News, Networks, and Narratives

A Language Model and Social Simulation Approach

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March 21, 2025

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My Time at NC State University

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
- Oustanding 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

Motivation

- 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

Thesis Statement

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.

Presentation Overview

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

Research Questions

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

- Compare news for the same entity across news publishers

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

- Analyze Twitter reactions to political news

Datset Curation

- 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

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[1] https://www.allsides.com/media-bias/ratings

Favorability of News

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

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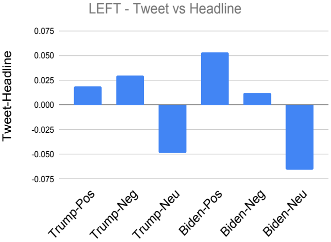
[2] Felix Hamborg and Karsten Donnay, *"NewsMTSC: A Dataset for (Multi-)Target-dependent Sentiment Classification in Political News Articles."* EACL, 2021, pp. 1663–1675

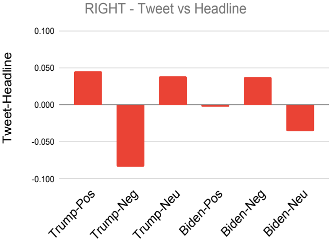
Left vs Right (News)

- 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**


LEFT - Tweet vs Headline


RIGHT - Tweet vs Headline

Political Slant in News

Understanding reader reactions through a moral lens

Moral Foundation Theory

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)

Left vs Right (User Response)

Moral Foundations	$p-$**value**	effects (ϵ^2)
Care	0.00*	0.0011
Harm	0.00*	0.0004
Fairness	0.00*	0.0011
Cheating	0.00*	0.0002
Authority	0.00*	0.0001
Subversion	0.00*	0.0001
Loyalty	0.156	0.0000
Betrayal	0.00*	0.0004
Sanctity	0.00*	0.0001
Degradation	0.00*	0.0000

Research Questions (Revisited)

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
- Shift in moral foundations differ across news topics

War News Analysis

War News Analysis

Moral Framing in War News

Research Questions

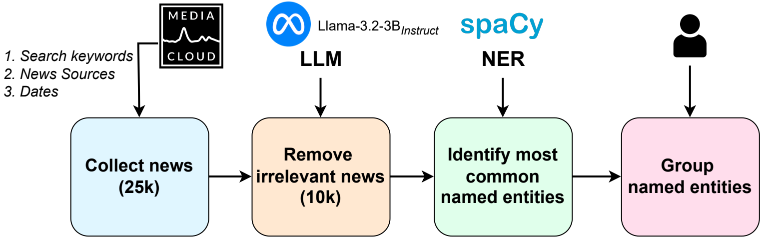
RQ$_{\mathbf{2a}}$ *Does moral framing of war news differ across news publishers?*

- Analyze news on the ongoing Gaza war

RQ$_{\mathbf{2b}}$ *Does war news from one publisher influence the news from another?*

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

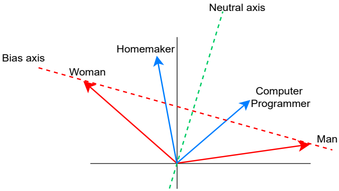
Data Curation



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

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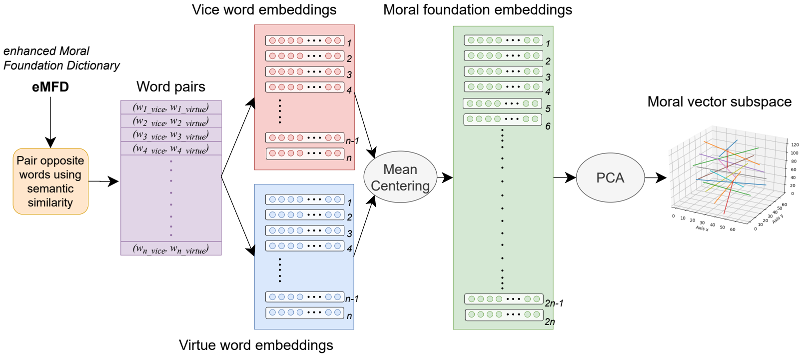
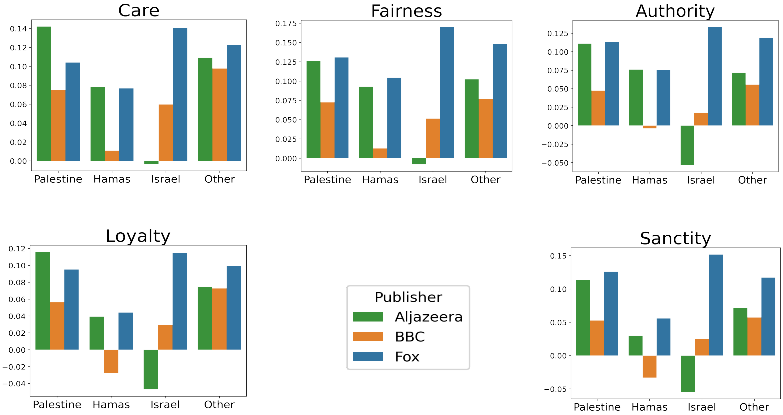
[3] Bolukbasi et al. *"Man Is to Computer Programmer as Woman Is to Homemaker? Debiasing Word Embeddings."* NIPS, Barcelona, 2016, pp. 4356–4364.

