Extracting Polarization Knowledge from News Media Articles

Techniques and Applications

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Funded by the European Union

University of Cyprus
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Funded in part by the European Union (Grant Agreement 101132686 ATHENA HORIZON-CL2-2023-DEMOCRACY-01.

Polarization: Definition & Motivation

Polarization

"the social process whereby a social or political group is segregated into **two** or **more opposing sub-groups** with **conflicting beliefs**"

- Witnessed in **politics**, **public policy**, issues of **gender**, **race**, **sports**, etc.
- Explanatory theories:
  - Social categorization
  - Social identification
  - Social comparison
  - Motivated reasoning
  - Tribalism/Naive realism

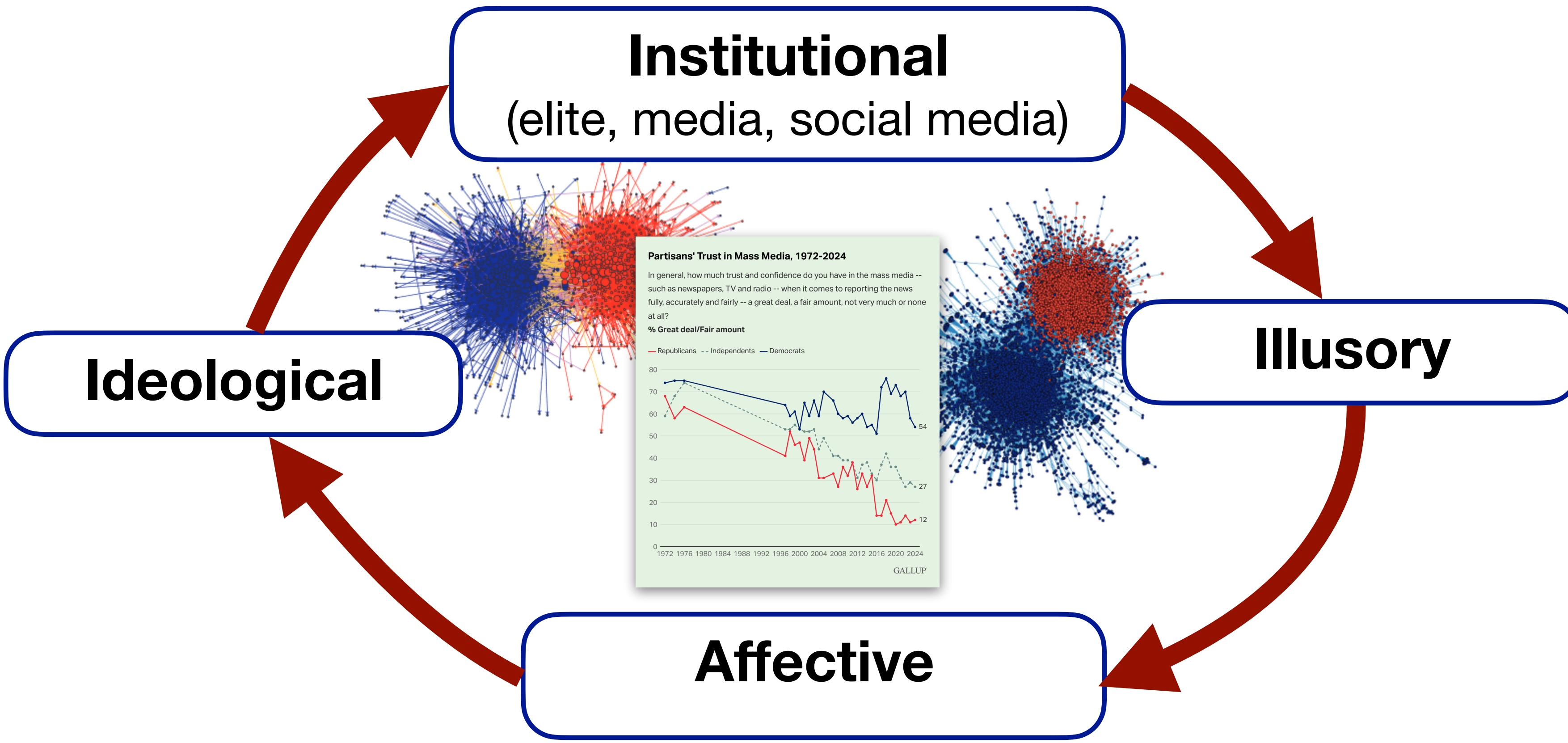
3-Step Intergroup Conflict, Tajfel (1979)

"An integrative theory of intergroup conflict," *H. Tajfel et al., The Social Psychology of Intergroup Relations, vol. 33, no. 47, p. 74, 1979.*

Polarization Aspects

- **Affective**: The degree to which political partizans "*dislike, distrust,* and *avoid the other side*".
- **Ideological**: The degree of division between opposing partisans with regard to their *preferred policy positions*.
- **Elite**: The *deliberate divergence* of political leaders and party elites in ideology and rhetoric, aimed at deepening partisan divisions and *mobilizing their respective bases*.
- **Media:** The shift from neutral reporting to partisan news coverage that amplifies extremes, deepening societal divisions ("*outrage*" *industry*).
- **Social media**: The amplification of political divisions through *algorithmic filtering*, group-based *identity signaling*, and exposure to hyper-partisan or *misleading content* within online networks.
- **Illusory**: Animosity towards opponents determined by what partisans *think* their opponents believe rather than what they actually believe.

A Vicious Cycle?



"The Political Blogosphere and the 2004 U.S. Election: Divided They Blog" *Adamic and Glance. 2005*

"Balancing information exposure in social networks," *K. Garimella, A. Gionis, N. Parotsidis, and N. Tatti, CoRR 2017.*

https://news.gallup.com/poll/651977/americans-trust-media-remains-trend-low.aspx

"Polarization in the contemporary political and media landscape" *Wilson A, Parker V., Feinberg M., Behavioral Sciences, 2020, 34:223-228.*

Polarization Impact

- Creates gridlock by:
  - crippling a society's ability to effectively process social information,
  - manipulating the opinion-formation of citizens,
  - corrupting the epistemological basis for truth-claim validation and deforming the public sphere,
  - coercing decision-makers to alter their policy preferences,
  - undermining the will-formation ability of governments, and
  - paralysing democratic decision-making processes.

"Digital propaganda, counter publics, and the disruption of the public sphere: the Finnish approach to building digital resilience" *C. Bola & K. Papadaki, The World Information War, 2021.*

Polarization Impact

"… companies controlling our global information ecosystem are […] by design – **dividing** us and **radicalizing** us.
Without facts, you can't have truth. Without truth, you can't have **trust**.
Without trust, we have no shared reality, no democracy, and it becomes impossible to deal with the existential problems of our times: climate, coronavirus, and the battle for truth."

