<Your Name>

Case Study: Social Media Analytics for Stance Mining

With Examples From COVID-19 Twitter Analysis

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Let's Define the Terms

- **Stance** is defined as a **mental or emotional position** adopted with respect to a proposition, a person, an idea, etc. [1].
- Users' Stance is categorized as:
  - **Pro** (Favor)
  - **Con** (Anti)
  - **Neutral** (or unknown)

1. https://www.thefreedictionary.com/stance

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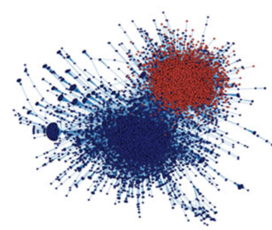
How to Learn Users' Stance (Pro/Anti)? Prior research on stance mining has appeared in two flavors

1. Language (Text) based Approach [1]



2. Network based Approach [2]

1. SemEval-2016 Task 6: Detecting Stance in Tweets, Mohammad et al., 2016
2. 2011, Conover, Michael, Jacob Ratkiewicz, Matthew R. Francisco, Bruno Gonçalves, Filippo Menczer, and Alessandro Flammini. "Political polarization on twitter." ICWSM 133 (2011): 89-96

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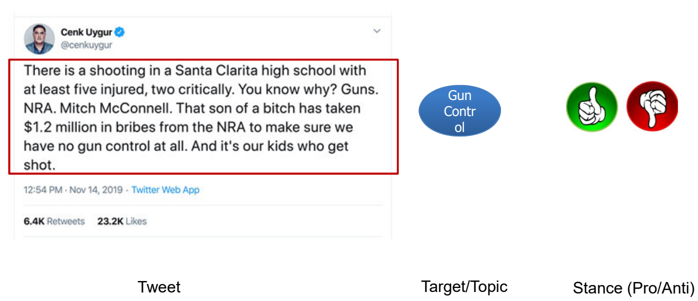
Prior work on Language Based Stance Learning is Mostly Supervised which Requires Labeled data. Labeling data is Expensive.



SemEval-2016 Task 6: Detecting Stance in Tweets, Mohammad et al., 2016

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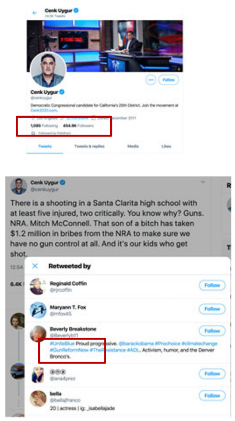
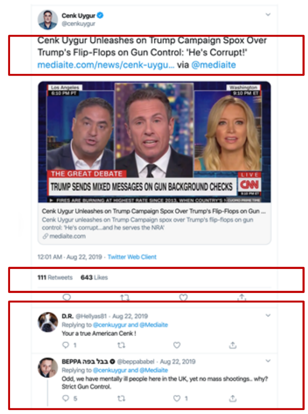
Stance could also be learned from other multi-modal interactions (Networks)





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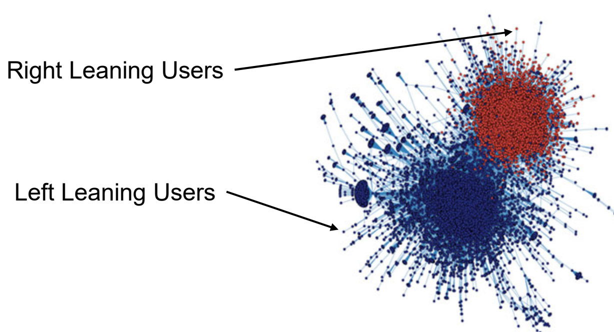
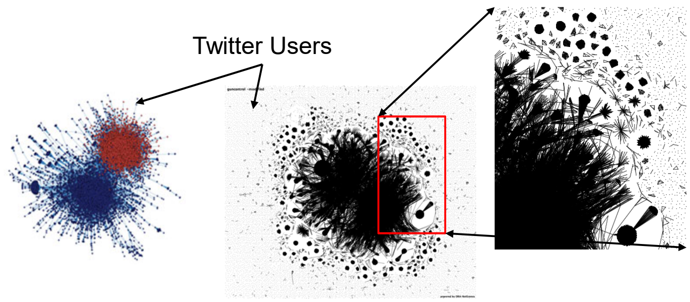
Network Based Stance Learning Methods are often Semi-Supervised, so Require Less Labeled Data. However, they can't handle isolates



2011, Conover, Michael, Jacob Ratkiewicz, Matthew R. Francisco, Bruno Gonçalves, Filippo Menczer, and Alessandro Flammini. "Political polarization on twitter." ICWSM 133 (2011): 89-96

In a Real (un-processed) Network, the Isolates in the Network form a Good Fraction of the Dataset



A retweets-based Network after removing the isolates
Conover et al. Political polarization on twitter." ICWSM 133 (2011): 89-96

Unprocessed gun-control conversations on Twitter Collected by searching gun-control related terms. Links are based on Retweets.

Three Main Challenges in Existing Approaches to Stance Mining

1. Most language-based stance mining models use supervised machine learning **which is expensive**
2. Network based semi-supervised approaches require less labeled data but **cannot handle isolates**
3. Topics change fast and new topics emerge **which make the problem more challenging**

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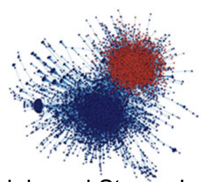
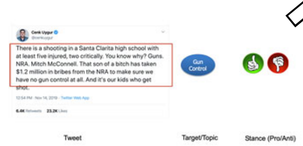
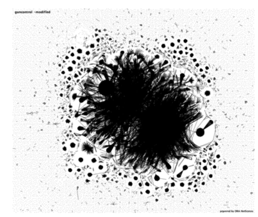
Goal of this New Methodology: Can we Combine the Strengths of Text based Methods and Networks based Methods?



Network based Stance Learner



Text based Stance Learner



Predict the Stance of All Users in a Realistic Network

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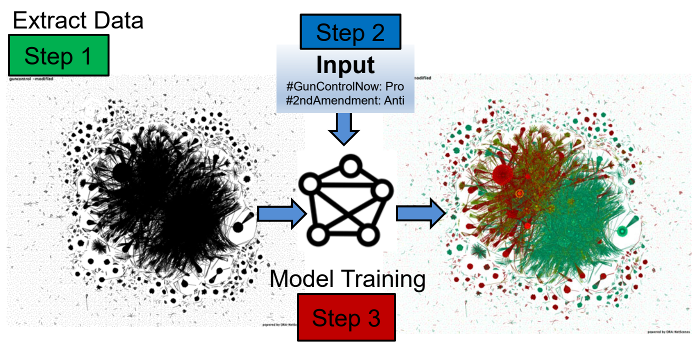
Co-Training on Social Networks: A Joint Network Label Propagation and Text Classification Approach for Stance Mining [2]



Gun-control users' Network. Links represent retweets-based interactions.