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

	Care	Fairness	Authority	Loyalty	Sanctity
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	0.7430
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

effect size

	Care	Fairness	Authority	Loyalty	Sanctity
Israel Alj—BBC	0.2520	0.2221	0.2640	0.2978	0.2936
Israel Fox—BBC	0.3045	0.4417	0.4267	0.3203	0.4610
Israel Alj—Fox	0.5579	0.6600	0.6905	0.6193	0.7541
Palestine Alj—BBC	0.2423	0.1903	0.2231	0.2109	0.2132
Palestine Fox—BBC	0.1096	0.2079	0.2365	0.1421	0.2626
Palestine Alj—Fox	0.1320	0.0167	0.0077	0.0712	0.0419
Hamas Alj—BBC	0.3051	0.3581	0.3609	0.3029	0.2755
Hamas Fox—BBC	0.2694	0.3734	0.3258	0.2979	0.3566
Hamas Alj—Fox	0.0055	0.0489	0.0033	0.0205	0.1069
Other Alj—BBC	0.0445	0.0987	0.0622	0.0076	0.0527
Other Fox—BBC	0.0958	0.2733	0.2442	0.1035	0.2276
Other Alj—Fox	0.0513	0.1792	0.1809	0.0948	0.1737

Granger Causality Test

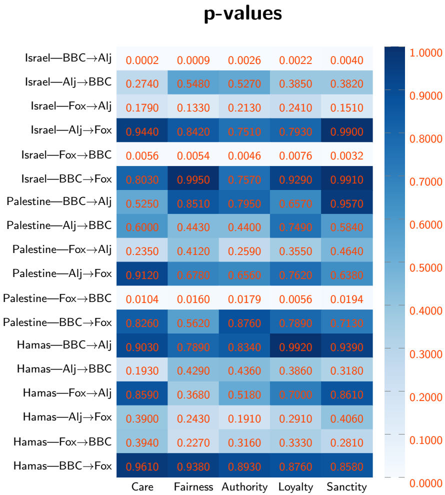
Influence across publishers

- 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


p-values

	Care	Fairness	Authority	Loyalty	Sanctity
Israel—BBC→Alj	0.0002	0.0009	0.0026	0.0022	0.0040
Israel—Alj→BBC	0.2740	0.5480	0.5270	0.3850	0.3820
Israel—Fox→Alj	0.1790	0.1330	0.2130	0.2410	0.1510
Israel—Alj→Fox	0.9440	0.8420	0.7510	0.7930	0.9900
Israel—Fox→BBC	0.0056	0.0054	0.0046	0.0076	0.0032
Israel—BBC→Fox	0.8030	0.9950	0.7570	0.9290	0.9910
Palestine—BBC→Alj	0.5250	0.8510	0.7950	0.6570	0.9570
Palestine—Alj→BBC	0.6000	0.4430	0.4400	0.7490	0.5840
Palestine—Fox→Alj	0.2350	0.4120	0.2590	0.3550	0.4640
Palestine—Alj→Fox	0.9120	0.6780	0.6560	0.7620	0.6380
Palestine—Fox→BBC	0.0104	0.0160	0.0179	0.0056	0.0194
Palestine—BBC→Fox	0.8260	0.5620	0.8760	0.7890	0.7130
Hamas—BBC→Alj	0.9030	0.7890	0.8340	0.9920	0.9390
Hamas—Alj→BBC	0.1930	0.4290	0.4360	0.3860	0.3180
Hamas—Fox→Alj	0.8590	0.3680	0.5180	0.7000	0.8610
Hamas—Alj→Fox	0.3900	0.2430	0.1910	0.2910	0.4060
Hamas—Fox→BBC	0.3940	0.2270	0.3160	0.3330	0.2810
Hamas—BBC→Fox	0.9610	0.9380	0.8930	0.8760	0.8580