*Maria Ressa, **Nobel Peace Prize Award Speech**, December 10, 2021*

A Global Risk (WEF 2025)

Risk categories

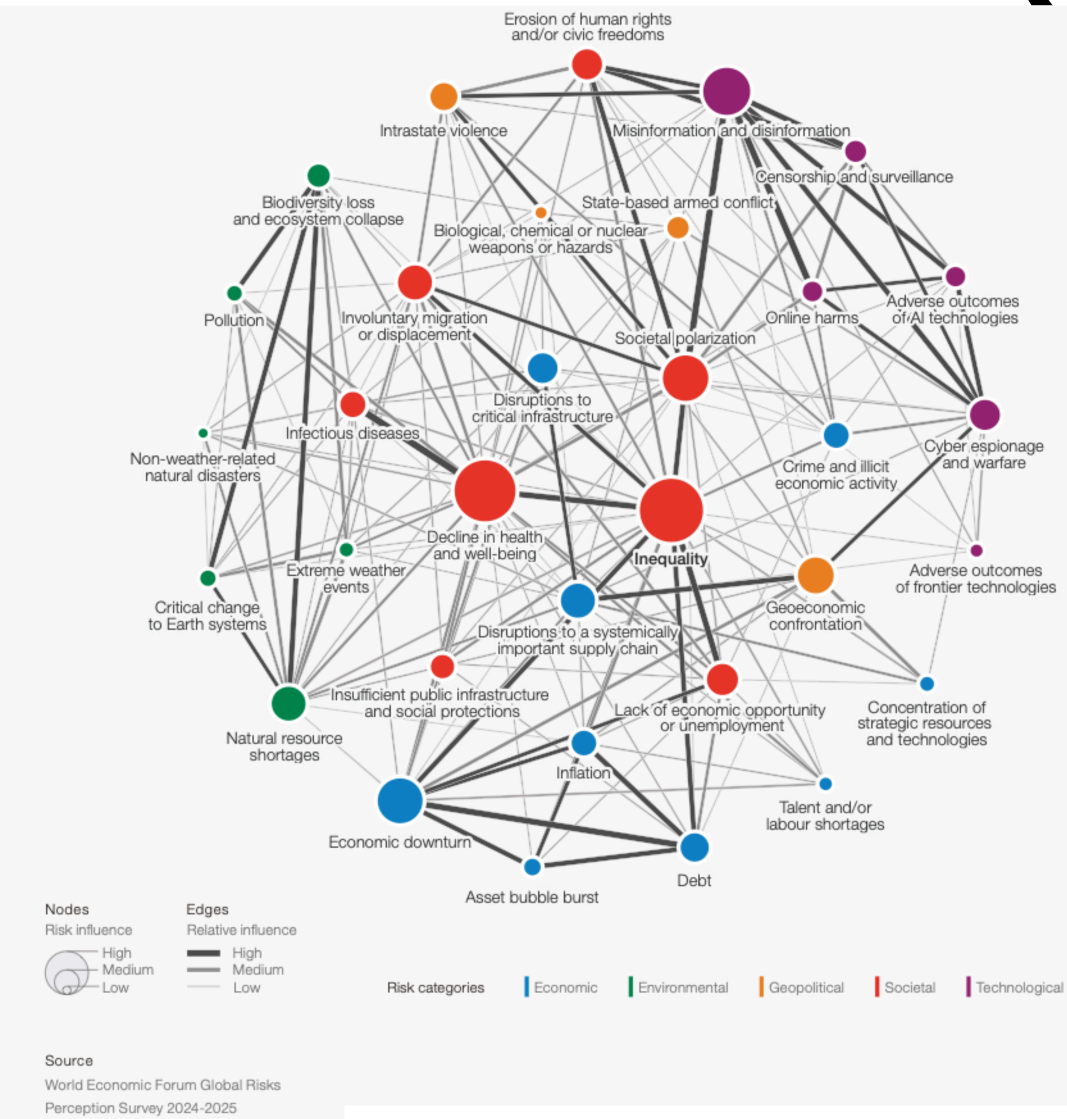
- Economic
- Environmental
- Geopolitical
- Societal
- Technological

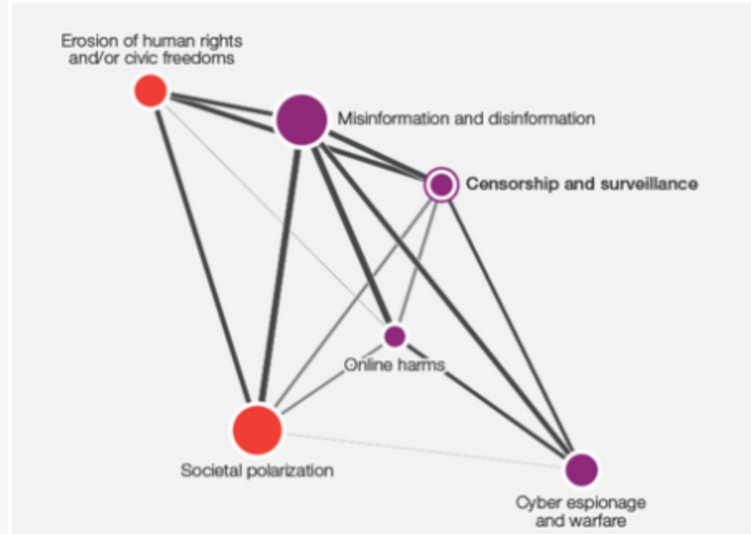
	2 years	10 years
1st	Misinformation and disinformation	Extreme weather events
2nd	Extreme weather events	Biodiversity loss and ecosystem collapse
3rd	State-based armed conflict	Critical change to Earth systems
4th	Societal polarization	Natural resource shortages
5th	Cyber espionage and warfare	Misinformation and disinformation
6th	Pollution	Adverse outcomes of AI technologies
7th	Inequality	Inequality
8th	Involuntary migration or displacement	Societal polarization
9th	Geoeconomic confrontation	Cyber espionage and warfare
10th	Erosion of human rights and/or civic freedoms	Pollution

Source

World Economic Forum Global Risks Perception Survey 2024-2025.

A Global Risk (WEF 2025)





Close connectivity between **societal polarization**, **misinformation** and **disinformation** and **online harms** highlights confluence of these risks in the digital ecosystem.

"The Editor vs. the Algorithm: Economic Returns to Data and Externalities in Online News." *Claussen, Peukert, & Sen. SSRN Electronic Journal. (2019).*

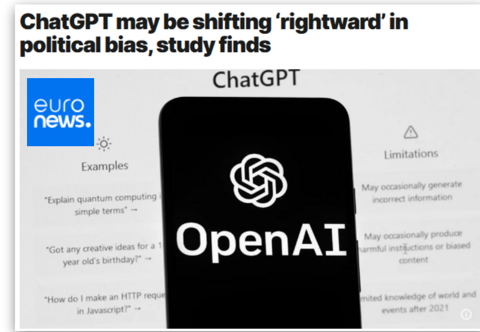
"Partisan Polarization Is the Primary Psychological Motivation behind Political Fake News Sharing on Twitter," *Osmundsen, Bor, Vahlstrup, Petersen, American Political Science Review (2021)*

The Role of Polarized Language

- **Language** is the medium through which both polarization and misinformation spread — intentionally or not.
- Shapes Public Opinion: Phrases like "*undocumented immigrants*" versus "*illegal aliens*" or "*climate crisis*" versus "*climate hoax*" frame issues differently, influencing public perception.
- Drives Engagement: Sensationalist and emotionally charged language increases user engagement, incentivizing media outlets to adopt more extreme framings.
- Amplifies Biases and Division: Individuals tend to consume media that align with their beliefs (confirmation bias), leading to fragmented information environments (echo chambers).
- Artificial Intelligence systems: Are shaping and being shaped by the polarized information ecosystem.

AI Models and Training Data

- LLMs (such as OpenAI's ChatGPT, Anthropic's Claude and Google's Gemini) learn from vast web corpora, including news, forums, and social media.
- These sources often reflect ideological and emotional bias, even when subtle.
- **Biased data → Biased models**:
  - Research shows LLMs can reflect political leanings, stereotypes, and framing preferences.
  - Prompt phrasing or topic framing can shift model responses.


