News, Networks, and Narratives

A Language Model and Social Simulation Approach

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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

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

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

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

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

Favorability of News

- Target-based sentiment analysis
  - Target: Presidential candidates
- NewsSentiment
  - Bidirectional GRU
  - Trained on NewsMTSC[2]

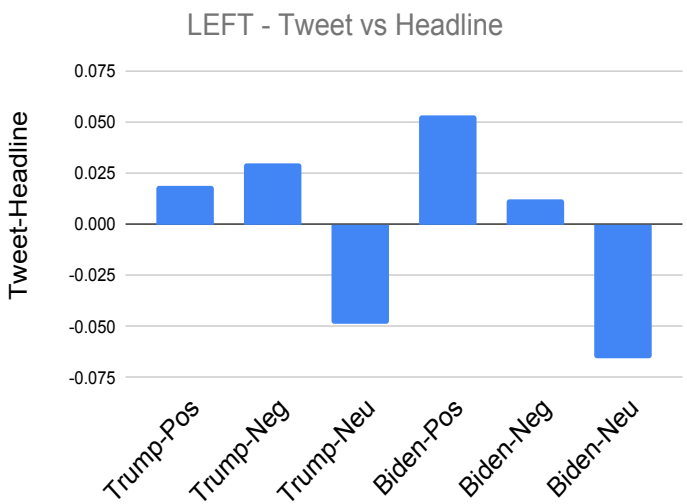
[2] Felix Hamborg and Karsten Donnay, *"NewsMTSC: A Dataset for (Multi-)Target-dependent Sentiment Classification in Political News Articles."* EACL, 2021, pp. 1663–1675

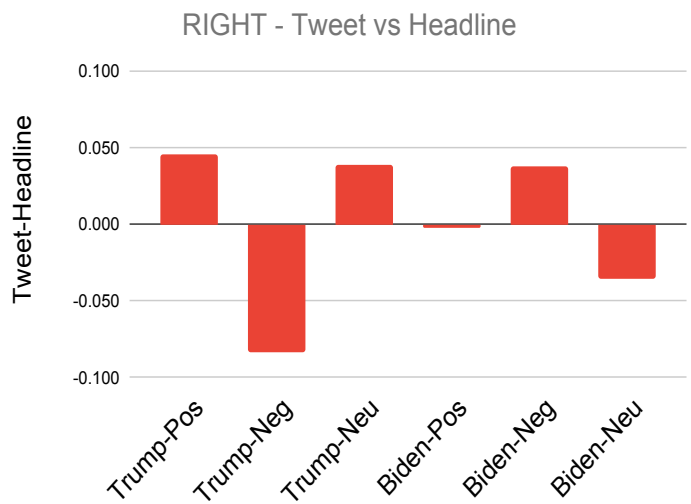
Left vs Right (News)

- News differ significantly between LEFT and RIGHT with small to moderate effects
- 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

Moral Foundation Theory [3]

- 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)

[3] Jesse Graham, Jonathan Haidt, and Brian A. Nosek. *"Liberals and Conservatives Rely on Different Sets of Moral Foundations"*. In: Journal of Personality and Social Psychology 96.5 (2009), pp. 1029–1046

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*	0.0004
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