Research Questions (Revisited)

$\mathbf{RQ_{2a}}$ *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

$\mathbf{RQ_{2b}}$ *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

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

Research Questions

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?*

Data Annotation

Phase 1

- Initial instructions
- 3 annotators
- 100 headlines annotated
- Post annotation discussions
- Update annotation instructions

Phase 2

- Updated instructions
- 33 annotators
- 50 headlines annotated
- Explanation for each annotation
- Update annotation instructions

Phase 3

- Final annotation instructions
- 33 annotators
- 3300 headlines annotated
- 3 annotations for each headline

Annotated Dataset

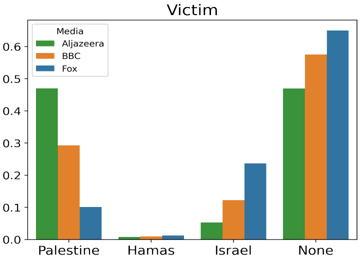
- Final label based on the majority vote
- Removed headlines with no agreement among annotators

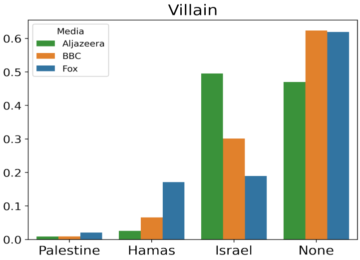
Class	**Labels**	**Count**	**Agreement**
Emotiveness Frame	{Sensationalized, Objective}	2601	0.42
Effect Frame	{Visible, Invisible, None}	2717	0.48
Source Frame	{Elite, People, None}	2834	0.51
Context Frame	{War, Broad, None}	2535	0.60
Role-Victim	{Israel, Palestine, Hamas, None}	2512	0.57
Role-Villain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

Fine-Tuned Language Models

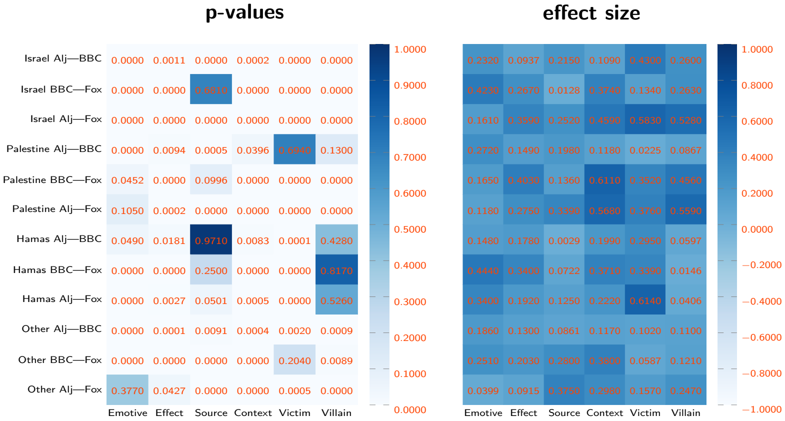
	War and Peace Frames				**Role**	
Model	Emotive	Effect	Source	Context	Victim	Villain
BERT	80.52	69.1	79.69	77.8	72.39	79.27
RoBERTa	83.83	**71.55**	**82.01**	**77.93**	**74.61**	81.16
ConfliBERT	**84.88**	61.46	81.66	75.81	72.01	**81.74**
ModernBERT	79.3	66.84	79.87	75.6	70.16	74.88
GPT-2	79.82	69.93	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



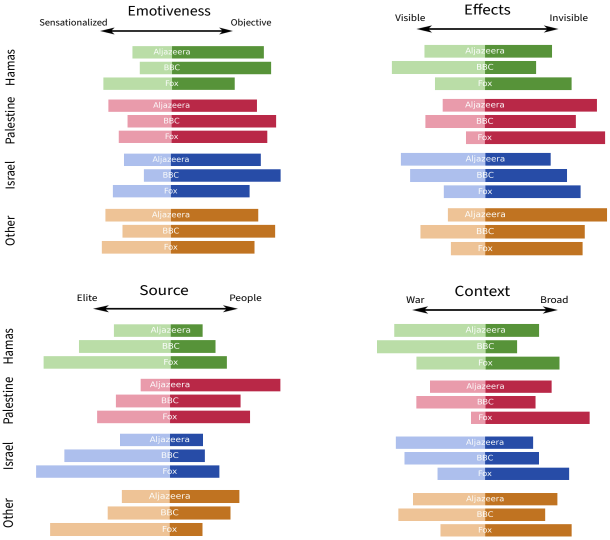
p-values

	Emotive	Effect	Source	Context	Victim	Villain
Israel Alj—BBC	0.0000	0.0011	0.0000	0.0002	0.0000	0.0000
Israel BBC—Fox	0.0000	0.0000	0.6810	0.0000	0.0000	0.0000
Israel Alj—Fox	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Palestine Alj—BBC	0.0000	0.0094	0.0005	0.0396	0.6940	0.1300
Palestine BBC—Fox	0.0452	0.0000	0.0996	0.0000	0.0000	0.0000
Palestine Alj—Fox	0.1050	0.0002	0.0000	0.0000	0.0000	0.0000
Hamas Alj—BBC	0.0490	0.0181	0.9710	0.0083	0.0001	0.4280
Hamas BBC—Fox	0.0000	0.0000	0.2500	0.0000	0.0000	0.8170
Hamas Alj—Fox	0.0000	0.0027	0.0501	0.0005	0.0000	0.5260
Other Alj—BBC	0.0000	0.0001	0.0091	0.0004	0.0020	0.0009
Other BBC—Fox	0.0000	0.0000	0.0000	0.0000	0.2040	0.0089
Other Alj—Fox	0.3770	0.0427	0.0000	0.0000	0.0005	0.0000

effect size

	Emotive	Effect	Source	Context	Victim	Villain
Israel Alj—BBC	0.2320	0.0937	0.2150	0.1090	0.4300	0.2600
Israel BBC—Fox	0.4230	0.2670	0.0128	0.3740	0.1340	0.2630
Israel Alj—Fox	0.1610	0.3590	0.2520	0.4590	0.5830	0.5280
Palestine Alj—BBC	0.2720	0.1490	0.1980	0.1180	0.0225	0.0867
Palestine BBC—Fox	0.1650	0.4030	0.1360	0.6110	0.3520	0.4560
Palestine Alj—Fox	0.1180	0.2750	0.3390	0.5680	0.3760	0.5590
Hamas Alj—BBC	0.1480	0.1780	0.0029	0.1990	0.2950	0.0597
Hamas BBC—Fox	0.4440	0.3400	0.0722	0.3710	0.3390	0.0146
Hamas Alj—Fox	0.3400	0.1920	0.1250	0.2220	0.6140	0.0406
Other Alj—BBC	0.1860	0.1300	0.0861	0.1170	0.1020	0.1100
Other BBC—Fox	0.2510	0.2030	0.2800	0.3800	0.0587	0.1210
Other Alj—Fox	0.0399	0.0915	0.3750	0.2980	0.1570	0.2470

Use of War and Peace Frames Across Publishers



Limitations of War and Peace Journalism

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

Research Questions (Revisited)

$\mathrm{RQ_{3a}}$ *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

$\mathrm{RQ_{3b}}$ *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

Research Questions

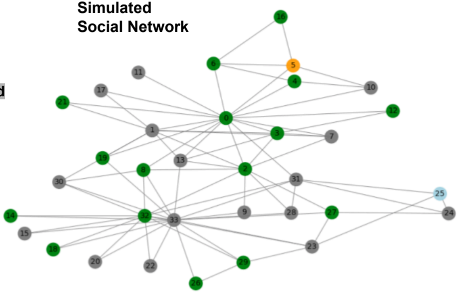
RQ$_{\mathbf{4a}}$ *Does higher tolerance (for noncongenial content) among users in a social network mitigates polarization?*

