Bridging the Narrative Divide

Mapping Cross-Platform Discourse to Reveal Hidden Pathways of Narrative Migration

Authors: Patrick Gerard, Hans W.A. Hanley, Luca Luceri, Emilio Ferrara

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Who Am I?

I'm Patrick Gerard, a second-year (hopeful) PhD student working under Prs. **Kristina Lerman** and **Emilio Ferrara**. I'm interested in the intersection of **machine learning and network science** and how they can be utilized to uncover the mechanisms of **information diffusion** and narrative evolution across media.

Kevin (handsome)

Me

Who Am I?

paper available on
patrickgerard.co *

Recent Timeline

May 2025: New Paper! 📝
Bridging the Narrative Divide: Cross-Platform Discourse Networks in Fragmented Ecosystems

March 2025: ICWSM Paper Accepted 🎉
Fear and Loathing on the Frontline: Decoding the Language of Othering by Russia-Ukraine War Bloggers

January 2025: ICWSM Paper Accepted 🎉
Modeling Information Narrative Evolution on Telegram During the Russia-Ukraine War

September 2024: Stanford ESRG Talk 🎤
Gave a talk on narrative evolution and othering frameworks for LLM-guided community analysis.

June 2024: Interview with CNBC 🎙️
Featured for my work analyzing Truth Social and the rise of fringe platforms.

March 2023: Dataset Paper Accepted at ICWSM 🎉
Truth Social Dataset

* this presentation is also there

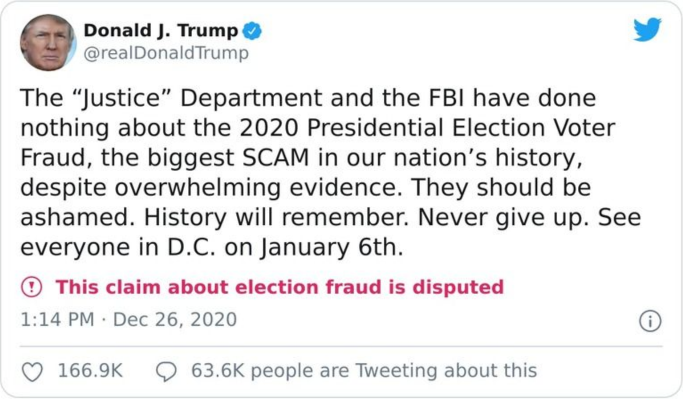
Modeling Narrative Flow Across Platforms

Can discourse-based networks capture the structural patterns of cross-platform narrative movement?

Cross-Platform Information Flow in Action

Modern narratives cross platforms faster than we can track them

January 6th: Same Narratives, Different Ecosystems



(Donovan et al.)

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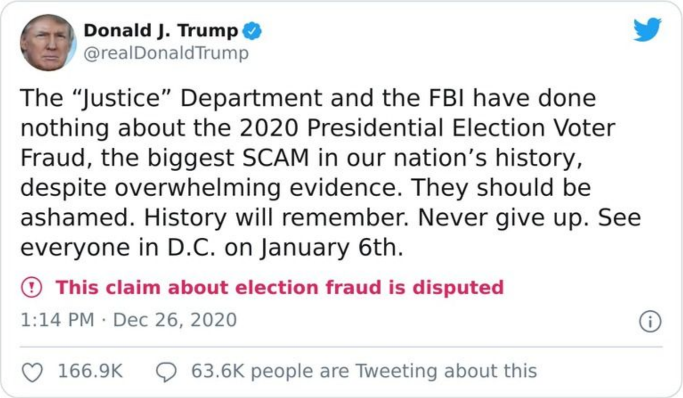

President Trump is calling us to FIGHT…He knows this is the only way to save our great country, show up @January6th

Parler: *Conservative-leaning social media platform marketed as a "free speech" alternative to Twitter, later banned by major tech companies after January 6th.*

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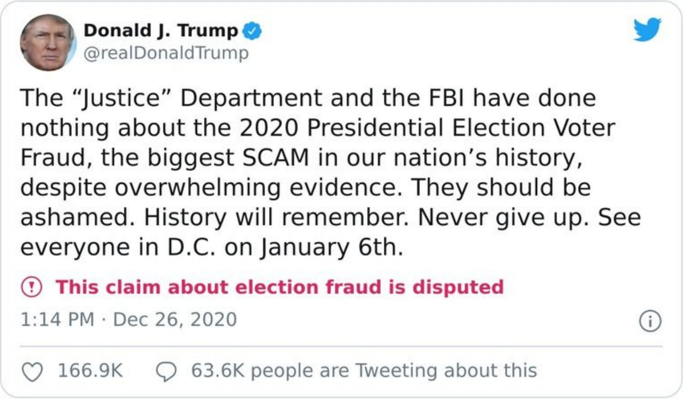
Donald J. Trump
@realDonaldTrump

The "Justice" Department and the FBI have done nothing about the 2020 Presidential Election Voter Fraud, the biggest SCAM in our nation's history, despite overwhelming evidence. They should be ashamed. History will remember. Never give up. See everyone in D.C. on January 6th.

This claim about election fraud is disputed

1:14 PM · Dec 26, 2020

166.9K 63.6K people are Tweeting about this

President Trump is calling us to FIGHT…He knows this is the only way to save our great country, show up @January6th

This is the third time he's tweeted about it. This isn't a joke, this is where and when we make our stand. #January6th. #LIVEFREEORDIE #FIGHTFORTRUMP

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63,885 Retweets **211,432** Likes

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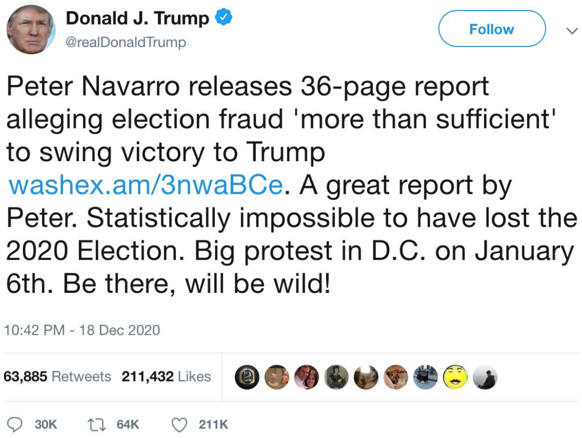
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Trump said It's gonna be wild!!!!!!!! It's gonna be wild!!!!!!! He wants us to make it WILD that's what he's saying. He called us all to the Capitol and wants us to make it wild!!! Sir Yes Sir!!! Gentlemen we are heading to DC pack your shit!!

(Donovan et al.)

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It's important that millions of Americans show up in DC on January 6th to support the legitimate President, Donald Trump, and show Democrats what they will be facing if they continue to try to steal the Presidency.! Gentlemen we are heading to DC pack your shit!!

(Donovan et al.)

January 6th: Same Narratives, Different Ecosystems

Source: BBC

President Trump has been right on just about everything he said. So when he says the election was rigged I'll bet my life on him being right.

(Donovan et al.)

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Source: BBC

President Trump has been right on just about everything he said. So when he says the election was rigged I'll bet my life on him being right.

We have witnessed the destruction of the very fiber of our freedom, the election process.

(Donovan et al.)

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January 6th: Same Narratives, Different Ecosystems

January 6th was fundamentally a **cross-platform event**—coordination happened across platforms, not just within them.

