

# Sentiment, Stance and Affective Analysis for Mis/Disinformation

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Informed DEMocracy And Social cyber-security

Computational Analysis of Social and Organizational Systems



**Carnegie Mellon University**



# Agenda


## ❑ Sentiment Analysis

- ❑ Linguistic Methods: NetMapper run through 

## ❑ Stance Analysis

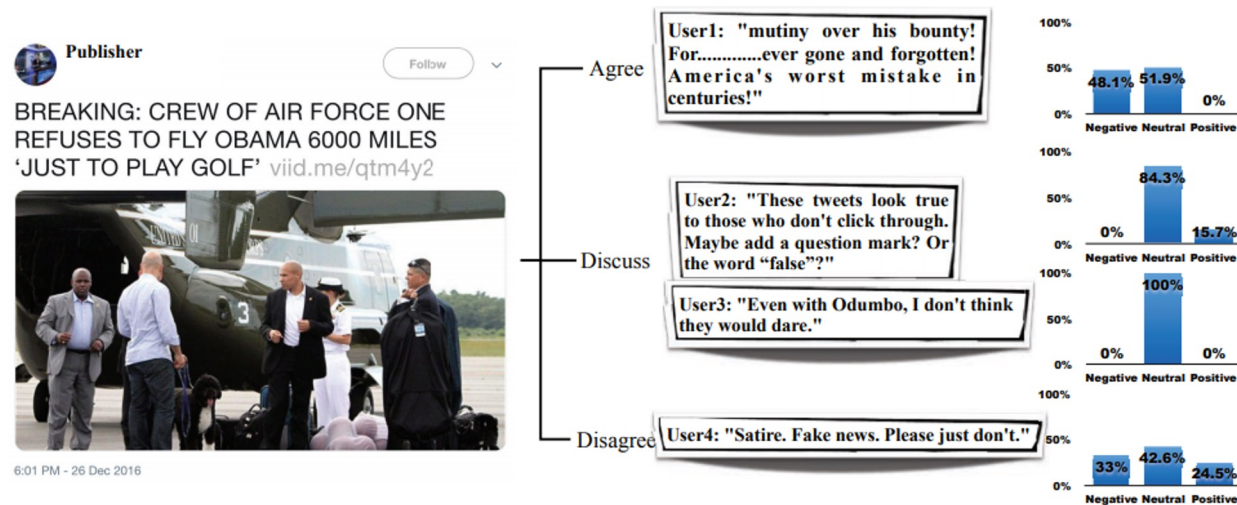
- ❑ Linguistic Methods
- ❑ Network Methods: Stance Propagation + ORA run through 
- ❑ Combining Linguistic + Network Methods 

## ❑ Affect Mining

- ❑ Textual Analysis
- ❑ Image Analysis 

# Sentiment Analysis

- “a view or attitude towards a situation or event”
- Fake News Detection as a Sentiment Analysis Problem:
  - If a news piece has an standard deviation of user sentiment scores greater than a threshold, then the news is weakly labeled as fake news.



