Analyzing Political Bias in the YouTube Recommendation Algorithm

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Motivation

YouTube
- 1.5 billion users
- Has more viewers in age range 18-49 yrs. than any single US news channel
- 70% of total viewing time driven by recommendation algorithm
- How ideologically varied is this algorithm?

Related Work

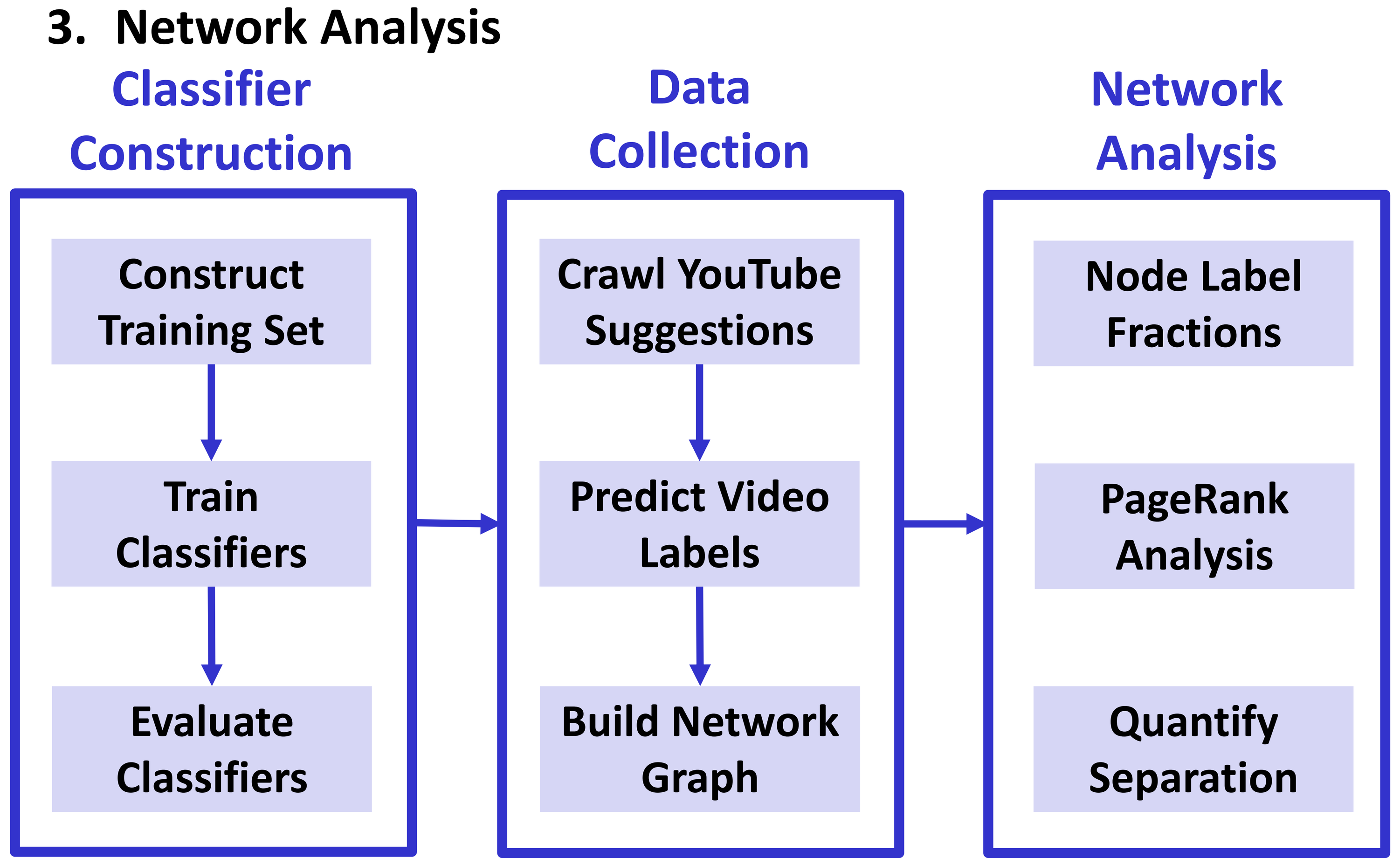
Wall Street Journal Investigation
- Investigated trends in YouTube video recommendations
- Conclusions:
  - Recommendation algorithm pushes users to partisan videos
  - Searching for a specific bias results in more recommendations of that bias
- Omissions:
  - Dataset of videos used in investigation
  - Methods to determine political bias of videos
  - Methods used to identify trends in recommendation algorithm

Goals

1. Identify trends in the YouTube recommendation algorithm
2. Quantify the separation between partisan political videos
3. Determine whether separation varies with video topic