Ng et al. showed that users on Parler and Twitter consumed **completely different information sources.**

Source: NPR

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From Mobilization to Victimization

The same information architecture that mobilizes crowds can also ***systematically target vulnerable populations****.*

One Local Rumor: A Cross-Platform Narrative Cascade

Late June 2024

Local Facebook Groups Begin Rumors

- Posts appear about Haitian children chasing ducks and geese in parks
- Conservative media characterizes Springfield as "flooded" with Haitian immigrants
- Anonymous claims emerge about missing waterfowl (no evidence provided)

("Before Trump")

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August 2024

Neo-Nazi Group Involvement Begins

August 10

- Blood Tribe (neo-Nazi group) holds small march in Springfield protesting Haitian immigration

Late August

- Blood Tribe members appear at Springfield city commission meeting
- Group begins posting racist content about Springfield on Telegram and Gab

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("Before Trump")

One Local Rumor: A Cross-Platform Narrative Cascade

Early September 2024

Conspiracy Moves to Fringe Social Media

Early September

- Blood Tribe posts hate-filled content on Gab claiming Haitians "eat the ducks out of the city parks"
- Posts include multiple racial epithets and target Black people generally

("Before Trump")

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One Local Rumor: A Cross-Platform Narrative Cascade

September 5-10, 2024

Rapid Mainstream Amplification

September 5

- Screenshot of undated Facebook post shared to X: *"Remember when my hometown of Springfield Ohio was all over National news for the Haitians? I said all the ducks were disappearing from our parks? Well, now it's your pets."*

September 6

- **1,100 posts** on X mentioning Haitians/immigrants eating pets
- @EndWokeness account posts viral screenshot and goose photo (**4.9 million views**)

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September 5-10, 2024

Rapid Mainstream Amplification

September 7

- **9,100 posts** on X (**720% increase** from previous day)
- AI-generated memes begin circulating on 4chan, then spread to MAGA communities

September 9

- **JD Vance amplifies** on X: *"Reports now show that people have had their pets abducted and eaten by people who shouldn't be in this country"*
- Posts spike to **47,000** on the platform
- Vance later adds: *"Keep the cat memes flowing"*

("Before Trump")

One Local Rumor: A Cross-Platform Narrative Cascade

September 5-10, 2024

Rapid Mainstream Amplification

September 10 - DEBATE DAY

- **5:19 PM**: Trump posts meme to Truth Social showing cats with MAGA hats
- **5:34 PM**: Trump posts second meme showing himself protecting cats and ducks
- **~9:30 PM**: Trump mentions during presidential debate: *"They're eating the dogs, they're eating the cats"*
- **67+ million viewers** witness the claim on live television

("Before Trump")

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One Local Rumor: A Cross-Platform Narrative Cascade

*This was **never** a single-platform story.*

Blood Tribe (Telegram/Gab) → Facebook → X → Debate Stage

Takeaway

Platform borders are arbitrary — ideas don't respect them.

Source: ABC

How can we connect this split information environment into one unified view, rather than tracing pathways after-the-fact?

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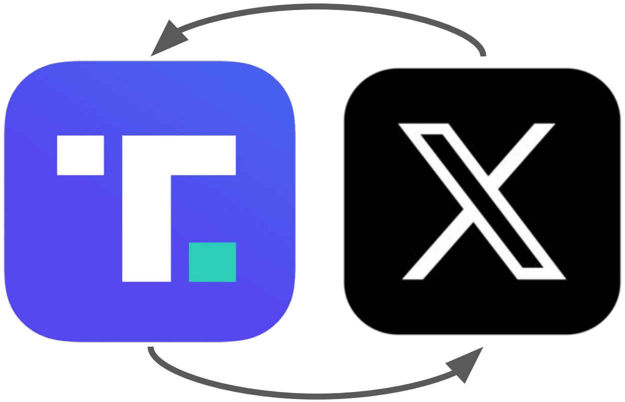
Information Flow in a Fragmented Online Ecosystem

The online information ecosystem is increasingly fragmented.

- Users consume and share political content across many platforms.
- The **borders between platforms are arbitrary — ideas and narratives do not respect them**.
- Without cross-platform visibility, we fail to anticipate real-world impacts.

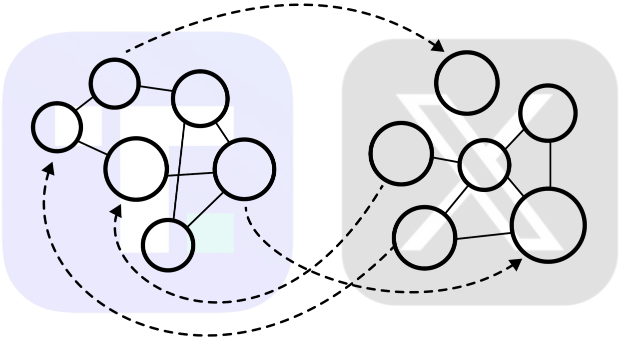


If we treat platforms as islands, we will always be surprised when ideas jump between them

To Model Information Flow, We Must Model Users

Information moves through users.

- User networks are essential for modeling how information spreads on platforms.
- Modeling users helps reveal **how information spreads** and which users spread it.
- Cross-platform analysis requires user **networks that transcend platform boundaries**.

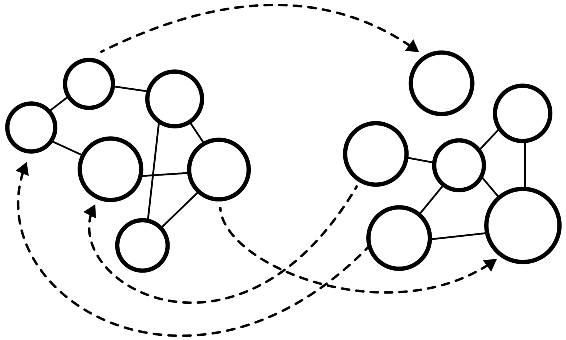


Understanding modern information flow requires understanding how users connect across platforms, not just within them.

The Challenge of Building Cross-Platform User Networks

Previous methods relied on platform interactions to connect users.

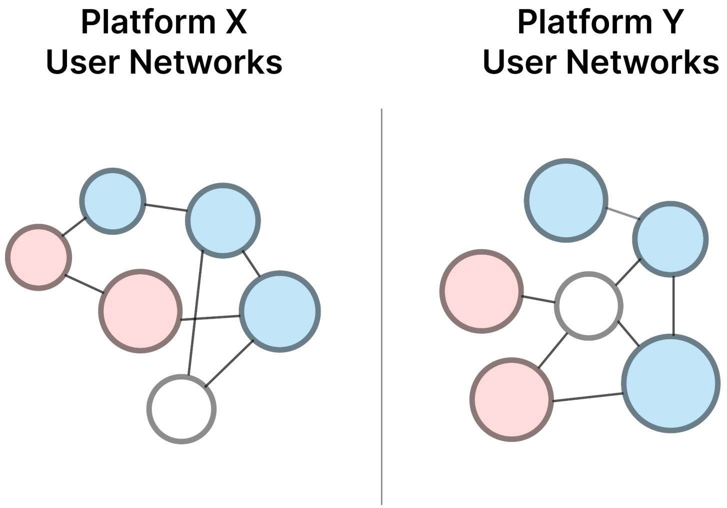
- Behavioral connections do not generalize across fragmented platforms (Cinelli et al. 2021, Tromble 2021).
- Semantic similarity alone is brittle across linguistic drift and platform variation (Ng et al. 2022, Ng et al. 2023).
- Modeling users across platforms requires **deeper signals** of alignment **than behavior** alone.



We need signals of connection that survive platform boundaries.

What Kind of Signal Connects Users Across Platforms?

Behavioral **ties fragment** across platforms.

