Sentiment, Stance and Affective Analysis for Mis/Disinformation

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The CMU centers for:

Informed DEmocracy And Social cyber-security

Computational Analysis of Social and Organizational Systems





Carnegie Mellon University



Linguistic Methods: NetMapper run through 🏛

□ Stance Analysis

□Linguistic Methods

Network Methods: Stance Propagation + ORA run through imit

Combining Linguistic + Network Methods 💷

□Affect Mining

Textual Analysis

□Image Analysis IIII





"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.





Limeng Cui and Suhang Wang Dongwon Lee. Same: Sentiment-aware **t** multi-modal embedding for detecting fake news. 2019.

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□Netmapper Example on COVID vaccine data

1. Import Tweets

Files Advan	ced Settings	Delete Lists	Thesauri					
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Domain Delete	List	Add R	emove					
Concepts	Of Interest cas	e sensitive						
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concepto or r		1100						
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File Name	Akan	Amharic	Arabic	Armenian	Assamese	Awadhi	Azerbaijani	Balochi

2. Select Fields

		*	
Select a file:	ents\2021_IDeaS_affective	emining\data\covid_ideas.json	Browse
JSON Field	^	Field Type	
contributors		Select	~
coordinates		Select	~
created_at		Date	~
display_text	range	Select	~
entities.hash	tags[].indices	Select	~
entities.hash	tags[].text	Select	~
entities.medi	a[].additional_media_info.mo	Select	~
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entities.medi	a[].sizes.large.resize	Select	\sim
entities.medi	a[].sizes.large.w	Select	~
entities.medi	a[].sizes.medium.h	Select	~
entities.medi	a[].sizes.medium.resize	Select	~

created_at: Date id_str: Tweet ID user.id_str: Author extended_tweet.full_text: Text





□ Netmapper Example on COVID vaccine data

3. Next

🖮 NetMapper 1.0.0.49 —	□ ×
File Help	File Help
Files Advanced Settings Delete Lists Thesauri Domain Thesaurus Add Remove	Network Type A meta-network is a network in which the concepts have been classified into types (e.g., agent, organization, location).In this case you can easily choose just a type of node, e.g., to just look at the agents and their connection to each other. A link indicates that the two concepts occurred within a certain distance of each other.
Domain Delete List Add Remove	A semantic network is a network in which each node is a concept. The links in this network represent whether the two concepts occurred within a certain distance of each other in the test. Semantic Network List of filtered concepts found in each text (filtered in advanced settings such as COI or Domain only
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3. Select Folder and Run

– 🗆 🗙

< Back Next >

师 NetMapper 1.0.0.49	– 🗆 ×	
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C:\Users\ynne\Documents\2021_IDeaS_affectivemining\VetMapper	Browse	
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	< Back Run •)	
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	5	
	Cornorio Mo	llon Universi
	Garnegie we	non oniversi



□Netmapper Example on COVID vaccine data

5. Sentiment is in .cues.tsv

A			
Name	Date modified	Туре	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.rnmf.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

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connectiv	positive	negative	1st persor	2nd perso	3rd p
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1	9	3	1		
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2	4	5			
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	5	2			

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6. Can be imported as attribute in ORA

	ments (2021_L0ed5_affectivemining	Internapper (contr_ldeas.)son.cues.t	5V			browse	Clea
Step 2: Select how to	o identify the node(s) to get attribu	te values from a line of the file:					
Match Node	ID with file column twitter_id						
O Match node	attribute DATE	\sim with the v	alue from file column	twitter_id			
O Nodes are in	the same order as the file						
step 3: Select the co	olumns of the file to import as attribu	ute values:					
0							
ctive	19-positive	20-negative	21-1st perso	1	22-2	2nd person	
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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





