Modeling Link Recommendations as a Network Growth Mechanism and their Impact on Social Contagion

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Background

Online Social Networks increasingly rely on link recommender systems to shape who connects with whom. This can reshape network structures in ways that influence how information and behaviour travels online. Understanding how these systems influence *both simple and complex contagions*—and how this compares to the organic growth of social networks is key to building more socially aware platforms.

Motivation

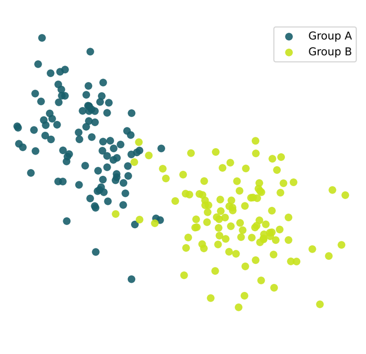
- **Simple vs. complex contagions:** Thrive in different network topologies.
- **Recommender systems:** Influence social dynamics by increasing clustering, reinforcing homophily, or amplifying hubs.
- **Gaps in existing studies:**
  - Counterfactuals (e.g., organic growth)
  - Varying recommendation strengths
  - Varying network topologies
- **Synthetic modeling:** Offers a powerful approach to systematically explore these effects.

Contributions

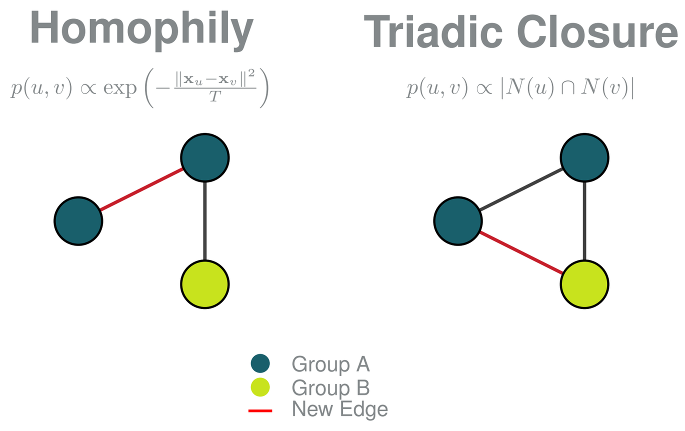
1. Propose a synthetic network model combining triadic closure and choice homophily.
2. Model link recommendations as an additional growth mechanism with adjustable strength.
3. Analyze contagion dynamics across network structures, recommendation algorithms, and relative recommendation strengths.

Network Model

We model a fixed set of nodes N, each assigned a group label $z_i \in \{1, \dots, K\}$ and a feature vector $\mathbf{x}_i \sim \mathcal{N}(\boldsymbol{\mu}_{z_i}, \Sigma_{z_i})$, generating a latent space that encodes similarity.



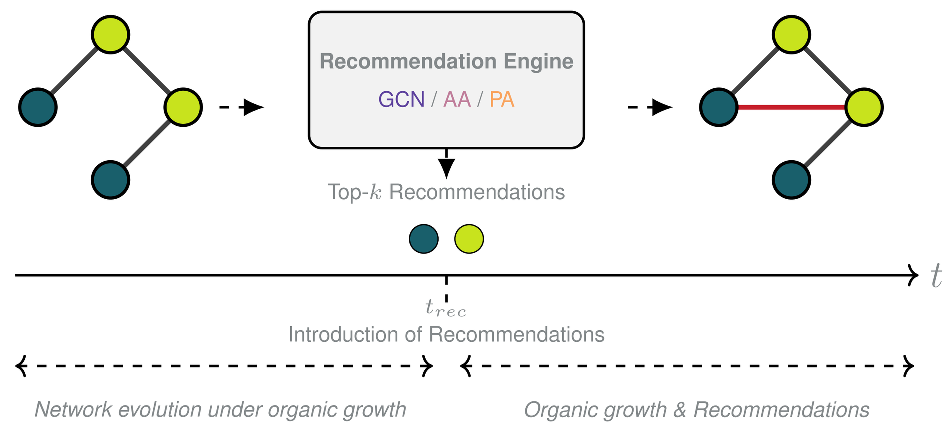
At each time step t, a focal node u forms an edge with a node v based on:



Mechanisms are selected probabilistically with weights γ and β, where $\gamma + \beta = 1$.

Link Recommendations

We extend the growth model by incorporating link recommendations as an **additional growth mechanism.**



- A Graph Convolutional Network (GCN) trained at time t_{rec}
- Two heuristic-based recommenders: Adamic-Adar (AA) and Preferential Attachment (PA)

The balance between recommended and organic links is controlled by $\theta \in [0, 1]$, with θ for recommendations and $1 - \theta$ for organic growth.

Social Contagion

We use these networks to evaluate the impact of link recommendations on social contagion.

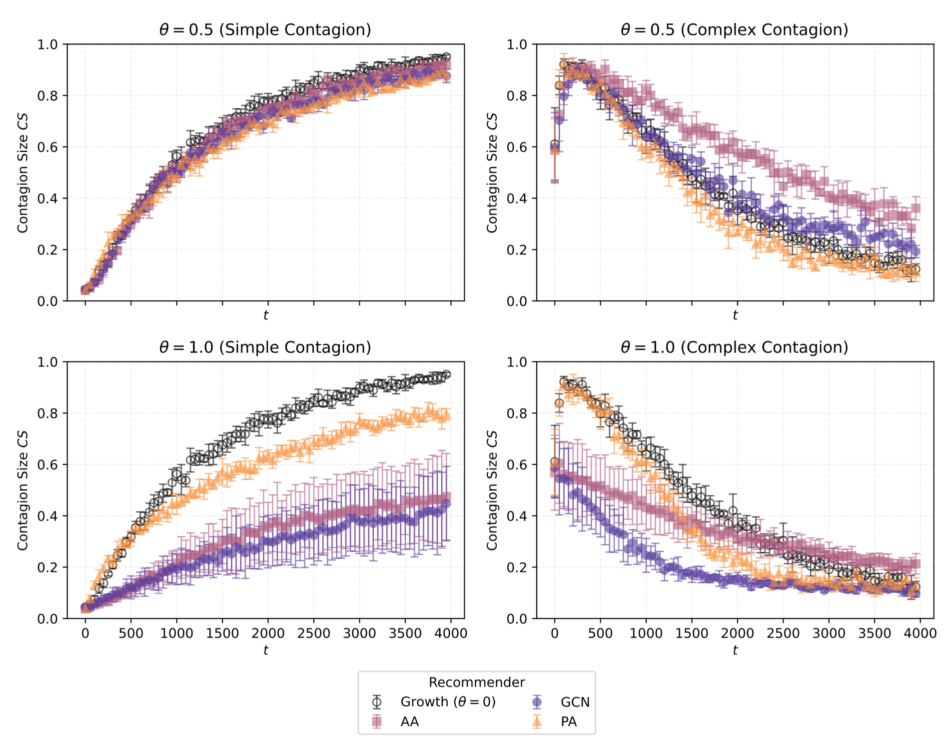
Simple Contagion: Information spreads like a virus

- Mechanisms: Independent cascade
- Examples: Novel information, misinformation

Complex Contagion: Adoption requires (social) reinforcement

- Mechanisms: Threshold-based adoption
- Examples: Social movements, collective behavior

Results I

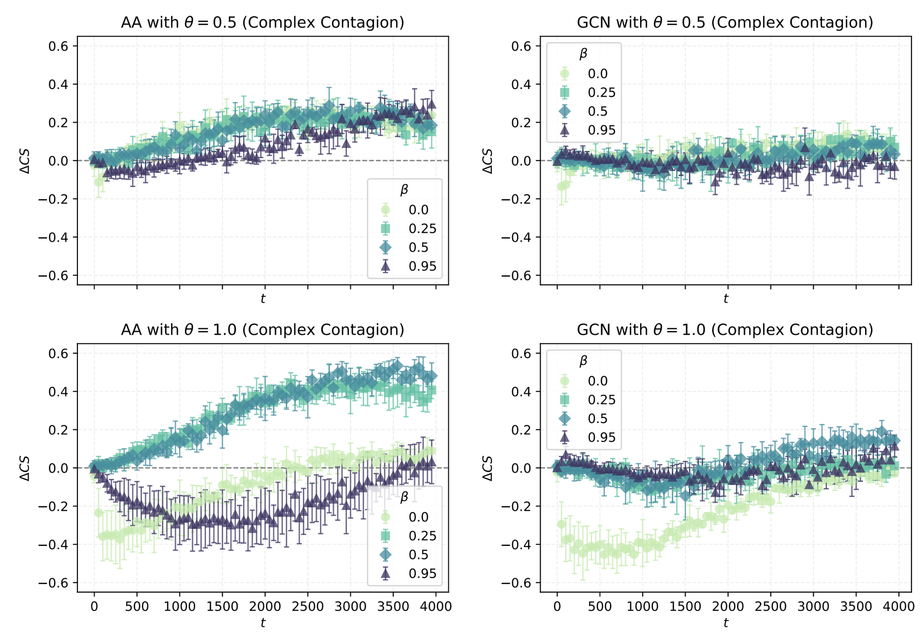


Simple Contagion: In homophilous networks ($\gamma = 1$), strong recommendations ($\theta = 1$) drastically reduce simple contagion spread, while moderate recommendations ($\theta = 0.5$) yield dynamics similar to organic growth.

Complex Contagion: At moderate recommendation strength ($\theta = 0.5$) both **AA** and **GCN** enhance complex contagions, but at $\theta = 1$, they suppress it.

Baseline Reference: Organic growth is necessary baseline to reason about the effects of contagion processes.

Results II



We vary triadic closure (β, with $\gamma = 1 - \beta$) and recommendation strength (θ) to measure changes in complex contagion size (ΔCS) relative to organic growth, comparing AA and GCN.

AA enhances contagion at $\theta = 0.5$ but suppresses it at $\theta = 1$, especially under high clustering. GCN has minimal impact, except under strong homophily.

Implications

Link recommendation algorithms can substantially alter both simple and *especially* complex contagions.

Effective recommendation design should consider the network structure, growth mechanisms, and how strongly users follow recommendations in link formation.

Which contagions should platforms support — and how should this shape algorithmic design?

Future Work

Bridge synthetic models and real-world data to improve relevance and validation

Scale up experiments in network size and contagion evaluation for broader applicability

Introduce and track co-evolution of algorithms and network by retraining GNNs multiple times

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References

Scan here for the paper, relevant literature, and some code.

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