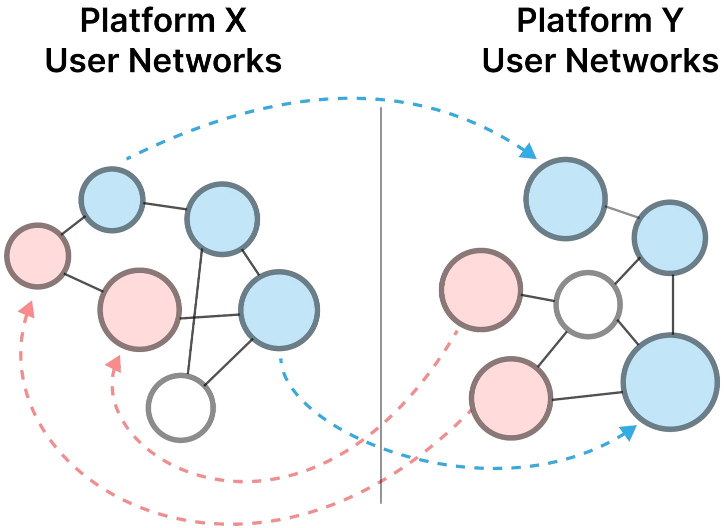


What Kind of Signal Connects Users Across Platforms?

But **ideas persist.**

Narrative 1

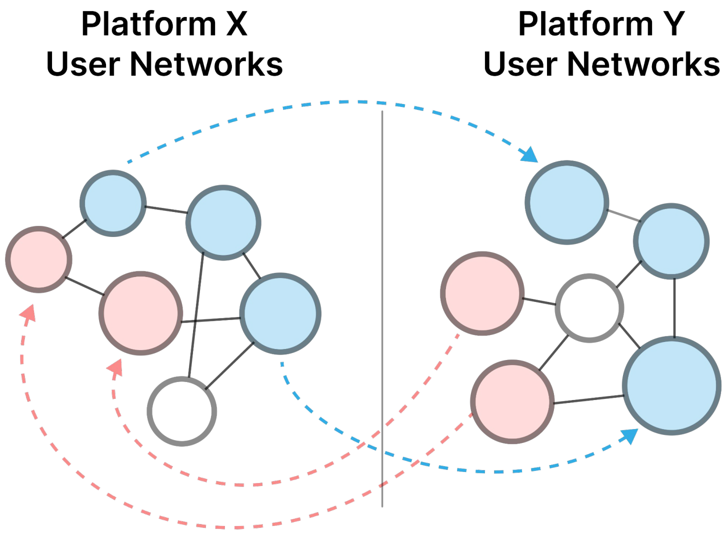
Narrative 2



What Kind of Signal Connects Users Across Platforms?

Behavioral **ties fragment** across platforms, but **shared ideas travel freely**.

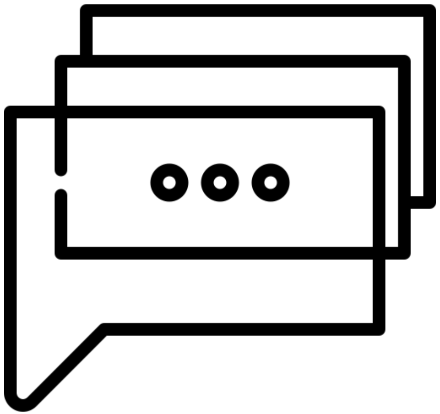
Shared discourse reveals patterns of alignment that **persist across platforms**.



Our Approach: Modeling Discourse as Network

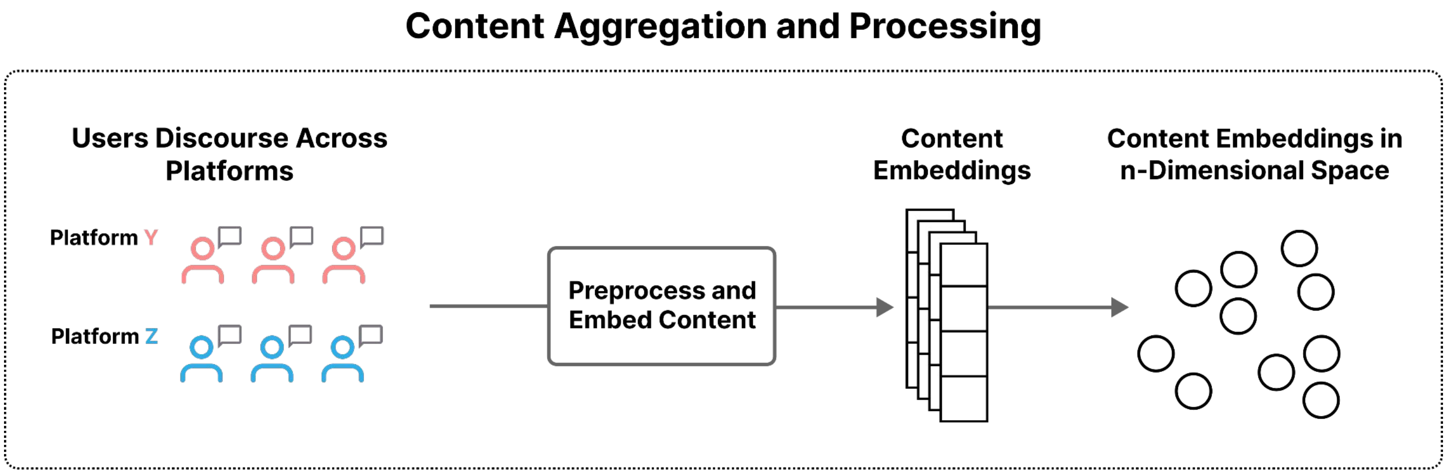
We model user alignment through shared participation in discourse.

- Discourse provides a stable signal of user alignment across fragmented ecosystems.
- Users who participate in similar discourse show patterns of connection that interactions alone cannot reveal.



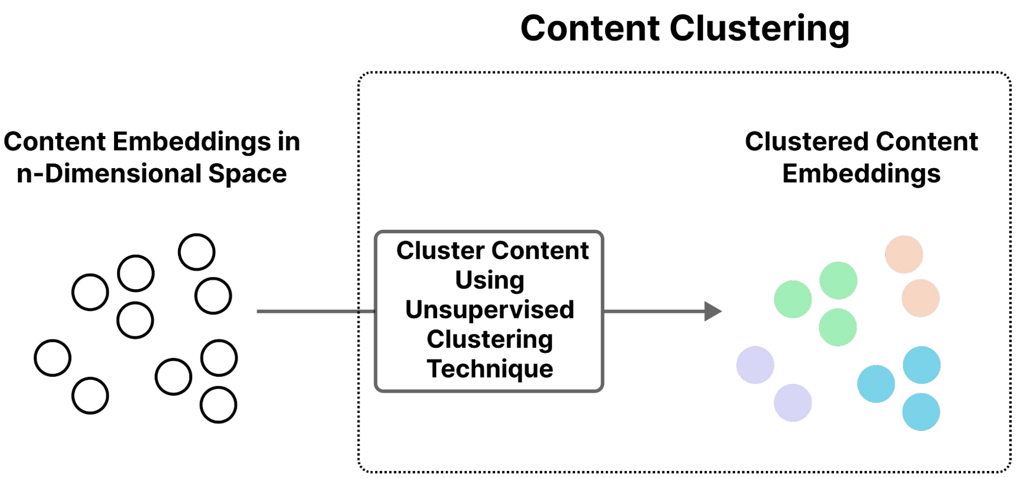
Discourse-first networks recover latent structure lost in fragmented ecosystems.