**Twee**

**User Opinion**

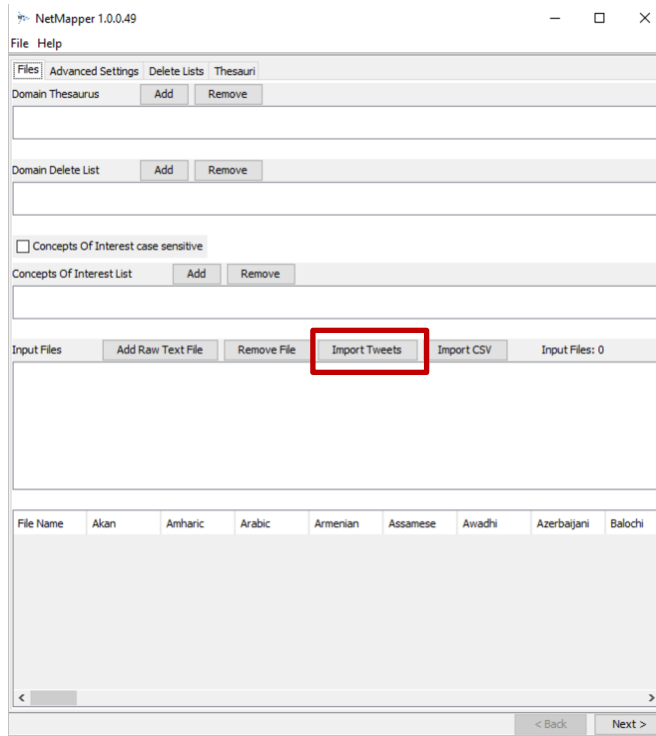
**Sentiment Distributions**

# Sentiment Analysis

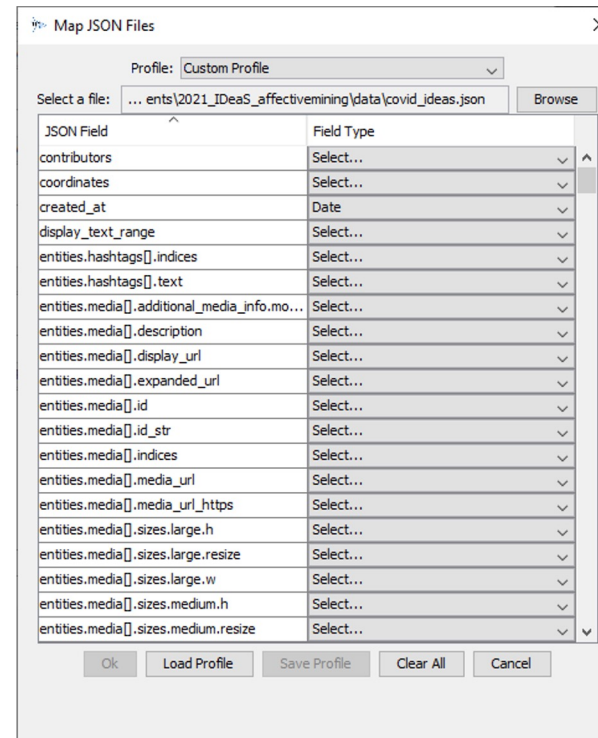


## Netmapper Example on COVID vaccine data

### 1. Import Tweets



### 2. Select Fields



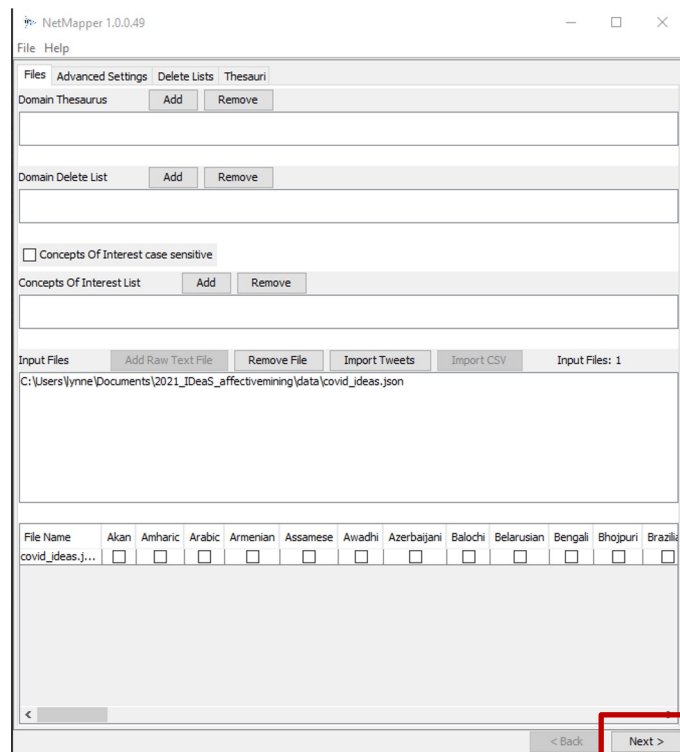
created\_at: Date  
id\_str: Tweet ID  
user.id\_str: Author  
extended\_tweet.full\_text: Text

# Sentiment Analysis

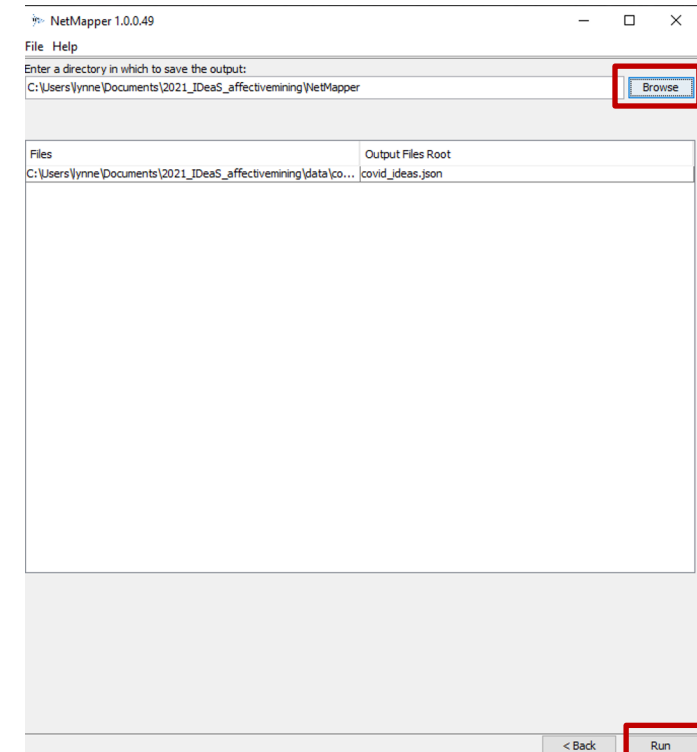
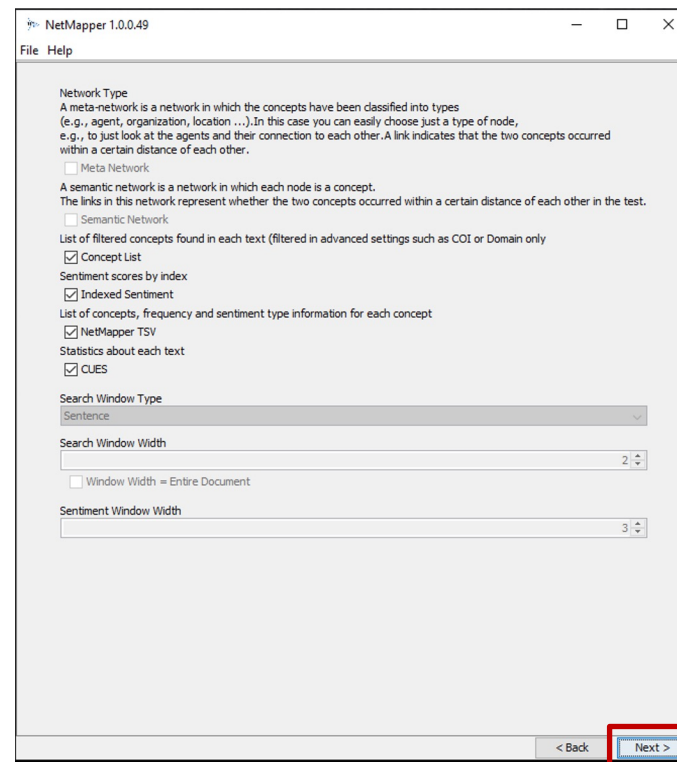


## Netmapper Example on COVID vaccine data

### 3. Next



### 3. Select Folder and Run



# Sentiment Analysis



## Netmapper Example on COVID vaccine data

### 5. Sentiment is in .cues.tsv

This PC > Documents > 2021\_IDeaS\_affectivemining > NetMapper

Name	Date modified	Type	Size
covid_ideas.json.concepts_per_line.tsv	5/17/2021 8:36 AM	TSV File	5 KB
covid_ideas.json.cues.tsv	5/17/2021 8:36 AM	TSV File	2 KB
covid_ideas.json.emoticon.tsv	5/17/2021 8:36 AM	TSV File	1 KB
covid_ideas.json.hashtag.tsv	5/17/2021 8:36 AM	TSV File	1 KB
covid_ideas.json.indexed_sentiment.tsv	5/17/2021 8:36 AM	TSV File	3 KB
covid_ideas.json.phone_number.tsv	5/17/2021 8:36 AM	TSV File	0 KB
covid_ideas.json.rmmf.tsv	5/17/2021 8:36 AM	TSV File	5 KB
covid_ideas.json.twitter_handle.tsv	5/17/2021 8:36 AM	TSV File	1 KB
covid_ideas.json.url.tsv	5/17/2021 8:36 AM	TSV File	1 KB
covid_ideas.json.zip_code.tsv	5/17/2021 8:36 AM	TSV File	0 KB
file_map.csv	5/17/2021 8:36 AM	Microsoft Excel C...	0 KB

R	S	T	U	V	W
connective	positive	negative	1st person	2nd person	3rd person
1	5				
	1				
1	9	3	1		
	6	4			
	4	1			
2	4	5			
	5	3			1
		1			
	5	2			

