

News, Networks, and Narratives

A Language Model and Social Simulation Approach

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Education

- MS in Computer Science under Dr. Lynch (2017 – 2019)
Prioritizing Blended Course Discussion Forum Posts Using Linguistic Features and Metadata With Limited Labeled Instances
- PhD in Computer Science under Dr. Munindar P. Singh (2019 - present)

Publications

- 4 as main author (1 workshop paper, 1 short paper, and 2 full papers)
- 3 as co-author (3 full papers) + 2 under review

Awards

- Outstanding TA Award 2021
- Outstanding Student Leader Award 2023

Industry

- Internship at Lenovo, Seagate, and Coupang
- Research scholar at LAS-SCADS 2024

Leadership

- President and Head of events, IGSA (Maitri), Spring 2022 – Fall 2023
- Smallpack leader, Summer 2019
- Hosted initial webinars for the AI in Society series, Fall 2022

- Rising polarization
 - Influences public discourse
 - Hinders effective discussions
- News reporting is slanted
 - Declining trust in readers
 - News source preference based on political party preference
- Social media Influence
 - Fastest growing platform for news dissemination
 - Selective exposure
 - Echo chambers

Computational news analysis reveals slants in political news and a moral divide on social media among audiences of different news sources as well as how news coverage by one publisher influences another.

1. Political Slant in News and User Engagement on Social Media

Favorability of news toward political figure

Understanding reader reactions through a moral lens

2. War News Analysis

Moral Framing in War News

War and Peace Journalism

3. Dynamics of Polarization in Social Networks

Political Slant in News

Political Slant in News

Favorability of news toward political figure

RQ_{1a} *Do news publishers contain political slant in election-related news?*

- Compare news for the same entity across news publishers

RQ_{1b} *Do reader reactions to election-related news on social media differ across news publishers?*

- Analyze Twitter reactions to political news

- 2020 US presidential elections (March 2020 to January 2021)
- News from traditional news websites and Twitter
- Reader reactions on Twitter

Publisher	Leaning ¹	News	Tweets	Reactions
CNN	LEFT	6485	6108	1 704 194
The Washington Post	LEFT	4678	6999	1 051 062
Fox News	RIGHT	8327	872	648 719
Breitbart News	RIGHT	7377	3243	474 525

¹<https://www.allsides.com/media-bias/ratings>

- Target-based sentiments
 - Target: Presidential candidates
- NewsSentiment
 - Bidirectional GRU
 - Trained on NewsMTSC^[2]

Model	Range	Interpretation
VADER	$[-1,1]$	-1: Neg, 1: Pos
Textblob	$[-1,1]$	-1: Neg, 1: Pos
NewsSentiment	$[0,1]$	Pos + Neg + Neu = 1

	Headline	VADER	Textblob	NewsSentiment
H1	<i>Trump Wants To Reopen the Economy, While <u>Biden</u> Wants To Shut It Down</i>	0.00	0.0814	Trump: 0.587 (positive) Biden: 0.864 (negative)
H2	<i>Trump's Inaction Causes More Deaths Due to Rising COVID-19 Cases Across the U.S.</i>	-0.25	0.1875	Trump: 0.800 (negative)
H3	<i>Trump Addresses the Press Amidst Rising Deaths Due to COVID-19 Surge in the U.S.</i>	0.00	-0.125	Trump: 0.833 (neutral)

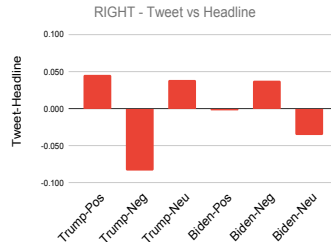
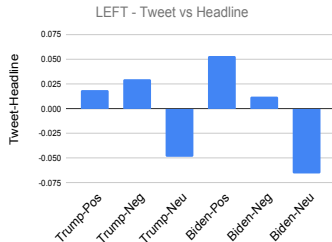
[2] Felix Hamborg and Karsten Donnay, "NewsMTSC: A Dataset for (Multi-)Target-dependent Sentiment Classification in Political News Articles." EACL, 2021, pp. 1663–1675

Left vs Right (News)

- News differ significantly between LEFT and RIGHT
- Effects are higher on social media than traditional online news platforms

Entity	Sentiment	Tweets		Headlines	
		p-value	effects (ϵ^2)	p-value	effects (ϵ^2)
Biden	Negative	3.56e-97	0.078	9.59e-143	0.068
	Positive	1.45e-112	0.090	1.78e-87	0.041
Trump	Negative	7.66e-107	0.036	1.39e-34	0.007
	Positive	1.04e-37	0.012	1.52e-25	0.005

