基於有限的使用者資訊還原社群網路結構

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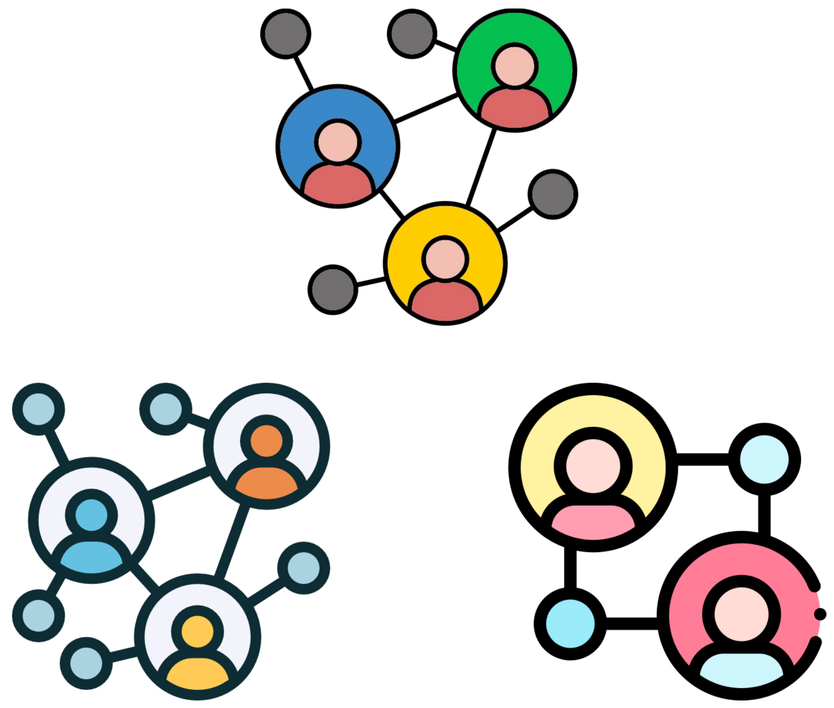
2023-11-29 Proposal

Objective



Link Prediction

k Subgraphs
(Learned by Explainer)

Motivations

1. Validate the quality of subgraphs generated by the Explainer.
2. Assess the privacy risks in social networks to understand if the explanatory subgraphs could leak users' friendship privacy.

Problem Statement

Any Task for Graphs

- Node feature matrix
- Edge adjacency matrix

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GNN model

↓

- Prediction $\hat{y}$

Explain the GNN model by Subgraphs

- Trained GNN model
- Node feature matrix
- Edge adjacency matrix

↓

Explainer

↓ * K times

- Subgraph
- Important features

Construct Social Network (Link Prediction)