ChatGPT may be shifting 'rightward' in political bias, study finds

Source: https://shorturl.at/EJS6x February 2025


Google chief admits 'biased' AI tool's photo diversity offended users

Sundar Pichai addresses backlash after Gemini software created images of historical figures in variety of ethnicities and genders

Human or fake? How AI is distorting beauty standards - video

Google's Gemini AI illustrations of a 1943 German soldier. Illustration: Gemini AI/Google

Source: https://shorturl.at/0uaDF February 2024

LLMs Can Amplify Polarization

- LLMs can be prompted (intentionally or not) to echo ideological viewpoints, contributing to the spread of: Misinformation, Conspiracy Theories, and Misleading Narratives.
- Creation of a feedback loop:
  - Polarized and biased content → Training data.
  - AI models generating biased outputs.
  - Biased outputs → Shared / Indexed → More polarized data.
- Use Cases:
  - News summaries with framing bias
  - Partisan chatbots
  - Deepfake political narratives

Propagandists are using AI too—and companies need to be open about it

OpenAI has reported on influence operations that use its AI tools. Such reporting, alongside data sharing, should become the industry norm.

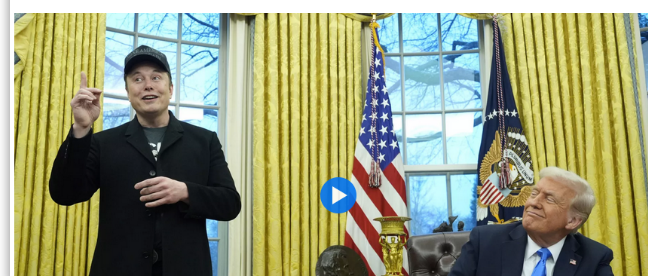
Source: "[Propagandists are using AI](#)", MIT Technology Review, 2024

We tried out DeepSeek. It worked well, until we asked it about Tiananmen Square and Taiwan

Donna Lu

Source: Guardian https://shorturl.at/JIzts January 2025

Is AI chatbot Grok censoring criticism of Elon Musk and Donald Trump?



Source: Euronews https://www.euronews.com/my-europe/2025/03/03/is-ai-chatbot-grok-censoring-criticism-of-elon-musk-and-donald-trump March 2025

"Combating misinformation in the age of LLMs: Opportunities and challenges." Chen, C., and K. Shu. 2024. AI Magazine 45: 354–368.
"Adopting Beliefs or Superficial Mimicry? Investigating Nuanced Ideological Manipulation of LLMs" Paschalides D, Pallis, G. and Dikaiakos M, ICWSM 2025

Open Problems

- Despite the impact of polarized language, we still lack:
  - Computational tools to automatically extract polarization signals from text.
  - Methods to assess and detect ideological bias in AI models.
  - Strategies to use polarization insights to improve AI trustworthiness.

Our Research Agenda

We develop computational approaches to answer three key questions:

- How is polarization expressed in textual content; how does it emerge from the narratives of news articles?
  - **Model** polarization at the level of **entities**, **groups**, and **topics**.
  - **Extract** polarization knowledge into **knowledge graphs**, without relying on labeled political data or party annotations.
- Can polarization insights help in detecting misinformation?
  - Use extracted polarization knowledge to identify **misleading** or **ideologically manipulative content**.
  - Assess the **contribution of polarization cues** on the performance of existing misinformation detection models.
- How ideologically sensitive are Large Language Models?
  - Assess whether **LLMs adopt beliefs** or **mimic styles** when exposed to polarized prompts.

In this talk

- How is polarization expressed in textual content; how does it emerge from the narratives of news articles?
  - **Model** polarization at the level of **entities**, **groups**, and **topics**.
  - **Extract** polarization knowledge into **knowledge graphs**, without relying on labeled political data or party annotations.
- Can polarization insights help in detecting misinformation?
- How ideologically sensitive are Large Language Models?

Other Related Work

- How is polarization expressed in textual content; how does it emerge from the narratives of news articles?
  - **Model** polarization at the level of **entities**, **groups**, and **topics**.
  - **Extract** polarization knowledge into **knowledge graphs**, without relying on labeled political data or party annotations.
- Can polarization insights help in detecting misinformation?

  “PARALLAX: Leveraging Polarization Knowledge for Misinformation Detection” Paschalides, D., Pallis, G., Dikaiakos, M.D., *Social Networks Analysis and Mining: 16th International Conference, ASONAM 2024*.
- How ideologically sensitive are Large Language Models?

  "Adopting Beliefs or Superficial Mimicry? Investigating Nuanced Ideological Manipulation of LLMs." Paschalides, D., Pallis, G., Dikaiakos, M.D., *International AAAI Conference on Web and Social Media (ICWSM 2025)*.

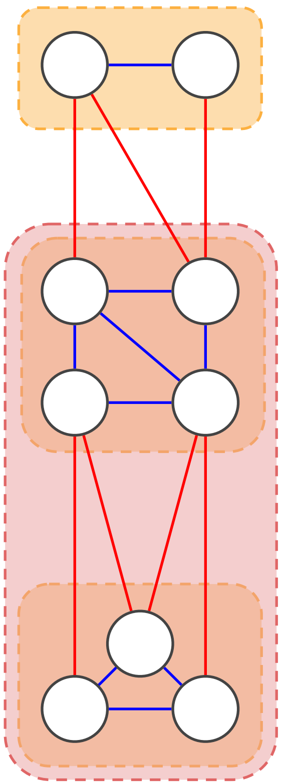
  "Large Language Models For Text Classification: Case Study And Comprehensive Review." Kostina, A., Dikaiakos, M.D., Stefanidis, D., Pallis, G. *arXiv:2501.08457*.

Polarization: Computational Modeling

Polarization: Multi-level Modeling

- Polarization is defined as the process where a (social or political) group is segregated into (two or more) opposing sub-groups with conflicting beliefs.
- Polarization operates in multiple levels:
  - Entity-level: Individuals adopt distinct ideologies and attitudes.
    - Cluster into **fellowships** with shared viewpoints.
  - Group-level: Fellowships collide with each other, forming fellowship **dipoles**.
    - Characterized by ideological and attitudinal differences.
  - Topic-level: Polarization manifests in contentious topics.
    - Dipole fellowships adopt **opposing positions** → increased disagreement.

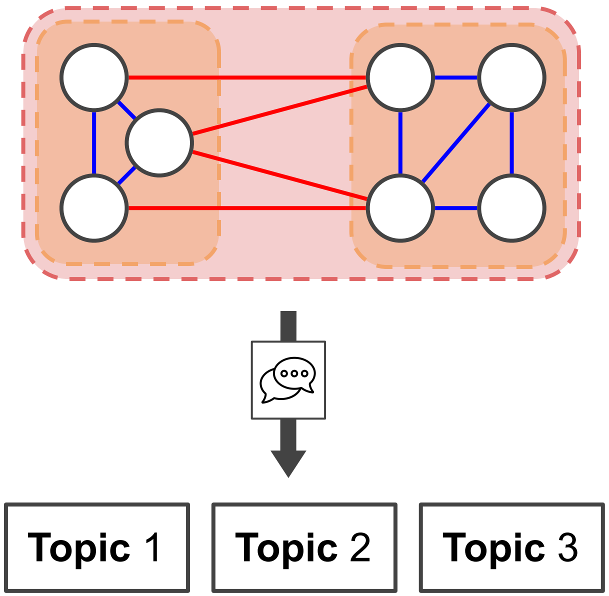
Polarization Data Model



- **Entity**: Real world presence, with abstract or physical existence, that individually or collectively possess / represents views on various topics. Can be a Person, Organization, Nationality, Religion, etc.
- **Entity Relationship**: Positive (supportive) or Negative (oppositional) nature.
- **Entity Fellowship**: Community described by the (mostly) positive entity relationships.
- **Fellowship Dipole**: Fellowship pairs with (mostly) Negative relationships between them.