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
		English Dat	asets			
Rumour Has It [Qazvinian et al., 2011]	y	Topic	Tweet		10K	Rumours
PHEME [Zubiaga et al., 2016a]	y	Claim	Tweet	Q	7.5K	Rumours
Emergent [Ferreira and Vlachos, 2016]	(DE)	Headline	Article*		2.6K	Rumours
FNC-1 [Pomerleau and Rao, 2017]	E	Headline	Article	E	75K	Fake news
RumourEval '17 [Derczynski et al., 2017]	y .	Implicit [‡]	Tweet	Q	7.1K	Rumours
FEVER [Thorne et al., 2018]	W	Claim	Facts		185K	Fact-checking
Snopes [Hanselowski et al., 2019]	Snopes	Claim	Snippets		19.5K	Fact-checking
RumourEval '19 [Gorrell et al., 2019]	¥0	Implicit [‡]	Post	Q	8.5K	Rumours
COVIDLies [Hossain et al., 2020]	¥	Claim	Tweet	Ē	6.8K	Misconceptions
TabFact [Chen et al., 2020]	W	Statement	WikiTable		118K	Fact-checking
	I	Non-English D	atasets			
Arabic [Baly et al., 2018]		Claim	Document	Ē	3K	Fact-checking
DAST (Danish) [Lillie et al., 2019]	•	Submission	Comment	9	3K	Rumour
Croatian [Bošnjak and Karan, 2019]		Title	Comment	Ē	0.9K	Claim verifiability
Arabic [Khouja, 2020]	E	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:* **Y** Twitter, **W** News, Wikipedia, **O** Reddit. *Evidence:* **B** Single, **W** Nultiple, **Q** Thread.



Hardalov, M., Arora, A., Nakov, P., & Augenstein, I. (2021). A survey on stance detection for mis-and disinformation identification. *arXiv preprint arXiv:2103.00242*. <u>https://arxiv.org/pdf/2103.00242.pdf</u>

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, multinominal 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).





1. Import Data

🔀 Import Data into ORA		×
What would you like to do?	Description	
twi Design a meta-network Design a meta-network Jesign a meta-network Jesign a meta-network Jimort SSON or Social Media data Jimort JSON or Social Media data Jimort Mata Jimort from another analysis tool Jimort tother data formats Jimort from a database	Import one or more twitter files and create one new dynamic meta-network per file.	
	Cancel < Back Next > Finis	sh

🚼 Import Data into ORA	×
Select the twitter data format: Twitter JSON	~
Select one or more data files:	
C: Users (yone Documents (2021_Deas_attectivemining (data (covid_ideas.)son	Browse
General Options Derived Networks Custom Attributes Import Error List	
General options:	^
Create only nodes	
Create URL nodes as domain name	
Anonymize tweeter names	
Filter options:	
Ignore tweets before: 2021 🗘 May 🧹 17 🗘 at 00:00:00 🗘	
☐ Ignore tweets after: 2021 ♀ May 17 ♀ at 00:00:00 ♀	
Import Location nodes and networks	~
	_
Cancel < Back Next >	Finish





2. Generate Reports

Meta-Network Name	Twitter JSON covid_ideas
Meta-Network Time	Click to create
Filename	
[Generate Reports
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
arear citory	Min: 4 Max: 75 Mean: 7 709677 Stddev: 12 381551

Select Stance Detection

6-6 Generate Reports	s - stance Detection
Select Report Filter Data Measures Negative Links Transform Data Remove Nodes	Benorts: select a report to run from the list or by category. Stance Detection Description Input Requirements 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.
	- Vitter JSON covid_ideas
	< Back Next > Cancel

Select Agent x Hashtag

gent		~			
Agent Concept Usage	Agent Interaction	Document Netwo	rks		
Select one or more Ag with the agent which initial seed pro/con sta	ent x Concept usage can be used to identi ance on the next par	e networks. Concep ify the agent's stan nel.	t is a general term ce. Nodes from the	and means anythi se nodesets will be	ng associated e assigned an
Agent x Hashtag					Select All
Agent X Tweet -	sender				Clear All
Agent x Url					