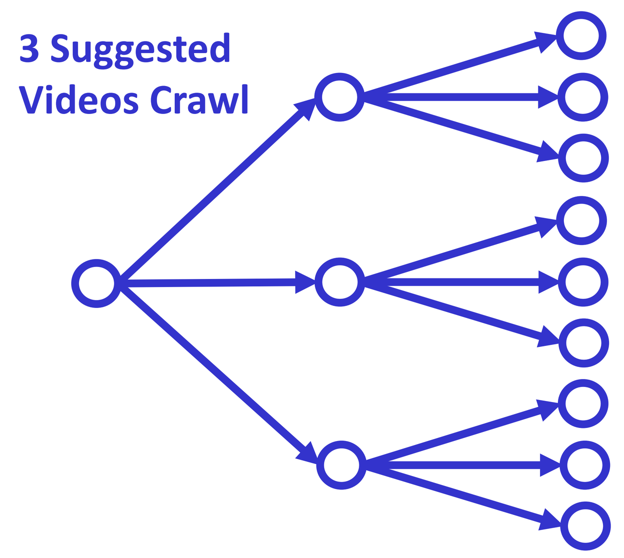
Approach

1. Political Bias Classifier Construction
   - Labels: Democratic, Republican, Centrist
   - Features: video title, description, top 100 comments
2. Data Collection
3. Network Analysis



Data Collection and Graph Construction

Data Collection:
- Two types of Crawls:
  - 3 suggested videos, max depth of 6
  - 10 suggested videos, max depth of 3
- 3 crawls per network
  - Differ in source bias → 1 crawl per label
- Topic-Specific Networks (2): Robert Mueller



Graph Construction:
- Node = video encountered in a crawl
- Directed edge from Video A to Video B if Video A recommends Video B
- Edge weight: duration of video providing recommendation

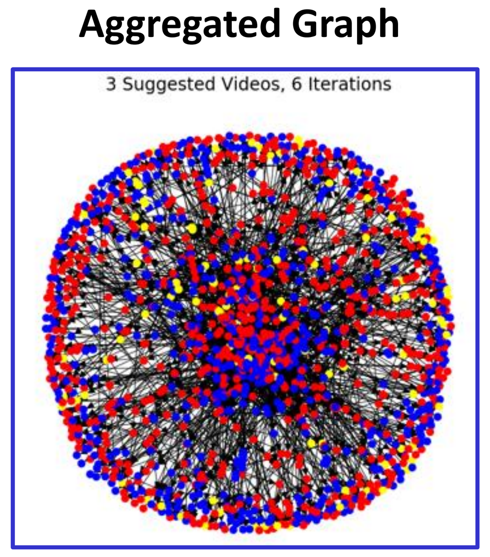
Network Analysis Metrics

PageRank
- Commonly used to rank website relevance in search engines
- Interpreted as stationary probabilities for random walk on network graph

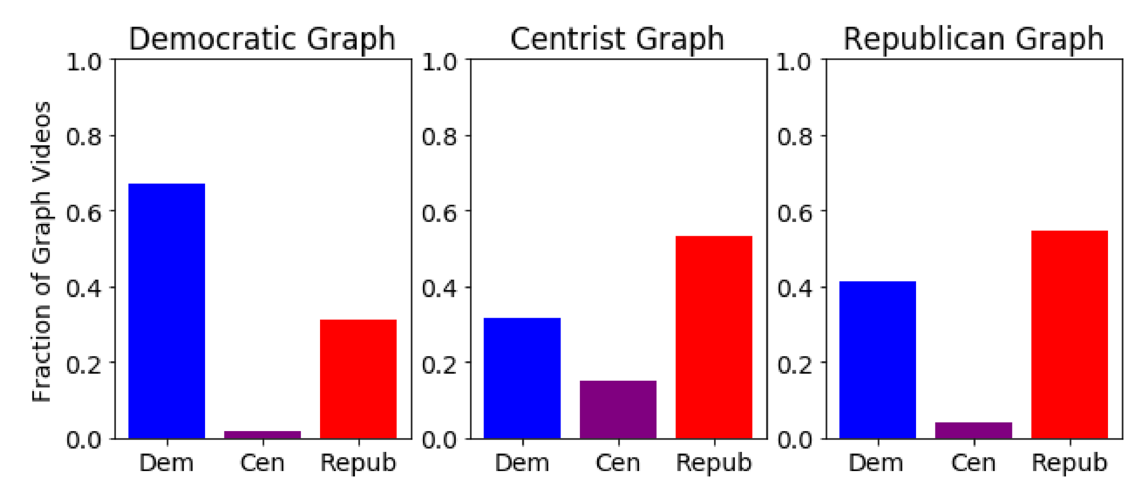
Average Separation
- For every node of Type A, calculate its shortest distance to a node of Type B
- Average over shortest distances for all nodes of Type A to Type B