Red nodes are `Pro' and Green nodes are `Anti' Users

2. Sumeet Kumar, Tom Mitchell, Kathleen M. Carley, Co-Training on Social Networks, Currently under review

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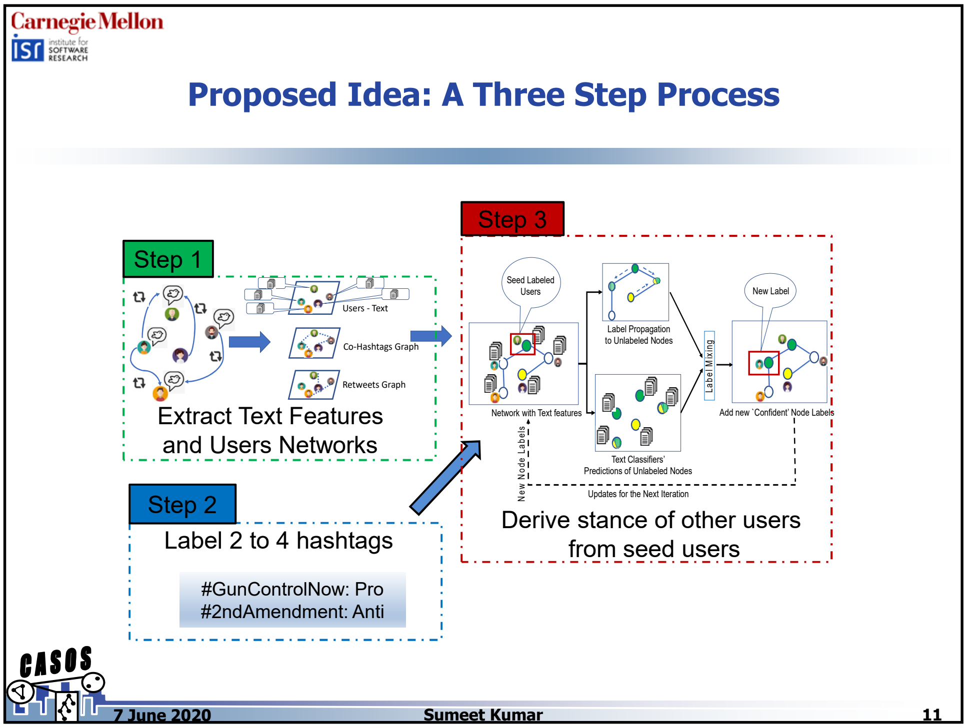

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Proposed Idea: A Three Step Process
Step 1
Users - Text
Co-Hashtags Graph
Retweets Graph
Extract Text Features and Users Networks
Step 2
Label 2 to 4 hashtags
#GunControlNow: Pro
#2ndAmendment: Anti
Step 3
Seed Labeled Users
Label Propagation to Unlabeled Nodes
New Label
Label Mixing
Network with Text features
Text Classifiers' Predictions of Unlabeled Nodes
Add new 'Confident' Node Labels
New Node Labels
Updates for the Next Iteration
Derive stance of other users from seed users
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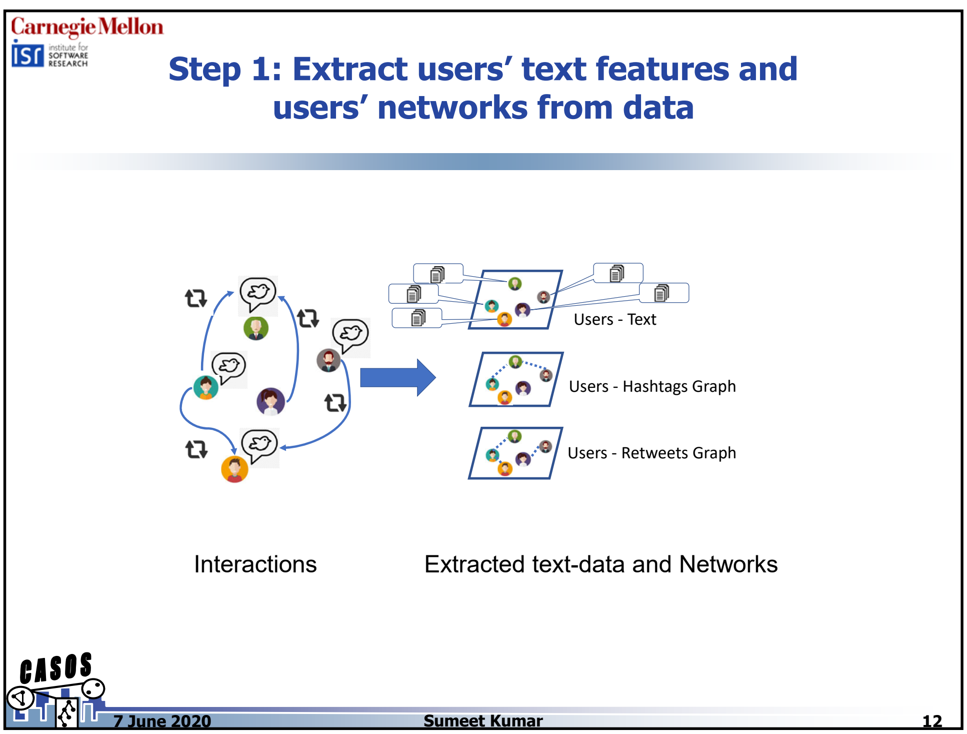

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Step 1: Extract users' text features and users' networks from data
Users - Text
Users - Hashtags Graph
Users - Retweets Graph
Interactions
Extracted text-data and Networks
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Step 1: Extract text features and users' networks from data

1. **Extract users text data**
2. **Extract networks**

Users' Text

User	Tag	Weight
cenkuygur	#IowaCaucuses	1
cenkuygur	#NotMeUS	1

Users-Hashtags (Networks)

User	Retweet	Weight
spthursby	cenkuygur	1

Users-Retweets (Networks)

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Step 2: Label 2 to 4 popular hashtags with clear stance

Steps:

1. Use hashtags that appear at the end of tweets
2. Sort hashtags by their popularity
3. **Label a few popular hashtags that have clear stance e.g. #GunControlNow**

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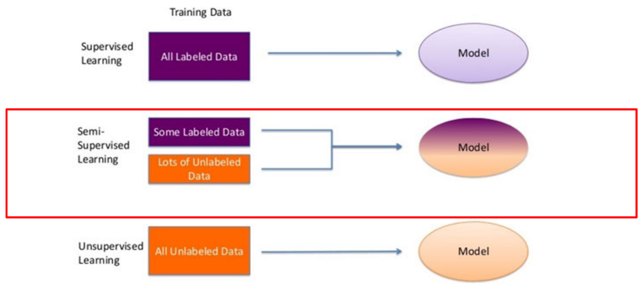
Step 3: A Semi-supervised Approach (Co-Training + Label Propagation)

- Semi-supervised approaches of machine learning is suitable for partially labeled data



- We use a **co-training setting**

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What is Co-Training?

- Co-training requires **two independent views to train two separate classifiers** (weak learners) iteratively [1]
- In the training process, **more confident predictions are used as new training data [1]**

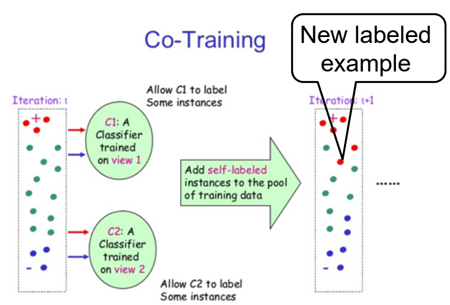

Image Source
https://www.slideshare.net/butest/semisupervised-learning

1: Blum, Avrim, and Tom Mitchell. "Combining labeled and unlabeled data with co-training." *Proceedings of the eleventh annual conference on Computational learning theory*. ACM, 1998.

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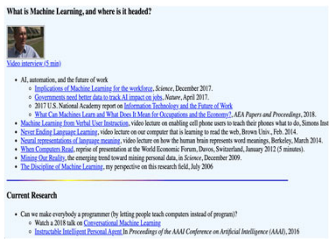
What is Co-Training? Applied to Website Classification

View 1 (website)



What is Machine Learning, and where is it headed?