3. Assign Stance Values

🔀 Generate Repor	rts - Stance Detection			×
Search for concepts	and assign stances:			
9				
Nodeset	Node ID	Agent Usage Count	Stance	
Hashtag	COVID 19vaccine	87	NEUTRAL	~ ^
Hashtag	CovidVaccine	464	NEUTRAL	~
Hashtag	COVID 19	1581	NEUTRAL	~
Hashtag	Vaccine	1060	NEUTRAL	~
Hashtag	vaccineinjuries	25	NEUTRAL	~
Hashtag	كرونا	15	NEUTRAL	~
Hashtag	كرونا	14	NEUTRAL	~
Hashtag	Vaccines/IAII	10	NEUTRAL	~
Hashtag	olderaduits	2	NEUTRAL	~
Hashtag	caregivers	2	NEUTRAL	~
Hashtag	SupportOurSeniors	1	NEUTRAL	~
Hashtag	GreyBruce	2	NEUTRAL	~
Hashtag	NoVaccines	10	CON	~
a taget tage	ofau		NEUTRAL	
Hashtag	BioNTech	12	NEUTRAL	~
Hashtag	TrumpIsPathetic	1	NEUTRAL	~
Hashtag	Covid_19	45	NEUTRAL	~
Hashtag	coronavirus	296	NEUTRAL	~
Hashtag	skynews	15	NEUTRAL	~
Hashtag	covid	175	NEUTRAL	~
Hashtag	COVIDIOTS	17	NEUTRAL	~ ~
Load	Save Set Al	Neutral		
		< Back	Next >	Cancel

Run!

	- Stance Detection			×
sve Options references	Reports can present their results in differen files that are saved to a specified location. I will be an extension of the one you give. Select the report formats to create: Text HTML CSV SON	nt formats. Each for When multiple files a	nat produces one o re created, each fi	r more ename
	PowerPoint All slides PDF Enter a directory in which to save the repor	v t:		
	C. R. Is second some a 10 second set a 10 second set and second secon			Berner and
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	C: User's tymes Documents affectmentgrad	Save to separ	ate files	prowse _





4. View Stance Detection Report

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 c standard deviation of the mean. Finally, the row is colored blue if the node has a lower than normal value (less than one

Show 10 v entries

Rank	 Hashtag 	Confidence
1	ACIP	1
2	COVID-19	1
3	CovidVaccines	1
4	FaceMasks	1
5	GTCB	1
6	GlobalTeamCoronaBusters	1
7	HealthyAtHome	1
8	IGotMyFluShot	1
9	SaveLives	1
10	TCB	1

5. Agents & Tweets are annotated with stance & confidence

stance 🔻	stance-confi 🔻
0	1
0	1
0	1
0	1
0	1
0	1
0	1
0	1
0	1
0	1
0	1
0	1



Combining Linguistic & Network Methods



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







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







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

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

Influence on an agent
$$I = \alpha [\sum_{i=0}^{n} Y_{\{1st \text{ deg } neighbors\}} + \sum_{i=0}^{n} \sum_{j=0}^{m} \beta Y_{\{2nd \text{ deg } neighbors\}}], \alpha = \frac{1}{n}, \beta = \frac{1}{m}$$

Influence from 1st degree neighbors Influence from 2nd degree neighbors (2 hops away)



Predicting Stance Flips with a Social Influence Model





(analyzed with ORA)

Previous stances Agent stance (analyzed with Linguistic Cues from NetMapper)

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 $2 + \text{stance strength}$	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:





Circle: Agent in focus Stance of agent depicted before flip

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Geria Construction 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

- **DEPA** projections of frames
- □Which frames are more dominant in climate change discourse ?
- UWhat 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





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Image Affect Analysis



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

1. Flickr Images (Putchnik emotional responses)





2. VGG Image Vector + CNN classifier



3. Annotate images in event





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For More Information

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- CASOS website http://www.casos.cs.cmu.edu/
- Social Cybersecurity Working Group http://social-cybersecurity.org
- Facebook: <u>@IDeasCMU</u>
- □ Twitter: <u>@IDeaSCMU</u>
- ☐ YouTube: <u>IDeaS Center</u>
- Email-Distro Lists



Network Affect Analysis



□Identifying emotions for deterrence of disinformation campaign with BEND maneuvers

Grab something from Janice