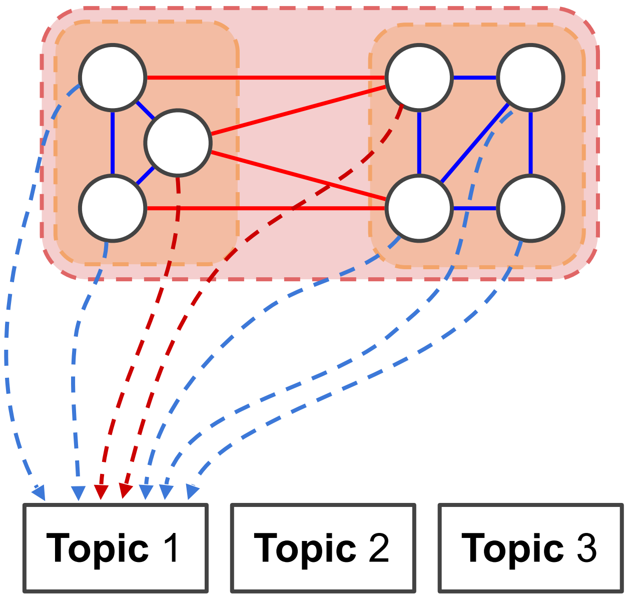
C. R. Sunstein, "The law of group polarization," University of Chicago Law School, no. 91, 1999.
H. Tajfel et al., "An integrative theory of intergroup conflict," The Social Psychology of Intergroup Relations 1979.

Polarization Data Model

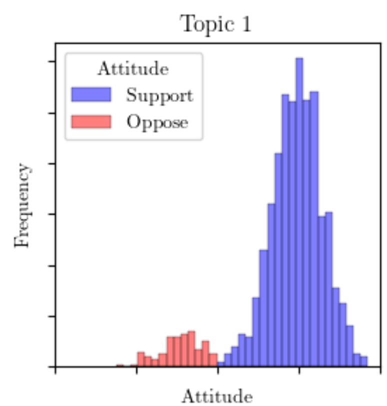


- **Dipole Discussion Topics**: Topics of discussion between dipole's conflicting fellowships.

Polarization Data Model



- **Dipole Discussion Topics**: Topics of discussion between dipole's conflicting fellowships.
- **Sentiment Attitudes**: **Opposition (O)** or **Support (S)** from entities toward topics.



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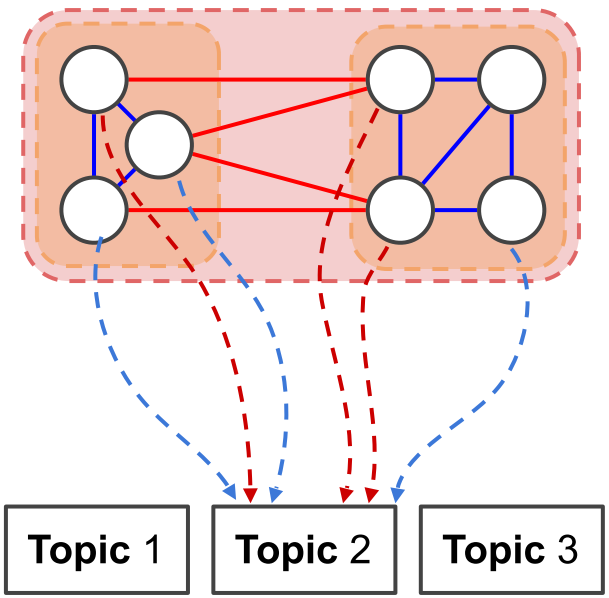

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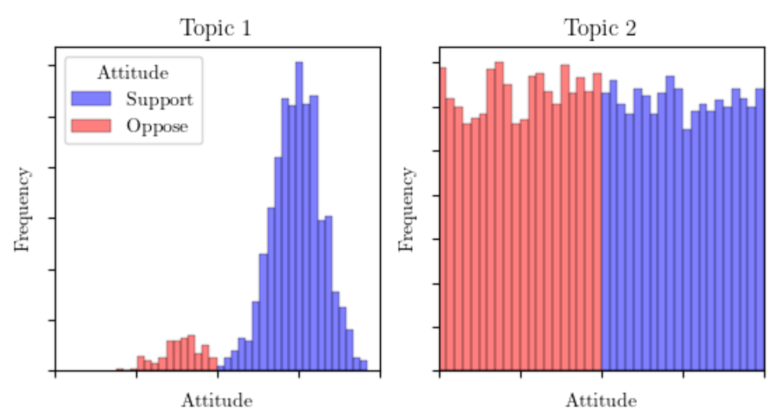

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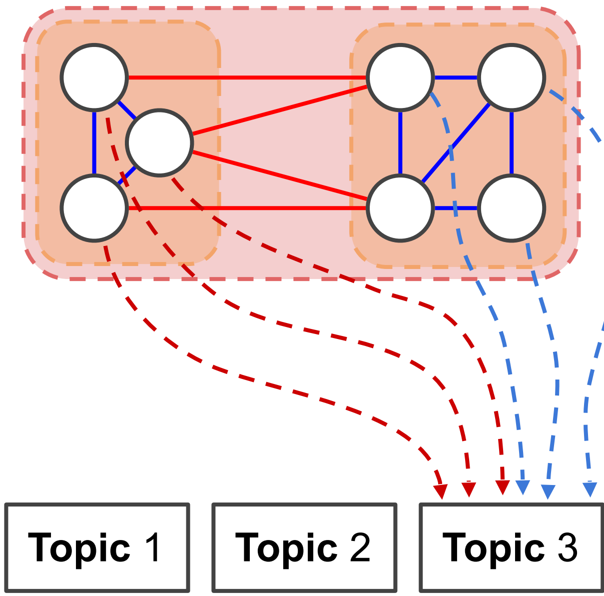

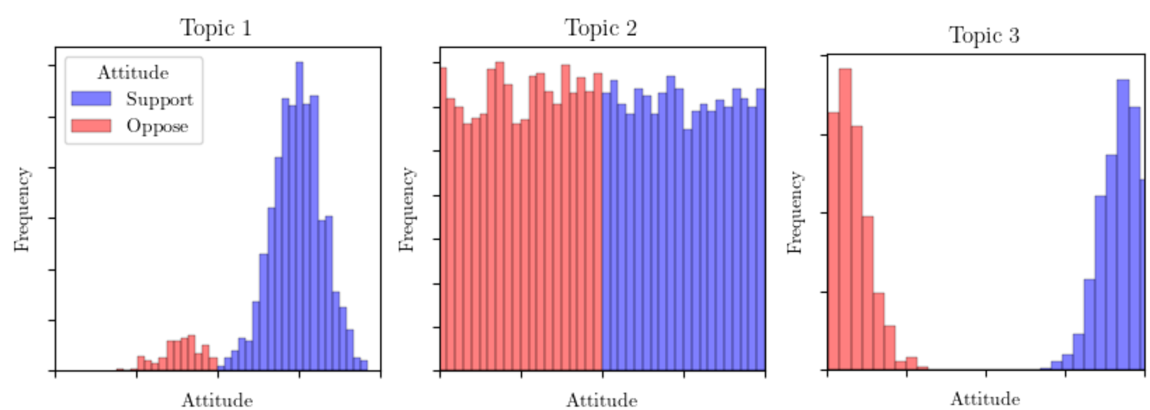

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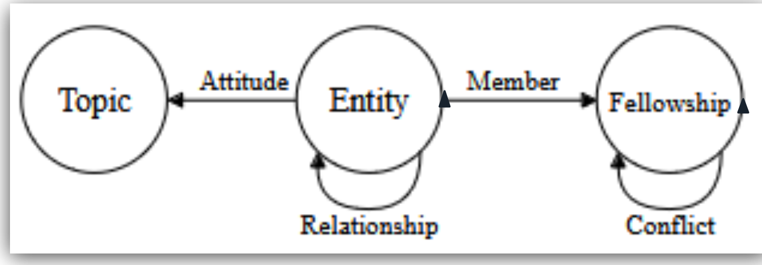
H. Tajfel et al., "An integrative theory of intergroup conflict," The Social Psychology of Intergroup Relations 1979.