Results: Network Analysis

Aggregated Graph



Node Label Fractions in Network of 3 Suggested Videos



Node Label Fractions
- Beginning in a particular bias results in a larger proportion of nodes of that bias across all labels
- Partisan videos recommended more than Centrist videos in Centrist graph

PageRank Analysis
- Observed label of video in each graph with highest PageRank value
  - Democratic video in 7 graphs, Republican video in 1 graph
- Observed majority label within top 10 PageRank values of each graph:
  - Democratic in 5 graphs, Republican in 1 graph, Dem/Rep tie in 2 graphs

Partisan Separation
- Average session time: approx. 40 minutes
  - Separation of general partisan videos is less
  - Separation of topic-specific partisan videos is less

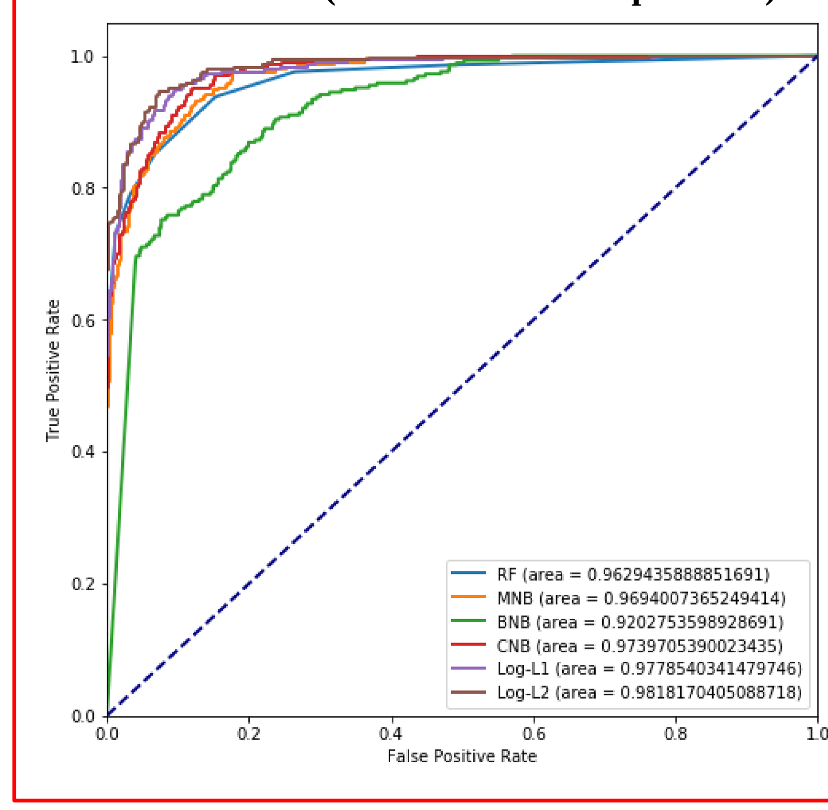
Source Label to Destination Label	Network of 3 Suggested Videos Avg Separation	Network of 10 Suggested Videos Avg Separation
Dem to Rep	**21.54**	12.75
Dem to Dem	14.81	11.79
Rep to Dem	**31.42**	13.75
Rep to Rep	23.82	14.12

Results: Political Bias Classifier

Performance metrics

	Random Forest	Multinomial NBC	Bernoulli NBC	Complement NBC	LR L1-Norm	LR L2-Norm
Accuracy	0.820	0.820	0.801	0.819	**0.855**	**0.865**
Precision	0.842	0.818	0.811	0.827	**0.861**	**0.858**
Recall	0.842	0.805	0.784	0.818	**0.857**	**0.855**
F1-Score	0.842	0.805	0.787	0.817	**0.858**	**0.857**

ROC Curve (Positive Label = Republican)



- Logistic Regression classifiers outperform other classifiers across all metrics.
- Based on ROC and AUC scores for each label, Logistic Regression with L2-Norm has the best predictive abilities
- Logistic Regression with L2-Norm chosen to predict video labels in YouTube crawl

Conclusions

- From node label fractions:
  - Recommendation algorithm pushes users to partisan videos
  - Searching for a specific bias results in more recommendations of that bias
- From PageRank analysis:
  - Recommendation algorithm is slightly biased – results in larger concentration of web traffic in Democratic videos
- From quantifying separation between partisan videos:
  - User can encounter a divergent video in a single session
    - Still holds when searching videos related to a specific topic

Future Work

- Consider additional network analysis metrics
  - Explore recommendation links using homophily
- Refine average separation calculation
  - Impose duration ceiling for source videos
- Improve political bias classifier
  - Expand training set
  - Reweight term frequencies based on video element
  - Add video transcripts to classifier features

Acknowledgments

Thank you to Professor Andrea LaPaugh and Molly Pan for their guidance and support. Also, thank you to Professor Barbara Engelhardt for general machine learning advice.