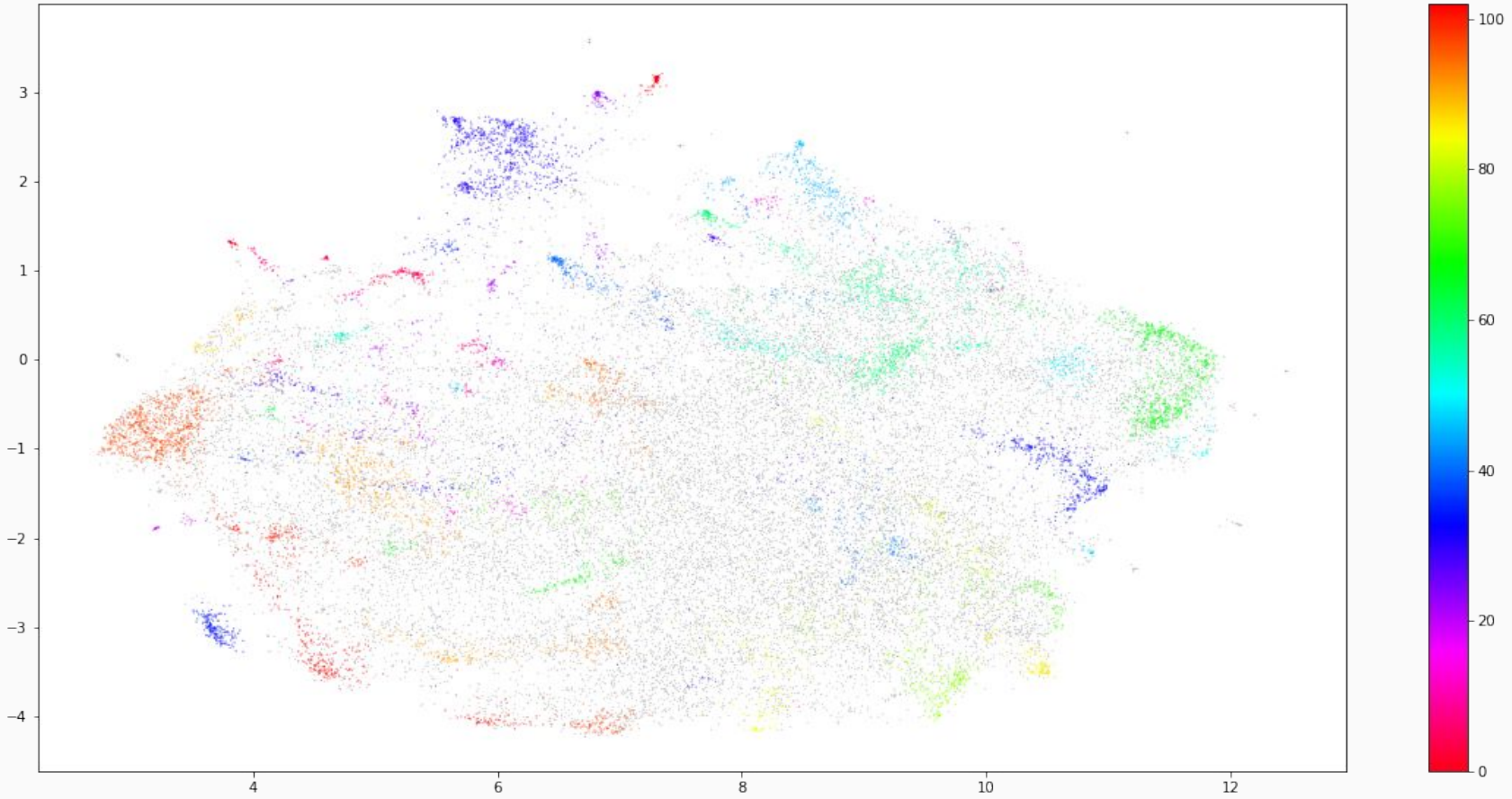

17.5b
15b
12.5b
10b
7.5b
5b
2.5b
T-NLG
17b
MegatronLM
8.3b
NVIDIA
OpenAI
GPT-2
1.5b
Ai2
Transformer
ELMo
465m
Ai2
ELMo
94m
OpenAI
GPT
110m
Google AI
BERT-Large
340m
MT-DNN
330m
UNIVERSITY of WASHINGTON
Grover-
Mega
1.5b
XLM 665m
XLNET
340m
Carnegie
Mellon
University
RoBERTa
355m
DistilBERT
66m
April 2018
July 2018
October 2018
January 2019
April 2019
July 2019
October 2019
January 2020