Polarization Data Model

- **PDM** is heterogeneous, directed, and weighted graph $G = (V,E)$ where:

$$V = \{v_i \mid \tau(v_i) \in \{Entity, Fellowship, Topic\}\}$$

$$E = \{e_k \mid r(e_k) \in \{Relationship, Member, Attitude, Conflict\}\}$$

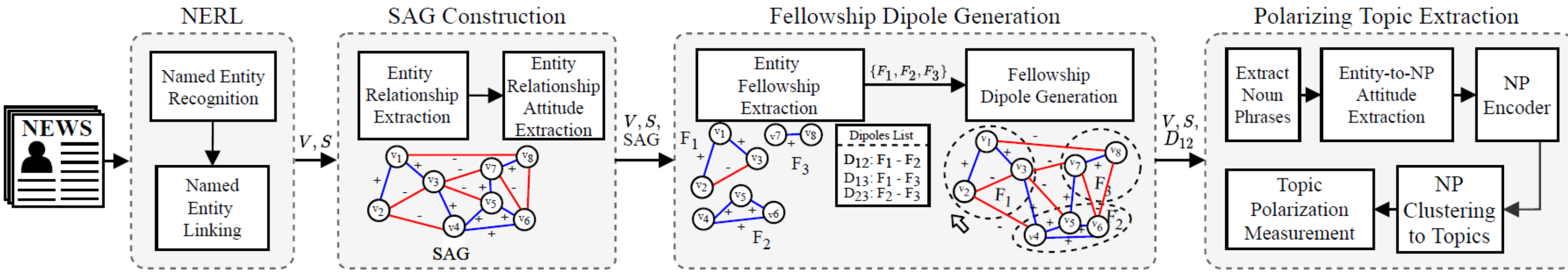


- Relationship: $Entity_i \leftrightarrow Entity_j$ with $\mathbf{w_{ij}} \in [-1, 1]$.
- Attitude: $Entity_i \rightarrow Topic_z$ with $\mathbf{w_{iz}} \in [-1, 1]$.
- Member: $Entity_i \rightarrow Fellowship_k$ with $\mathbf{w_{ik}}$ constant.
- Conflict: $Fellowship_k \leftrightarrow Fellowship_q$ with $\mathbf{w_{kq}} \in [0, 1]$.

- **Sentiment Attitude Graph** (**SAG**): $G[v_i \in V \mid \tau(v_i) = Entity]$

Polarization Knowledge Extraction

POLAR Framework



- Automated identification of polarizing people/organizations/topics in News Media, based on NLP of News Corpuses.
- Algorithms for automated, comprehensive polarization analysis including:
  - Identification of entities, groups (fellowships) and dipoles.
  - Ideological and attitudinal cohesiveness of groups (fellowships).
  - Identification of primary polarizing entities and their polarization contribution: protagonists and antagonists.
  - Ranking of polarizing topics.

"POLAR: A Holistic Framework for the Modelling of Polarization and Identification of Polarizing Topics in News Media." *Paschalides, Pallis, Dikaiakos. IEEE/ACM Conference on Advances in Social Network Analysis and Mining (2021).*
"A Framework for the Unsupervised Modeling and Extraction of Polarization Knowledge from News Media" *Paschalides, D., Pallis, G., Dikaiakos, D. M. on Social Media. ACM Trans. Soc. Comput. 2024*

Input Dataset

- OSN posts are: short, noisy, and informal.
- We focus on news articles:
  - Written in formal language.
  - Typically contain coherent narratives.
  - Provide additional context.
  - Discuss specific subjects.
- Ideal for knowledge extraction.

- **Thematic Keywords**
  e.g. "COVID-19," "vaccine"
- **Geographical Regions**
  e.g. "United States"
- **Relevant Timeframes**
  e.g., Jan. 2020 - Dec. 2021

- Use meta-information to query **GDELT Project**

News Corpus: Input Dataset

Processing Pipeline

Example News Article

"Minneapolis police officer, Derek Chauvin, has been charged with the murder of Floyd. … The Black Lives Matter movement demanded justice for the death of George Floyd from Minneapolis and president Trump, with Benjamin Crump and Erica McDonald promised to deliver. … Trump assigns National Guard to the disposal of states' governors as riots respond similarly to Minneapolis."

Apply Article Segmentation

Example News Article

"Minneapolis police officer, Derek Chauvin, has been charged with the murder of Floyd. … The Black Lives Matter movement demanded justice for the death of George Floyd from Minneapolis and president Trump, with Benjamin Crump and Erica McDonald promised to deliver. … Trump assigns National Guard to the disposal of states' governors as riots respond similarly to Minneapolis."

Sentence Segmentation

Article Sentences S

"Minneapolis police officer, Derek Chauvin, has been charged with the murder of Floyd.

The Black Lives Matter movement demanded justice for the death of George Floyd from Minneapolis and president Trump, with Benjamin Crump and Erica McDonald promised to deliver.

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Named Entity Recognition

Example News Article

"Minneapolis police officer, Derek Chauvin, has been charged with the murder of Floyd. ... The Black Lives Matter movement demanded justice for the death of George Floyd from Minneapolis and president Trump, with Benjamin Crump and Erica McDonald promised to deliver. ... Trump assigns National Guard to the disposal of states' governors as riots respond similarly to Minneapolis."

Sentence Segmentation

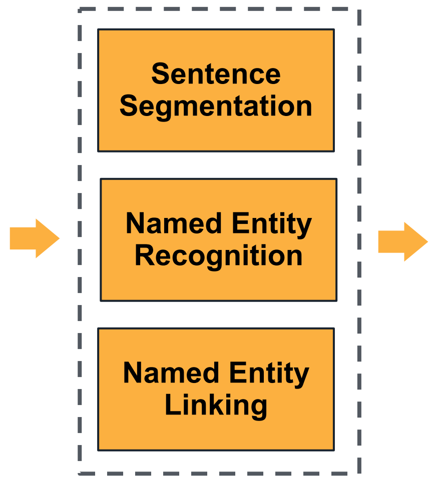
Named Entity Recognition

Article Sentences S	**Named Entities V**
"Minneapolis police officer, Derek Chauvin, has been charged with the murder of Floyd.	(Minneapolis police, ORG), (Derek Chauvin, PERSON), (Floyd, PERSON)
The Black Lives Matter movement demanded justice for the death of George Floyd from Minneapolis and president Trump, with Benjamin Crump and Erica McDonald promised to deliver.	(Black Lives Matter, ORG), (George Floyd, PERSON), (Minneapolis, LOC), (Benjamin Crump, PERSON), (Trump, PERSON), (Erica McDonald, PERSON)
Trump assigns National Guard to the disposal of states' governors as riots respond similarly to Minneapolis."	(Trump, PERSON), (National Guard, ORG), (Minneapolis, LOC)

Named Entity Linking

Example News Article

"Minneapolis police officer, Derek Chauvin, has been charged with the murder of Floyd. … The Black Lives Matter movement demanded justice for the death of George Floyd from Minneapolis and president Trump, with Benjamin Crump and Erica McDonald promised to deliver. … Trump assigns National Guard to the disposal of states' governors as riots respond similarly to Minneapolis."