Effect Size	Interpretation
[0.00, 0.06]	Small
[0.06, 0.14]	Moderate
[0.14, 1.00]	Large



Political Slant in News

**Understanding reader reactions through
a moral lens**

Moral Foundation Theory

- Seeks to explain human moral reasoning
- Five foundational dimensions of morality

Virtue	Vice
Care	Harm
Fairness	Cheating
Loyalty	Betrayal
Authority	Subversion
Sanctity	Degradation

Identifying moral foundations in tweets

- RoBERTa (retrained on tweets)
- Fine-tuned on the Moral Foundation Twitter Corpus (MFTC)

Moral Foundations	<i>p</i> -value	effects (ϵ^2)
Care	0.00*	0.0011
Harm	0.00*	0.0004
Fairness	0.00*	0.0004
Cheating	0.00*	0.0002
Authority	0.00*	0.0001
Subversion	0.00*	0.0001
Loyalty	0.00*	0.0000
Betrayal	0.00*	0.0004
Sanctity	0.00*	0.0001
Degradation	0.00*	0.0000

RQ_{1a} *Do news publishers contain political slant in election-related news?*

News shows signs of political slant

- Significant difference between LEFT and RIGHT
- Effects higher on social media
- RIGHT shows more favorability on social media than LEFT

RQ_{1b} *Do reader reactions to election-related news on social media differ across news publishers?*

Reader reactions show a moral divide across news sources

- Significant difference in moral foundations between LEFT and RIGHT
- Effects are small

War News Analysis

War News Analysis

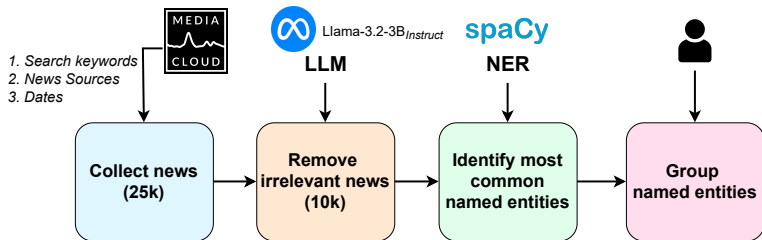
Moral Framing in War News

RQ_{2a} *Does moral framing of war news differ across news publishers?*

- Analyze news on the ongoing Gaza war

RQ_{2b} *Does war news from one publisher influence the news from another?*

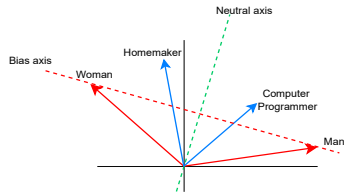
- Use Granger's causality test to evaluate cross-publisher influence



Source	PALESTINE	HAMAS	ISRAEL	OTHERS
Aljazeera	1372	807	3036	665
BBC	442	558	1310	392
Fox	479	1507	2423	485

Identifying Moral Framing: A Vector Subspace Approach

Debiasing word embeddings [3]



[3] Bolukbasi et al. 2016

Advantages

- Less resource intensive
- More interpretable than supervised training

Limitations

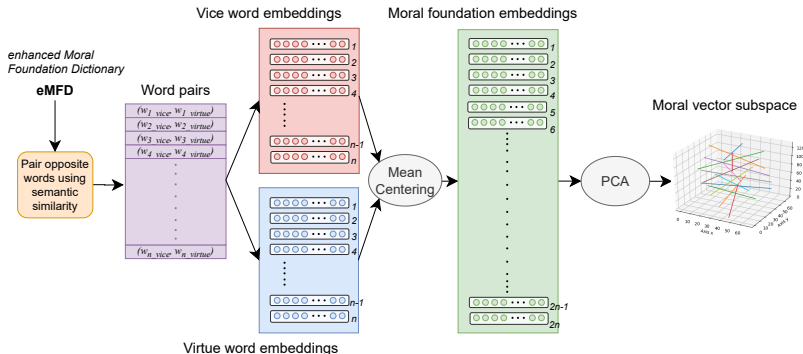
- Poor performance than supervised training
- Some vector subspaces may not be separable