- K* (Subgraphs + Important features)
- Node feature matrix

↓

GNN model

↓

- Whether an edge exists between node pairs

Technical Challenges

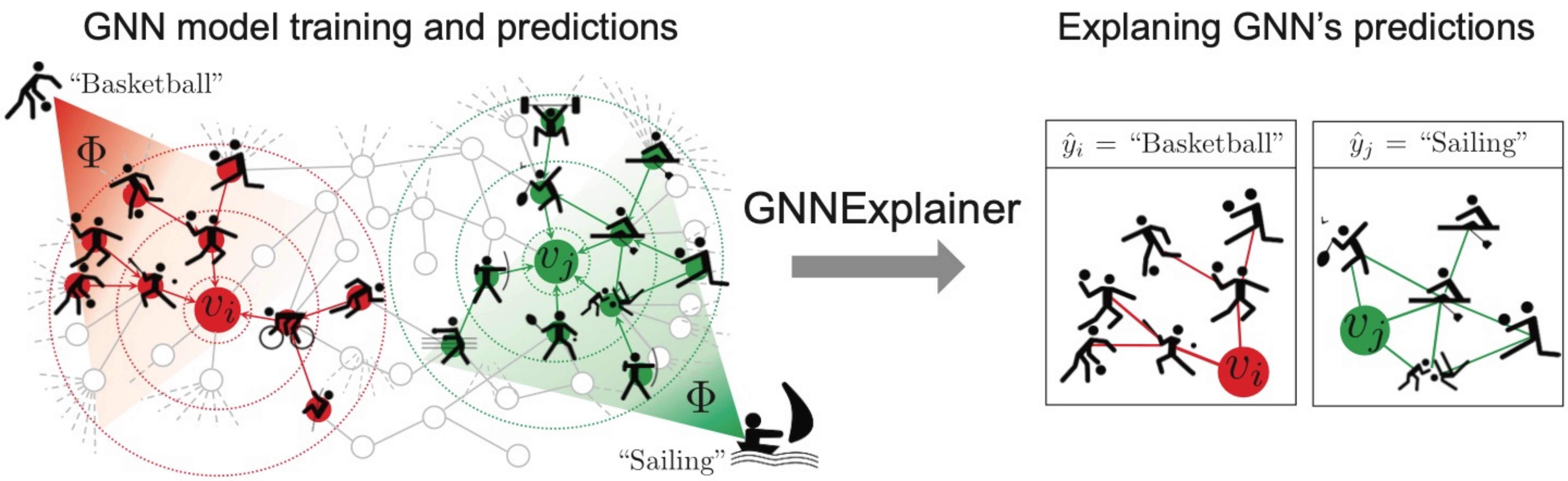
1. The model learned from a small number of subgraphs may not capture the entire network structure.
2. How to select the edges to generate a subgraph, and how many should be selected.
3. How to merge the subgraphs and important features obtained from the Explainer with the original nodes.
4. Each stage is tightly interconnected.

Related Work

1. Ying et al. **“GNNExplainer: Generating Explanations for Graph Neural Networks”** NeurIPS 2019. https://arxiv.org/abs/1903.03894
2. Tan et al. **“Learning and Evaluating Graph Neural Network Explanations based on Counterfactual and Factual Reasoning”** WWW 2022. https://arxiv.org/abs/2202.08816
3. Zhang et al. **“MixupExplainer: Generalizing Explanations for Graph Neural Networks with Data Augmentation“** KDD 2023. https://arxiv.org/abs/2307.07832

GNNExplainer: Generating Explanations for Graph Neural Networks

- The first general, model-agnostic approach for providing interpretable explanations for predictions of any GNN-based model on any graph-based machine learning task.
- Given an instance, GNNEXPLAINER identifies a compact subgraph structure and a small subset of node features that have a crucial role in GNN's prediction.



Learning and Evaluating Graph Neural Network Explanations based on **C**ounterfactual and **F**actual Reasoning