Topic Modeling

Pipeline for Topic Model

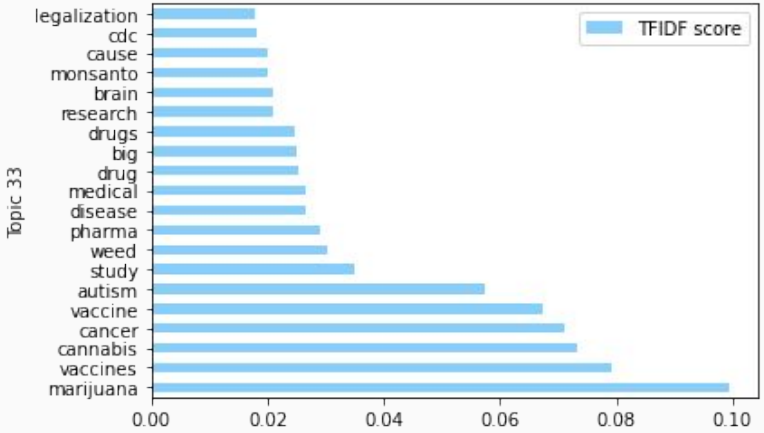
1. distilBERT - for text embeddings, creating 512 dimensional vectors
2. UMAP - dimension reduction
3. HDBSCAN - density based clustering
4. TFIDF on topic clusters to find most important words defining each cluster
5. “Top words” as human readable labels

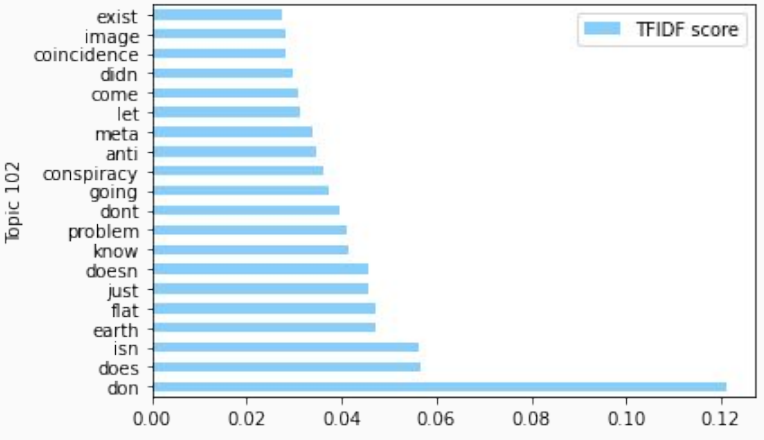
HDBSCAN topics represented in 2D space

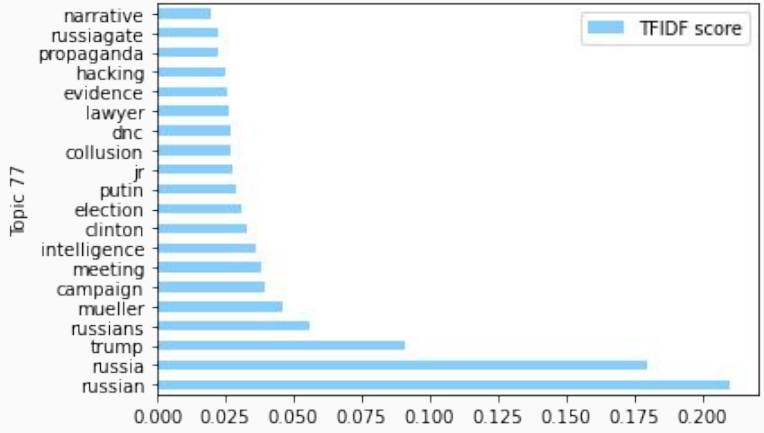


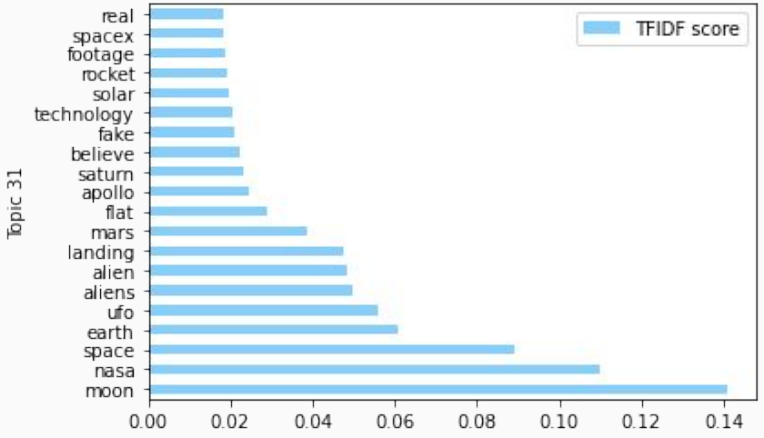
Human Readable Topics

	Topic	Size
0	-1	22211
1	97	832
2	31	777
3	67	674
4	33	459
5	92	431
6	60	350
7	77	292
8	45	266
9	102	231









Conclusion

Takeaways

- Both models were successful within expectations of their relative tasks
- Interaction between topic modeling and text generation applications
- Hosting Streamlit from Google Colab provides a convenient and free environment for rapid prototyping with larger models
- Future NLP research into conspiracy theories can help with an understanding of the size spread of misinformation, and the real world impact on believers

Resources and Thanks

- Maarten Grootendorst, author of BERTopic
- Max Woolf, author of gpt-2-simple
- Jay Alammar, author of The Illustrated Transformer blog post
- Jesse E. Agbe, for YouTube video on running Streamlit from Google Colab

Special thanks to GA DSI-13 instructors and students!

The truth is out there!