Male	Female
he	she
his	her
man	woman
son	daughter
boy	girl

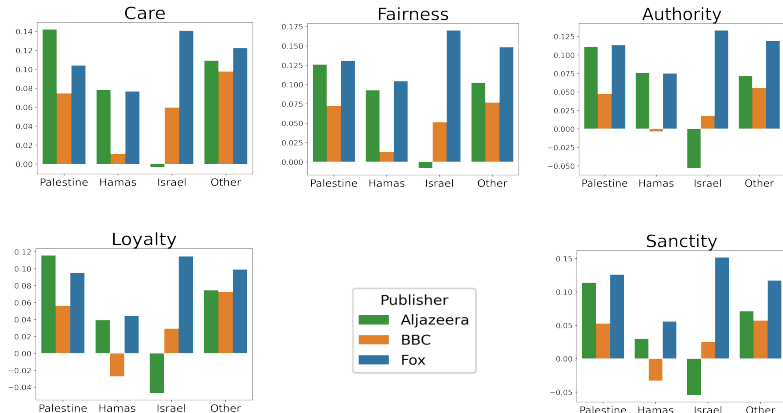
[3] Bolukbasi et al. "Man Is to Computer Programmer as Woman Is to Homemaker? Debiasing Word Embeddings." NIPS, Barcelona, 2016, pp. 4356–4364.

Identifying Moral Vector Subspace

Care		Fairness		Authority		Loyalty		Sanctity	
Vice	Virtue	Vice	Virtue	Vice	Virtue	Vice	Virtue	Vice	Virtue
danger	safety	killed	honored	desperate	eager	dirty	clean	killed	honored
detained	freed	enemies	friends	failure	success	lying	honest	contempt	respect
suffered	benefited	accident	safety	poor	rich	injustice	justice	reject	welcome
hatred	compassion	fraud	oath	denounced	endorsed	feared	respected	punished	praised
weapons	tools	prosecuted	celebrated	defeat	win	killer	hero	attacker	defender



Moral Framing of War News



Differences Across Publisher

p-values

Israel Alj—BBC	0.0000	0.0000	0.0000	0.0000	0.0000
Israel Fox—BBC	0.0000	0.0000	0.0000	0.0000	0.0000
Israel Alj—Fox	0.0000	0.0000	0.0000	0.0000	0.0000
Palestine Alj—BBC	0.0104	0.0501	0.0202	0.0276	0.0263
Palestine Fox—BBC	0.4620	0.1580	0.1090	0.3340	0.0753
Palestine Alj—Fox	0.3040	0.8980	0.9520	0.5760	0.7330
Hamas Alj—BBC	0.0194	0.0062	0.0058	0.0203	0.0346
Hamas Fox—BBC	0.0108	0.0005	0.0022	0.0053	0.0009
Hamas Alj—Fox	0.9580	0.6360	0.9750	0.8440	0.3030
Other Alj—BBC	0.4360	0.0850	0.2760	0.8940	0.3570
Other Fox—BBC	0.2390	0.0008	0.0026	0.2040	0.0051
Other Alj—Fox	0.5180	0.0261	0.0219	0.2320	0.0282
	Care	Fairness	Authority	Loyalty	Sanctity

effect size

0.2520	0.2221	0.2640	0.2978	0.2936	1.0000
0.3045	0.4417	0.4267	0.3203	0.4610	0.9000
0.5579	0.8600	0.6905	0.6193	0.7541	0.8000
0.2423	0.1903	0.2231	0.2109	0.2132	0.7000
0.1096	0.2079	0.2365	0.1421	0.2626	0.6000
0.1320	0.0167	0.0077	0.0712	0.0419	0.5000
0.3051	0.3581	0.3609	0.3029	0.2755	0.4000
0.2694	0.3734	0.3258	0.2979	0.3566	0.3000
0.0055	0.0489	0.0033	0.0205	0.1069	0.2000
0.0445	0.0987	0.0622	0.0076	0.0527	0.1000
0.0958	0.2733	0.2442	0.1035	0.2276	0.0000
0.0513	0.1792	0.1809	0.0948	0.1737	
	Care	Fairness	Authority	Loyalty	Sanctity