### 6. Can be imported as attribute in ORA

# Stance Analysis

- ❑ An “expression of speaker’s standpoint and judgement towards a given proposition” (Biber and Finegan, 1988)
- ❑ A “mental or emotional position adopted with respect to a proposition, a person, an idea etc” (The Free Dictionary)
- ❑ Typically, a user’s stance is characterized as: Pro, Con, Neutral



**Tweet**



**Target/Topic**



**Stance (Pro/Con)**

# Linguistic Methods

- ❑ Fact checking as a stance analysis problem
- ❑ Fake News Challenge: detect the relatedness of a news article's body to a headline based on the stance a former takes regarding the latter, annotated by AGREE/ DISAGREE/ DISCUSSES
- ❑ FEVER: claim-evidence pairs annotated by SUPPORTED/ REFUTED/ NOT ENOUGH INFO; helps fact-checkers understand the decision models made in assessment of claim veracity



# Linguistic Methods

## □ Key datasets in Stance Analysis for Disinformation

□ Note: Non-Comprehensive

Dataset	Source(s)	Target	Context	Evidence	#Instances	Task
<b>English Datasets</b>						
<i>Rumour Has It</i> [Qazvinian et al., 2011]		Topic	Tweet		10K	Rumours
<i>PHEME</i> [Zubiaga et al., 2016a]		Claim	Tweet		7.5K	Rumours
<i>Emergent</i> [Ferreira and Vlachos, 2016]		Headline	Article*		2.6K	Rumours
<i>FNC-1</i> [Pomerleau and Rao, 2017]		Headline	Article		75K	Fake news
<i>RumourEval '17</i> [Derczynski et al., 2017]		Implicit <sup>‡</sup>	Tweet		7.1K	Rumours
<i>FEVER</i> [Thorne et al., 2018]	W	Claim	Facts		185K	Fact-checking
<i>Snopes</i> [Hanselowski et al., 2019]	Snopes	Claim	Snippets		19.5K	Fact-checking
<i>RumourEval '19</i> [Gorrell et al., 2019]		Implicit <sup>‡</sup>	Post		8.5K	Rumours
<i>COVIDLies</i> [Hossain et al., 2020]		Claim	Tweet		6.8K	Misconceptions
<i>TabFact</i> [Chen et al., 2020]	W	Statement	WikiTable		118K	Fact-checking
<b>Non-English Datasets</b>						
<i>Arabic</i> [Baly et al., 2018]		Claim	Document		3K	Fact-checking
<i>DAST (Danish)</i> [Lillie et al., 2019]		Submission	Comment		3K	Rumour
<i>Croatian</i> [Bošnjak and Karan, 2019]		Title	Comment		0.9K	Claim verifiability
<i>Arabic</i> [Khouja, 2020]		Claim	Title		3.8K	Claim verification

Table 1: Key characteristics of the stance detection datasets for mis- and disinformation detection. #Instances denotes dataset size as a whole; the numbers are in thousands (K) and are rounded to the hundreds. \*the article's body is summarised. †the stance is expressed towards a topic, which is not present in the data. Sources: Twitter, News, Wikipedia, Reddit. Evidence: Single, Multiple, Thread.

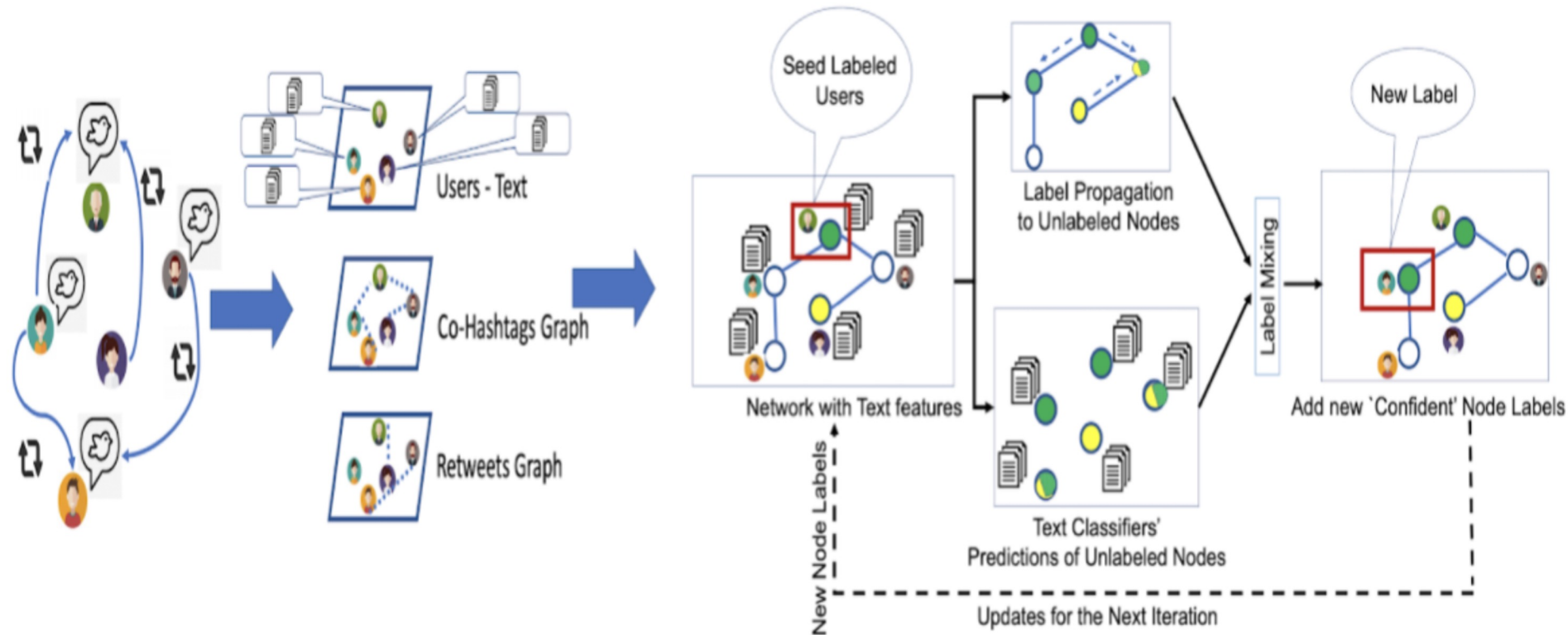
# Linguistic Methods

## □ General methods and features used for Stance Analysis

□ Note: Non-Comprehensive

Authors	Approach	Features	Subtask
[Taulé et al. 2017]	Majority class, LDR (baselines)	Term weights	Spanish & Catalan
[Lai et al. 2017]	SVM, logistic regression, decision tree, random forest, multinomial naïve Bayes, ensemble learner combining these classifiers, majority voting	Stylistic (word and character ngrams, POS tags, lemmas), structural (hashtags/mentions, hashtag frequencies, uppercase words, punctuation marks, numbers of words and characters), contextual (language, URL) features	Spanish & Catalan
[García and Flor 2017]	SVM and ANN	TF-IDF vectors of unigram and hashtag features	Spanish & Catalan
[Vinayakumar et al. 2017]	RNN, LSTM, GRU, and logistic regression	Word embeddings	Spanish & Catalan
[González et al. 2017]	SVM, LSTM, CNN, multilayer perceptron	Character and word ngrams, word embeddings vectors, character one-hot vectors, and a sentiment lexicon feature	Spanish
[Barbieri 2017]	FastText	Word embeddings considering subword information	Spanish & Catalan
[Swami et al. 2017]	SVM	Character (1-3) and word (1-5) ngrams, and stance indicative words	Spanish & Catalan
[Wojatzki and Zesch 2017]	SVM, LSTM, and a decision tree based hybrid system	Word (1-3) ngrams, character (2-4) ngrams, and word embeddings	Spanish & Catalan
[Ambrosini and Nicolo 2017]	LSTM, bidirectional LSTM, CNN	Word embeddings	Spanish & Catalan

# Network Methods – Stance Propagation



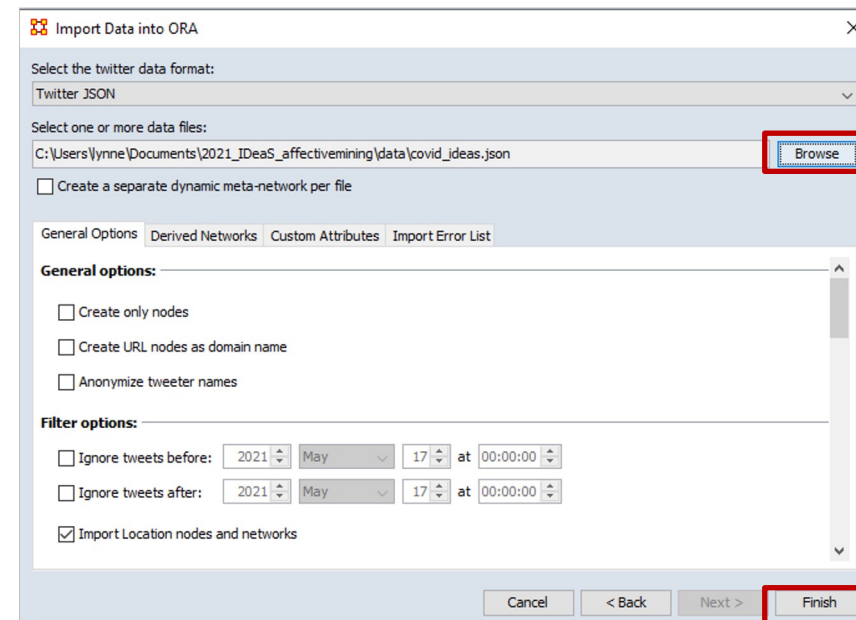
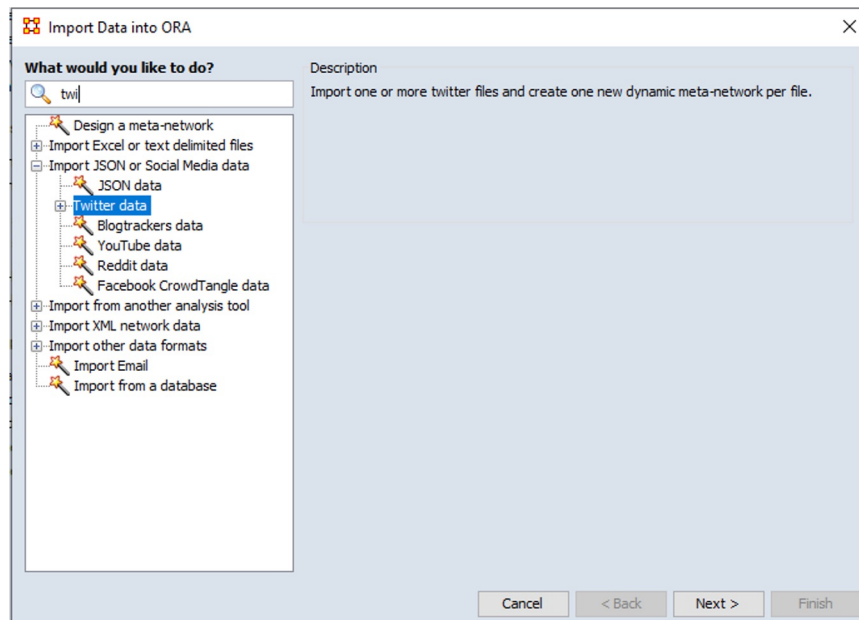
Kumar, S. (2020). *Social media analytics for stance mining a multi-modal approach with weak supervision* (Doctoral dissertation, Carnegie Mellon University).

# Network Methods – Stance Propagation



## ORA Example on COVID vaccine data

### 1. Import Data



# Network Methods – Stance Propagation



□ ORA Example on COVID vaccine data

## 2. Generate Reports

Meta-Network Name: Twitter JSON covid\_ideas

Meta-Network Time: Click to create...

Filename: [Red Box] Generate Reports... Visualize Measure Charts...

General statistics:

- Source count: 0
- Nodeset count: 4
- Node count: 254
- Network count: 16
- Total density: 0.005317

Link statistics:

- All links: 631
- All link values: Min: 1, Max: 4, Mean: 1.060222, Stddev: 0.274978, Sum: 669, Mean + Stddev: 1.335199
- Non self-loops: 628
- Non self-loop values: Min: 1, Max: 4, Mean: 1.06051, Stddev: 0.275602, Sum: 666, Mean + Stddev: 1.336111
- Self-loops: 3
- Self-loop values: Binary

Component statistics:

- Isolates: 0
- Dyads: 0
- Triads: 5
- Larger: 31
- Larger sizes: Min: 4, Max: 75, Mean: 7.709677, Stddev: 12.381551

## Select Stance Detection

Generate Reports - Stance Detection

Select Report: Reports: select a report to run from the list or by category.

Filter Data: [Red Box] Stance Detection Categories

Description: Input Requirements Output Formats

Using an author's concepts and words used in documents and interaction determines from user-provided seed concept stances the stance of users across the dataset.

Meta-Networks: select one or more to analyze in the report.

- Twitter JSON covid\_ideas

< Back Next > Cancel

## Select Agent x Hashtag

Generate Reports - Stance Detection

Detect stance values for nodes using an Agent nodeset, Agent x Concept networks, and initial (seed) stance values. Using (optional) Agent x Document authorship and Document x Word networks can improve results.