RQ$_{\mathbf{4b}}$ *Does selective exposure to congenial content lead to more polarization?*

Social Simulation

Simulated Social Network

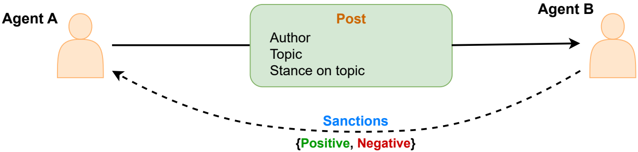
Author
Spreader
Disinterested
Nonreciever



Diffusion of a Post in a subnetwork

Attributes

Activity	[0,1]
Privacy Preference	[0,1]
Stance on topics	[-1,1]
Satisfaction	[0,1]



Post
Author
Topic
Stance on topic

Sanctions
{Positive, Negative}

Experimental Setup

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

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

Agent Actions and Goals

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

Evaluation Metrics

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

Operationalizing Tolerance and Selective Exposure

Tolerance

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

Selective exposure

- Filter content based on difference in user stance

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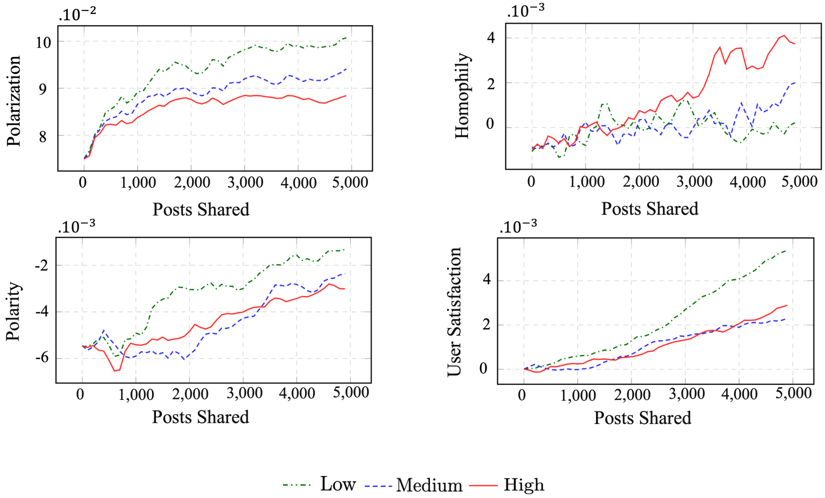
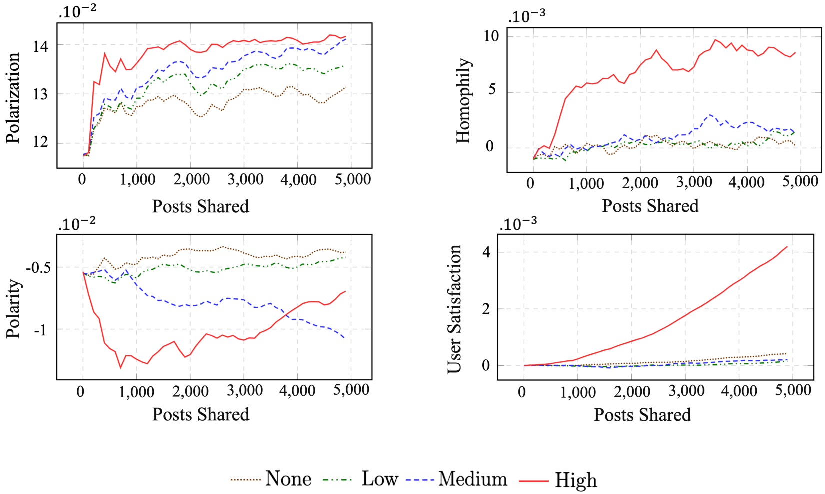
[5] M. Sherif and C.I. Hovland. *"Social Judgment: Assimilation and Contrast Effects in Communication and Attitude Change."* New Haven, CT: Yale University Press, 1961.

Varying User Tolerance



Varying Selective Exposure



Final User States

Exp	**Config**	**Agent State**		
			Receiver	
		Nonreceiver	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

Research Questions (Revisited)

RQ$_{\textbf{Tolerance}}$ *Does higher tolerance among users in a social network help mitigate polarization?*

Higher tolerance

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

RQ$_{\textbf{Selective Exposure}}$ *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?
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