



## BACKGROUND & PROBLEM STMT

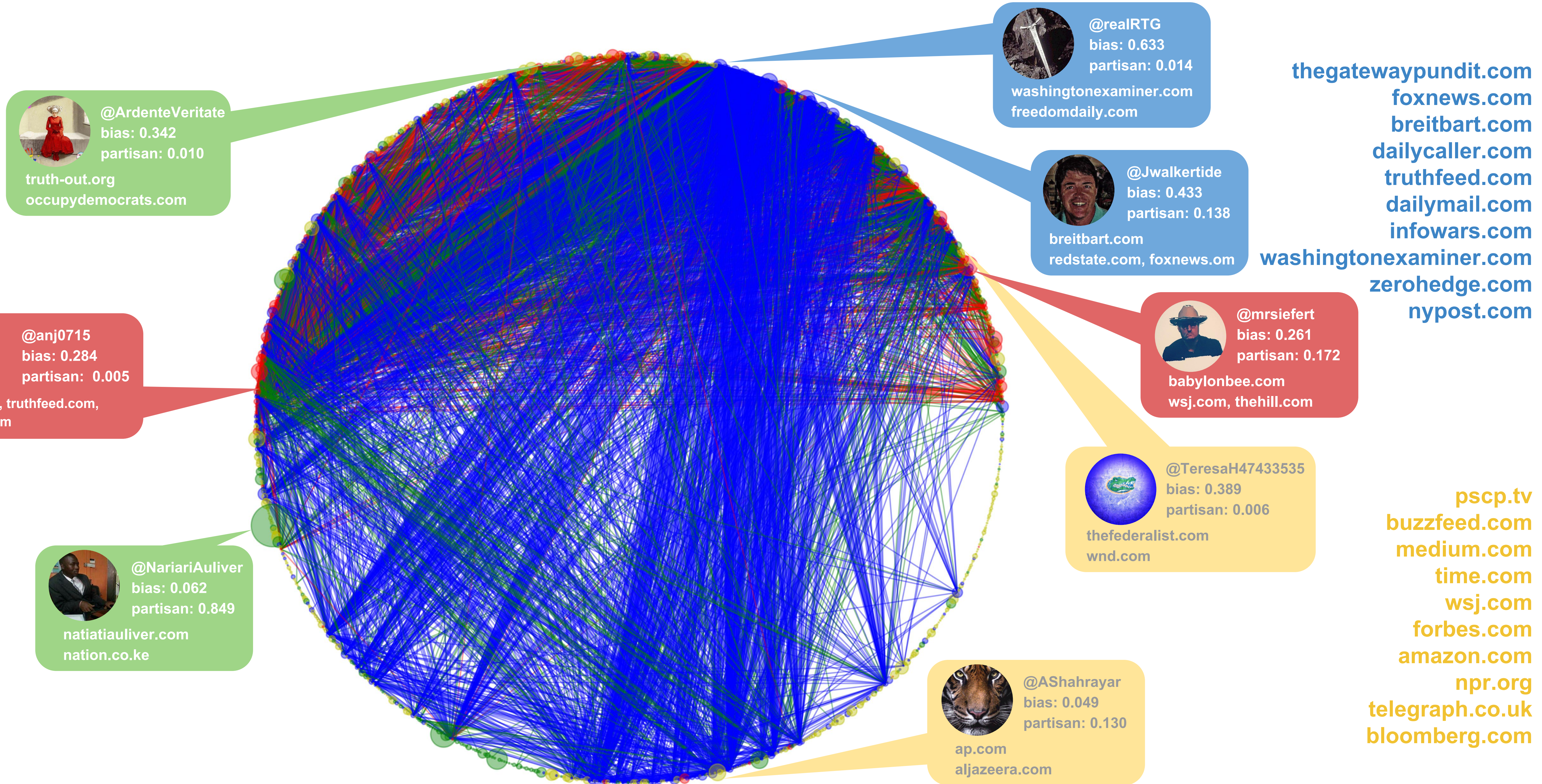
- Echo chambers: communities that share content with similar viewpoint; rarely interact with other communities in positive terms
- Studies that have focused on echo chambers:
  - Use real network of follower/friends, but:
    - Complete network info is hard to obtain.
    - Follower/followee relations don't necessarily reflect political agreement.
  - Use labeled data, but:
    - Labels may be biased themselves.
    - Labels may change over time, e.g. many former UKIP supporters voted for Labour in UK's general election of '17.
- After echo-chambers are identified, all of their content is dismissed as biased.
- **Problem:**
  - Identify echo-chambers on Twitter, such that:
    - **Network info** is not required.
    - No **human labeling** is required.
    - Model can identify **which topics are subject to misrepresentation** by each echo-chamber.
  - Do all of this in a way that the model can be updated in **real-time**.