Select the Agent nodeset:

Agent

Agent Concept Usage Agent Interaction Document Networks

Select one or more Agent x Concept usage networks. Concept is a general term and means anything associated with the agent which can be used to identify the agent's stance. Nodes from these nodesets will be assigned an initial seed pro/con stance on the next panel.

- Agent x Hashtag
- Agent x Tweet - Sender
- Agent x Url

Select All Clear All

< Back Next > Cancel



# Network Methods – Stance Propagation



□ ORA Example on COVID vaccine data

## 3. Assign Stance Values

Run!

Nodeset	Node ID	Agent Usage Count	Stance
Hashtag	COVID19vaccine	87	NEUTRAL
Hashtag	CovidVaccine	464	NEUTRAL
Hashtag	COVID19	1581	NEUTRAL
Hashtag	Vaccine	1060	NEUTRAL
Hashtag	vaccineinjuries	25	NEUTRAL
Hashtag	كرونا	15	NEUTRAL
Hashtag	كرونا	14	NEUTRAL
Hashtag	Vaccines4All	10	NEUTRAL
Hashtag	olderadults	2	NEUTRAL
Hashtag	caregivers	2	NEUTRAL
Hashtag	SupportOurSeniors	1	NEUTRAL
Hashtag	GreyBuce	2	NEUTRAL
Hashtag	NoVaccines	10	CON
Hashtag	DFree	20	NEUTRAL
Hashtag	BioNTech	12	NEUTRAL
Hashtag	TrumpsPathetic	1	NEUTRAL
Hashtag	Covid_19	45	NEUTRAL
Hashtag	coronavirus	296	NEUTRAL
Hashtag	skynews	15	NEUTRAL
Hashtag	covid	175	NEUTRAL
Hashtag	COVIDIOTS	17	NEUTRAL

Reports can present their results in different formats. Each format produces one or more files that are saved to a specified location. When multiple files are created, each filename will be an extension of the one you give.

Select the report formats to create:

- Text
- HTML
- CSV
- JSON
- PowerPoint All slides
- PDF

Enter a directory in which to save the report:  
C:\Users\Yvonne\Documents\affectmining\data\ORAREports Browse

Enter a filename without extension:  
Stance Detection

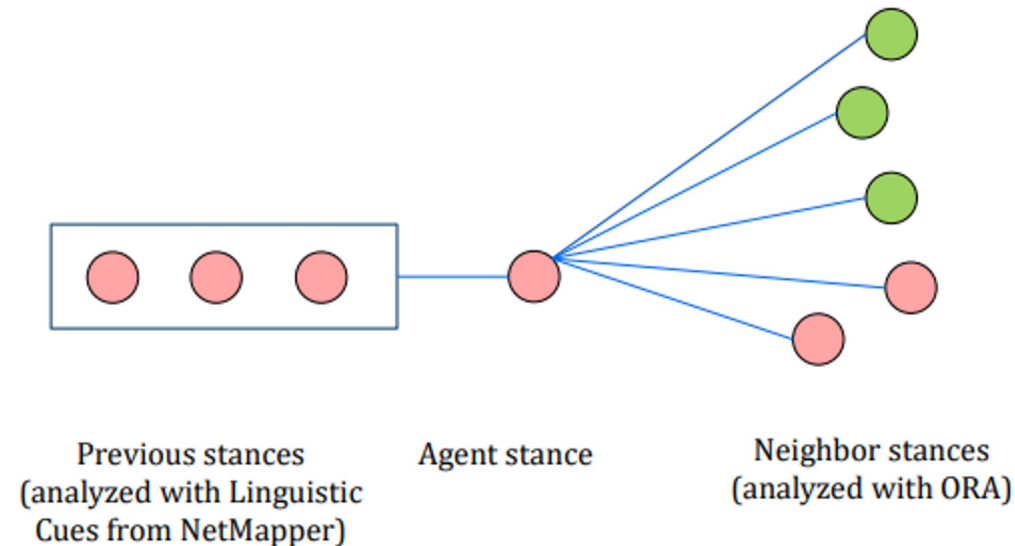
Run report once per meta-network Save to separate files



# Combining Linguistic & Network Methods



- Predicting stance flipping on Twitter using a Social Influence Model (ie provax > antivax)