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Named Entities V

(Minneapolis police, ORG),
(Derek Chauvin, PERSON),
(George Floyd, PERSON)

(Black Lives Matter, ORG),
(George Floyd, PERSON),
(Minneapolis, LOC),
(Benjamin Crump, PERSON),
(Donald Trump, PERSON),
(Erica McDonald, PERSON)

(Donald Trump, PERSON),
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SAG Generation: Entity Relationship Identification

Article Sentences S

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(Donald Trump, PERSON), (National Guard, ORG), (Minneapolis, LOC)

Entity-to-Entity Relationship Extraction

Entity 1 (v_1)	Entity 2 (v_2)
Derek Chauvin	George Floyd
Minneapolis	George Floyd
Minneapolis Police Dpt.	George Floyd
...	
Minneapolis Police Dpt.	Derek Chauvin
Black Lives Matter	George Floyd
Black Lives Matter	Minneapolis

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(Donald Trump, PERSON), (National Guard, ORG), (Minneapolis, LOC)

Entity-to-Entity Relationship Extraction

Sentiment Attitude Calculation

Entity 1 (v_1)	Entity 2 (v_2)	Status
Derek Chauvin	George Floyd	Neg.
Minneapolis	George Floyd	Neg.
Minneapolis Police Dpt.	George Floyd	Neg.
...		
Minneapolis Police Dpt.	Derek Chauvin	Pos.
Black Lives Matter	George Floyd	Pos.
Black Lives Matter	Minneapolis	Neg.

SAG Generation: Entity Relationship Identification

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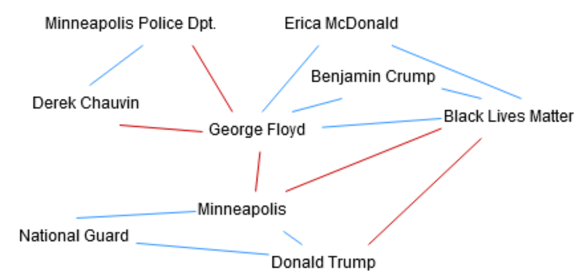
Entity-to-Entity Relationship Extraction

Sentiment Attitude Calculation

Generate SAG



Identifying Entity Relationships

- **Learning by Continuity**: Objects, once experienced together, tend to be related to each other.
  - Calculate entity co-occurrence frequencies in sentences.
  - Higher the co-occurrence frequency → Higher likelihood of a real-life relationship.
  - ≥ 95th quantile (top 5% of co-occurring pairs with the highest frequencies).

Example Sentences

- "Minneapolis Police Dpt. officer, Derek Chauvin, has been charged with the murder of Floyd.
- George Floyd was murdered by Derek Chauvin.

Entity 1 (v_1)	Entity 2 (v_2)	Co-occurrence Frequency
Derek Chauvin	**George Floyd**	**2**
Minneapolis Police Dpt.	George Floyd	1
Minneapolis Police Dpt.	Derek Chauvin	1

Sentiment Attitude Calculation

- Sentiment Attitude: Directed sentiment from one entity in the text towards another.
  - Calculated as the sentiment score of the **syntactical dependency path** of Entity 1 and Entity 2 within a sentence.

Example Sentences

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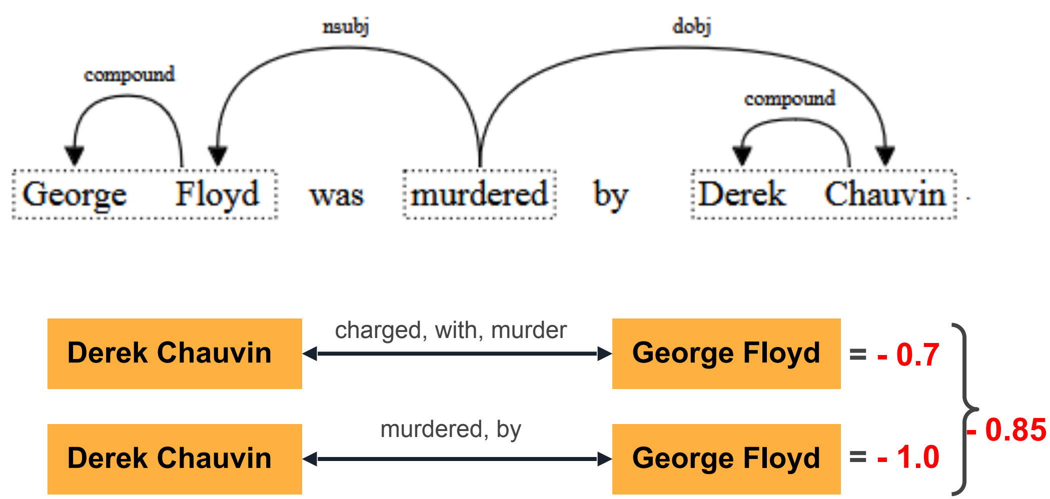
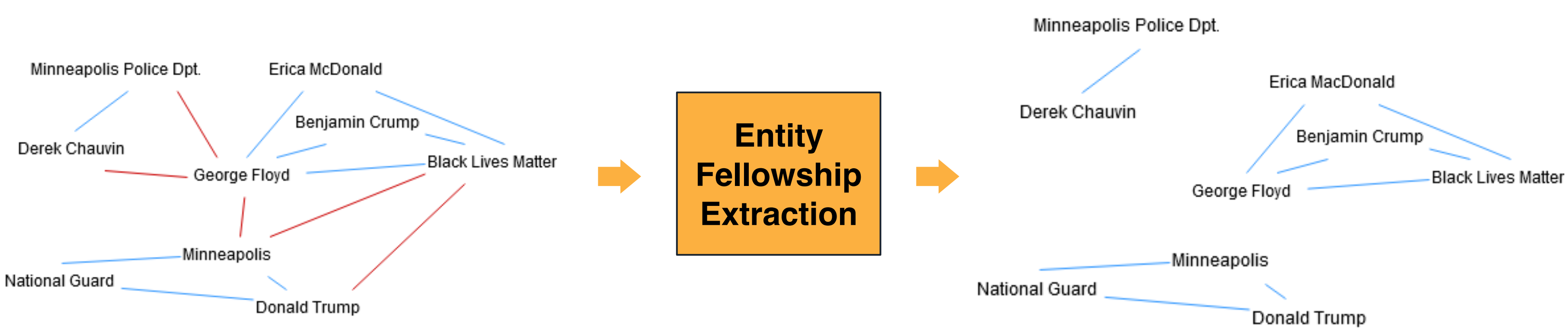
- George Floyd was murdered by Derek Chauvin.