Our Approach: Modeling Discourse as Network



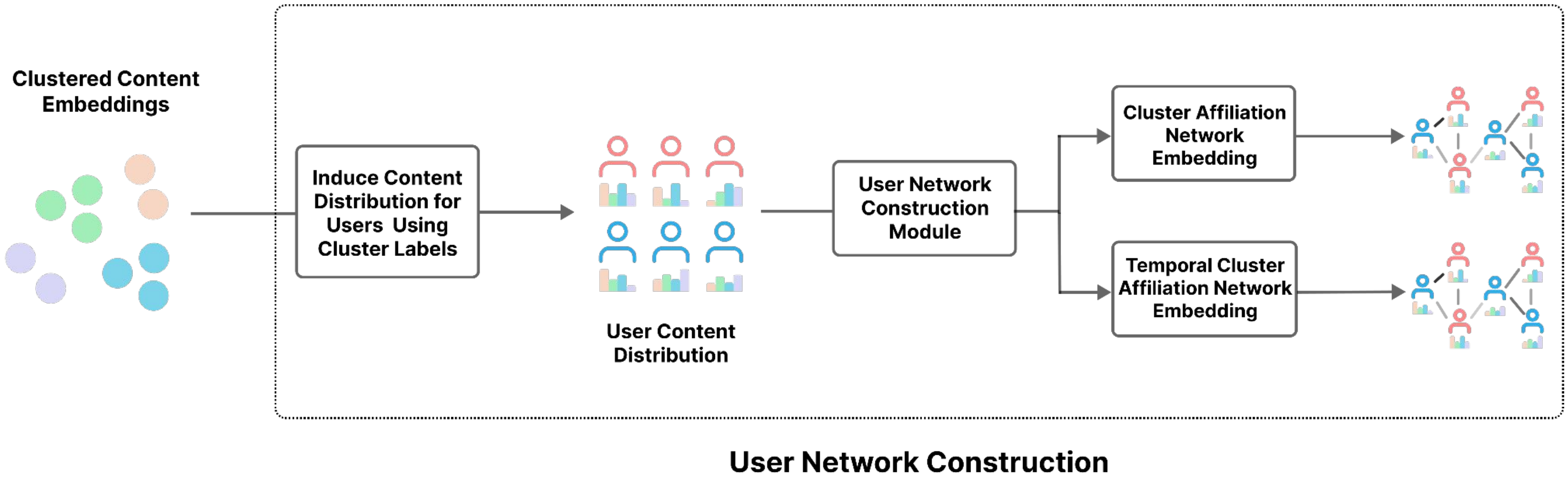
Step 1: Content Aggregation and Processing *Collect cross-platform discourse and transform text into comparable embeddings*

Our Approach: Modeling Discourse as Network



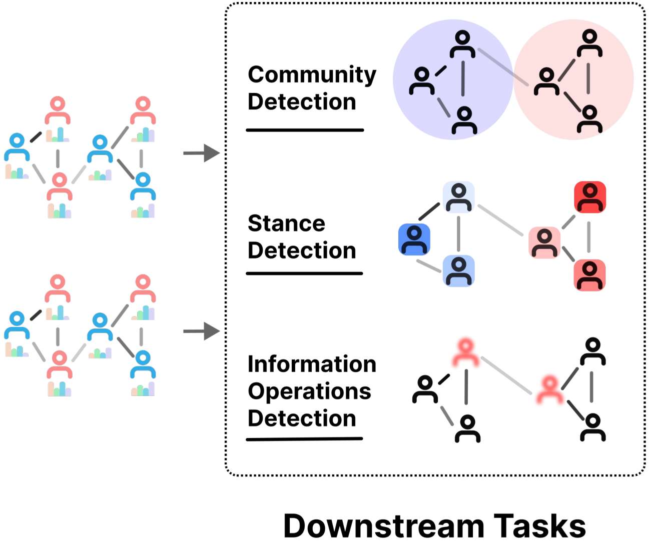
Step 2: Content Clustering *Group similar discourse into thematic clusters using unsupervised learning*

Our Approach: Modeling Discourse as Network



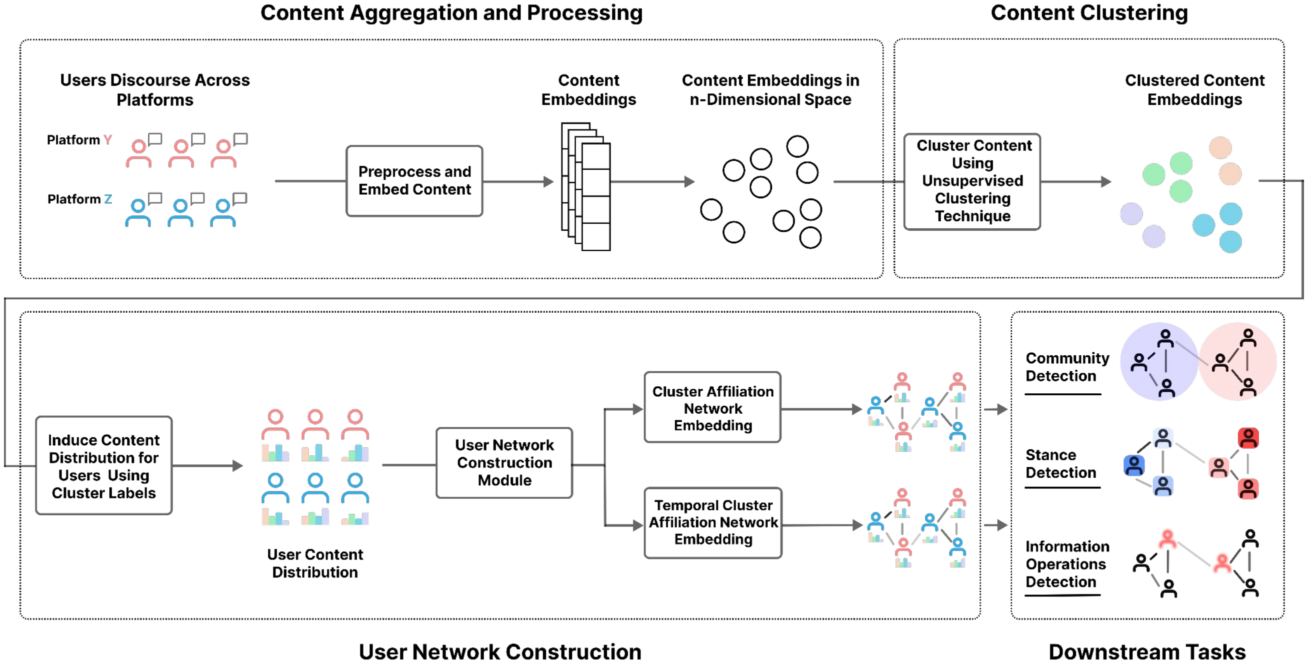
Step 3: User Network Construction *Transform content clusters into user networks based on shared discourse patterns*

Our Approach: Modeling Discourse as Network



Step 4: Network Applications *Use the constructed networks for traditional network analysis and detection tasks*

Our Approach: Modeling Discourse as Network

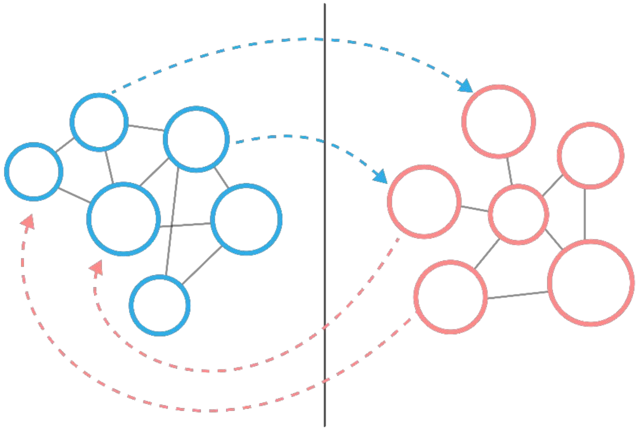


Full Pipeline: From Cross-Platform Discourse to User Networks *Building behavioral networks from shared discourse patterns across platform boundaries*

How It Works: Recovering Structure where Others Fail

Modeling users through shared discourse exposes patterns that interaction graphs miss.

- Robust to fragmented or missing behavioral data
- Captures communities grounded in shared ideas
- Operates across platforms without needing interaction data
- Reconstructs user alignment even when traditional ties break



Discourse networks see the structure others miss

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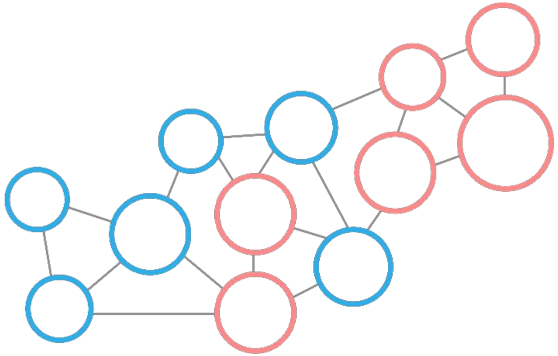

Discourse networks see the structure others miss

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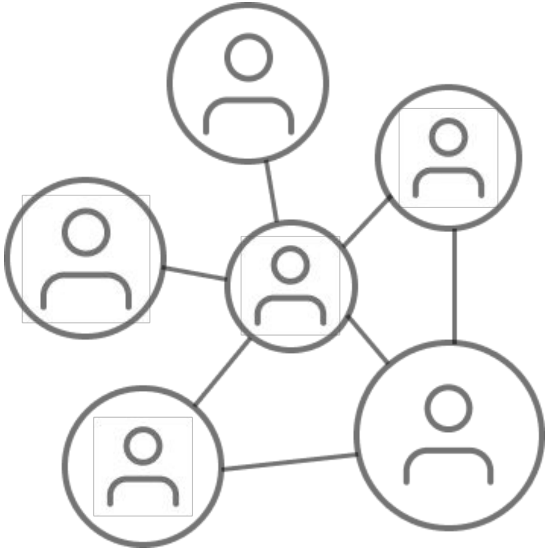
Why It Works: How Do We Validate it?

We validate our approach on both established and novel tasks in online information analysis.



Influence Operation Detection
Detecting covert accounts that promote coordinated influence campaigns (Seckin et al. 2024).

Ideological Stance Prediction
Inferring a user's political leaning based on their network position.

Cross-Platform Engagement Prediction
Predicting which users will engage with content as it moves across platforms.

Why It Works: How Do We Validate it?

We compare against **classic network construction methods**, using a consistent set of classifiers to evaluate network quality (Minici et al. 2025, Ng et al. 2023).

Network Type	How Users Are Connected
Co-Repost	Repost the same content
Co-URL	Share the same URLs
Fast Repost	Repost identical content within a short window
Hashtag Sequence	Use the same ordered hashtag sequences
Text Similarity	Post highly similar text
k-NN Embedding Graph	Close in overall text embedding space
Fused Graph	Linked if connected in any of the above networks

Cross-platform methods

Why It Works: How Do We Validate it?

State-Backed Information Operations

Country	IO Drivers [Posts]	Control Users [Posts]
China	5,191 [13.8M]	76,286 [3.5M]
Iran	209 [9.9M]	16,885 [2.5M]

Data sourced from platform-disclosed state-backed account takedowns on X, where IO drivers represent confirmed state-affiliated accounts and control users are randomly sampled organic accounts from the same time periods.

Political Stance Detection Dataset

Platform	Label	Count	Percentage
X (Twitter)	Liberal	503	24%
	Conservative	1,641	65%
	Other/NA	446	21%
TikTok	Liberal	408	23%
	Conservative	631	35%
	Other/NA	670	38%

Users manually annotated by trained coders for political stance based on profile information and posting behavior, with high inter-annotator agreement (κ = 0.86-0.88).

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Why It Works: How Do We Validate it?

Cross-Platform Narrative Tracking

Metric	**Value**
Total Narrative Themes	321
Total Posts	374K
Total Users	261K
Median Posts per Theme	154
Median Users per Theme	116
Mean X Post %	72.3
Mean TS Post %	27.7
Median X User Count	89
Median TS User Count	15

Example Narratives

Comparing Jan 6 and Tiananmen Square

Nuclear Energy Conspiracy Theories

FBI Investigations and Federal Overreach

Narrative themes computationally identified through multilingual MPNet embeddings and DP-means clustering of posts from X and Truth Social. Themes and accuracy validated by domain expert annotators.

Discourse-Based Networks Outperform Baselines Across Tasks

Better expressivity, less data, broader reach.

Influence Operation Detection

- Outperforms baselines by at least 17 pts AUC.

Ideological Stance Prediction

- Outperforms baselines on X and TikTok by at least 14 pts Macro-F1.
- Covers **100% of labeled users** vs. **<6% on X** for closest traditional method.

Cross-Platform Engagement Prediction

- Outperforms baselines by at least 30 pts AUC.
- Delivers **3x better predictive accuracy**.

*Discourse-based networks recover **latent structure** missed by traditional methods. They do so with **significantly less data** and **broader reach**.*

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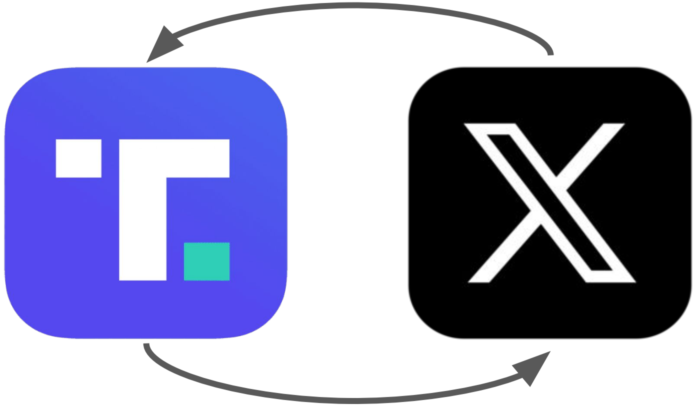
Modeling Narrative Flow Across Platforms

Can discourse-based networks capture the structural patterns of cross-platform narrative movement?

Truth Social ↔ X: Modeling Users Across Platform Boundaries

With unified discourse networks, we can now ask: How do narratives really move between platforms?



Two Distinct Platforms:

- Truth Social: Trump's platform, launched 2022, smaller user base
- X: Established mainstream platform, broader reach
- Different audiences, norms, and content dynamics

2024 Election Context: High-stakes political discourse across fragmented media landscape

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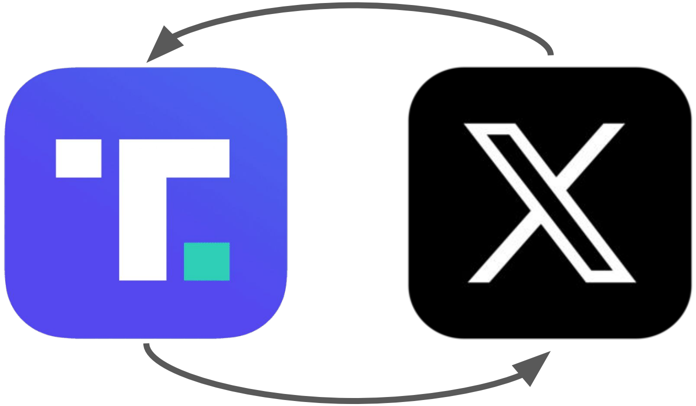


How do **narratives migrate** between X and Truth Social, and through what **pathways**?

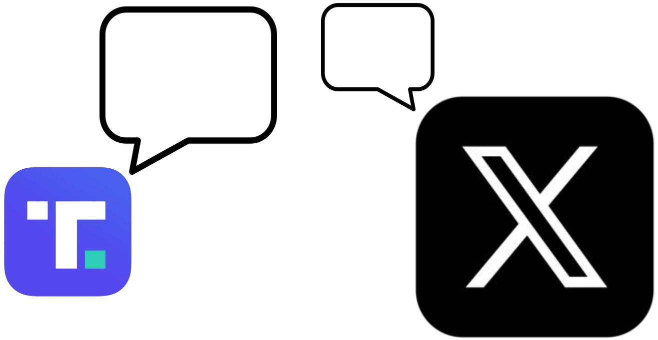
Do shared **narrative communities** emerge despite different ecosystems?

Which **users drive cross-platform narrative diffusion**, and what roles do they play?

Takeaway 1: Truth Social Punches Above Its Weight

How do narratives migrate between X and Truth Social, and through what pathways?

- **1.7% of posts → 18.9% of originating narratives** (11× overrepresentation)
- Migration follows **structured, predictable patterns**



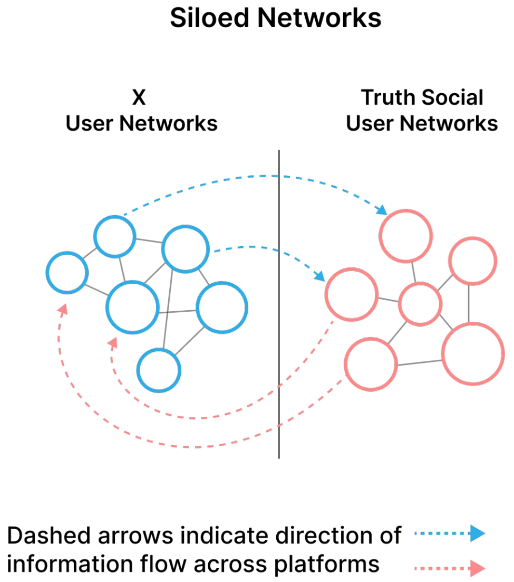
Small platform, a big influence: Truth Social disproportionately seeds narratives that X amplifies.

Takeaway 2: A Tiny Bridge Zone Spans Both Worlds

Do shared narrative communities emerge despite different ecosystems?

- **0.33% of users** form one highly influential mixed-platform community
- Only visible through **discourse modeling**, not traditional metrics

There's a hidden bridge between these platforms, but you need the right lens to see it.



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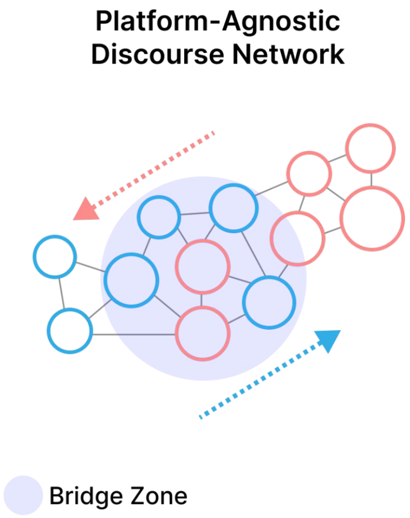
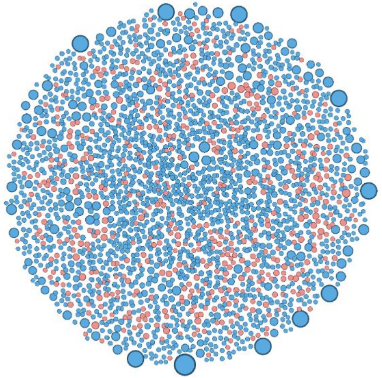


Takeaway 3: Bridge Users Are Narrative Gatekeepers

Which users drive cross-platform narrative diffusion, and what roles do they play?

- **0.33% of users** carry **68% of migrating narratives**
- Cross-platform diffusion correlates with **position, not popularity**

Narrative migration correlates with network position, not popularity.



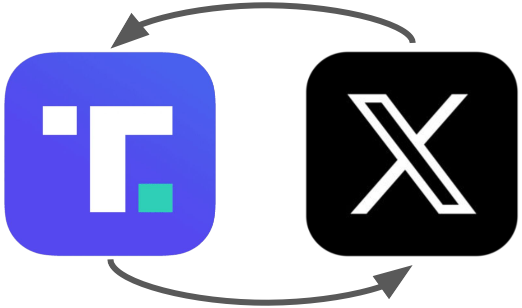
Cross-platform bridge zone associated with high cross-platform narrative migration.

Blue: X User
Red: Truth Social User
Size: Connectivity

What Truth Social ↔ X Reveals

What happens when we model cross-platform discourse strategically?

- **Small platforms can have outsized narrative influence** (11× expected rate)
- **Tiny bridge networks help drive most cross-platform diffusion** (0.33% → 68%)
- **Traditional influence metrics miss the real infrastructure** of cross-platform discourse



Truth Social and X aren't separate worlds; they're connected by invisible bridges.

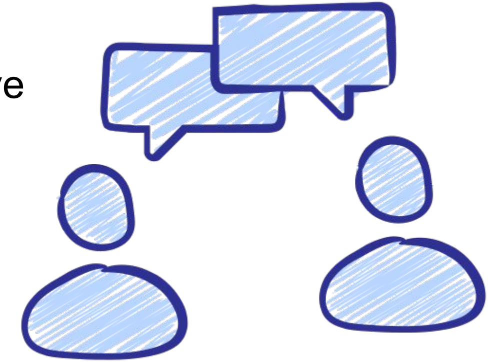
The Big Picture: Rethinking Cross-Platform Influence

We've been looking at the wrong metrics to understand how ideas actually move.

Traditional view: Influence = followers, engagement, virality

What we found: A tiny, hidden network associated with most narrative migration

New reality: Cross-platform discourse has invisible architecture



Instead of reconstructing how ideas spread, we can now see the invisible bridges they travel across.

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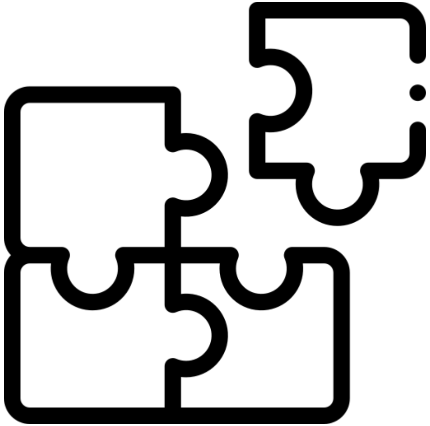
Implication 1: New Tools for Fragmented Media Ecosystems

Discourse modeling approach opens entirely new possibilities for studying fragmented media landscapes:

- **New capability**: Model discourse communities across any platform ecosystem
- **Strategic advantage**: See narrative flows invisible to platform-specific approaches
- **Scalable solution**: Works despite API access or platform cooperation

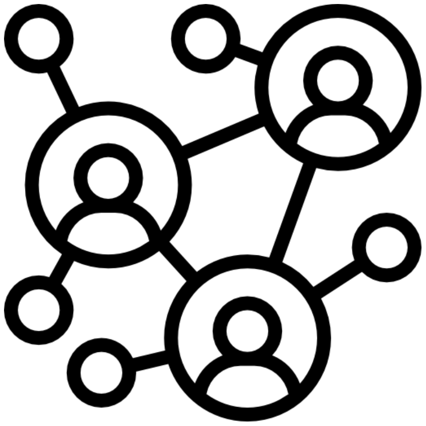


We can now study cross-platform influence at scale: the fragmented ecosystem is no longer a barrier.