## DATA & METHODOLOGY

- Seed set: domains mentioned in Kaggle's fake news dataset (2016-10-25 to 2016-11-25).
- Download all tweets that mentioned those domains within the same time period: **25,742,785** tweets from **131,552** unique accounts
- Use **PMI**-like measure to score domains by
  - similarity to each other
  - similarity to Kaggle domains
- Score users based on the domains they share:
  - **Bias**: similarity of a given user's domains to Kaggle domains.
  - **Partisanship**: similarity of a given user's domains to each other.
- Draw network of co-shared domains:
  - **Node size**: partisanship of each user.
  - **Edge width**: number and cumulative bias of two nodes' shared domains.
- Run **Louvain modularity detection** to identify echo-chambers (color-coded).
- Calculate each chamber's deviation:
  - **Word2Vec deviation** from a large global set.
  - **TF-IDF deviation** from other chambers.
- **High Word2Vec deviation AND low TF-IDF deviation ⇒ potentially misrepresented topic.**

usatoday.com  
 nbcnews.to  
 nymag.com  
 theonion.com  
 dailycos.com  
 theintercept.com  
 businessinsider.com  
 insider.foxnews.com  
 reddit.com  
 economist.com

washingtonpost.com  
 newyorktimes.com  
 huffingtonpost.com  
 cnn.com  
 theguardian.com  
 change.org  
 independent.co.uk  
 thehill.com  
 bbc.com  
 latimes.com



FBI, bad, witch | covering, Mueller, investigated | Obama, Comey, million | shooter, apology, MSM

death, travel, Muslims | wikileaks, alleged, brothers | vaccines, reckless, study

Tory, legal, politician | Corbyn, #LastMinuteCorbynSmears, @jeremycorbyn | #bbcsp, industry, MSM

## EVALUATION

- BuzzFeed's list of **60 true stories and 60 fake stories** propagated on Facebook in the period leading up to 2016 U.S. presidential election.
- Download tweets linking to the same articles (**no seed set ⇒ no bias score**).
- Apply echo-chamber analysis to the users.
- Train linear classifier based on: **user partisanship, domain exclusivity, content match against each chamber's set of deviating terms**
- F1 scores show the features are robust & informative, even for simple classifiers

Features	LogReg	DTree	SVMLinear
user + domain	0.73	0.71	0.74
user + content	0.69	0.67	0.69
domain + content	0.75	0.70	0.76
All	<b>0.77</b>	<b>0.73</b>	<b>0.78</b>

## DISCUSSION

- Suggested setup for real-time setting:
  - Network of chambers (re)constructed on a daily/weekly basis
  - An index constructed to score domains based on their popularity in each chamber
  - Tweets stream from the public API (e.g. using Spark streaming)
  - Stories are tracked by their URL
  - Users are benchmarked against the network
    - To avoid exhausting rate limits, a KB of users' common domains can be stored in a cache
  - Each story's score based on:
    - **User scores**
    - **Content score**
    - **Domain score**

SEE WHERE YOU STAND  
 TRY THE LIVE DEMO