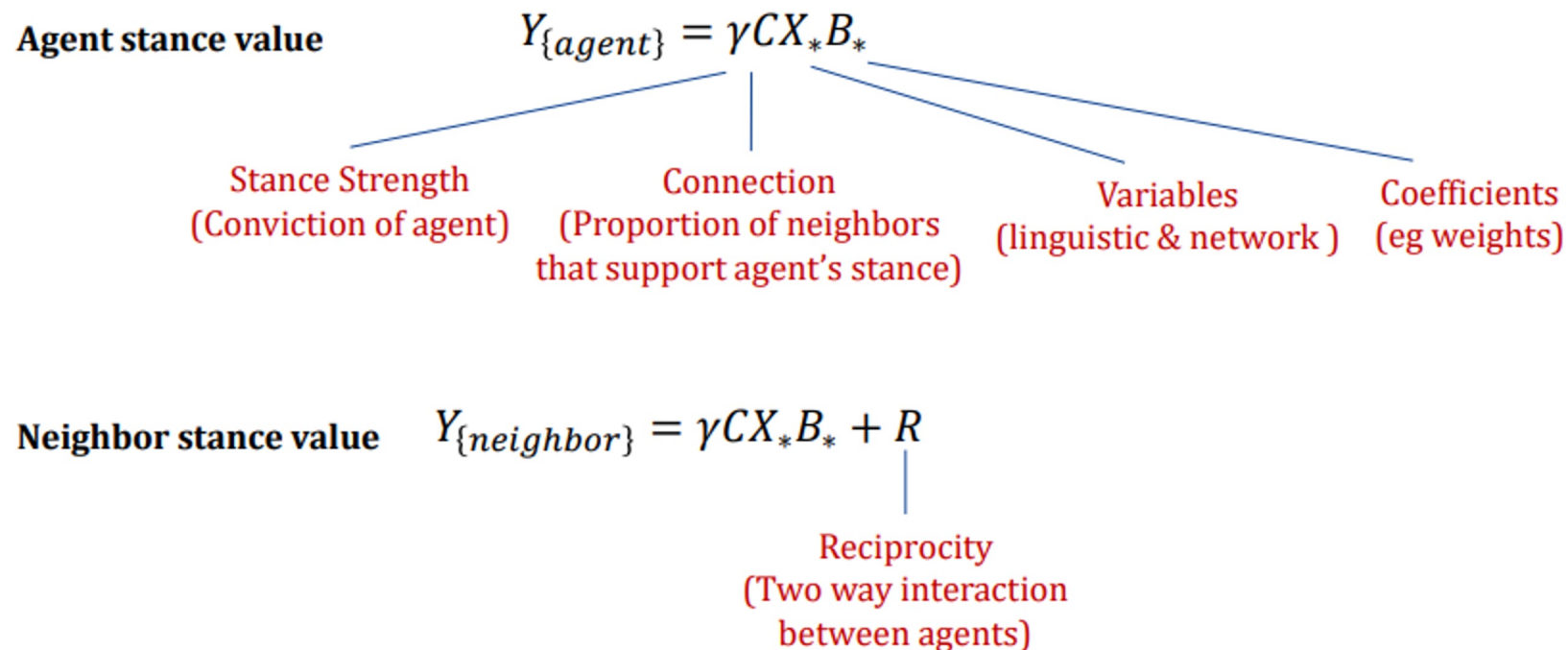




# Predicting Stance Flips with a Social Influence Model



- Predicting stance flipping using a Social Influence Model  
(ie provax > antivax)



# Predicting Stance Flips with a Social Influence Model



- Predicting stance flipping using a Social Influence Model  
(ie provax > antivax)

$$Y_{\{agent\}} = \gamma C X_* B_*$$

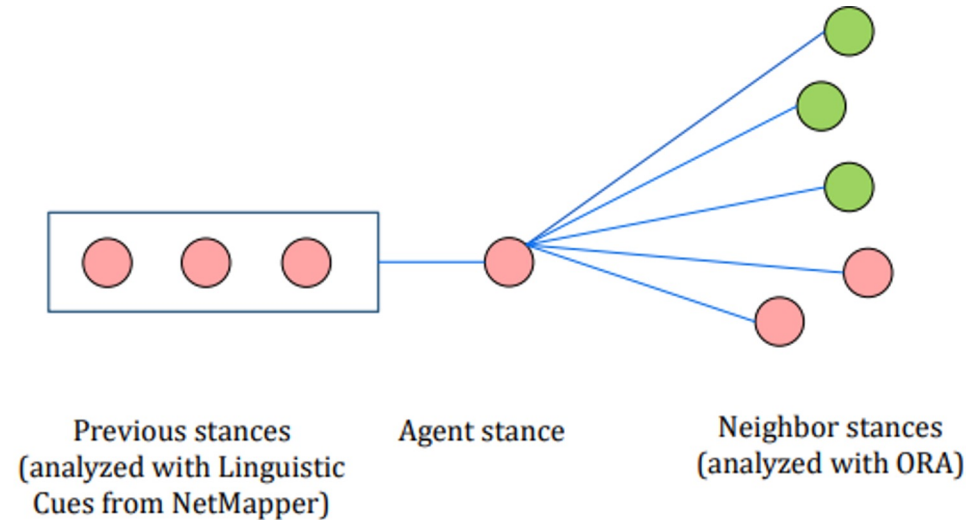
$$Y_{\{neighbor\}} = \gamma C X_* B_* + R$$

**Influence on an agent**

$$I = \alpha \left[ \sum_{i=0}^n Y_{\{1st\ deg\ neighbors\}} + \sum_{i=0}^n \sum_{j=0}^m \beta Y_{\{2nd\ deg\ neighbors\}} \right], \alpha = \frac{1}{n}, \beta = \frac{1}{m}$$

Influence from 1<sup>st</sup> degree neighbors  
(1 hop away)
Influence from 2<sup>nd</sup> degree neighbors  
(2 hops away)

# Predicting Stance Flips with a Social Influence Model



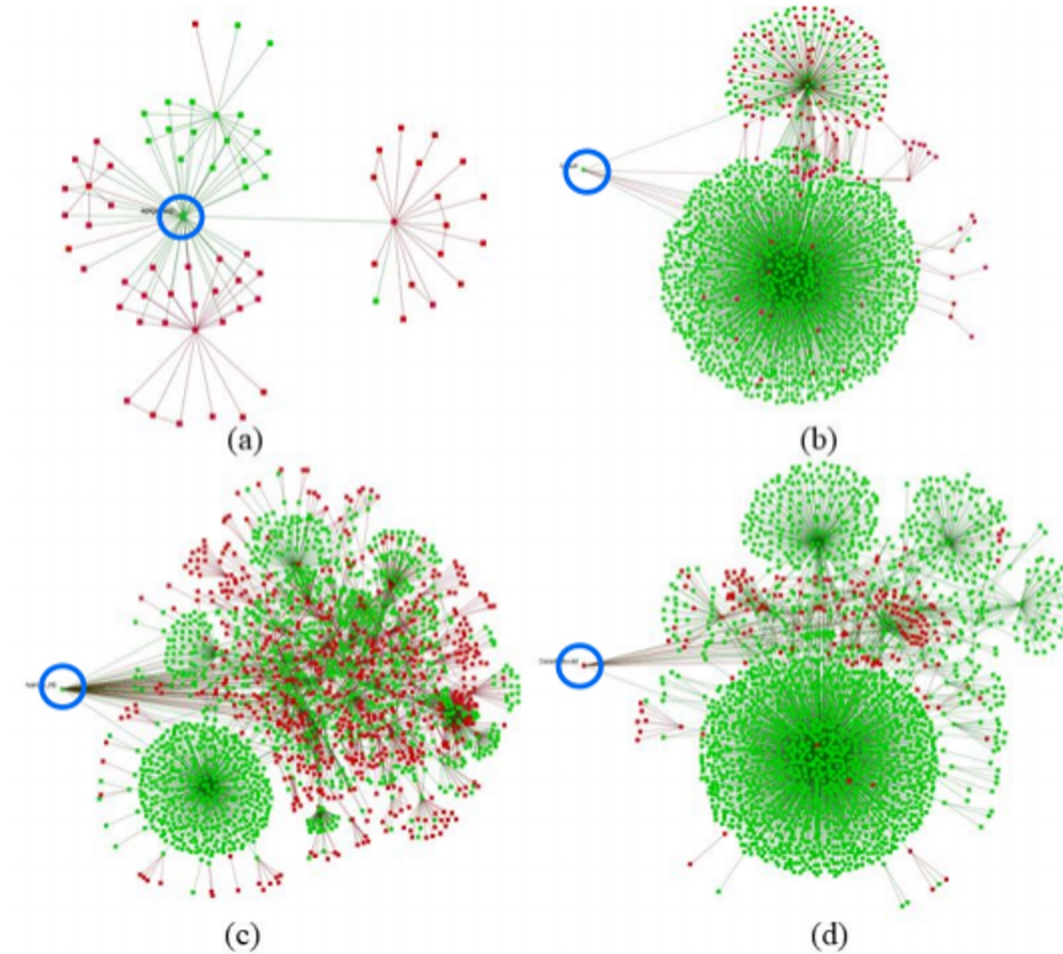
Model #	Model	Accuracy
Baseline	Decision Tree	0.53
Base - network	Base social influence model without network variables	0.47
Base - linguistic	Base social influence model without linguistic variables	0.55
Base Model 1	Base social influence model	0.50
Model 2	Model 1 + 2nd deg neighbor information	0.59
Model 3	Model 2 + stance strength	0.72
Model 4	Model 3 + connection	0.73
Model 5	Model 4 + reciprocity	0.86

Table 2: Results of Social Influence Models. The base social influence model is agent stance with 1st degree neighbor information.