Implication 2: Bridge Users as Structural Boundary Spanners

Our findings confirm classic network theory but extend it to the cross-platform era:

- **Classic insight**: Weak ties and brokers drive information flow across structural holes
- **New application**: Bridge users occupy cross-platform structural positions, not popularity peaks
- **Strategic implication**: Influence correlates with network position, not follower count



Granovetter's weak ties may span platforms, not just social circles (Granovetter 1973).

Practical Implications: Beyond Academic Theory

Our Truth Social↔X case study points toward actionable applications:

- **Content moderation**: Monitor structural positions in cross-platform networks, not just viral content
- **Information operations**: Target bridge zones where narratives actually migrate between platforms
- **Platform governance**: Cross-platform coordination requires cross-platform detection tools

Policy interventions need cross-platform intelligence, not single-platform snapshots.

Limitations & Future Directions

Our study provides a proof of concept, but significant questions remain:

- **Scope constraints**: Two platforms during one election period with observational data only
- **Platform expansion**: Test discourse modeling across TikTok, Telegram, Reddit, and emerging platforms
- **Information operations**: Apply methods to state-sponsored campaigns (currently analyzing Russian-funded Tenet Media across YouTube/Rumble)
- **Temporal dynamics**: Track how bridge users form, persist, and dissolve over time

Source: Tech Policy Press

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Conclusion: Seeing Cross-Platform Discourse Clearly

Modern Methodology
Discourse modeling reveals cross-platform influence invisible to behavioral approaches

Broader potential
Platform-agnostic methods work despite API restrictions and ecosystem fragmentation

Discourse modeling reveals cross-platform networks that behavioral metrics completely miss.

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Conclusion: Seeing Cross-Platform Discourse Clearly

Hidden infrastructure
Narrative migration follows predictable structural patterns between platforms

Strategic insight
A tiny group of bridge users (0.33%) linked to most cross-platform narrative flow (68%)

When 0.33% of users drive 68% of narrative migration, that's predictable structure.

Thank you!

Questions?

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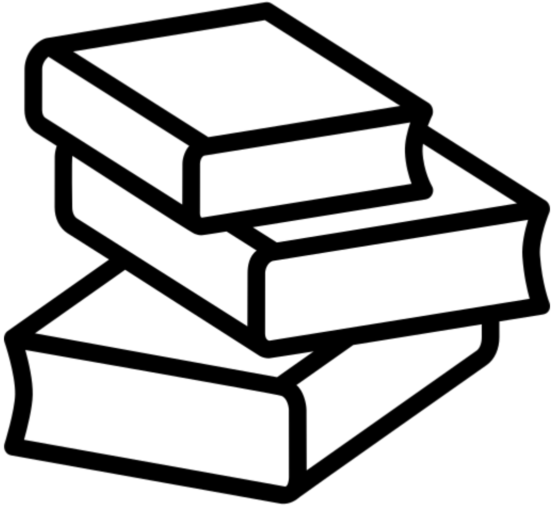

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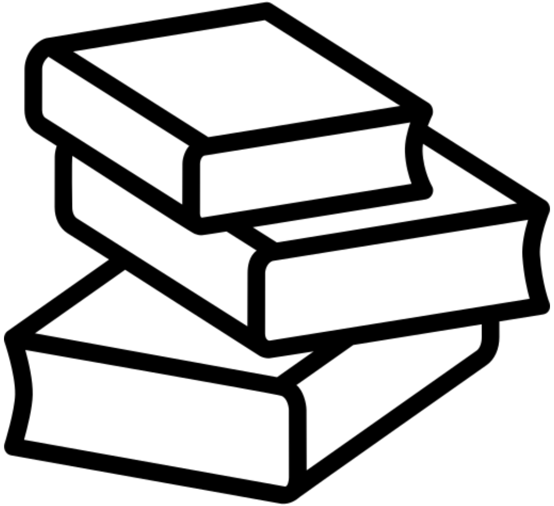

Questions?

Appendix

Time Complexity

Method	Embedding	Clustering	Graph Construction
Our Methods			
CANE (FAISS)	$O(Nd)$	$O(NKT)$	$O(U \log U + Uk)$
t-CANE (FAISS)	$O(Nd)$	$O(NKT)$	$O(T \cdot (U \log U + Uk))$
Baselines			
Embedding Averaging	$O(Nd)$	—	$O(U^2 d)$
k-NN Embedding Graph	$O(Nd)$	—	$O(N \log N + kN)$

Table 10: Breakdown of computational costs for different network construction methods. All methods require embedding N posts into d-dimensional space. CANE and t-CANE include clustering via DP-Means (K clusters), and use approximate user-user graph construction via FAISS. Baseline methods compute similarity at the post or user level without intermediate clustering. **Notation:** N - posts, U - users, d - embedding dim, K - clusters, T - time bins, k - neighbors.

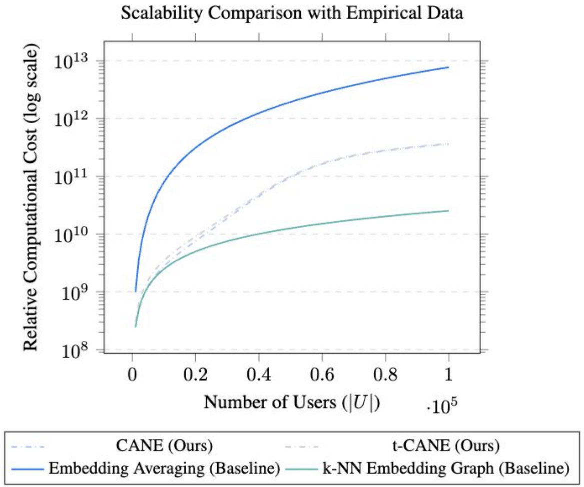

Figure 3: Comparison of computational complexity across network construction methods using empirically-informed scaling trends. CANE and t-CANE scale more efficiently with users due to FAISS and clustering, while baselines exhibit steep cost increases tied to post or user volume.

t-Cane Component Ablation

Model Variant	**ROC-AUC**	**Precision**	**Recall**	**F_1**
Full t-CANE	**0.98 ± 0.01**	**1.00 ± 0.00**	**0.75 ± 0.01**	**0.83 ± 0.01**
w/o Memory (α=0)	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00
w/o Decay (β=0)	0.98 ± 0.01	1.00 ± 0.00	0.73 ± 0.02	0.81 ± 0.02
No Memory or Decay (Average Similarity)	0.96 ± 0.01	1.00 ± 0.00	0.72 ± 0.02	0.79 ± 0.02
No Memory or Decay (Naive Aggregation)	0.97 ± 0.00	0.99 ± 0.00	0.71 ± 0.02	0.80 ± 0.01

Table 13: Ablation study on key components of **t-CANE** based on results from the China Information Operations detection task. All metrics are macro-averaged. The full model incorporates temporal memory (α) and decay smoothing (β). Removing memory (α=0) leads to a collapse in performance, as user similarity cannot meaningfully propagate across time. The final two rows reflect ablations of both components, where user similarity is computed independently at each timestep and aggregated via averaging or summation.

Baseline Network Construction Methods

Network Type	Construction Description
Co-Repost	Connect users who repost the same piece of content.
Co-URL	Connect users who share the same URLs in their posts.
Fast Repost	Connect users who repost identical content within a short time window.
Hashtag Sequence	Connect users based on ordered sequences of shared hashtags.
Text Similarity	Connect users if they post at least one highly similar post; edge weight reflects average text similarity across matches (Pacheco et al. 2021).
k-NN Embedding Graph	Build a full text-to-text kNN graph first, then induce a user-to-user graph reflecting overall proximity across all posts (Ng, Cruickshank, and Carley 2023).
Fused Graph	Construct a unified network where users are linked if they are connected in any underlying similarity network (Co-Repost, Co-URL, Fast Repost, Hashtag Sequence, or Text Similarity) (Luceri et al. 2024a).

Table 1: Baseline similarity network construction methods.

Information Operations Results

Method	Macro-F_1	AUC
Co-Repost	0.71 ± 0.02	0.77 ± 0.03
Co-URL	0.50 ± 0.02	0.56 ± 0.06
Fast Repost	0.46 ± 0.01	0.54 ± 0.02
Hashtag Sequence	0.51 ± 0.04	0.49 ± 0.03
Text Similarity	0.53 ± 0.01	0.33 ± 0.00
k-NN Embedding Graph	0.58 ± 0.02	0.39 ± 0.01
Fused Graph	0.74 ± 0.02	0.81 ± 0.02
CANE	0.72 ± 0.02	0.91 ± 0.01
t-CANE	$\mathbf{0.83} \pm \mathbf{0.01}$	$\mathbf{0.98} \pm \mathbf{0.01}$

Table 2: Performance on the China IO dataset.

Method	Macro-F_1	AUC
Co-Repost	0.80 ± 0.01	0.73 ± 0.01
Co-URL	0.49 ± 0.00	0.52 ± 0.01
Fast Repost	0.59 ± 0.01	0.60 ± 0.01
Hashtag Sequence	0.54 ± 0.03	0.48 ± 0.01
Text Similarity	0.62 ± 0.03	0.52 ± 0.02
k-NN Embedding Graph	0.65 ± 0.01	0.57 ± 0.00
Fused Graph	0.81 ± 0.01	0.76 ± 0.01
CANE	0.82 ± 0.01	0.94 ± 0.00
t-CANE	$\mathbf{0.90} \pm \mathbf{0.01}$	$\mathbf{0.94} \pm \mathbf{0.02}$

Table 3: Performance on the Iran IO dataset.

Ideology Prediction Results

Method	Similarity Network	Macro-F_1	AUC
Baseline	Co-Repost	0.43 ± 0.30	0.56 ± 0.22
	Co-URL	0.51 ± 0.26	0.53 ± 0.05
	Fast Repost	0.48 ± 0.04	0.51 ± 0.03
	Hashtag Sequence	0.65 ± 0.22	0.63 ± 0.14
	Text Similarity	0.39 ± 0.12	0.32 ± 0.09
	k-NN Embedding Graph	0.41 ± 0.03	0.34 ± 0.11
	Fused Graph	0.69 ± 0.15	0.70 ± 0.05
	CANE	0.81 ± 0.01	0.73 ± 0.02
Ours	t-CANE	$\mathbf{0.83 \pm 0.01}$	$\mathbf{0.76 \pm 0.02}$

Table 4: Ideological classification on X.

Method	Similarity Network	Macro-F_1	AUC
Baseline	Hashtag Sequence	0.71 ± 0.03	0.62 ± 0.01
	Text Similarity	0.38 ± 0.14	0.42 ± 0.07
	k-NN Embedding Graph	0.45 ± 0.10	0.45 ± 0.08
	(Partial) Fused Graph	0.71 ± 0.03	0.64 ± 0.02
Ours	CANE	$\mathbf{0.83 \pm 0.02}$	$\mathbf{0.83 \pm 0.01}$
	t-CANE	0.82 ± 0.02	$\mathbf{0.83 \pm 0.03}$

Table 5: Ideological classification on TikTok.

Cross-Platform Narrative Prediction Results

Method	Similarity Network	Macro-F_1	AUC
Baseline	Random GCN	0.00 ± 0.00	0.56 ± 0.03
	Co-URL	0.01 ± 0.00	0.43 ± 0.04
	Hashtag Sequence	0.11 ± 0.04	0.48 ± 0.08
	Text Similarity	0.02 ± 0.00	0.58 ± 0.05
	k-NN Embedding Graph	0.02 ± 0.01	0.61 ± 0.06
	(Partial) Fused Graph	0.05 ± 0.01	0.64 ± 0.06
Ours	CANE	0.30 ± 0.02	0.89 ± 0.02
	t-CANE	$\mathbf{0.35} \pm \mathbf{0.06}$	$\mathbf{0.94} \pm \mathbf{0.02}$

Table 6: Performance of similarity networks for cross-platform narrative engagement prediction (t=7).

Data Efficiency Comparisons

Category	Method	China	Iran
Baseline	Co-Repost	15%	20%
	Co-URL	20%	25%
	Fast Repost	20%	20%
	Hashtag Sequence	80%	60%
	Text Similarity	**5%**	10%
	k-NN Embedding Graph	10%	**5%**
	Fused Graph	15%	30%
Ours	CANE	**5%**	10%
	t-CANE	**5%**	**5%**

Table 15: Percentage of training data required to reach 95% of peak AUC for each method on the China and Iran IO campaigns. Lower values reflect higher data efficiency.

Category	Method	X	TikTok
Baseline	Co-Repost	15%	–
	Co-URL	20%	–
	Fast Repost	20%	–
	Hashtag Sequence	80%	60%
	Text Similarity	**5%**	10%
	k-NN Embedding Graph	10%	**5%**
	Fused Graph	15%	30%
Ours	CANE	**5%**	10%
	t-CANE	**5%**	**5%**

Table 21: Percentage of training data required to reach 95% of peak AUC for each method on the X and TikTok datasets. Lower values indicate faster convergence toward near-optimal performance.

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Migration Statistics

Cluster Type	Top 1	Top 2	Top 3	Top 4	Top 5
Significant Migration	69.33%	77.73%	79.41%	79.83%	80.67%
Simple Migration	67.72%	76.61%	78.29%	78.99%	79.45%

Table 28: Percentage of cross-platform narrative clusters where a bridge user appeared within the first n posts on the receiving platform.

Bridge User Engagement Metrics

Metric	Median	Bridge Percentile (Platform-Normalized)
Total Posts	14.00	58.49%
Reply Count	0.16	47.06%
Like Count	0.58	53.26%
Repost Count	0.02	55.19%

Table 26: Median engagement metrics and corresponding platform-normalized percentile ranks for bridge users. Percentiles are calculated within each platform and then averaged.

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Bridge User Detection Across Network Construction Methods

Graph Type	% Users	% Posts	% Narratives Introduced
Co-URL	0.00%	0.00%	0.00%
Hashtag Sequence	0.04%	0.37%	4.21%
Text Similarity	1.42%	2.21%	15.70%
kNN Embedding Graph	1.73%	2.41%	25.90%
Fused Graph	2.68%	3.19%	27.00%
Ours (Discourse)	0.33%	2.14%	67.72%

Table 27: Comparison of bridge user detection and narrative introduction across graph construction methods.

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