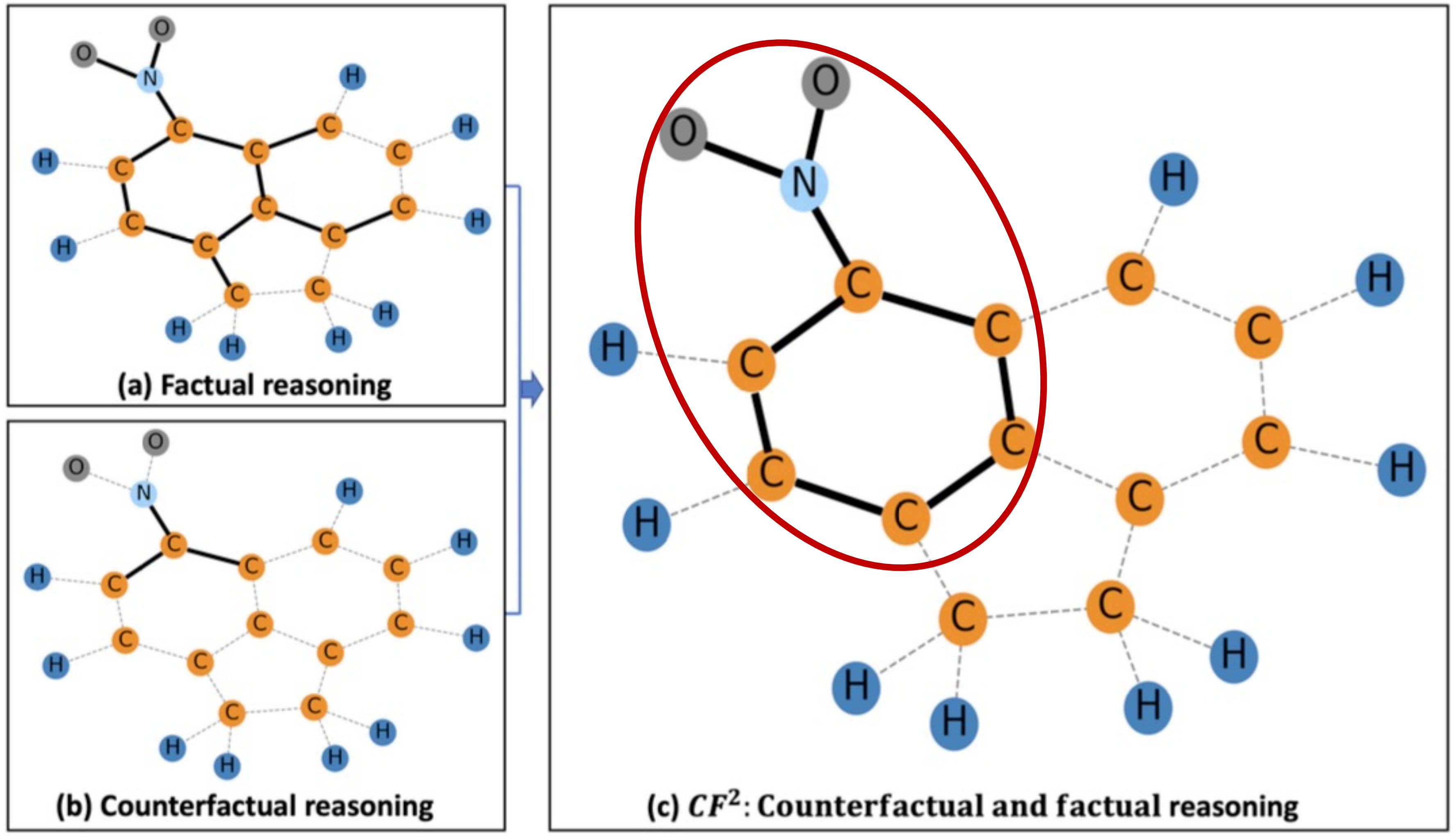
- Propose a model-agnostic framework by formulating an optimization problem based on the insight of Factual and Counterfactual from causal inference theory.
- Extract explanations that are both sufficient and necessary.

- Factual (事實推導)