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?*

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

War News Analysis

War News Analysis

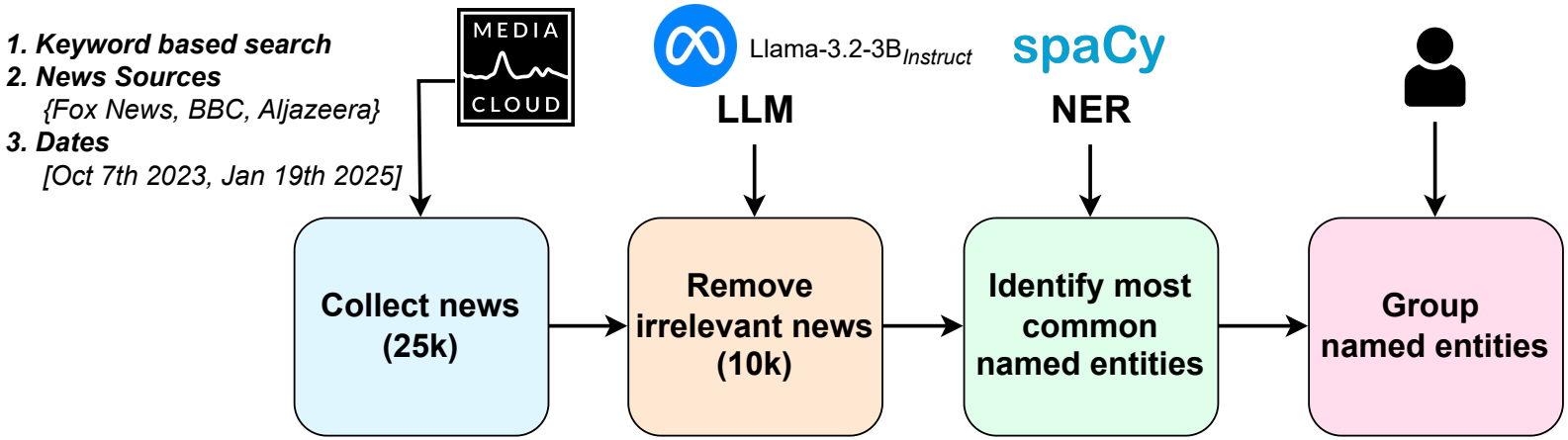
Moral Framing in War News

Research Questions

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

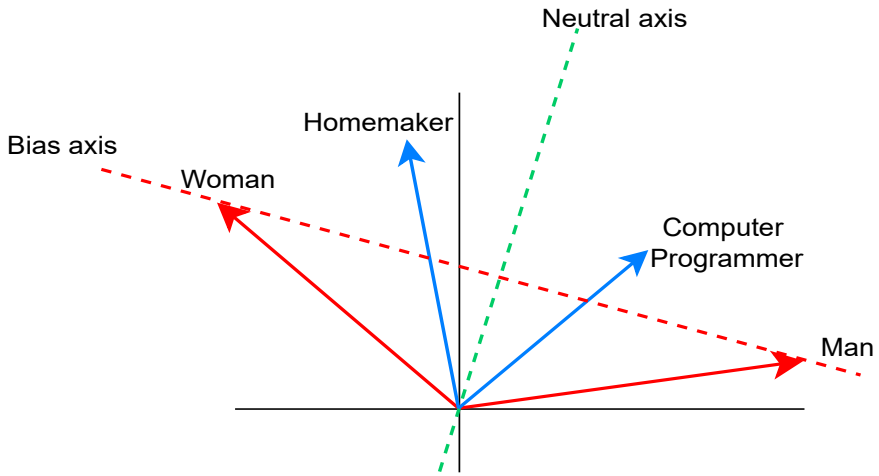
RQ$_{2b}$ *Does war news from one publisher influence the news from another?*

Data Curation



Source	Palestine	Hamas	Israel	Others
Aljazeera	1372	807	3036	665
BBC	442	558	1310	392
Fox	479	1507	2423	485

Debiasing word embeddings [4]



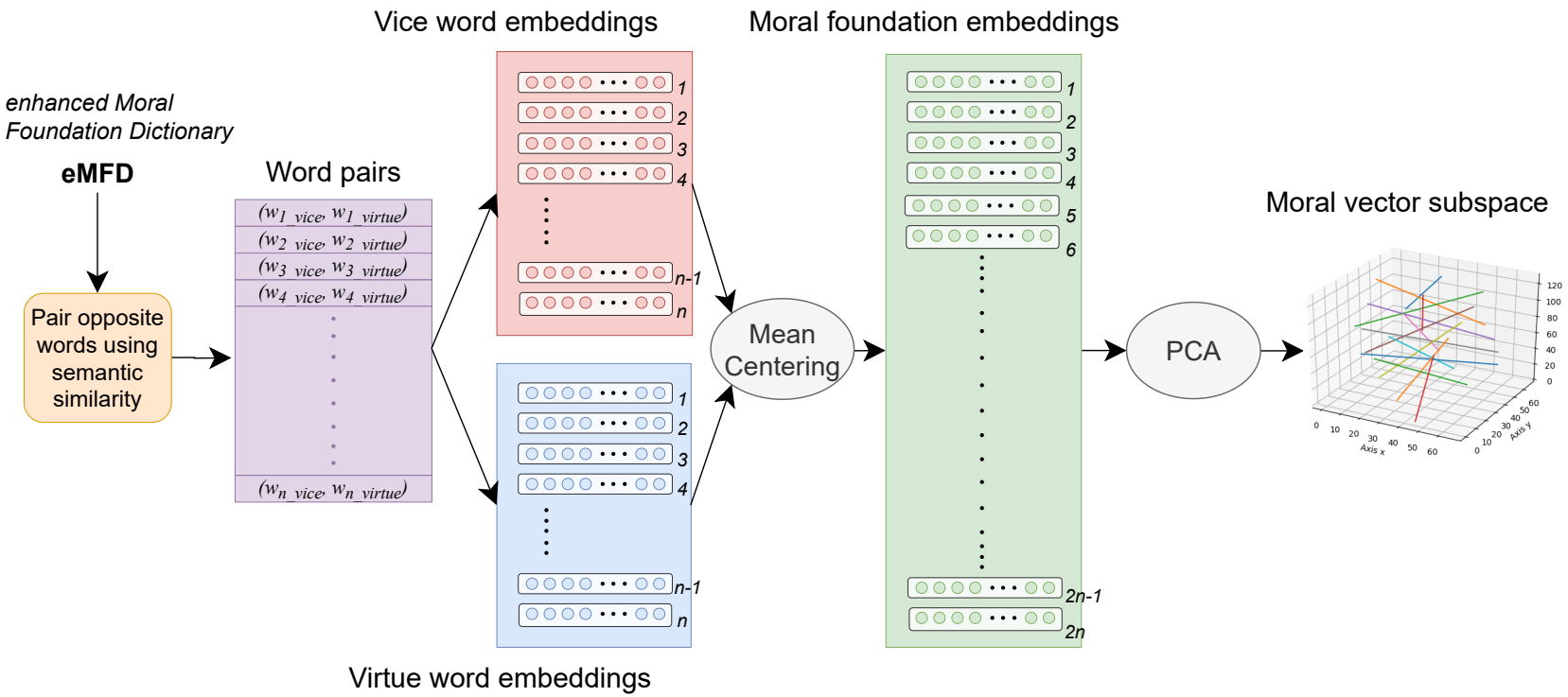
[3] Bolukbasi et al. 2016

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

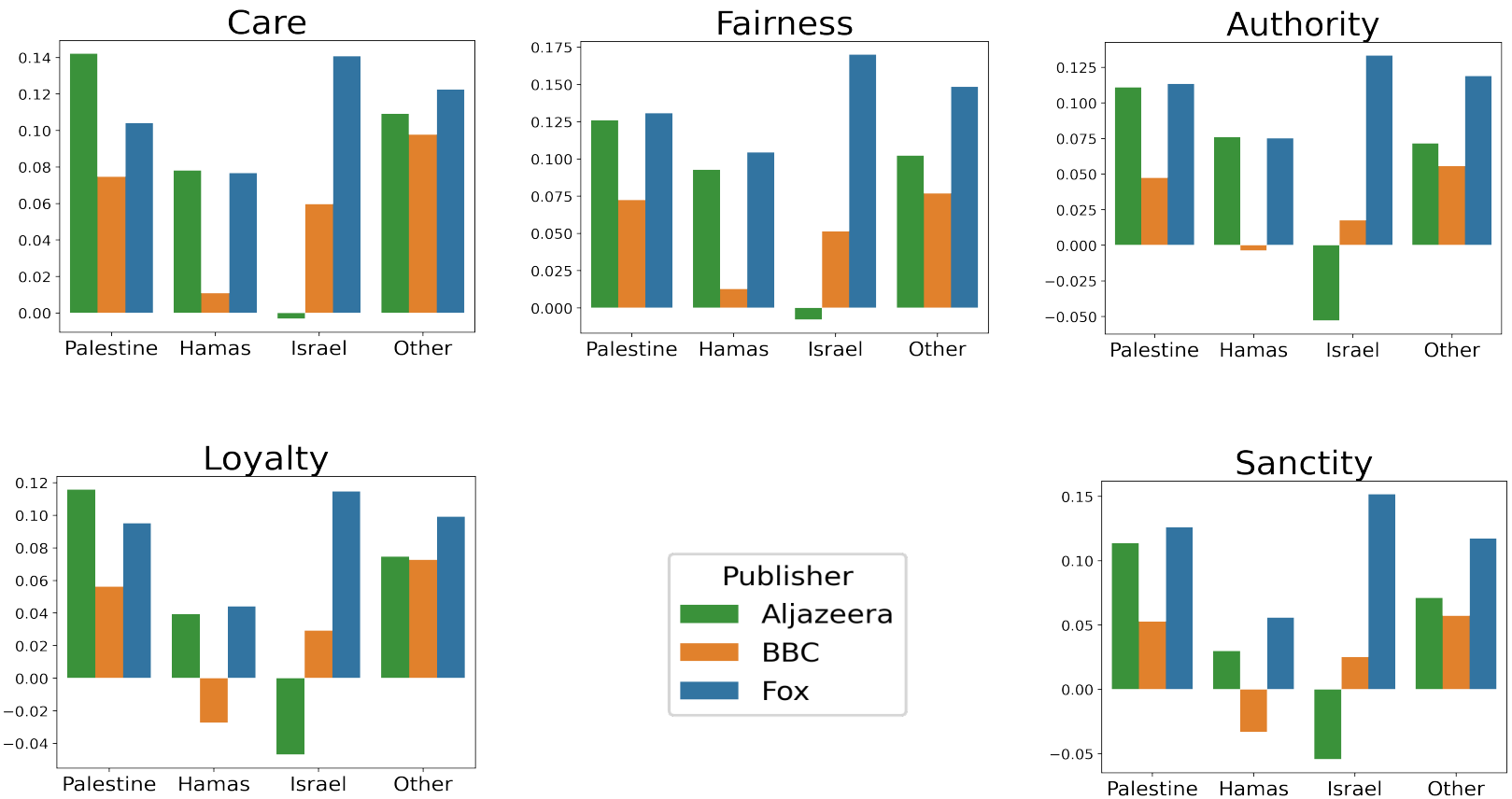
[4] Bolukbasi et al. *"Man Is to Computer Programmer as Woman Is to Homemaker? Debiasing Word Embeddings."* NIPS, Barcelona, 2016, pp. 4356–4364.

Identifying Moral Vector Subspace

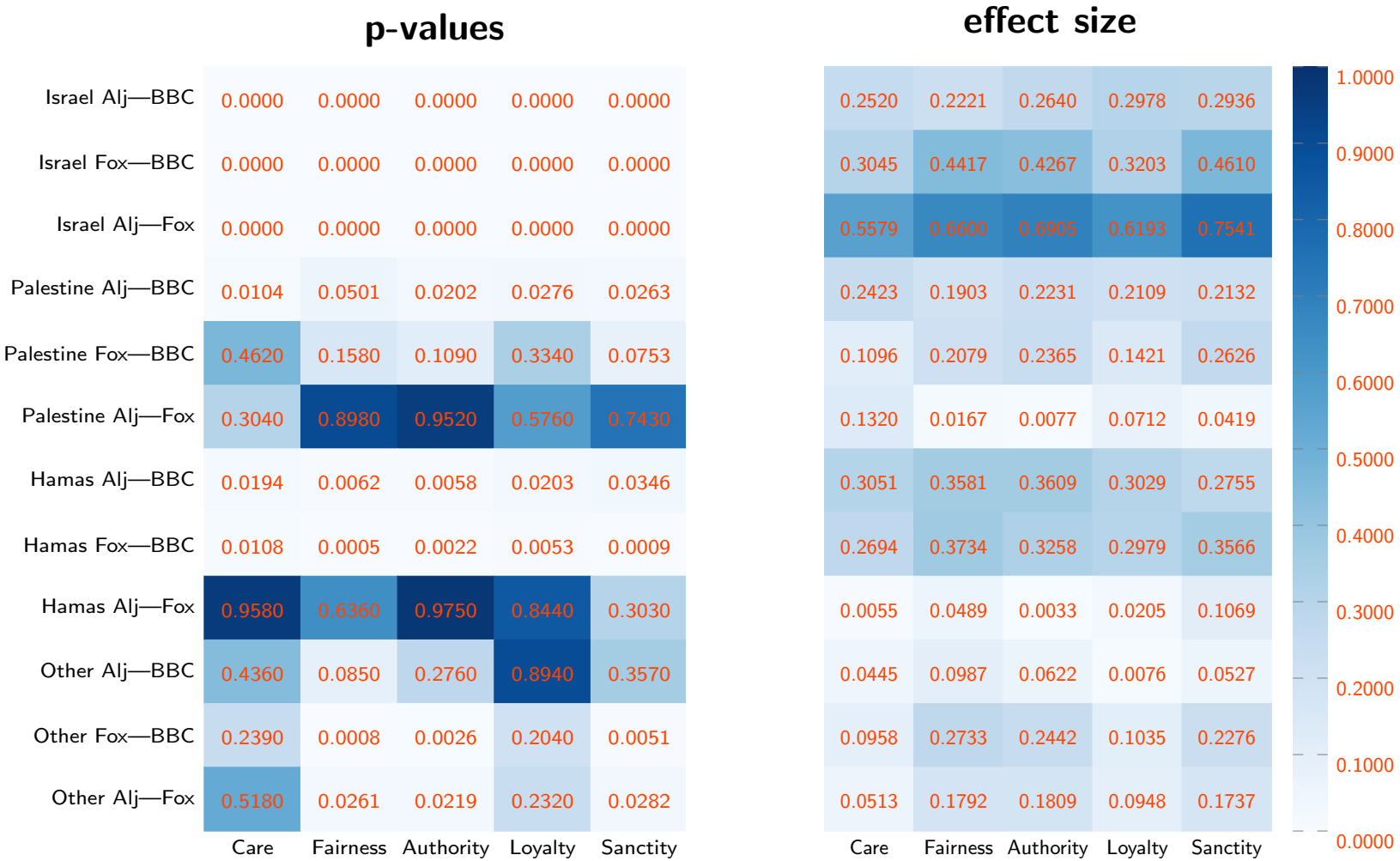
Care		Fairness		Authority		Loyalty		Sanctity	
Vice	**Virtue**	**Vice**	**Virtue**	**Vice**	**Virtue**	**Vice**	**Virtue**	**Vice**	**Virtue**
danger	safety	killed	honored	desperate	eager	dirty	clean	killed	honored
detained	freed	enemies	friends	failure	success	lying	honest	contempt	respect
suffered	benefited	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



Cross Publisher Influence

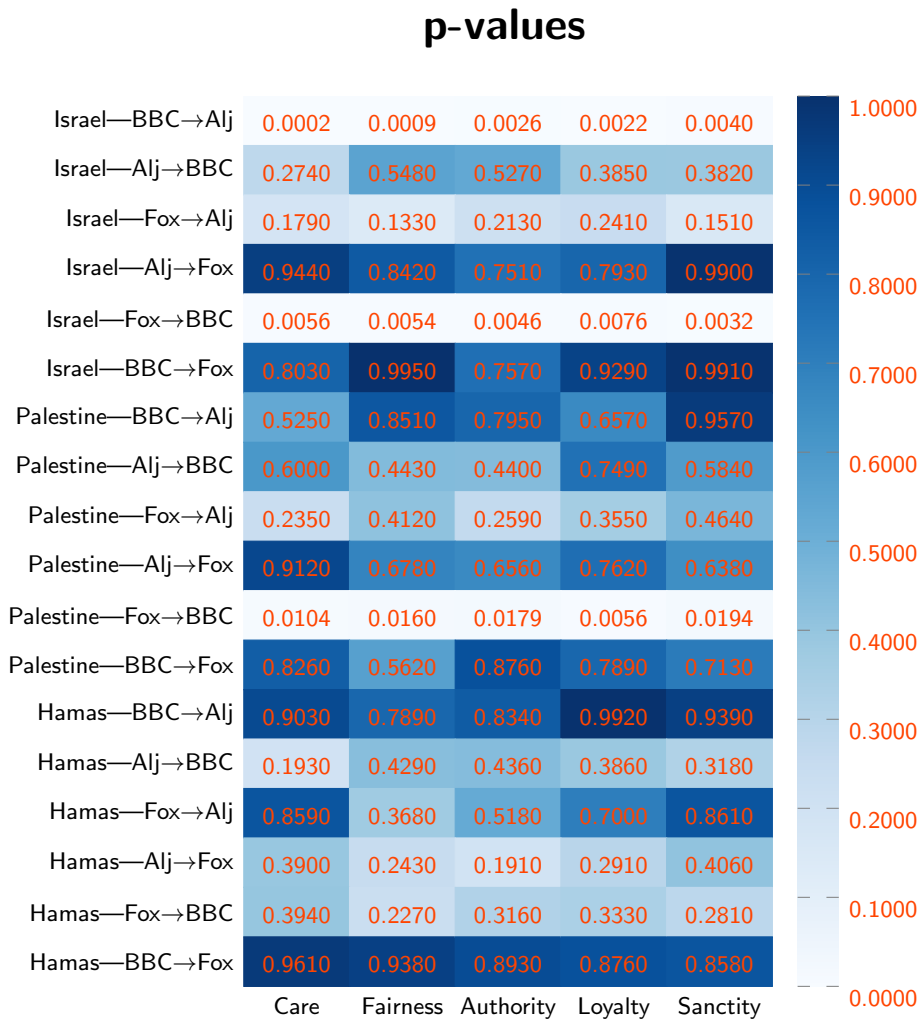
Influence across publishers

- 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



Research Questions (Revisited)

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

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	Phase 2	Phase 3
• Initial instructions • 3 annotators • 100 headlines annotated • Post annotation discussions • Update annotation instructions	• Updated instructions • 33 annotators • 50 headlines annotated • Explanation for each annotation • Update annotation instructions	• Final annotation instructions • 33 annotators • 3300 headlines annotated • 3 annotations for each headline

Annotated Dataset

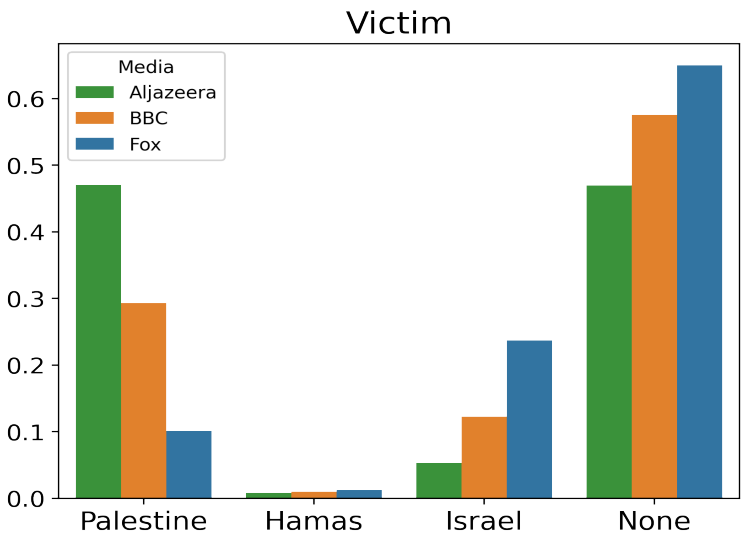
- Final label based on the majority vote
- Removed headlines with no agreement among annotators

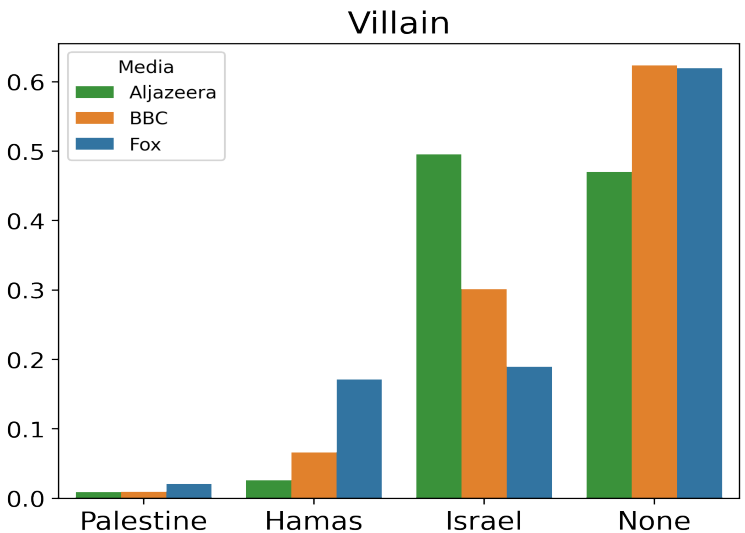
Class	Labels	Count	Agreement
Emotiveness Frame	{Sensationalized, Objective}	2601	0.42
Effect Frame	{Visible, Invisible, None}	2717	0.48
Source Frame	{Elite, People, None}	2834	0.51
Context Frame	{War, Broad, None}	2535	0.60
Role-Victim	{Israel, Palestine, Hamas, None}	2512	0.57
Role-Villain	{Israel,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

Fine-Tuned Language Models

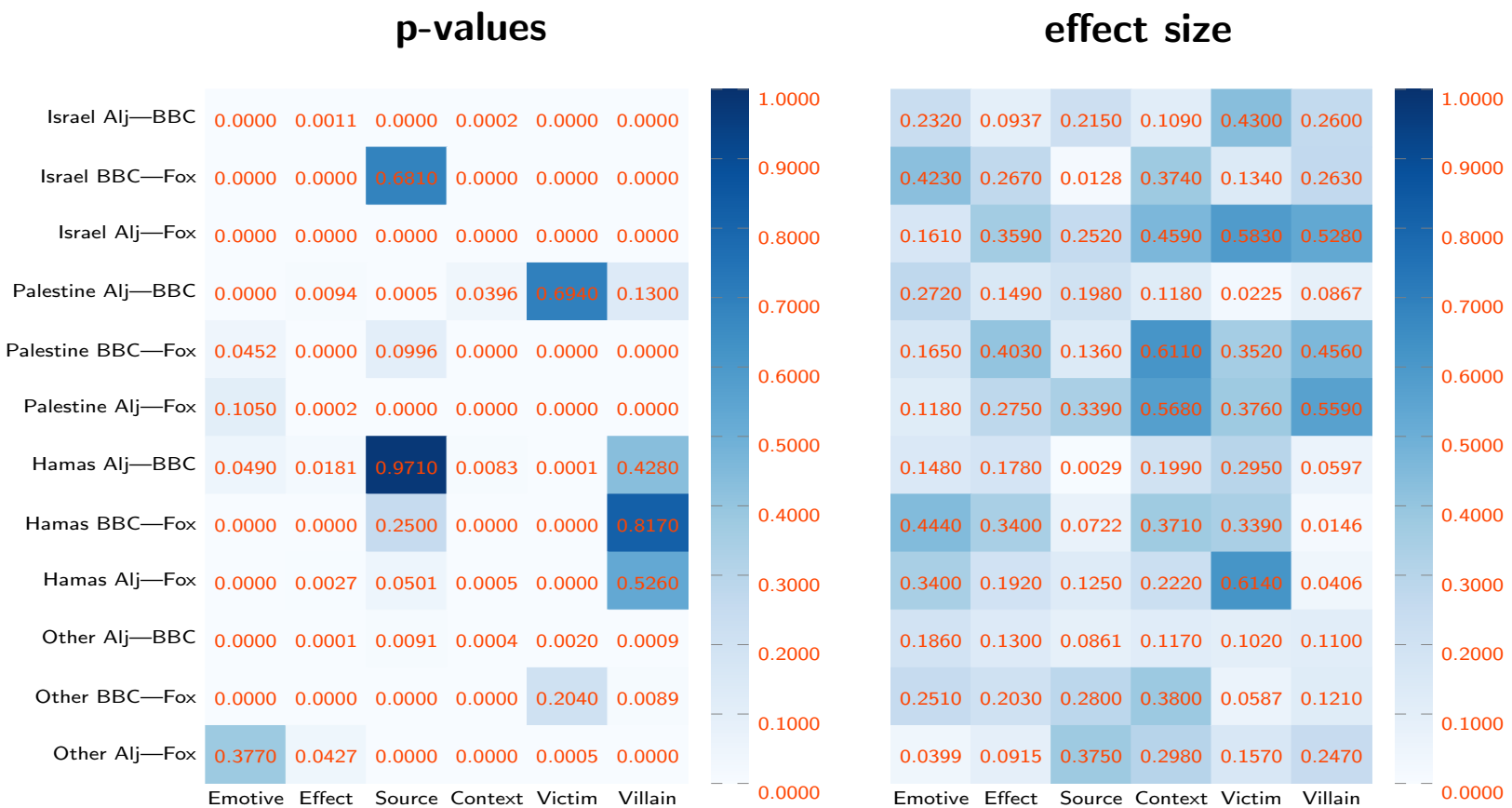
	War and Peace Frames				Role	
Model	Emotive	Effect	Source	Context	Victim	Villain
BERT	80.52	69.1	79.69	77.8	72.39	79.27
RoBERTa	83.83	**71.55**	**82.01**	**77.93**	**74.61**	81.16
ConfliBERT	**84.88**	61.46	81.66	75.81	72.01	**81.74**
ModernBERT	79.3	66.84	79.87	75.6	70.16	74.88
GPT-2	79.82	69.93	78.79	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

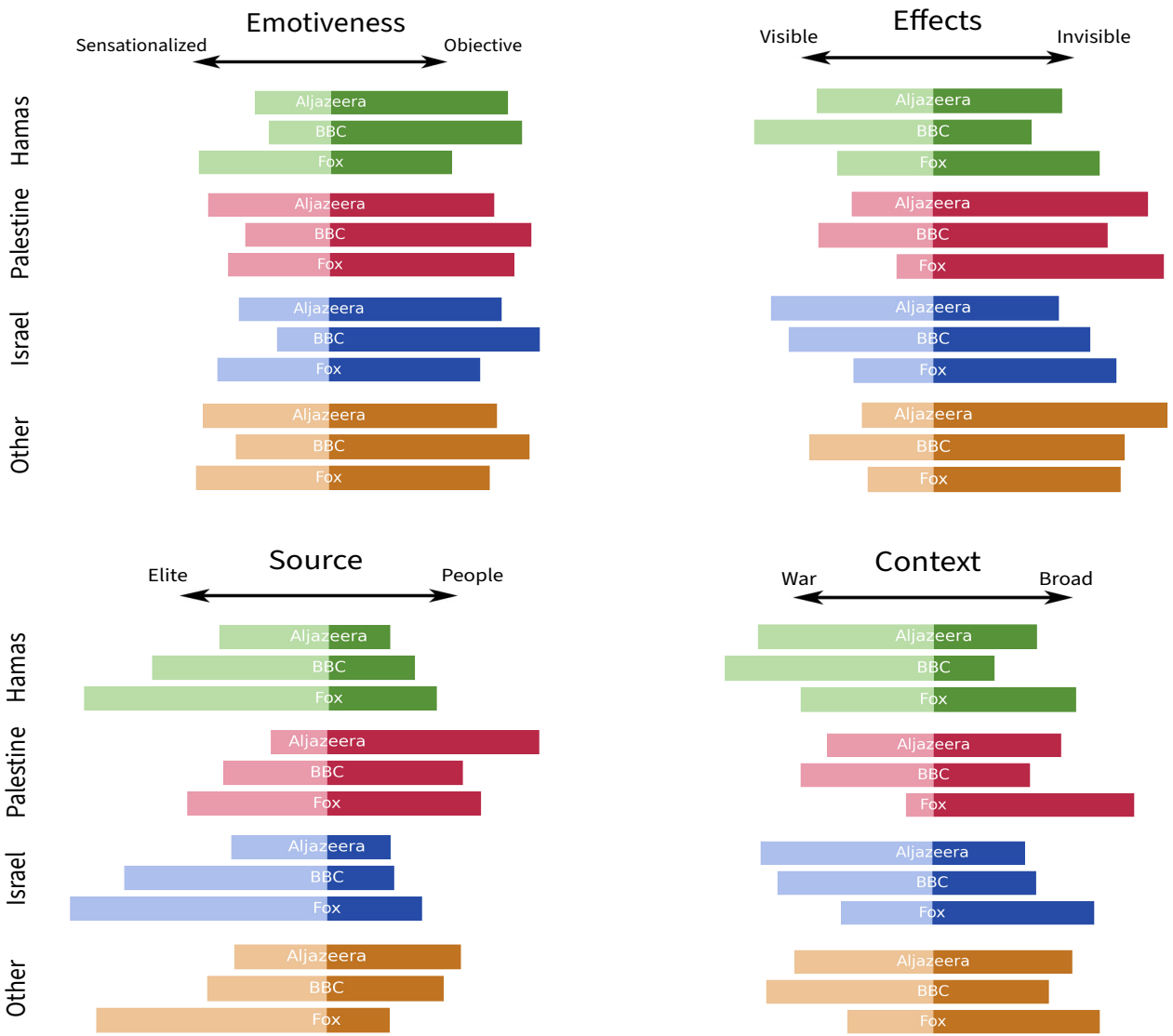




Statistical Analysis Results



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)

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

Challenges of Data Centric Approaches

Collecting data

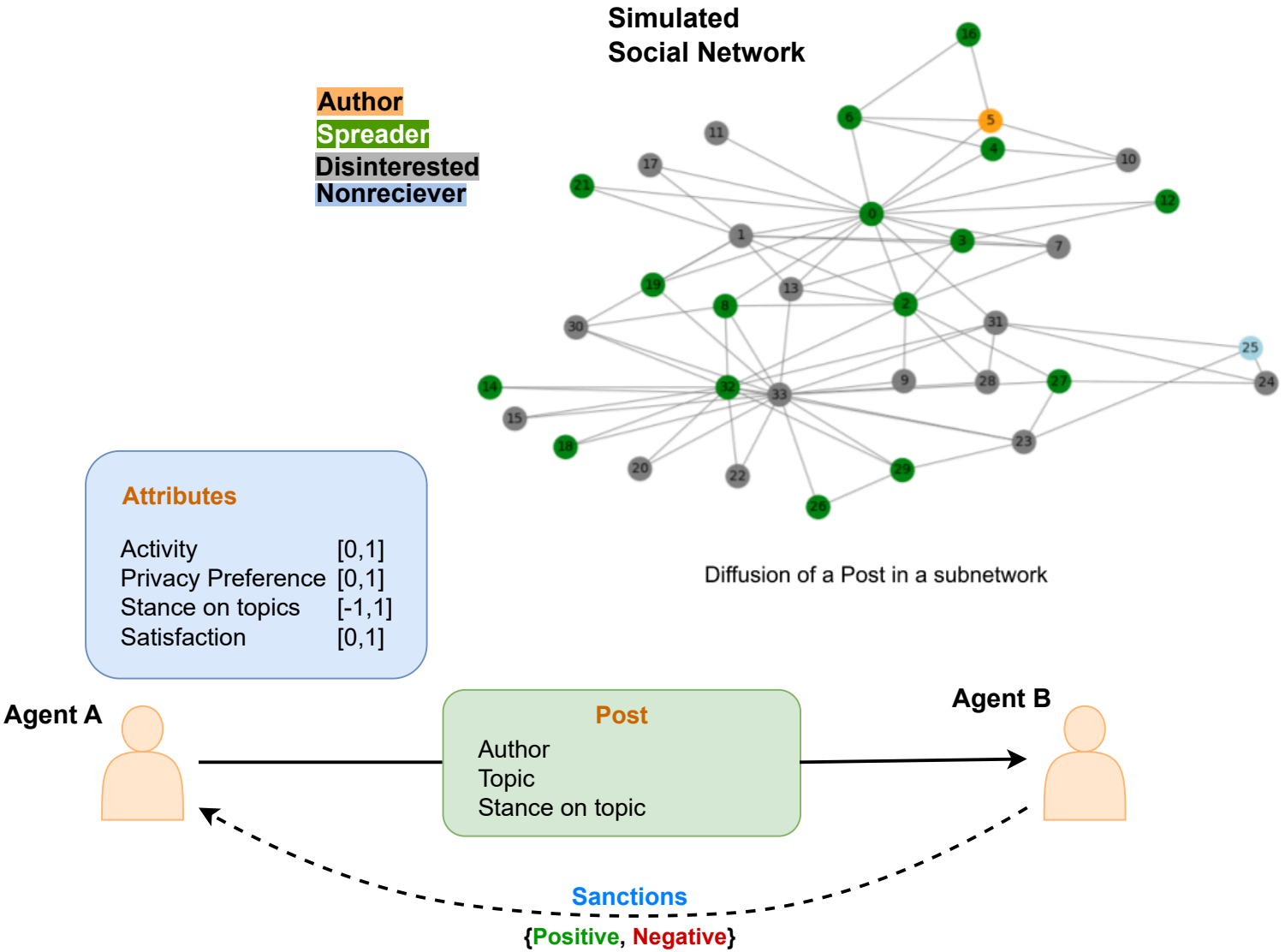
- Expensive
- Privacy concerns

Require annotations

- Non-scalable
- Annotator Bias

Simulation-based evaluation offers a solution

Social Simulation Design



Experimental Setup

Facebook Social Network[5]

- 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

[5] 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 agent 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 agent satisfaction

Research Questions

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?*

Operationalizing Tolerance and Selective Exposure

Tolerance

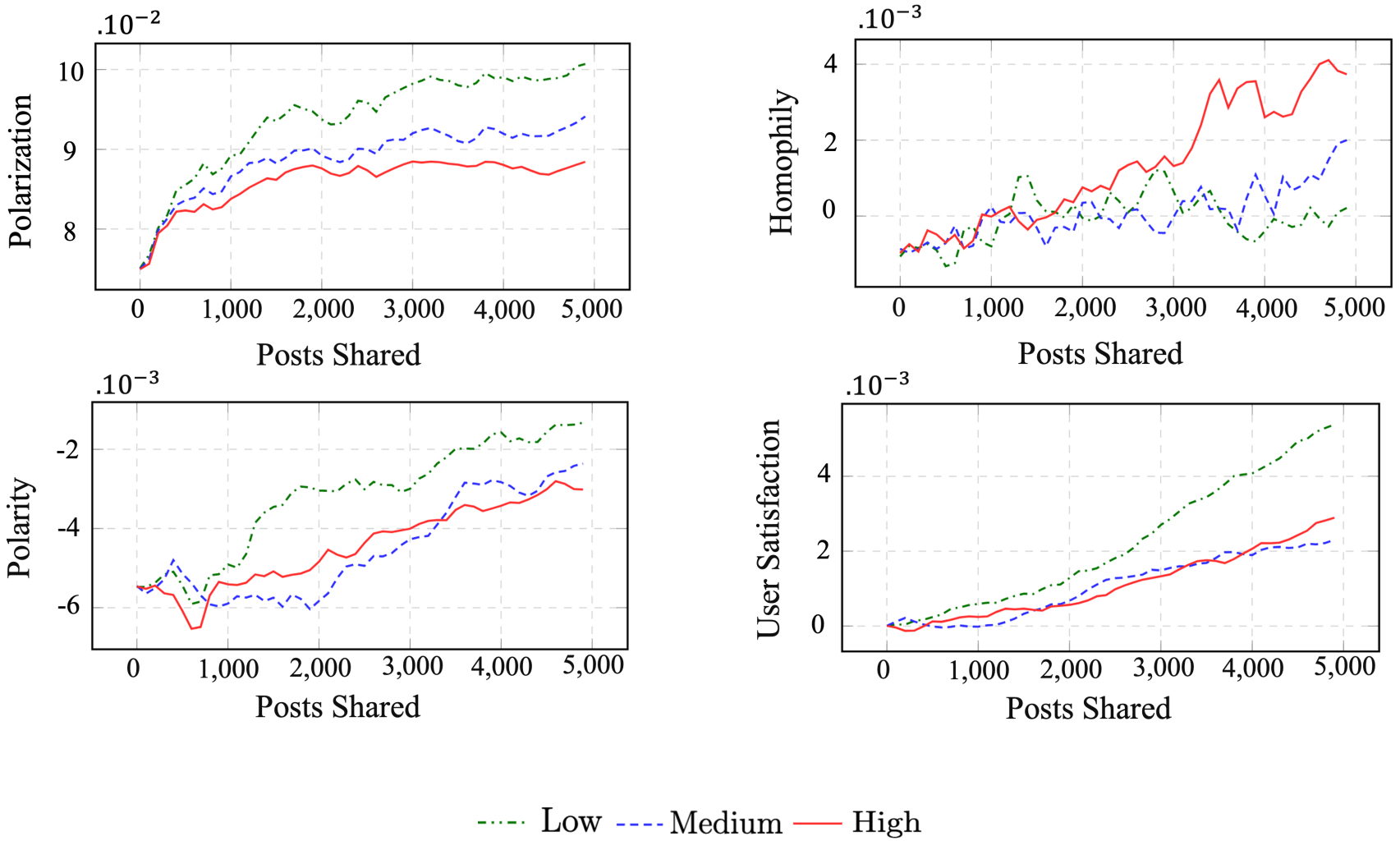
- Social Judgment Theory [6]
  - Explains shift in attitude when two people interact
  - Tolerance $= |\text{Latitude}_{acceptance} - \text{Latitude}_{rejection}|$