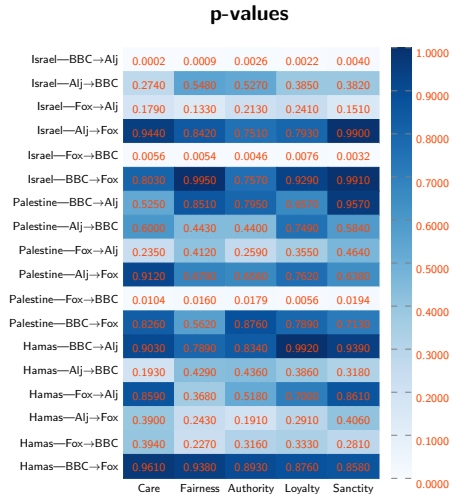
Influence across publishers

- Granger's causality test

$$Y_t = \alpha_1 + \sum_{i=1}^p \beta_i Y_{t-i} + \sum_{i=1}^p \gamma_i X_{t-i} + \epsilon_t$$

$$X_t = \alpha_2 + \sum_{i=1}^p \delta_i X_{t-i} + \sum_{i=1}^p \theta_i Y_{t-i} + \eta_t$$

Cross-Publisher Influence for Same Entity



RQ_{2a} *Do moral framing of war news differ across news publishers?*

- Significant difference across publishers
- Effects from small to large
- Fox uses positive moral frames for Israel, whereas Aljazeera uses negative

RQ_{2b} *Does war news from one publisher influence the news from another?*

- Significant Granger causality for some entities and publishers
- Signs of cross-publisher agenda-setting

War News Analysis

War and Peace Journalism

War and peace journalism (Johan Galtung (1965, 1986, 1998))

- Framework to analyze conflict-related news
- Sports vs healthcare news metaphor

War journalism

- Sensationalized
- Immediate visible effects
- Elite source
- War context

Peace journalism

- Objective
- Long-term less obvious effects
- People stories
- Broad context

RQ_{3a} *Do different news publishers covering a conflict portray the same victims and villains?*

RQ_{3b} *Does the use of war and peace frame in conflict news reporting differ across news publishers?*

Phase 1	Phase 2	Phase 3
<ul style="list-style-type: none">• Initial instructions• 3 annotators• 100 headlines annotated• Post annotation discussions• Update annotation instructions	<ul style="list-style-type: none">• Updated instructions• 33 annotators• 50 headlines annotated• Explanation for each annotation• Update annotation instructions	<ul style="list-style-type: none">• Final annotation instructions• 33 annotators• 3300 headlines annotated• 3 annotations for each headline

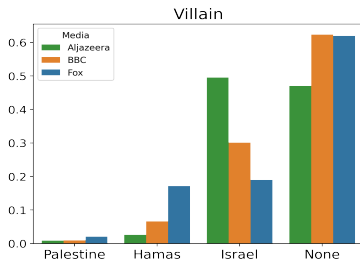
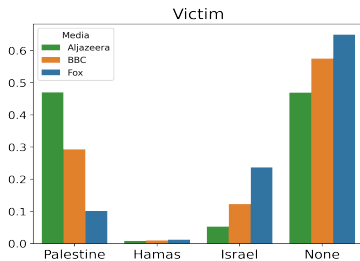
Annotated Dataset

- Final label based on the majority vote
- Removed headlines with no agreement among annotators

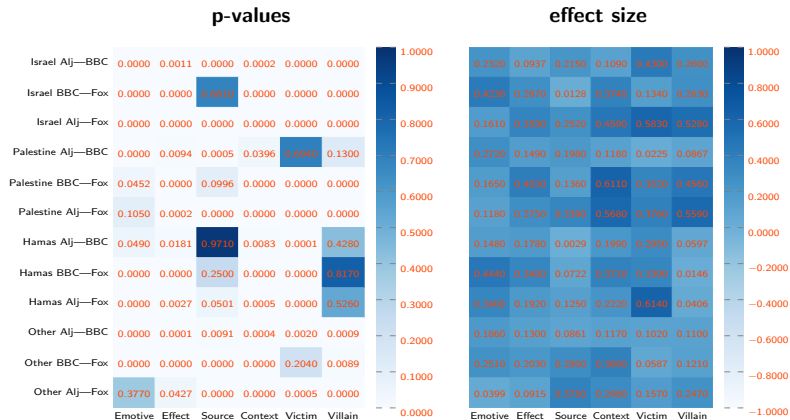
Class	Labels	Count	Agreement
Emotiveness Frame	{Sensationalized, Objective}	2601	0.42
Effect Frame	{Visible, Invisible, None}	2717	0.48
Source Frame	{Elite, People, None}	2834	0.51
Context Frame	{War, Broad, None}	2535	0.60
Role-Victim	{Israel, Palestine, Hamas, None}	2512	0.57
Role-Villain	{Israel, Palestine, Hamas, None}	2819	0.66