  尋找一組足夠的邊/特徵，足以產生與使用整個圖相同的預測結果。

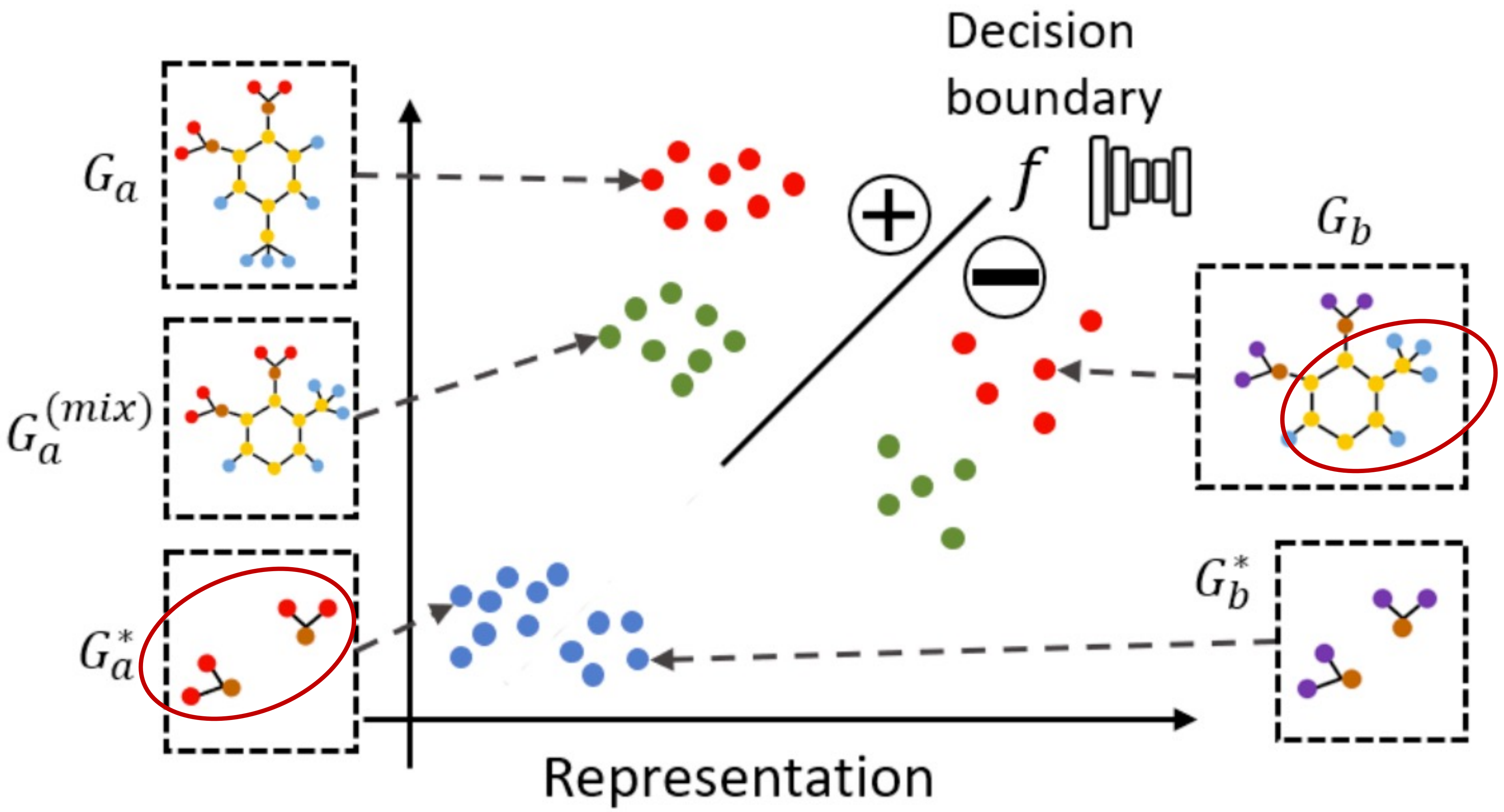
- Counterfactual (反事實推導)

  尋找一組必要的邊/特徵，移除將導致不同的預測結果。



MixupExplainer: Generalizing Explanations for Graph Neural Networks with Data Augmentation