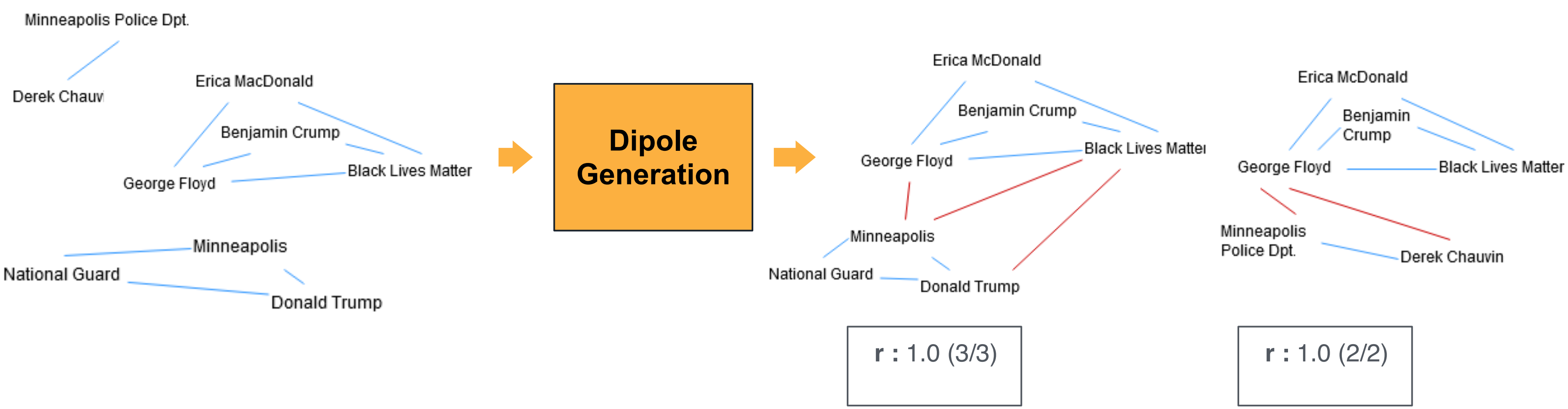
Fellowship Extraction

- Fellowship: Densely connected subgraph of SAG with mostly positive attitudes.
- Signed Network Clustering: Find clusters such that most edges within clusters are positive, and most edges across clusters are negative.
- Avoid spectral clustering (definition of k) → Use Signed Modularity-based clustering (SiMap) based on resolution **λ**.



Dipole Calculation

- **Greedy approach**: Initial Dipole Set → All possible fellowship pairs.
- Maximize the probability of a polarized state using heuristics that take into account the following metrics for potential dipoles:
  - Negative Across (r): The ratio of the number of negative edges to the **total** number of edges connecting the two fellowships → Threshold set to 0.5.
  - Frustration index: Measures the level of dipole's structural balance and polarized state → Threshold set to 0.7



Dipole Topic Extraction

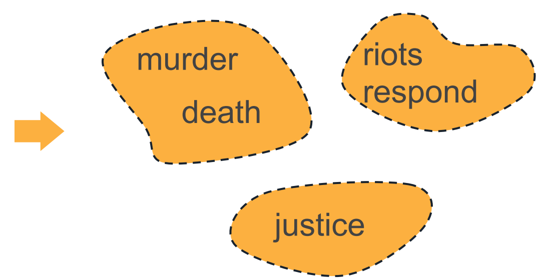
- **Topics**: defined as sets of **semantically similar** Noun Phrases (NPs)
  - Noun-phrases: phrases that include nouns → important in understanding context.

Article Sentences S

“Minneapolis Police Dpt. officer, Derek Chauvin, has been charged with the murder of George Floyd.

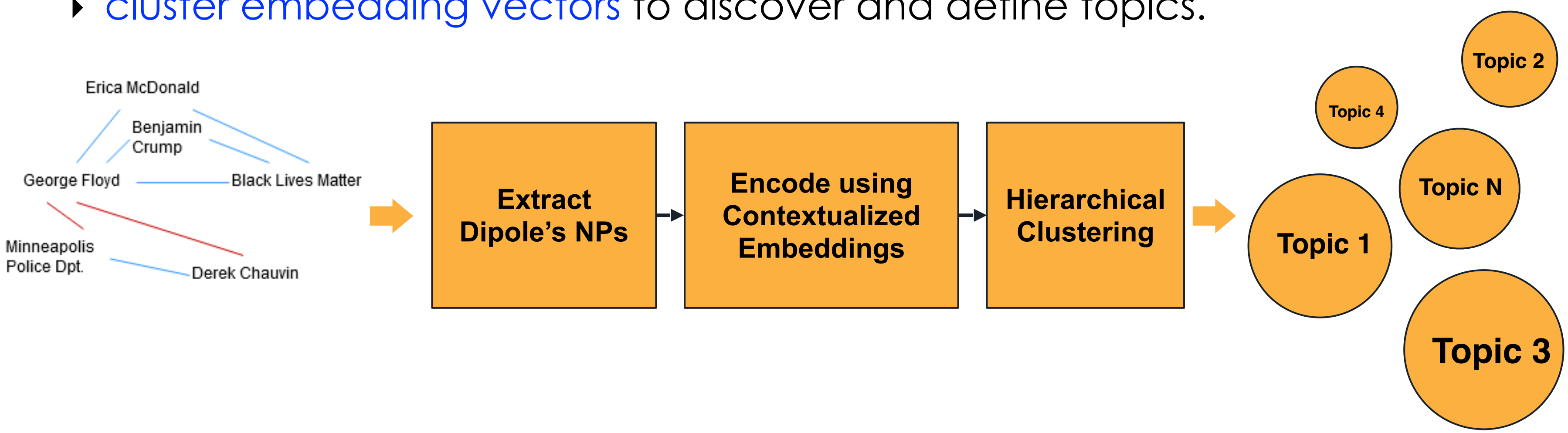
The Black Lives Matter movement demanded justice for the death of George Floyd from Minneapolis and president Donald Trump, with Benjamin Crump and Erica McDonald promised to deliver.

Donald Trump assigns National Guard to the disposal of states’ governors as riots respond similarly to Minneapolis.”



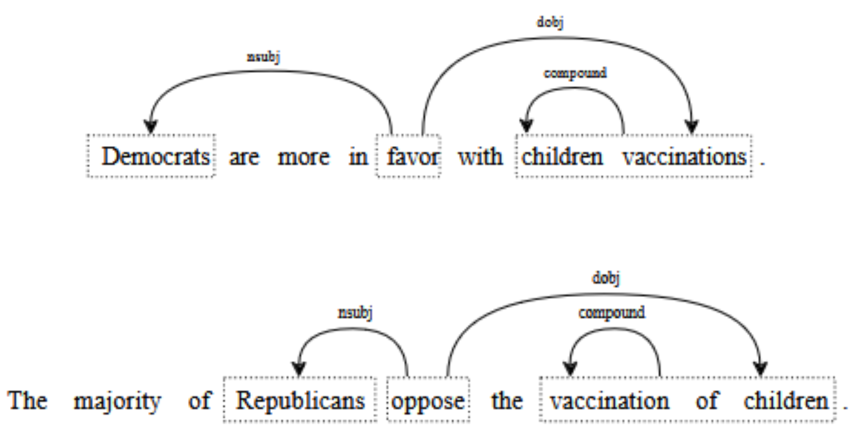
Calculating Dipole Topics

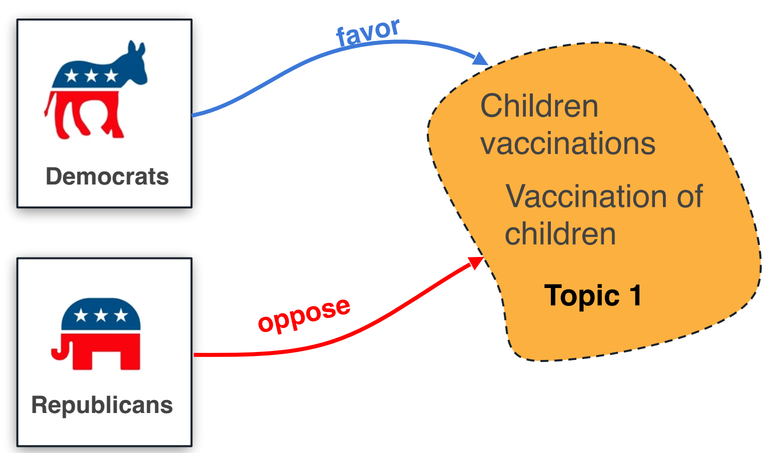
- Traditional topic modeling techniques (LDA) do not work well here, due to the small number of noun-phrases associated per dipole, and the presence of entity mentions in many NPs.
- To achieve **semantic clustering** and derive **topics related to dipoles**, we:
  - remove entity mentions from the NPs,
  - convert NPs to word embeddings, and
  - cluster embedding vectors to discover and define topics.



Topic Attitude Extraction

- Sentiment Attitude: Directed sentiment from an **entity** towards a **topic-related NP**.
- Calculated

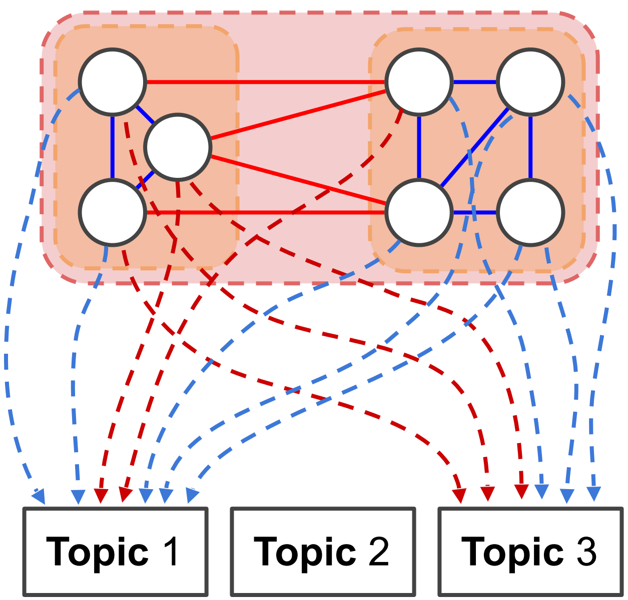


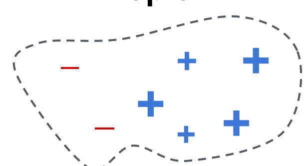
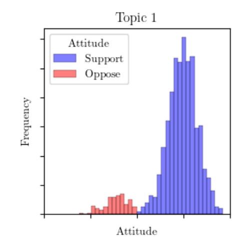
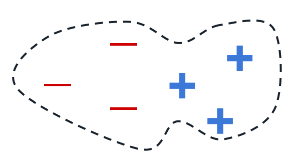
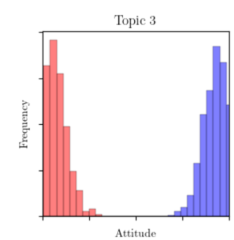


Quantifying Topic Polarization

- Polarization Index μ: a population is perfectly polarized when divided into two groups of the same size and with opposite attitudes.
- μ=1 if attitudes are perfectly polarized, and μ=0 if not polarized at all.

$$\mu = (1 - \Delta A)d.$$



Attitude Populations	Attitude Distributions	Polarization Index μ
Topic 1 		μ = 0.26
Topic 3 		μ = 1.00

Evaluation: Methodology and Results

Evaluation of Polarization Knowledge

- We establish an evaluation methodology for assessing the correctness of the PK across its levels, by utilizing external sources and tailored metrics, with respect to the following questions:
- **Q1:** What is the framework's effectiveness in capturing entity attitudes towards topics?
- **Q2:** What is the extent of alignment of ideologically cohesive fellowships with their respective political parties?
- **Q3:** What is the effectiveness of capturing the polarization level of each topic?

Case studies' datasets

- **Abortion**:
  - Articles: **3,437** Left vs. **3,039** Right
  - 80% Published: ≥ 2010
  - **Topics**: **20**

- **Immigration**:
  - Articles: **3,496** Left vs. **5,020** Right
  - 80% Published: ≥ 2016
  - **Topics**: **22**

- **Gun Control**:
  - Articles: **3,198** Left vs. **3,455** Right
  - 80% Published: ≥ 2011
  - **Topics**: **19**

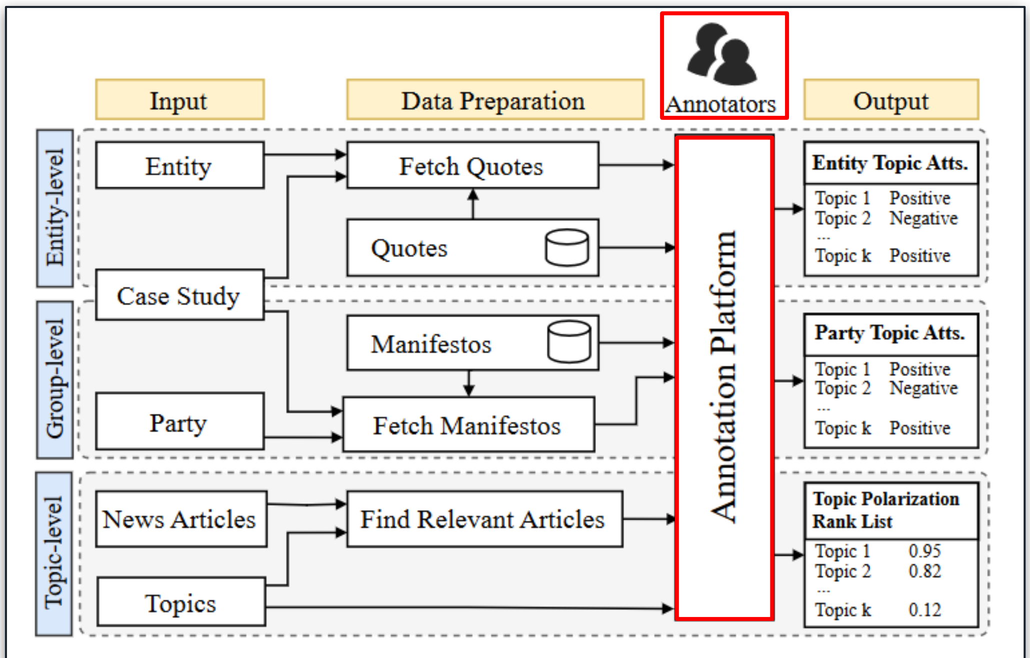
POLAR Application

- We applied POLAR on the news corpus of each case study:

	Abortion	Immigration	Gun Control
Entities:	8,113	18,409	15,217
SAG Nodes:	228	459	194
SAG Edges:	523	1,440	478
Fellowships:	49	156	69
Dipoles:	16	34	42
Noun Phrases:	107,521	298,918	201,419
Topics:	533	2,517	1,262

Ground truth Development

- We define a polarization knowledge annotation methodology for the construction of the ground-truth datasets for each polarization level.



3 Annotators with CS background: 1 experienced annotator and 2 MSc students.

For the annotation, we have developed an annotation platform.

Results

- Accurate prediction of fellowship attitudes toward topics.
- Extracted fellowships:
  - High cohesiveness
  - High degree of alignment between their attitudes and their party manifestos.
- Strong Topic Identification Accuracy (TIA)
- Topic Polarization Ranking Agreement (TPRA)

http://www.cs.ucy.ac.cy/mdd

http://linc.ucy.ac.cy