Selective exposure

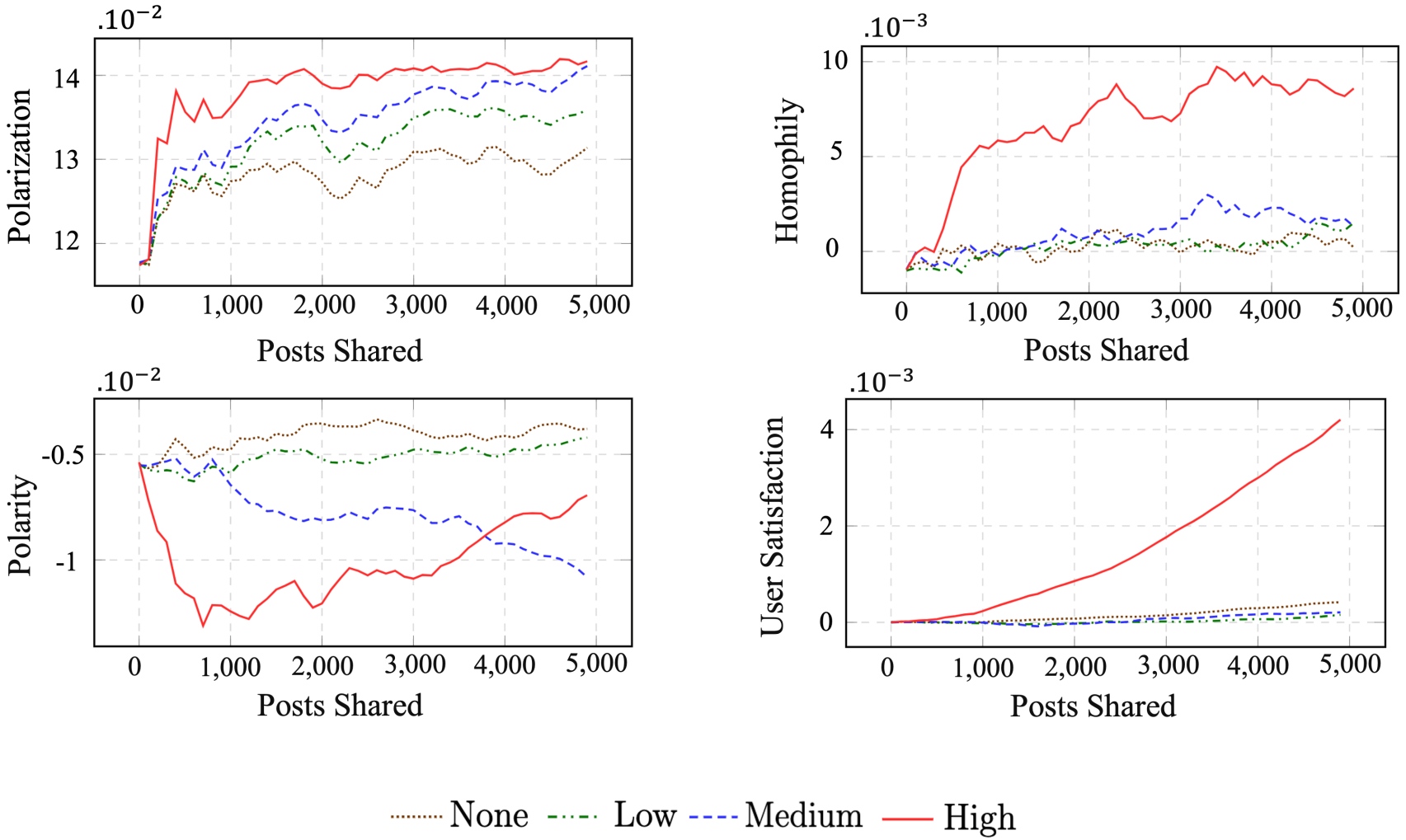
- Filter content based on difference in agent stance

[6] 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$_{\text{Tolerance}}$ *Does higher tolerance among users in a social network help mitigate polarization?*

Higher tolerance

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

RQ$_{\text{Selective Exposure}}$ *Does selective exposure to congenial information contribute to polarization?*

Higher selective exposure

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

Conclusion

- Political news shows slant and favoritism toward political figures
- Social media shows significant differences across audiences of different news sources
- Moral framing in war news differs across publishers
- Use of war and peace frames and portrayal of victim and villain in war news differ across publishers
- Selective exposure to congenial content leads to more polarized social networks and a higher aggregate user satisfaction
- Higher tolerance for noncongenial content slows down polarization in social networks and lead to a lower aggregate user satisfaction

Thank you!

Have questions or suggestions?
Email me at *ahaque2@ncsu.edu*