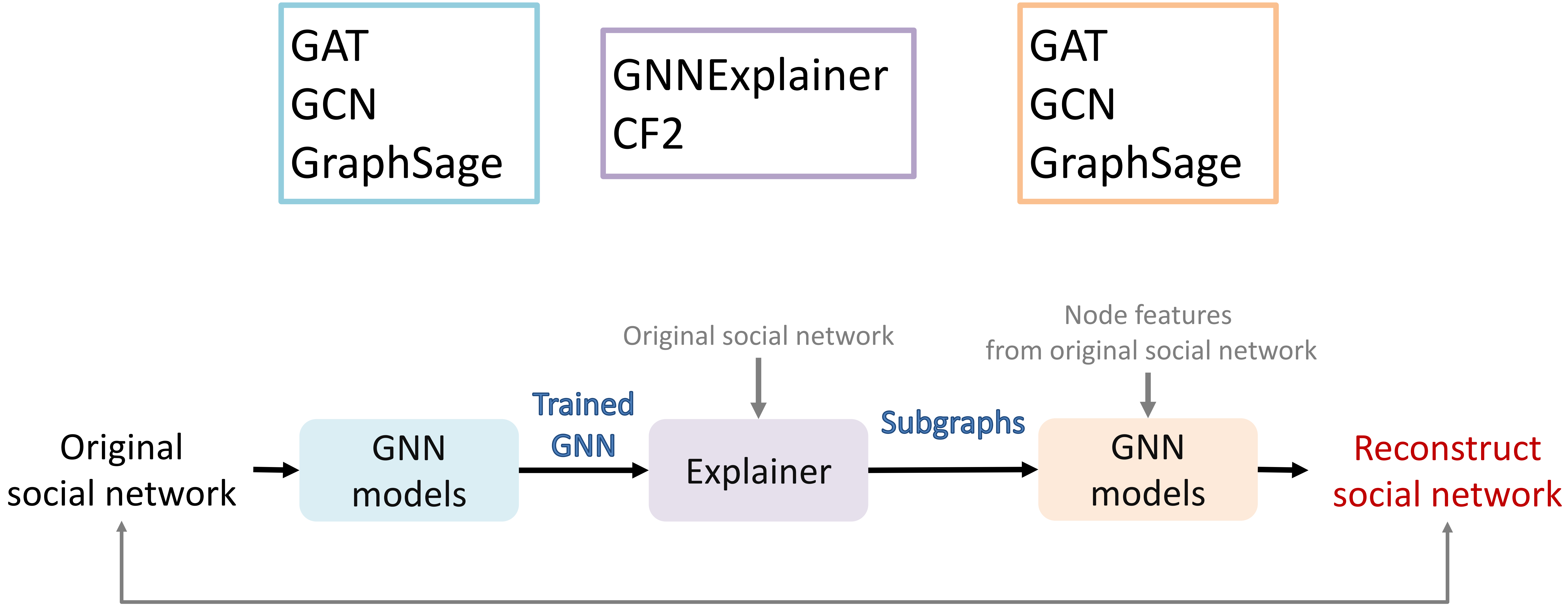
- Point out that the distribution shifting problem is prevalent in the most popular post-hoc explanation framework for graph neural networks.
- MixupExplainer first generates an augmented graph G (mix) by mixing up the explanation subgraph $G*$ with the label-independent part from another randomly sampled graph.



Dataset

- Social circles: Facebook
- From **S**tanford **N**etwork **A**nalysis **P**latform (**SNAP**)
- Data description:
  - Nodes: 4039, Edges: 88234
  - Node features are represented using one-hot encoding, totaling 205 features.
  - Both the users' IDs and features have been anonymized.
  - The dataset is made up of 10 anonymized Facebook networks, each being an "egonet" centered on a user and their friends.

Preliminary Methods

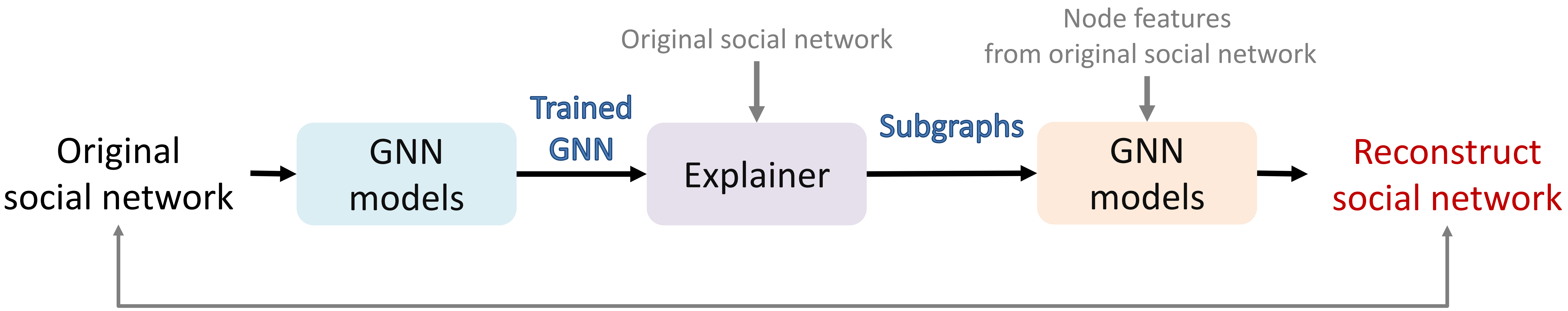


Evaluation Plans

Accuracy
Precision
Recall
F1-score

GNNExplainer: x
CF2: PS, PN

Accuracy
Precision
Recall
F1-score



Expected Time Schedule

Preliminary results: