Project Proposal: Differentiable Influence Minimization and Continuous Relaxation

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Motivation & Background

- Social networks amplify information — and misinformation.
- Influence minimization: Which connections should we cut to limit spread?
- Challenge: The process is **combinatorial and non-differentiable**.
- **Goal:** Develop a differentiable framework for influence minimization, leveraging continuous relaxation and graph-based surrogate modeling.

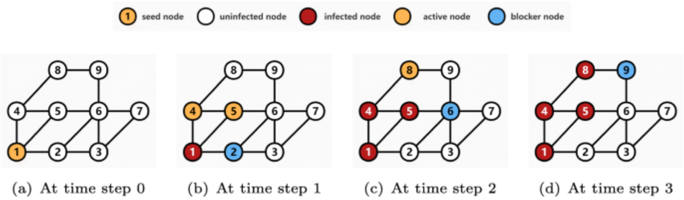

Figure: Source: https://link.springer.com/article/10.1007/s10489-023-04555-y

Influence Minimization and the IC Model

- **Independent Cascade (IC) model:** Each active node has one chance to activate its neighbors with a given probability.
- **Influence Minimization (IMIN):** Remove or weaken edges to minimize total spread.
- Difficult because:
  - Stochastic influence function $\implies$ requires Monte Carlo simulation.
  - Edge removal decisions are discrete.

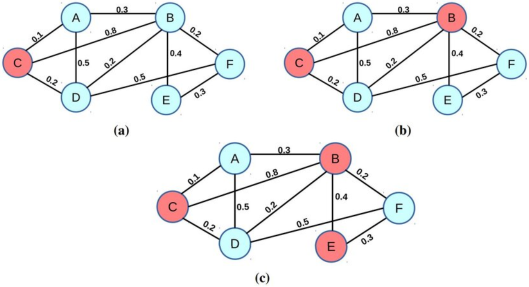

Figure: Source: https://www.researchsquare.com/article/rs-2871290/v1

Differentiable Programming and Continuous Relaxation

- Discrete optimization = no gradients.
- **Continuous Relaxation:**
  - Represent discrete variables (e.g., edge existence) as continuous values in [0,1].
  - Allows smooth optimization via backpropagation.
- Binary switch $\rightarrow$ *dimmer knob*.
- Enables gradient-based reasoning over combinatorial spaces.

From Discrete to Continuous Relaxation

- In the **Independent Cascade (IC)** model, each edge (i, j) has an activation probability p_{ij}.
- For **influence minimization**, we decide whether to keep or remove an edge:

$$p_{ij}^* = p_{ij} \cdot z_{ij}, \quad z_{ij} \in \{0, 1\}$$

- But this binary variable z_{ij} is non-differentiable $\rightarrow$ no gradients!

Continuous Relaxation

Replace the discrete decision z_{ij} with a continuous variable $w_{ij} \in [0, 1]$:

$$p_{ij}^* = p_{ij} \cdot w_{ij}$$

Now each edge has a *soft existence weight* that can be optimized via gradient descent.

- Common parameterizations:
  - Sigmoid: $w_{ij} = \sigma(\alpha_{ij})$
  - Softmax: normalized weights $\sum w_{ij} = 1$

Optimization Objective

- Let $f(w)$ be the differentiable surrogate model estimating influence spread.
- The optimization problem becomes:

$$\min_{w \in [0,1]^{|E|}} f(w) + \lambda \|w\|_1$$

- λ controls how many edges are removed (sparsity regularization).
- After optimization, threshold w_{ij}:

$$z_{ij} = \mathbb{I}(w_{ij} > \tau)$$

This bridges discrete combinatorial reasoning and differentiable optimization.

Inspired by DiffIM: Differentiable Influence Minimization

1. **Surrogate Modeling:**
   - Train a Graph Neural Network (GNN) to approximate the influence function.
   - Avoids expensive Monte Carlo simulations.
2. **Continuous Relaxation of Edge Removal:**
   - Treat edge weights as continuous and learnable.
   - Optimize them directly via gradients from the surrogate model.

Proposed Tasks and Research Plan

- **Short-term (by mid-November):**
  - Reproduce key results from DiffIM using public datasets (e.g., Twitter).
  - Implement a GNN-based surrogate for influence estimation.
  - Explore alternative continuous relaxations (e.g., Gumbel-softmax, sigmoid annealing).
- **Long-term (by end of semester):**
  - Extend model to dynamic or weighted diffusion.
  - Evaluate robustness under noisy or adversarial perturbations.
  - Document reproducible pipeline and prepare final report.

Possible Directions and Alternatives

- **Alternative Surrogates:** Try diffusion-aware GNNs with temporal decay or message passing.
- **Alternative Relaxations:** Probabilistic pruning, entropy-regularized relaxation, or reinforcement learning.
- **Extension Ideas:**
  - Apply to epidemic modeling or rumor spread control.
  - Integrate fairness or trust-weighted diffusion metrics.

Expected Milestones

- **By Nov. 18–20, 2025:**
  - Working DiffIM reimplementation.
  - Preliminary tests on small synthetic graphs.
  - Visualization of edge removal via continuous relaxation.
- **By Dec. 15, 2025:**
  - Complete differentiable IM pipeline.
  - Comparative analysis vs. discrete baselines.
  - Final written report + demonstration notebook.

Summary

- Influence minimization remains a key challenge in social and information networks.
- Differentiable methods can bridge discrete combinatorial reasoning and smooth optimization.
- Extend DiffIM to evaluate robustness and scalability in influence control.

Questions or feedback?

Sources

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