# Latent Behavioral Structure in Online Communities

## Case Study in `/r/science`

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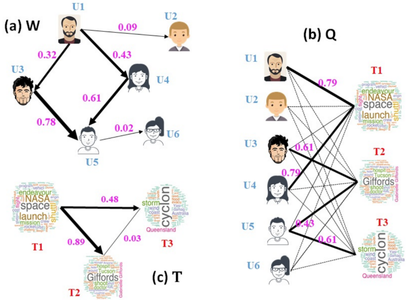
# Overview

## Problem statement

In social forums, observable behavior is often limited to who you talk to (interaction) and what you talk about (topics). Can we learn the underlying relational structure of the community given these observables? Is the structure predictive of behavior over time?

# Related work

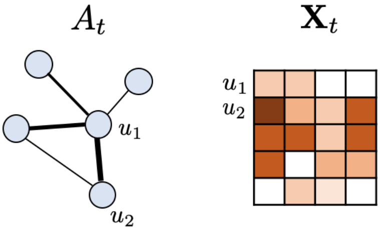
- Latent variable approaches based on features [Hoff et al., 2002, Airoldi et al., 2008]
- ... based on timing [Linderman and Adams, 2014]
- Topic modeling [Chang and Blei, 2009]
- Dynamic community-topic modeling [Zhang et al., 2019, Li et al., 2012]
- Dynamic networks [Pareja et al., 2020, Sankar et al., 2020]
- Graph autoencoders [Kipf and Welling, 2016, Simonovsky and Komodakis, 2018]
- Joint graph + feature learning [Lerique et al., 2020]




[Choudhari et al., 2021]

# Data overview and preparation

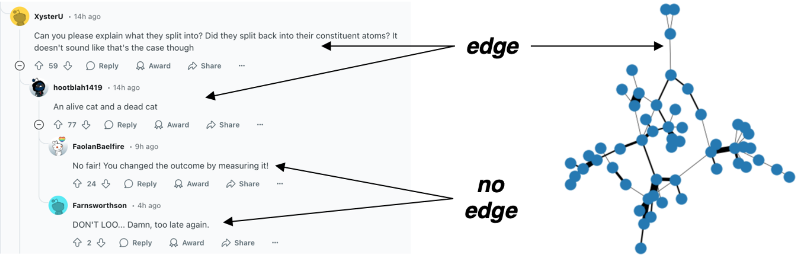
- Reddit: $>$ 12.7 billion comments over 17 years (2007-2022) [Baumgartner et al., 2020]
- We focus on 2007-2011 in the `/r/science` subreddit to enforce the idea of community.
- We engineer two inputs to our model:
  - Co-reply interaction graph
  - User topic participation signature



# User-to-user co-reply interaction

## Interaction graph

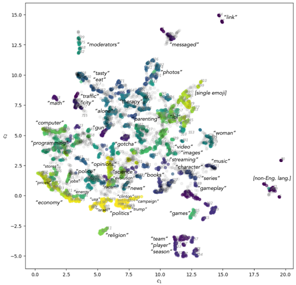
Define $G^{(\tau)} = (V, E)^{(\tau)}$ with $e_{uv} = m$ such that $m$ is a count of occurrences where $u$ replies to $v$ (or $v$ to $u$) within two comments and within two months, during $\tau$.



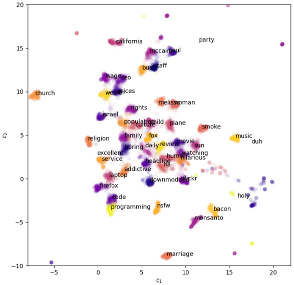
## Contextualized semantic clustering

Given an embedder $\mathcal{E} : \mathcal{S}_\ell \to \mathbb{R}^d$ and clustering $\mathcal{C} : \mathbb{R}^d \to L$,

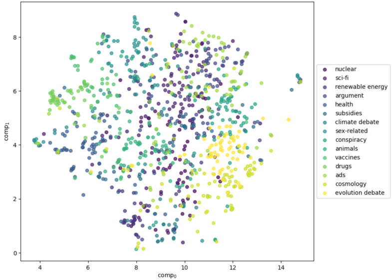
$$\mathcal{D} = \{(s_i, u_i, t_i)\}_i \quad \longrightarrow \quad \mathcal{D}_L = \{(\mathbf{e}_i, u_i, t_i, l_i)\}_i$$




2007-2022




July 2008 (All)




July 2008 (`/r/science`)

# User participation over topics

## User topic signature

Define a user $u$'s participation in $k$ topics at time $\tau$ as the signature:

$$\mathbf{x}_u^{(\tau)} = (x_k^{(\tau)}) \quad \text{with} \quad \hat{x}_k^{(\tau)} = |\mathcal{D}_L : u_i = u, t_i \in \tau, l_i = k|, \quad x_k^{(\tau)} = \frac{\hat{x}_k^{(\tau)}}{||\hat{\mathbf{x}}_u^{(\tau)}||}$$

...

***March 2007:***
13 (cosmology): Human understanding of time cannot be complete as long as …
7 (sex-related): The sudden reduction of pain is a powerful simulacrum of pleasure.
1 (sci-fi): Time Cub(beaten by an angry horde)
9 (animals): The title make a good quote, but the implications of a city as an organism ….
0 (nuclear): It's like there's an anti-progressive monster inside California struggling to get out. :-(
11 (drugs): Uhhh....for me yes. I want the drugs *now* :-(
3 (argument): There's an important point about politics that needs to be made. Americans are …
0 (nuclear): That wasn't my point at all - in fact most Western countries *including* France …
5 (subsidies): I'm not an anti-oil nut, but drilling in our own territory is indeed more .... palatable.

...

$\hat{\mathbf{x}}_u^{(\tau)}$

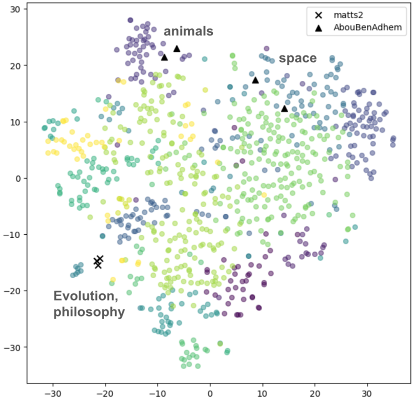
| | author | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | total_posts |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 485 | Prysorra | 4 | 1 | 2 | 1 | 4 | 1 | 3 | 1 | 2 | 11 | 5 | 9 | 4 | 0 | 3 | 51 |

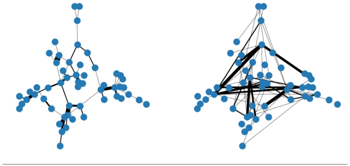
$\mathbf{x}_u^{(\tau)}$

[0.23 0.06 0.11 0.06 0.23 0.06 0.17 0.06 0.11 0.63 0.29 0.52 0.23 0.00 0.17]

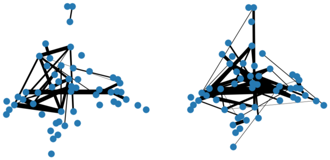
# Observations

- Users' signatures and their co-reply behaviors evolve over time.
- Topic signatures and co-reply interaction are only weakly correlated.



Interaction graphs $(t_0, t_1)$



Feature similarities $(t_0, t_1)$

# (Temporal) Dual-decoder Graph Autoencoder (TDGAE)

- Learn a latent graph $Z$ of behavioral homophily
- Encoder:

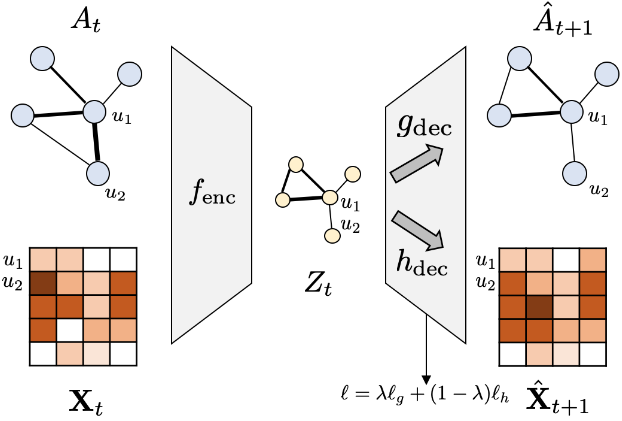
$$\mathbf{h}^{(1)} = \mathrm{GCN}(\mathbf{x}, E)$$
$$\mathbf{h}^{(2)} = \mathrm{GCN}(\mathbf{h}^{(1)}, E)$$
$$\mathbf{z}_{uv} = \mathrm{MLP}([\mathbf{h}_u^{(2)}, \mathbf{h}_v^{(2)}])$$

- (Graph) Decoder:

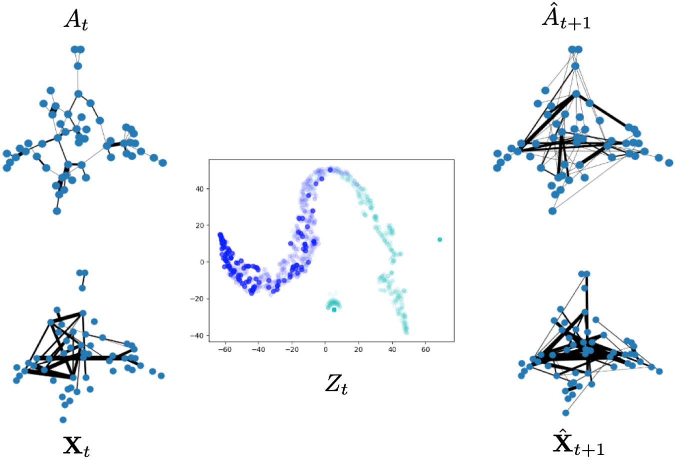
$$\mathbf{v} = \mathrm{MLP}(\mathbf{z})$$
$$p(e_{uv}) = \sigma(\mathbf{v})$$

- (Feature) Decoder:

$$\mathbf{a} = \mathrm{Agg}(\mathbf{z})$$
$$\mathbf{x} = \mathrm{MLP}(\mathbf{a})$$

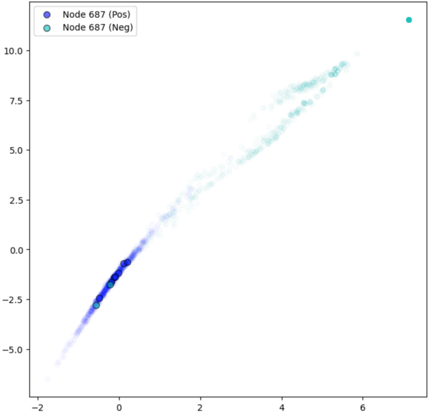


# Example




2007: Jan-Jun ($t$), Jul-Dec ($t + 1$)

# Example




With latent dimension $d = 2$, single node highlighted

# Performance

- "Naive" model:
  - Edges: $e_{uv}^{(\tau)} = e_{uv}^{(\tau+1)}$
  - Features: $\mathbf{x}_u^{(\tau)} = \mathbf{x}_u^{(\tau+1)}$
- LR (features-only) is linear regression $f : \mathbb{R}^d \to \mathbb{R}^d$
- GCN: single-layer $\mathrm{GCN}(A_\tau, \mathbf{X}_\tau)$

| | Edges (AUC) | Features (MSE) |
|---|---|---|
| Naive | 0.508 | 0.0685 |
| LR | - | **0.0410** |
| GCN | 0.894 | 0.0433 |
| DGAE | **0.903** | 0.0445 |

# Next steps

- https://github.com/stmorse/sgg
- More data; non-social network data
- Deeper networks, harder baselines
- Re-examine model architecture (e.g. $h(Z_t)$ or $h(g(Z_t))$ or something else)
- Latent space dimension tuning

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# Questions?