# Predicting Stance Flips with a Social Influence Model



- ❑ Model accurately predicts 86% of the stance flips
- ❑ Positive examples:



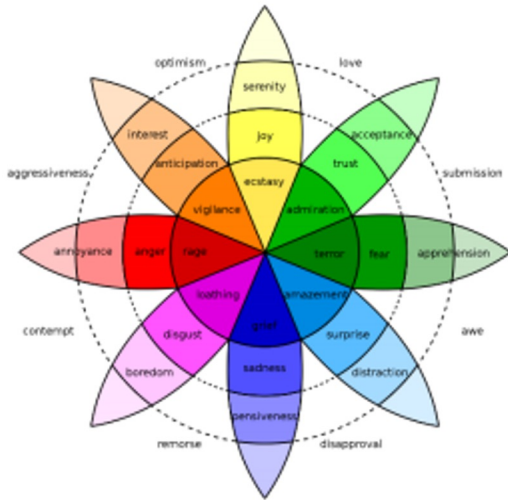
Green: provax  
Red: antivax

Circle: Agent in focus  
Stance of agent depicted before flip

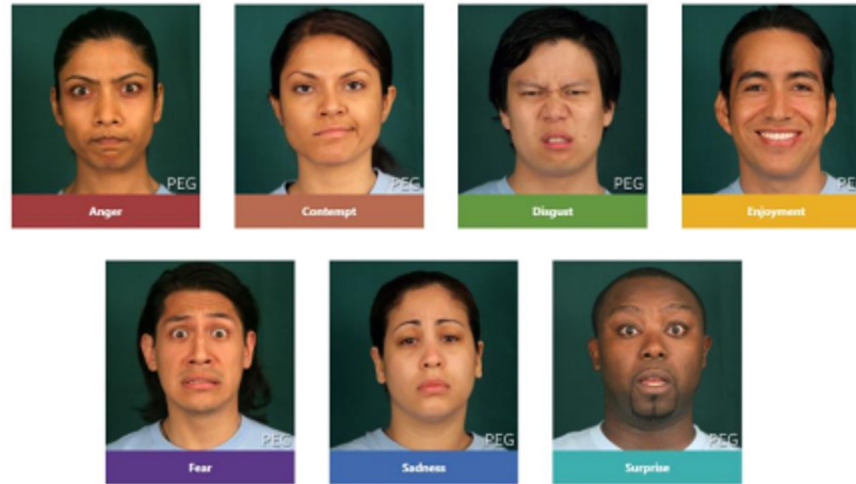
# Affect

□ “emotion or attitude a speaker brings to an utterance” (Besiner, 1990)

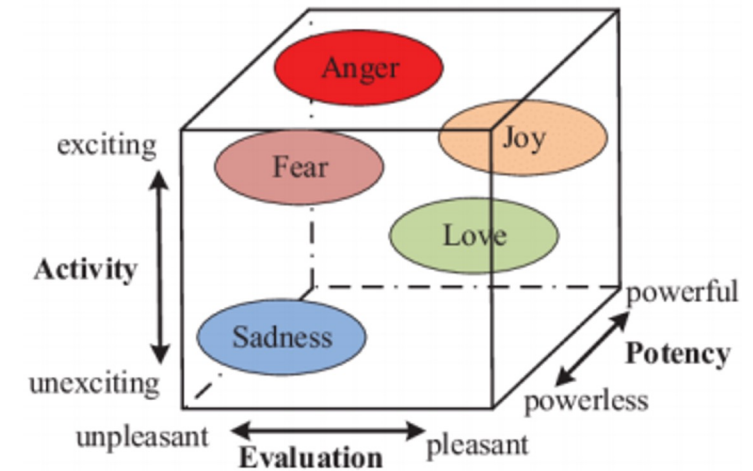
Putchnik



Ekman



Osgood



# Affect Control Theory

- ❑ Individuals maintain affective meanings (measured by EPA) through their actions and interpretations of events
- ❑ Deflections: distances in the EPA space, which can lead to actions
- ❑ Actions: a social behavior
- ❑ Emotions: events generate emotions for individuals
- ❑ Identity: who a person is (eg child, teacher)