Video interview (5 min)

- AI, automation, and the future of work
  - Implications of Machine Learning for the workforce, *Science*, December 2017.
  - Governments need better data to track AI impact on jobs, *Nature*, April 2017.
  - 2017 U.S. National Academy report on Information Technology and the Future of Work
  - What Can Machines Learn and What Does It Mean for Occupations and the Economy?, *AEA Papers and Proceedings*, 2018.
- Machine Learning from Verbal User Instruction, video lecture on enabling cell phone users to teach their phones what to do, Simons Inst
- Never Ending Language Learning, video lecture on our computer that is learning to read the web, Brown Univ., Feb. 2014.
- Neural representations of language meaning, video lecture on how the human brain represents word meanings, Berkeley, March 2014.
- When Computers Read, reprise of presentation at the World Economic Forum, Davos, Switzerland, January 2012 (5 minutes).
- Mining Our Reality, the emerging trend toward mining personal data, in *Science*, December 2009.
- The Discipline of Machine Learning, my perspective on this research field, July 2006

Current Research

- Can we make everybody a programmer (by letting people teach computers instead of program)?
  - Watch a 2018 talk on Conversational Machine Learning
  - Instructable Intelligent Personal Agent In *Proceedings of the AAAI Conference on Artificial Intelligence (AAAI)*, 2016

View 2 (Text on the Links to the website)

My advisor is Tom Mitchell and I work on…..
Prof. Mitchell's work on never ending learning …
Prof. Mitchell, an expert in machine learning, mentioned …

Academic / Non- Academic Webpage Classification

Blum, Avrim, and Tom Mitchell. "Combining labeled and unlabeled data with co-training." *Proceedings of the eleventh annual conference on Computational learning theory*. ACM, 1998.

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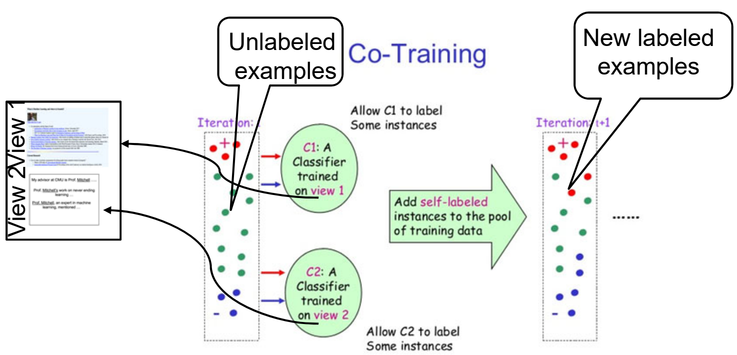
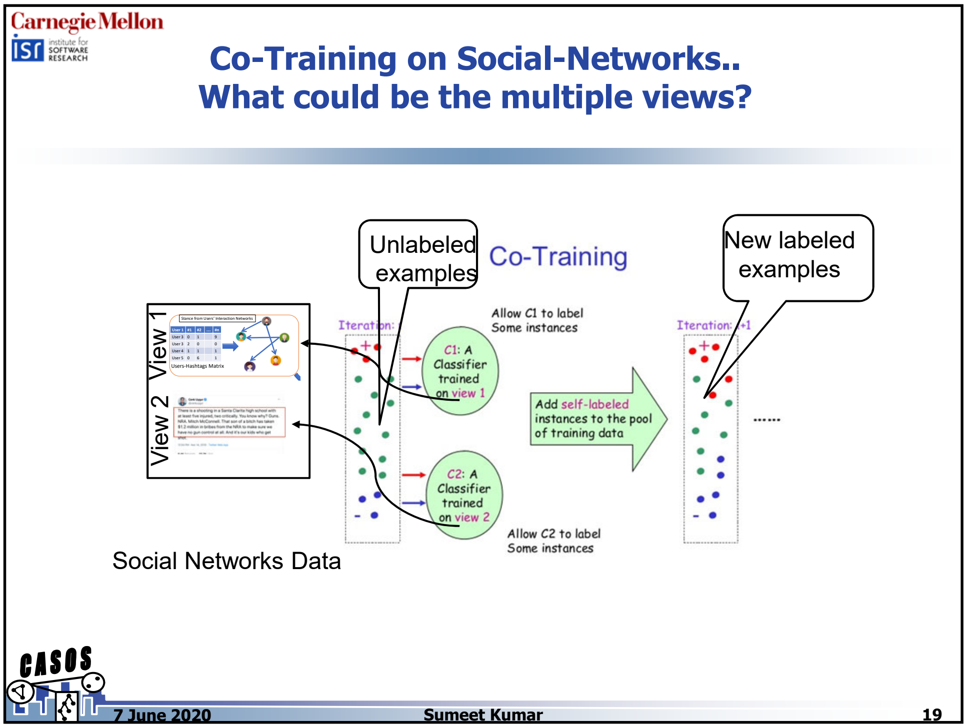
Co-Training could be useful if each data point has two (or more) views



Blum, Avrim, and Tom Mitchell. "Combining labeled and unlabeled data with co-training." *Proceedings of the eleventh annual conference on Computational learning theory*. ACM, 1998.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Co-Training on Social-Networks..
What could be the multiple views?
Unlabeled examples
Co-Training
New labeled examples
View 1
View 2
Iteration:
Allow C1 to label Some instances
C1: A Classifier trained on view 1
Add self-labeled instances to the pool of training data
C2: A Classifier trained on view 2
Allow C2 to label Some instances
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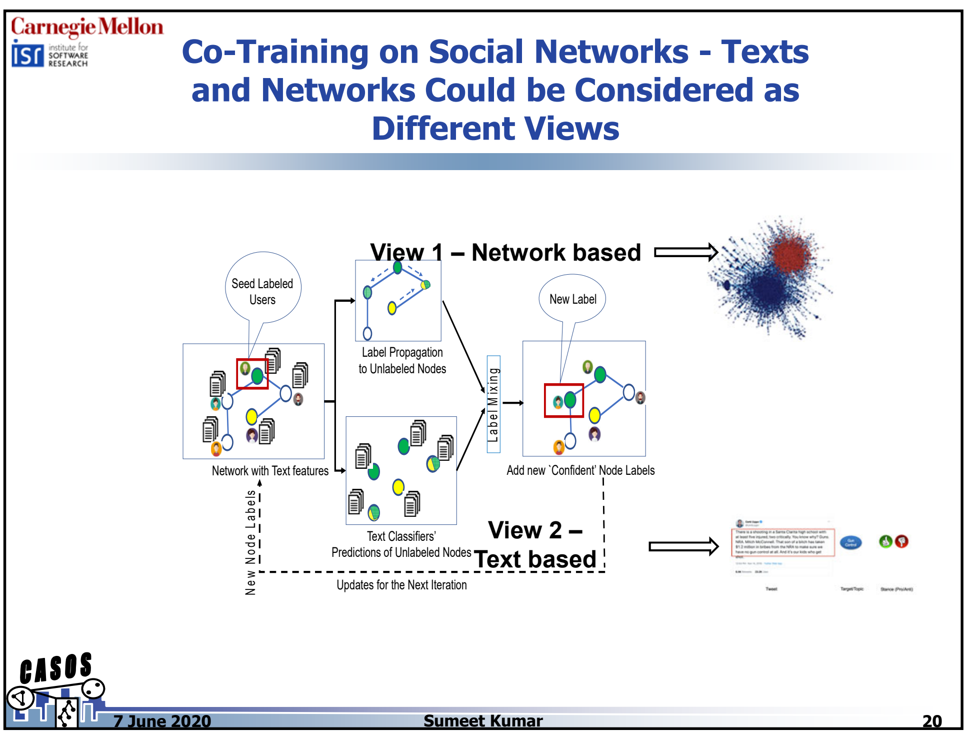
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Co-Training on Social Networks - Texts and Networks Could be Considered as Different Views
View 1 – Network based
Seed Labeled Users
Label Propagation to Unlabeled Nodes
New Label
Label Mixing
Network with Text features
Add new 'Confident' Node Labels
Text Classifiers' Predictions of Unlabeled Nodes
View 2 – Text based
New Node Labels
Updates for the Next Iteration
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Co-Training on Social Networks. Texts and Networks form Different Views

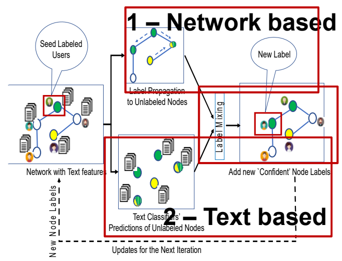
Algorithm 3 Co-Training: Joint training of hashtag based label-propagation model and text classifier

Require: T is the set of tweets collected

function CO-TRAIN SOCIAL NETWORKS(T)
- Extract User-Text D
- Extract User-Hashtag Network H
- Label Seed hashtags ▷ e.g, #Prochoice +1
- Get Seed users (UL)
- Get Unlabeled users (UU)
- **while** until convergence **do**
  - **STEP 1: Label Propagation**
  - Label hashtags (H) using UL
  - Predict the Stance S^l of UU using H
  - Estimate stance confidence (C^l)
  - **STEP 2: Text based classification**
  - Train a text classifier $f_{text}(\theta)$ using UL
  - Use $f_{text}(\theta)$ to Predict UU stance S^T
  - Estimate stance confidence (C^T)
  - **STEP 3: Update UL**
  - L=LabelMixing(S^l, C^l, S^T, C^T)
  - UL= UL + L
- **end while**
- **return** UL

end function

Proposed Algorithm



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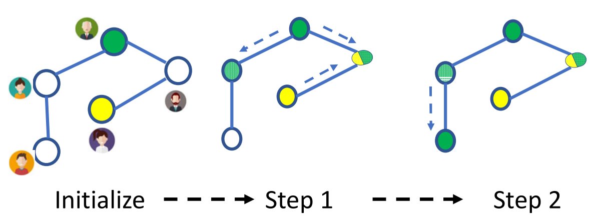
Classifier 1: Network Classifier – A Label Propagation Model



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Classifier 1: Label propagation on user-user networks has shortcomings

- Many Social-Media Networks are bi-partitie i.e. users relate to other entities
- Often entities on Social Media follow power law distribution
- **Converting user-posts network to user-user network explodes the size**
  - For example. 100,000 users and 200 hashtags get converted to 100,000 x 100,000 size user-user network

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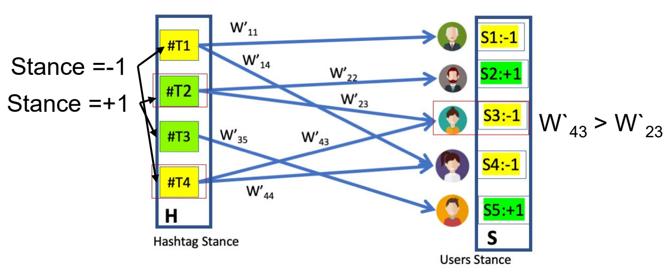
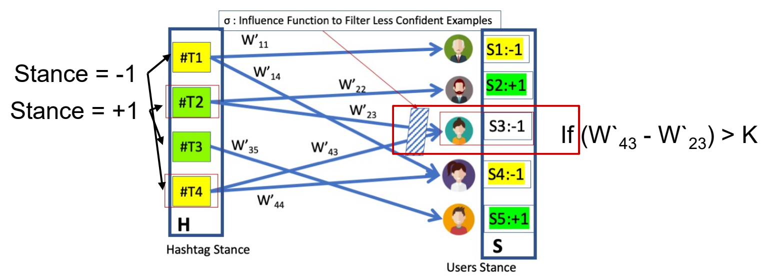
Label Propagation Model on Bipartite Networks



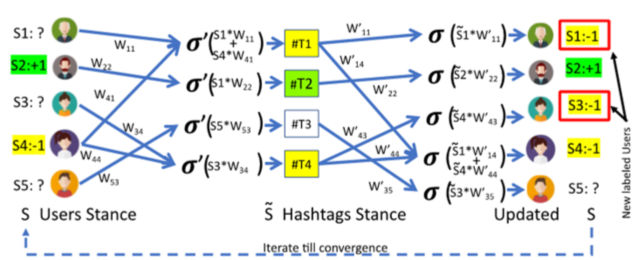
- New users are labeled by propagating hashtag stance to users

Label Propagation Model on Bipartite Networks With Influence Functions



- Influence functions are used to filter less confident predictions
- **In a Linear Threshold function, if a user gets higher then a certain level of influence from the influencers, the user gets influenced**
- New users are labeled by propagating hashtag stance to users

Classifier 1: Label Propagation Model on Bipartite Networks Better Suits our Needs



- **Influence functions are used to filter less confident predictions**
- Influence functions ***σ***' and ***σ*** are threshold functions and used to filter out not confident hashtags and users respectively

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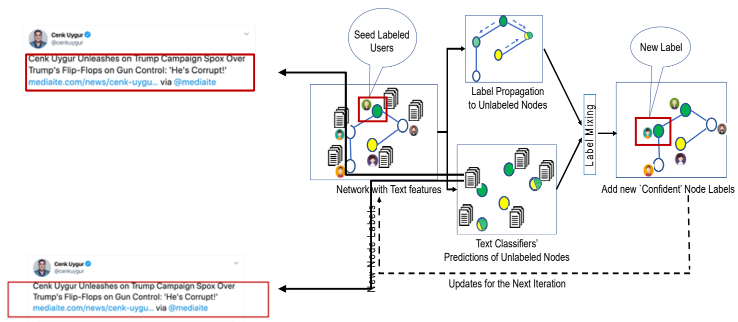
Classifier 2: Learn Stance from Text in Users' Tweets



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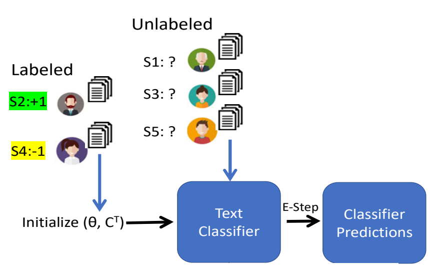
Classifier 2: A Typical Text Based Classifier

- A simple text classifier (e.g. Support Vector Machine) uses labeled data to train a model
- The trained model is used to predict labels of unlabeled data



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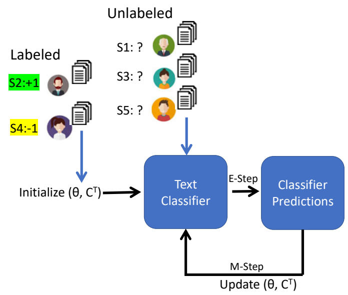
Classifier 2: A Text Classifier with Self-Training

- When plenty of unlabeled data is available, models' predictions could be used to train a better model… also called self-training [1]

- **Self-training exploits unlabeled data**

- In self-training, in every iteration, **new 'confident' predictions are used as new training examples**



Users with high confidence (C_j^T > Threshold)

1. Nigam, Kamal, and Rayid Ghani. "Analyzing the effectiveness and applicability of co-training." In *Proceedings of the ninth international conference on Information and knowledge management*, pp. 86-93. 2000.

Classifier 2: An SVM Text Classifier with Confidence Estimate and a Decreasing Threshold Function

$$s_j^T = \begin{cases} 1, & \text{if } \frac{\sum_{k=1}^{m} \mathbf{1}_{s_k>0}}{\sum_{k=1}^{m} 1} > f_t(\theta^T) \\ -1, & \text{elif } \frac{\sum_{k=1}^{m} \mathbf{1}_{s_k<0}}{\sum_{k=1}^{m} 1} > f_t(\theta^T) \\ 0, & \text{otherwise} \end{cases}$$

$$c_j^T = \begin{cases} \frac{\sum_{k=1}^{m} \mathbf{1}_{s_k>0}}{\sum_{k=1}^{m} 1}, \text{if } s_j^T > 0 \\ \frac{\sum_{k=1}^{m} \mathbf{1}_{s_k<0}}{\sum_{k=1}^{m} 1}, \text{elif } s_j^T < 0 \\ 0, \qquad \text{otherwise} \end{cases}$$

s_j^T = stance of j^{th} user
s_k = stance of k^{th} text message of user j
f_t = Uniformly decreasing function
θ^T = text threshold
c_j^T = user text-based confidence estimate

Stance and confidence estimate of user j based on his/her tweets' text

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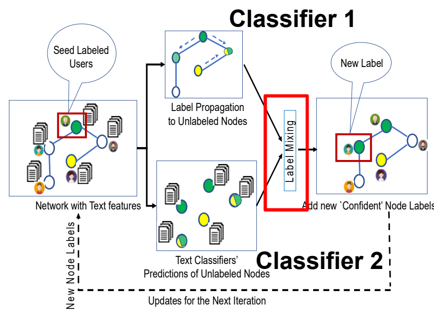
In 'Label Mixing', add the top 5% confident predictions as new training examples in the next iteration



- In **co-training**, more confident predictions (of both classifiers) are added as new training data in each iteration
- In each iteration, we use the **top 5% predictions of both classifiers** as new training examples. In case of a conflict among classifiers, we use the the more confident prediction

Joint Model: It Combines the Predictions of Both the Text and the Network Classifier

$$s_j = \begin{cases} 0, \text{if } C_j^T = C_j^I = 0 \\ s_j^T, \text{elif } C_j^T >= C_j^I \\ s_j^I, \text{Otherwise} \end{cases}$$

s_j = stance of j^{th} user (joint model)
s^T_j = stance of j^{th} user based on text
s^I_j = stance of j^{th} user based on interaction
c^T_j = user text based confidence estimate
c^I_j = user interaction based confidence

The joint model uses the predictions of the more confident of the two classifiers (text and network) to predict the final stance

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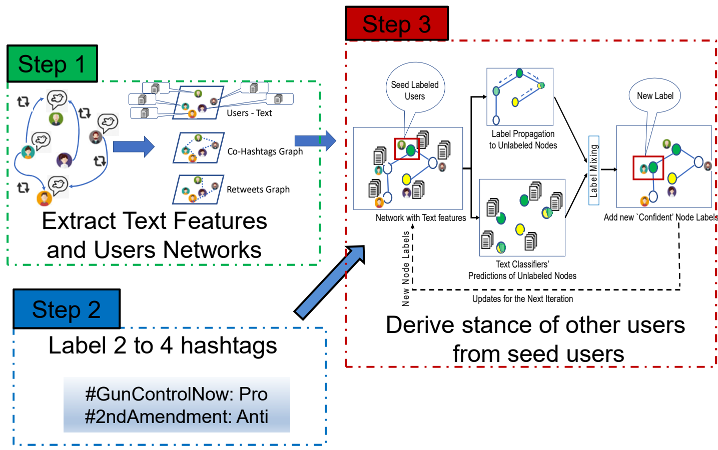
Summary - Three Steps to Train Two Stance Classifiers



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Experiment: Users' Stance Dataset on Three Controversial Topics

Events	Users	Tweets	RT Users	Hashtags	Endtags
Gun-control	70387	117679	15635	8587	5505
Obamacare	67937	123320	14807	11559	7376
Abortion	111463	173236	26818	15646	9784

Dataset

Events	Neutral	Pro	Anti	Total
Gun-control	60	156	288	504
Obamacare	33	108	363	504
Abortion	55	169	280	504

Labeled Users in the Dataset

Haokai Lu, James Caverlee, and Wei Niu. 2015. BiasWatch: A Lightweight System for Discovering and Tracking Topic-Sensitive Opinion Bias in Social Media. In Proceedings of the 24th ACM International on Conference on Information and Knowledge Management (CIKM '15). ACM, New York, NY, USA, 213-222. DOI: https://doi.org/10.1145/2806416.2806573

Experiment: Manually Labeled Four Hashtags in Each Dataset

Dataset	Seed Hashtags	No. of Seed Users
Gun-control	#guncontrolnow: Pro, #endgunviolence: Pro, #2ndamendment: Anti, #secondamendment: Anti	Pro:782, Anti:321
Obamacare	#uniteblue: Pro, #ilikeobamacare: Pro, #defundobamacare: Anti, #dontfundit: Anti	Pro:1342, Anti:3883
Abortion	#prochoice: Pro, #reprorights: Pro, #prolife: Anti, #stand4life: Anti	Pro:499, Anti:2183

Labeled two pro and two anti hashtags in each dataset

Experiment Details

- 3 hop label propagation is used by the network classifier
- SVM classifier is used as the text classifier
  - TF-IDF features
  - Unigrams and bigrams are used
- Hyper-parameters were determined by evaluating them on the gun-control dataset
  - Top 250 hashtags are used
  - Top 5000 retweets are used

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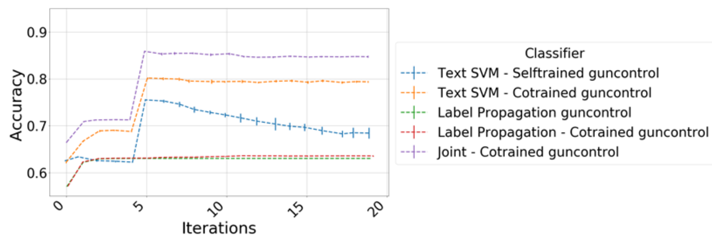
Result: Co-Trained Classifiers Perform Better than Self-Trained



Test Accuracy Trend for the Gun-Control dataset

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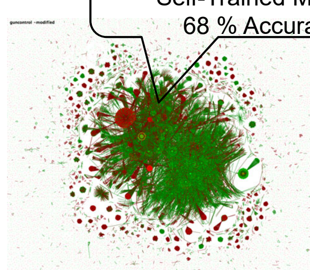
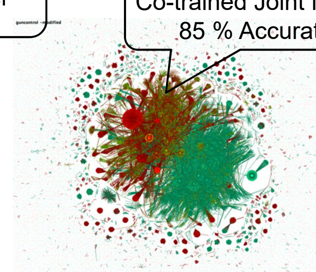
Result: Co-trained Models Outperform Self-Trained Models

Text based
Self-Trained Model
68 % Accurate



Co-trained Joint Model
85 % Accurate



Gun-Control Dataset

Red nodes are `Pro' and Green are `Anti'

Red nodes are `Pro' and Green are `Anti'

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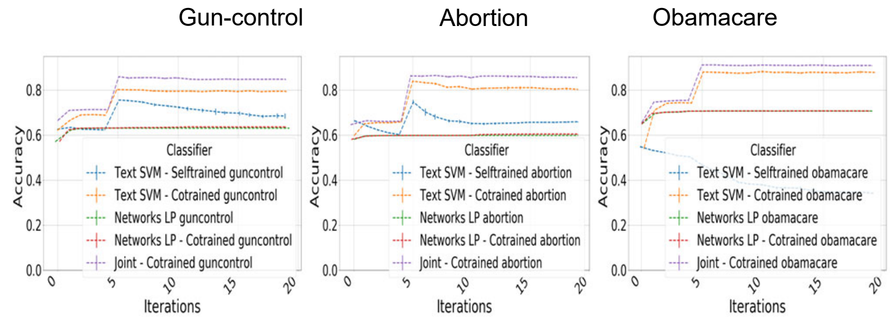
Result: Co-Trained Classifiers Perform Better than Self-Trained on All Dataset



- Text classifier improves by more than 17% on all three datasets
- LP in the figure implies bi-partitie label propagation

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Results: Comparing Different Seed Hashtags

Seed Hashtags	Classifier Type	Metric→ Dataset↓	Accuracy	Precision	Recall	F1-Score	Labeled Users (Fraction)
#stand4life:+1, #prochoice:-1	Hashtags + Retweets + Text Joint	abortion	0.38	0.38	0.98	0.54	0.98
#prolife:+1, #prochoice:-1	Hashtags + Retweets + Text Joint	abortion	**0.83**	0.77	0.78	0.78	0.94
#reprorights:+1, #stand4life:-1	Hashtags + Retweets + Text Joint	abortion	**0.83**	0.76	0.80	0.78	0.94
#endgunviolence:+1, #secondamendment:-1	Hashtags + Retweets + Text Joint	guncontrol	0.68	1.00	0.09	0.16	0.96
#2ndamendment:+1, #guncontrolnow:-1	Hashtags + Retweets + Text Joint	guncontrol	**0.81**	0.87	0.55	0.67	0.92
#2ndamendment:+1, #endgunviolence:-1	Hashtags + Retweets + Text Joint	guncontrol	0.68	1.00	0.10	0.18	0.96
#ilikeobamacare:+1, #defundobamacare:-1	Hashtags + Retweets + Text Joint	obamacare	0.80	0.81	0.16	0.26	0.95
#uniteblue:+1, #defundobamacare:-1	Hashtags + Retweets + Text Joint	obamacare	0.90	0.87	0.67	0.75	0.92
#uniteblue:+1, #dontfundit:-1	Hashtags + Retweets + Text Joint	obamacare	**0.91**	0.84	0.75	0.79	0.90

Comparison of Seed Hashtags: Some Seed Hashtags May lead to Poor Models

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Any Questions So Far?

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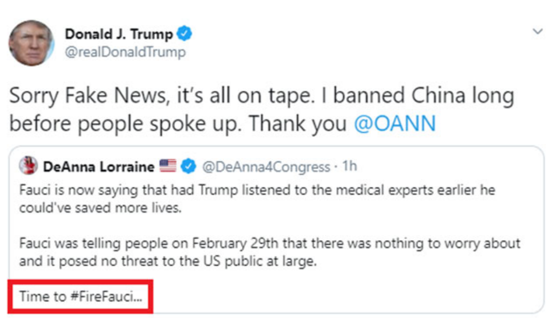
Case Study- Twitter COVID-19 Data
Analyze Users Stance on `Fire Dr. Fauci'

Topic -- Fire Dr. Fauci



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Case Study- Twitter COVID-19 Data
Analyze Users Stance on `Fire Dr. Fauci'

Input:

1. Twitter data as Json file
2. Labeled Hashtags

Output:

1. Users Stance Labels
2. Other Hashtags Stance Labels
3. URL Stance labels

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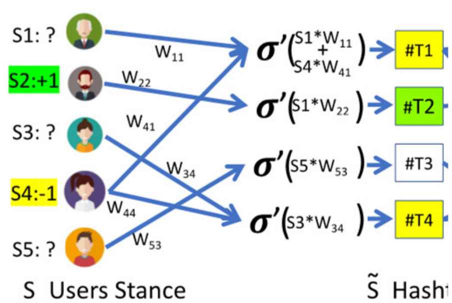
Model for Propagating Stance from Users to Other Entities E.g. From Users' Stance to Stance Given by Hashtags



Users Stance → Hashtags Stance
Users Stance → URLs (Websites) Stance
Users Stance → Media URLs (Pictures) Stance

Stance Mining Applied to 'Fire Dr. Fauci' in Covid Data

– Fire Dr. Fauci (vs Save Dr. Fauci)

Tags used for data filtering: 'fauci', 'firing fauci', '#firefauci', '#firetrump' ,'#savefauci',

– Labeled seed hashtags for stance analysis

firefauci:1,firedrfauci:1,faucithefraud:1,
savefauci:-1,fauciisahero: -1,keepfauci: -1,firetrumpkeepfauci: -1

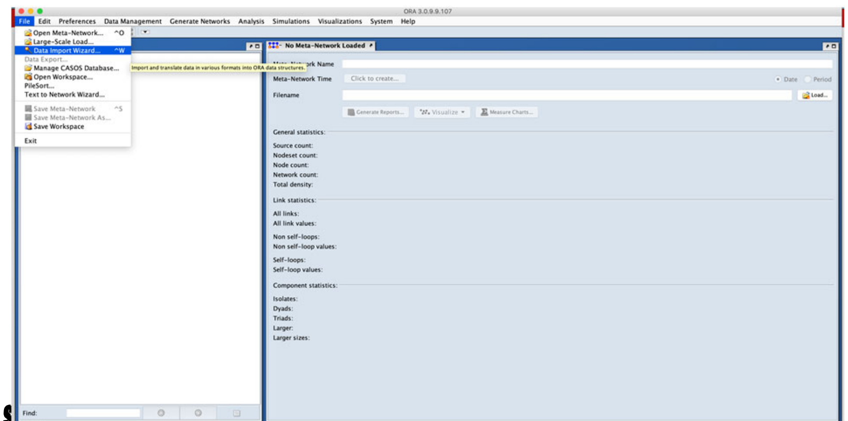
Agenda - I Try to Answer Two Questions in This part of the Talk

1. How to identify the users that are pro (or anti) a given topic?
2. How the users differ in their usage of hashtags?

<Your Name>

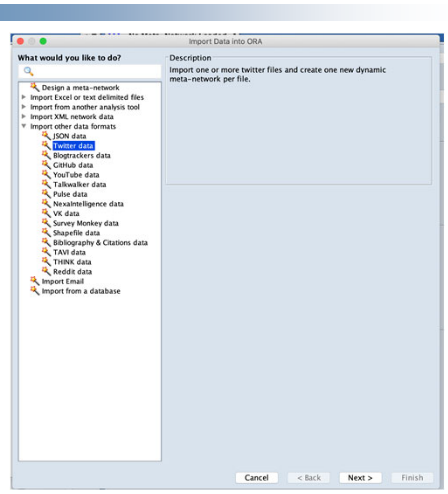
Start ORA

- Start ORA and Import Data



Import Twitter Data

- Pick Twitter Data



<Your Name>

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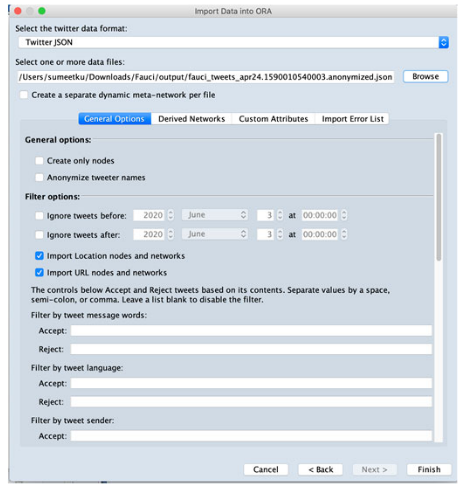
Import Twitter Data

- Pick Twitter Data
- Select Import Options



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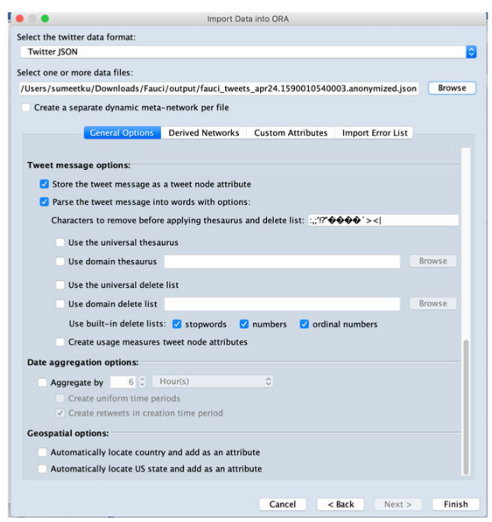
Import Twitter Data

- Pick Twitter Data
- Select Import Options



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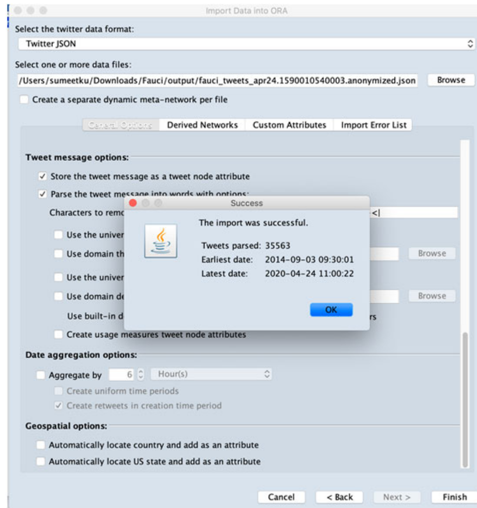
Import Twitter Data

- Pick Twitter Data
- Select Import Options



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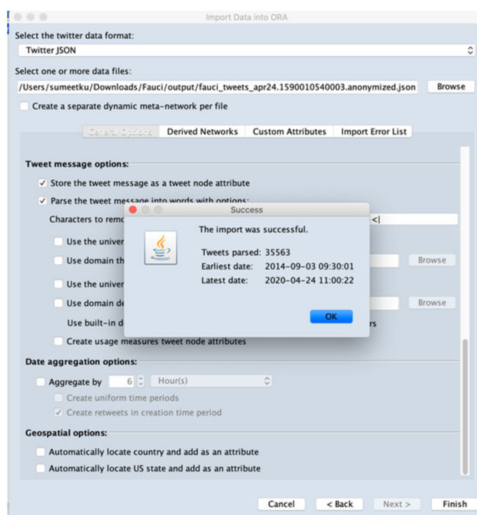
Import Twitter Data

- Pick Twitter Data
- Select Import Options
- Import Data



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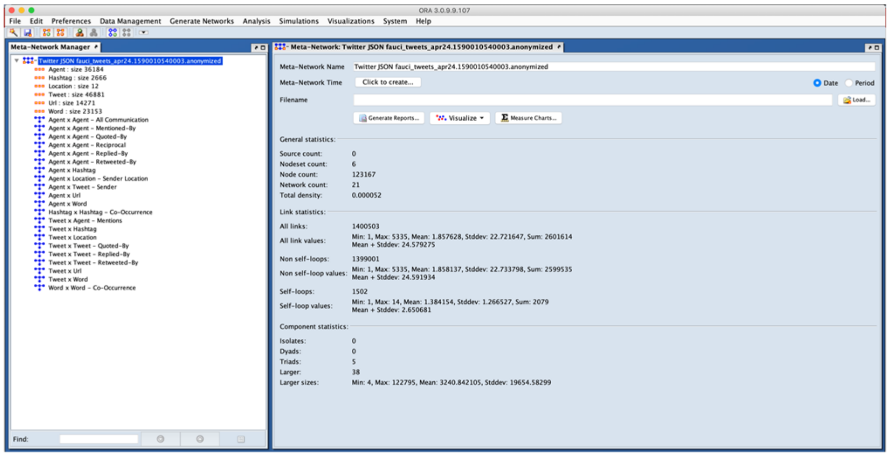
Import Twitter Data



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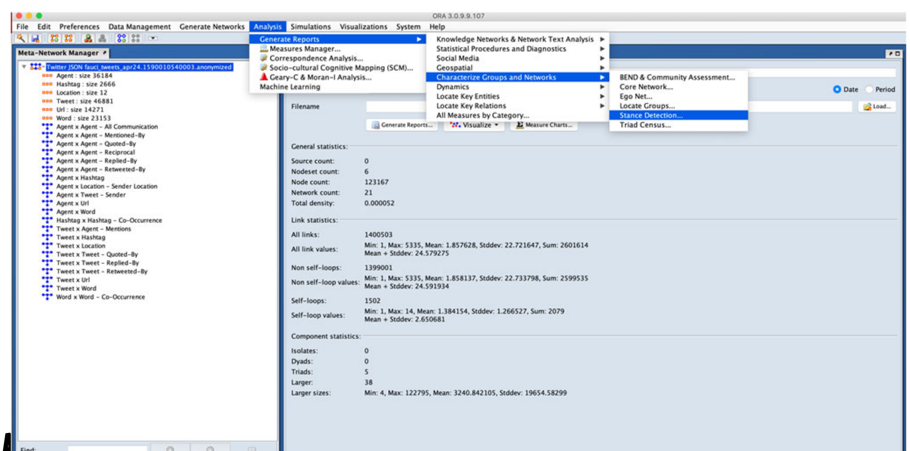
Start Stance Detection Analysis

- Pick the option shown below



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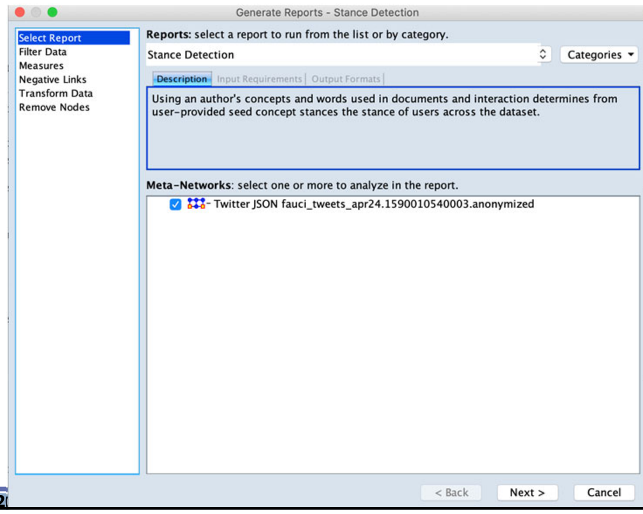
Start Stance Detection Analysis

- Pick the option shown below



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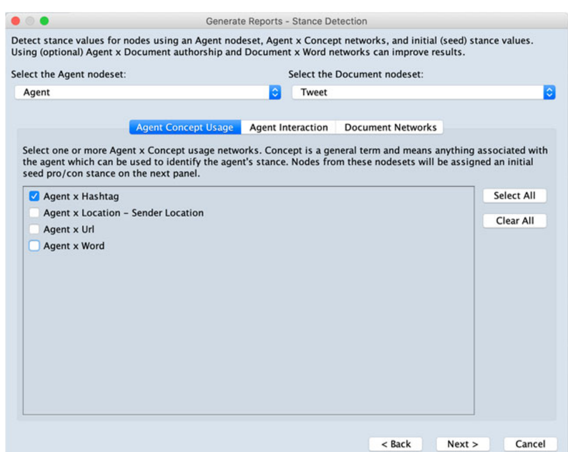
Stance Detection Analysis

- Pick the option shown below



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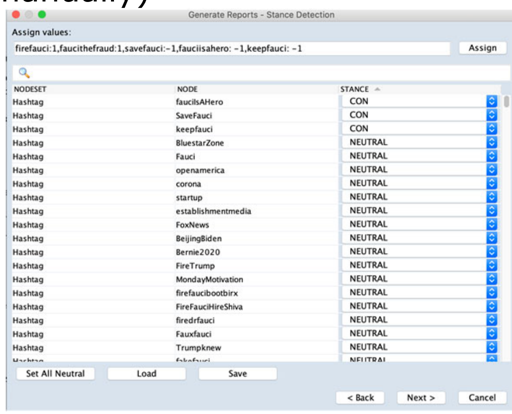
Stance Detection Analysis

- Assign stance values to a selected set of hashtags
- You can copy paste the values from the slide (or enter it manually)



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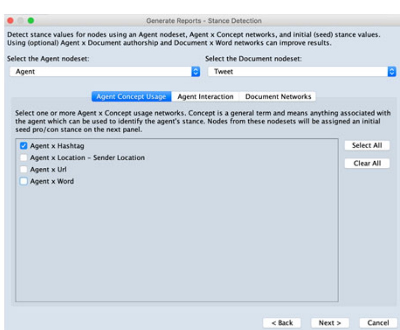
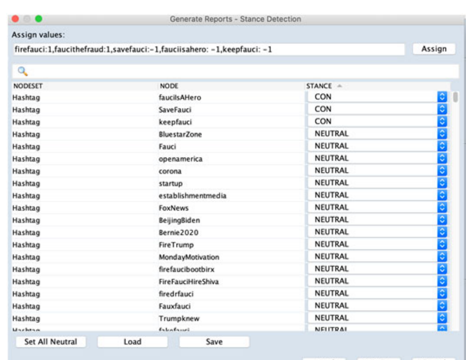
Stance Detection Analysis

- Assign stance values to a selected set of hashtags
- You can copy paste the values from the slide (or enter it manually)





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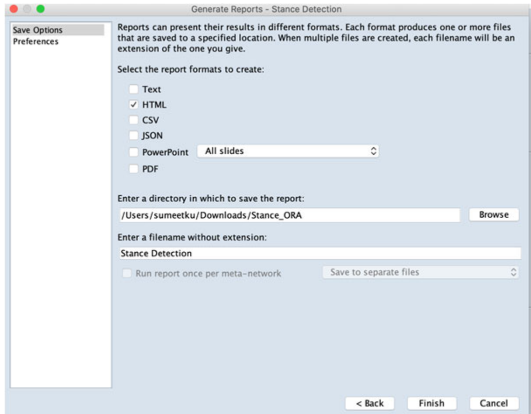
Stance Detection Analysis

- Select save option
- Stance detection report will be generated



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Stance Detection Analysis

- Stance detection report – shows selected options

STANCE DETECTION REPORT

Input data: Twitter JSON fauci_tweets_apr24.1590010540003.anonymized

Start time: Wed Jun 3 10:03:29 2020

Data Description

Parameters

Agent nodeset	Agent
Concept nodesets:	Hashtag
Agent x Concept networks:	Agent x Hashtag
Agent Interaction networks:	Agent x Agent - Quoted-By, Agent x Agent - Reciprocal, Agent x Agent - Mentioned-By, Agent x Agent - Retweeted-By, Agent x Agent - Replied-By, Agent x Agent - All Communication
Document nodeset	Tweet
Document Authorship network	Agent x Tweet - Sender
Document Word network	Tweet x Hashtag

Initial Node Stances (seeds)

Show 10 entries Search:

Nodeset	Node	Stance
Hashtag	firefauci	pro
Hashtag	FauciTheFraud	pro
Hashtag	fauciIsAHero	contra
Hashtag	SaveFauci	contra
Hashtag	keepfauci	contra

Showing 1 to 5 of 5 entries Previous 1 Next

Agent Stance Summary

	Number of nodes	Mean node confidence
Pro Nodes	23827	0.688
Contra Nodes	4953	0.793
Not Assigned	7404	

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Stance Detection Analysis

- Stance detection report – shows Pro/Con Users

Agent Pro Stance

The pro-stance Agent nodes ranked by the confidence of the stance calculation.

If the node of interest has a higher than normal value (greater than 1 standard deviation(s) above the mean) the row is colored red. The row is green if the node is within 1 standard deviation of the mean. Finally, the row is colored blue if the node has a lower than normal value (less than one standard deviation(s) below the mean).

Show 10 entries Search:

Rank	Agent	Value
1	00723701865095	1
2	00723705268049	1
3	00723724294048	1
4	00723725977048	1
5	00723733944057	1
6	0116Elliott	1
7	01Cole	1
8	0ctoberReignz	1
9	10723698727057	1
10	10723699813048	1

Showing 1 to 10 of 100 entries Previous 1 2 3 4 5 … 10 Next

Agent Contra Stance

The contra-stance Agent nodes ranked by the confidence of the stance calculation.

If the node of interest has a higher than normal value (greater than 1 standard deviation(s) above the mean) the row is colored red. The row is green if the node is within 1 standard deviation of the mean. Finally, the row is colored blue if the node has a lower than normal value (less than one standard deviation(s) below the mean).

Show 10 entries Search:

Rank	Agent	Value
1	007plus100	1
2	10723697569052	1
3	10723697919108	1
4	10723698624057	1
5	10723701960083	1
6	10723702125057	1
7	10723702364116	1
8	10723702820057	1
9	10723702823057	1
10	10723702991115	1

Showing 1 to 10 of 100 entries Previous 1 2 3 4 5 … 10 Next

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Stance Detection Analysis

- Stance detection report – shows Pro/Con hashtags by confidence

Hashtag Pro Stance

The pro-stance Hashtag nodes ranked by the confidence of the stance calculation.

If the node of interest has a higher than normal value (greater than 1 standard deviation(s) above the mean) the row is colored red. The row is green if the node is within 1 standard deviation of the mean. Finally, the row is colored blue if the node has a lower than normal value (less than one standard deviation(s) below the mean).

Show 10 entries Search:

Rank	Hashtag	Value
1	3D	1
2	4MoreYears	1
3	5GCoronavirus	1
4	5g	1
5	AAG	1
6	AAG2020	1
7	ANTHONYFAUCHI	1
8	After	1
9	AllLivesMatter	1
10	AmericaOpenForBusiness	1

Showing 1 to 10 of 100 entries Previous 1 2 3 4 5 … 10 Next

Hashtag Contra Stance

The contra-stance Hashtag nodes ranked by the confidence of the stance calculation.

If the node of interest has a higher than normal value (greater than 1 standard deviation(s) above the mean) the row is colored red. The row is green if the node is within 1 standard deviation of the mean. Finally, the row is colored blue if the node has a lower than normal value (less than one standard deviation(s) below the mean).

Show 10 entries Search:

Rank	Hashtag	Value
1	25thAmendmentNow	1
2	Anthony_Causi	1
3	ByeDon2020	1
4	COVIDActNow	1
5	DigitalMarketing	1
6	Dumptrump	1
7	FactsMatter	1
8	KeepFauciFireTrump	1
9	LiarInChief	1
10	Lizzo	1

Showing 1 to 10 of 66 entries Previous 1 2 3 4 5 6 7 Next

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Stance Detection Analysis

- Stance detection report – shows Pro/Con hashtags by usage

Agent Pro Stance, Hashtag Usage

The Hashtag nodes used the most by pro-stance agents, weighted higher when not used by contra-stance agents.

If the node of interest has a higher than normal value (greater than 1 standard deviation(s) above the mean) the row is colored red. The row is green if the node is within 1 standard deviation of the mean. Finally, the row is colored blue if the node has a lower than normal value (less than one standard deviation(s) below the mean).

Show 10 entries Search:

Rank	Hashtag	Value
1	BluestarZone	195
2	FireBirx	101
3	arrestfauci	61
4	FirefauciNow	52
5	indictfauci	44
6	qanon	38.091
7	BillGatesBioTerrorist	35
8	tuesdayvibes	31
9	firefaucibootbirx	29.333
10	MondayMood	28

Showing 1 to 10 of 100 entries Previous 1 2 3 4 5 … 10 Next

Agent Contra Stance, Hashtag Usage

The Hashtag nodes used the most by contra-stance agent, weighted higher when not used by pro-stance agents.

If the node of interest has a higher than normal value (greater than 1 standard deviation(s) above the mean) the row is colored red. The row is green if the node is within 1 standard deviation of the mean. Finally, the row is colored blue if the node has a lower than normal value (less than one standard deviation(s) below the mean).

Show 10 entries Search:

Rank	Hashtag	Value
1	corona	97.241
2	faucilsAHero	69
3	Resistance	45.667
4	killbill	33
5	SaveFauci	32.875
6	exposes	31
7	keepfauci	27
8	Resisters	20.500
9	Fauci	16
10	FauciBirxAreFrauds	16

Showing 1 to 10 of 100 entries Previous 1 2 3 4 5 … 10 Next

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Thank You

Please feel free to ask/send your questions

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