Model	War and Peace Frames				Role	
	EMOTIVE	EFFECT	SOURCE	CONTEXT	VICTIM	VILLAIN
BERT	80.52	69.1	79.69	77.8	72.39	79.27
RoBERTa	83.83	71.55	82.01	77.93	74.61	81.16
ConflIBERT	84.88	61.46	81.66	75.81	72.01	81.74
ModernBERT	79.3	66.84	79.87	75.6	70.16	74.88
GPT-2	79.82	69.93	78.79	67.68	74.02	75.72
BART	84.18	69.79	80.94	77.36	71.61	80.49
T5	77.79	69.52	65.37	56.18	69.52	69.55

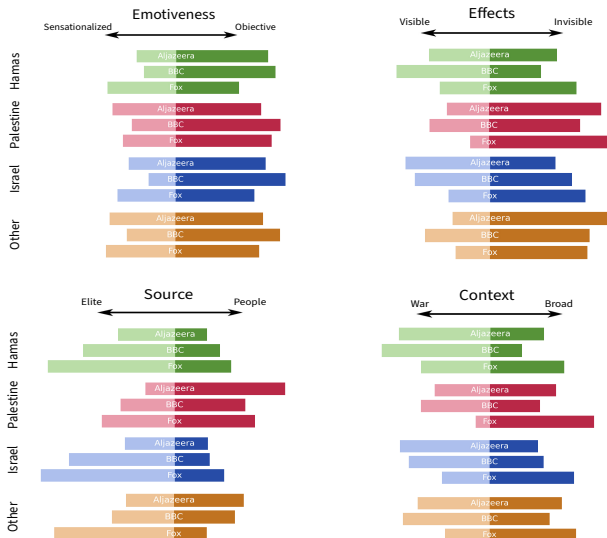
Victims and Villains Across News Publishers



Statistical Analysis Results



Use of War and Peace Frames Across Publishers



Peace frame \neq Peace journalism

- Headlines from Fox News classified as peace frame (broader context and indirect effects)

Anti-Israel agitators shut down traffic, disrupt cities all across US in demand for Gaza ceasefire.

'Radical' pro-Palestinian groups increasingly target houses of worship for protests in alarming trend.

- Multiple factors influence
 - Geographical location
 - Newsworthiness for publisher's audience

RQ_{3a} *Do different news publishers covering a conflict portray the same victims and villains?*

- Significant difference with small to large effects
- Fox portrays Hamas as villain, whereas Aljazeera portrays Israel as villain

RQ_{3b} *Does the use of war and peace frame in conflict reporting differ across news publishers?*

- Significant difference with small to large effects
- Other factors may influence use of war and peace frame

Dynamics of Polarization in Social Networks

Collecting data

- Expensive
- Privacy concerns

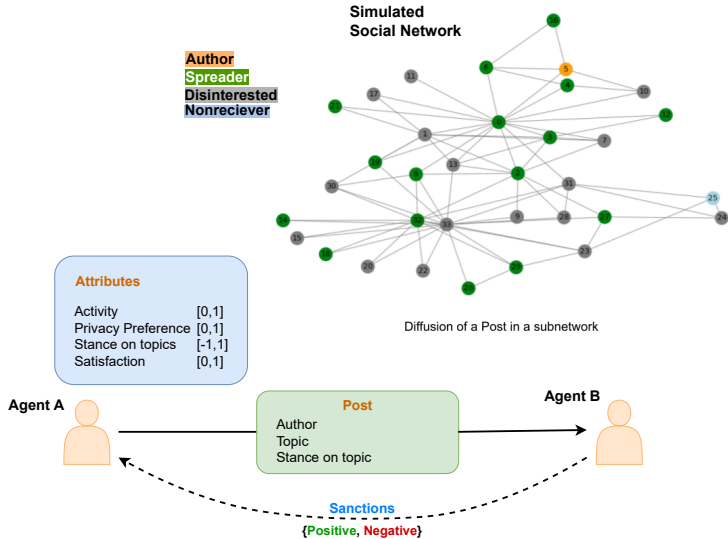
Require annotations

- Annotator Bias
- Non-scalable

Simulation-based evaluation offers a solution

RQ_{4a} *Does higher tolerance (for noncongenial content) among users in a social network mitigates polarization?*

RQ_{4b} *Does selective exposure to congenial content lead to more polarization?*



Facebook Social Network^[4]

- 4039 nodes (agents)
- 88234 edges (connections)

Artificially generated posts

- 6 topics (5000 total posts)
- Stance follows a normal distribution ($\mu = 0.00, \sigma = 0.52$)

Initial agent attributes

- Normal distributions

[4] Jure Leskovec and Julian McAuley. "Learning to Discover Social Circles in Ego Networks," NIPS. Vol. 25. Lake Tahoe, 2012.

Actions

- Share Post
 - Can start a new post
 - Share a post they receive
- Provide Sanctions
 - Positive sanctions to congenial content
 - Negative sanctions to noncongenial content

Goals

- Social acceptance
 - Change stance to get positive sanctions
- Promote views
 - By providing sanctions

Polarity

- Mean user stance

Polarization

- Based on electric dipole moment
- Measure distance between two opposing ideologies

Homophily

- Measures assortativity of the social network
- Homogeneity in the network

Satisfaction

- Mean user satisfaction

Tolerance

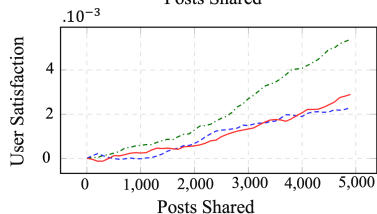
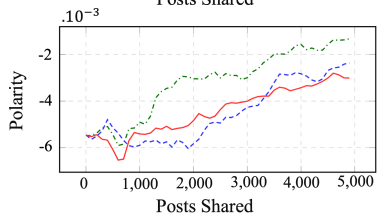
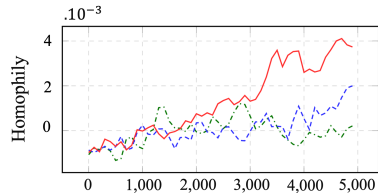
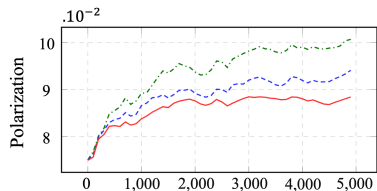
- Social Judgment Theory ^[5]
 - Explains shift in attitude when two people interact
 - $\text{Tolerance} = |\text{Latitude}_{\text{acceptance}} - \text{Latitude}_{\text{rejection}}|$

Selective exposure

- Filter content based on difference in user stance

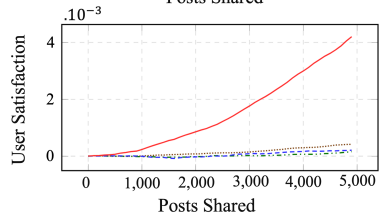
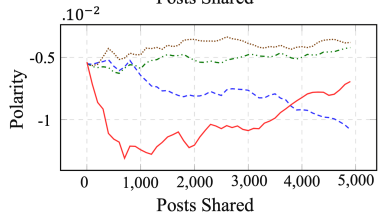
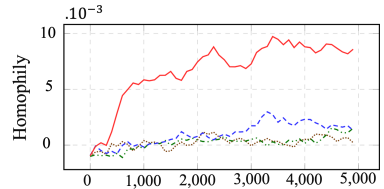
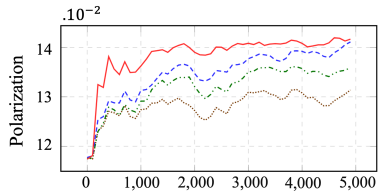
[5] M. Sherif and C.I. Hovland. "Social Judgment: Assimilation and Contrast Effects in Communication and Attitude Change." New Haven, CT: Yale University Press, 1961.

Varying User Tolerance



--- Low --- Medium --- High

Varying Selective Exposure



..... None -.-.- Low --- Medium — High

Exp	Config	Agent State		
		Nonreceiver	Receiver	
			Spreader	Disinterested
Tolerant Users	LOW	60.12	14.49	25.39
	MEDIUM	53.95	17.30	28.75
	HIGH	62.99	13.36	23.65
Selective Exposure	NONE	54.76	16.88	28.36
	LOW	55.44	16.48	28.08
	MEDIUM	58.90	13.80	27.30
	HIGH	82.63	4.97	12.40

RQ_{Tolerance} *Does higher tolerance among users in a social network help mitigate polarization?*

Higher tolerance

- Slows down polarization
- Lower aggregate satisfaction
- Higher network homophily

RQ_{Selective Exposure} *Does selective exposure to congenial information contribute to polarization?*

Higher selective exposure

- Speeds up polarization
- Higher aggregate satisfaction
- Higher network homophily
- Lower content reach

Thank you!

Have questions or suggestions?

Email me at *ahaque2@ncsu.edu*