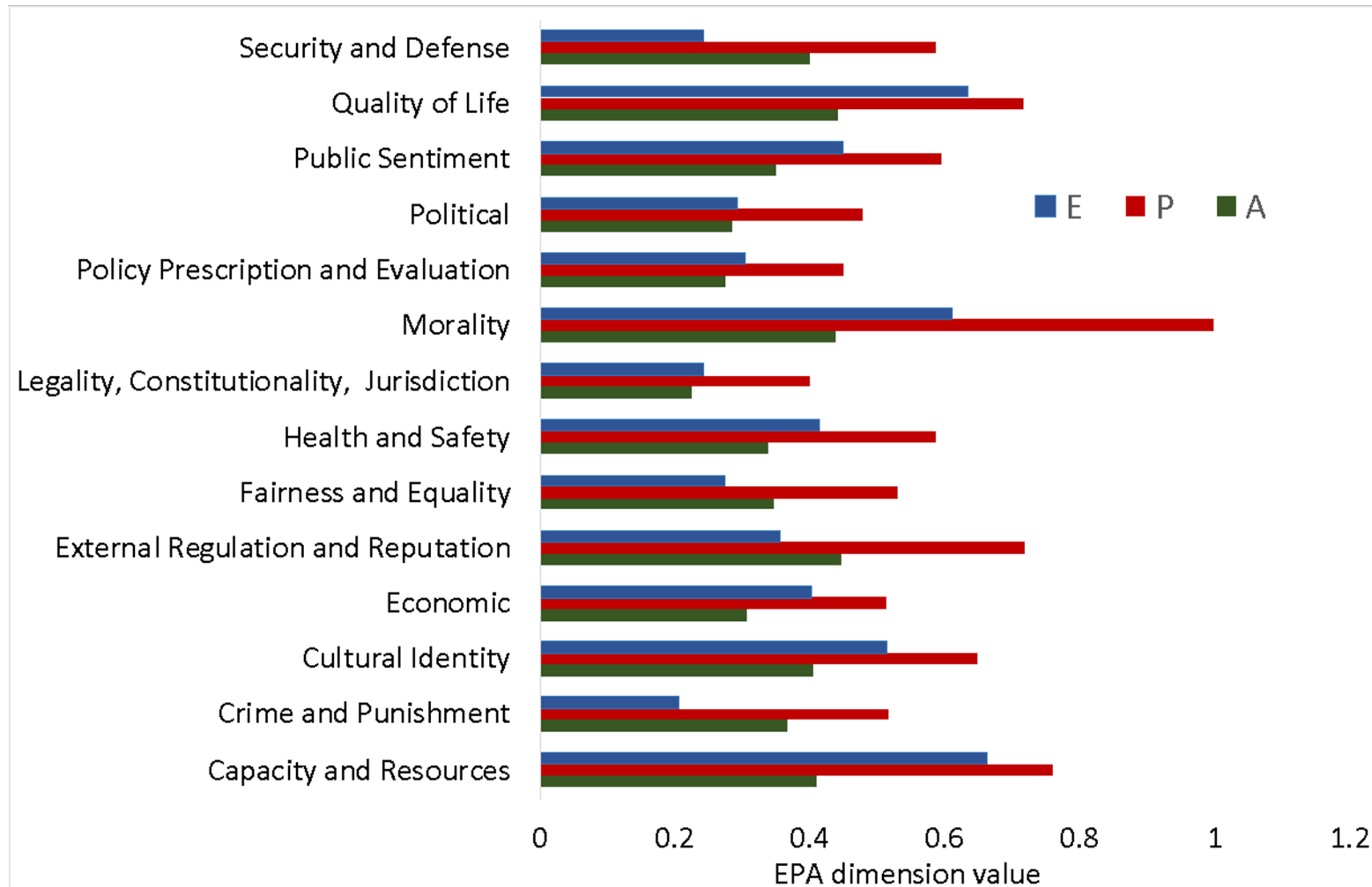


# Textual Affect Analysis



- Identifying dominant frames in climate change discourse
- EPA projections of frames
- Which frames are more dominant in climate change discourse ?
- What are the EPA projections of different frames
  - How does EPA projections of frames used in Climate Change news articles change with time
- Does frames with higher emotions lead to more reshare?

# Textual Affect Analysis





# Image Affect Analysis

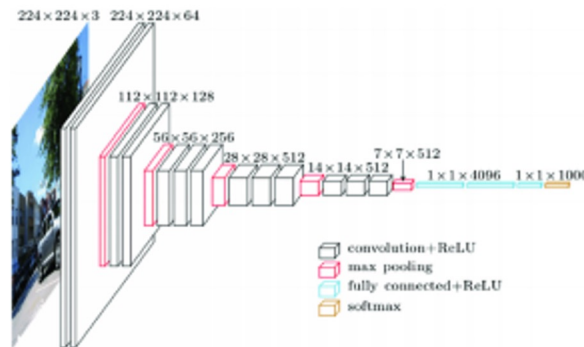


- Image affect classifier based off Flickr images
- Applied to recent social-cybersecurity event

## 1. Flickr Images (Putchnik emotional responses)



## 2. VGG Image Vector + CNN classifier



## 3. Annotate images in event



# References – Sentiment Analysis

- ❑ Ajao, O., Bhowmik, D., & Zargari, S. (2019, May). Sentiment aware fake news detection on online social networks. In *ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)* (pp. 2507-2511). IEEE.
- ❑ Bhutani, B., Rastogi, N., Sehgal, P., & Purwar, A. (2019, August). Fake news detection using sentiment analysis. In *2019 Twelfth International Conference on Contemporary Computing (IC3)* (pp. 1-5). IEEE.
- ❑ Kai Shu, Amy Sliva, Suhang Wang, Jiliang Tang, and Huan Liu. Fake news detection on social media: A data mining perspective. KDD exploration newsletter, 2017.
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- ❑ Shu, K., Wang, S., Lee, D., & Liu, H. (2020). Mining disinformation and fake news: concepts, methods, and recent advancements. In *Disinformation, Misinformation, and Fake News in Social Media* (pp. 1-19). Springer, Cham.

# References – Stance Analysis

- ❑ Dilek Küçük and Fazli Can. 2020. Stance Detection: A Survey. *ACM Comput. Surv.* 53, 1, Article 12 (February 2020), 37 pages. <https://doi.org/10.1145/3369026>
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- ❑ Friedkin, N. E., & Johnson, E. C. (1999). Influence networks and opinion change. *Advances in Group Processes*, 16(1), 1-29.
- ❑ Ghanem, B., Rosso, P., & Rangel, F. (2018). Stance detection in fake news a combined feature representation. In *Proceedings of the first workshop on fact extraction and VERification (FEVER)* (pp. 66-71). <https://www.aclweb.org/anthology/W18-5510.pdf>
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# References – Affect Mining

- ❑ Beskow, D. M., & Carley, K. M. (2019). *Social cybersecurity: an emerging national security requirement*. Carnegie Mellon University Pittsburgh United States.
- ❑ Besnier, N. (1990). Language and Affect. *Annual Review of Anthropology*, 19, 419-451. Retrieved May 10, 2021, from <http://www.jstor.org/stable/2155972>
- ❑ Osgood, Charles; May, W. H.; Miron, M. S. (1975), *Cross-Cultural Universals of Affective Meaning*, Urbana: University of Illinois Press.
- ❑ Ghanem, B., Rosso, P., & Rangel, F. (2020). An emotional analysis of false information in social media and news articles. *ACM Transactions on Internet Technology (TOIT)*, 20(2), 1-18.
- ❑ Heise, D. R. (1987). Affect control theory: Concepts and model. *Journal of Mathematical Sociology*, 13(1-2), 1-33.

# For More Information

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- ❑ IDeaS website - <https://www.cmu.edu/ideas-social-cybersecurity/>
- ❑ CASOS website - <http://www.casos.cs.cmu.edu/>
- ❑ Social Cybersecurity Working Group - <http://social-cybersecurity.org>
- ❑ Facebook: [@IDEasCMU](#)
- ❑ Twitter: [@IDeaSCMU](#)
- ❑ YouTube: [IDeaS Center](#)
- ❑ Email-Distro Lists

# Network Affect Analysis



- Identifying emotions for deterrence of disinformation campaign with BEND maneuvers
- Grab something from Janice**