Generating Robust Counterfactual Witnesses for Graph Neural Networks

Dazhuo Qiu^{*#}, Mengying Wang^{+#}, Arijit Khan^{*}, Yinghui Wu⁺ *Aalborg University, Denmark, ⁺Case Western Reserve University, USA # Equal Contribution

OVERVIEW

Background/Motivation

"Black-Box" GNNs:

- The inference of GNN models are black-box.
- Hard to understand which part of the input causes the results.

"Explainability":

- Domain experts requires reliable predictions.
- Highly related to trustworthy challenges.



Explanation Structures

Factual Explanation:

• M(v, G) = M(v, Gs) = l

Counterfactual Explanation:

• $M(v, G) \neq M(v, G \setminus Gs) \neq l$

Robust Explanation:

• Gs remains consistent under disturbance.

RCW Verification & Generation Problem

Verification Problem: Given G, decide if G is a *k*-RCW for a set of test nodes Vt, w.r.t a model M.

- Witness verification \bigcirc <u>PTIME</u>.
- CW verification <u>FTIME</u>.
- k-RCW verification rightarrow NP-hard.

Generation Problem: Given a graph G and Vt, compute a *k*-RCW if exists.

- *k*-RCW generation in general $\oint \frac{\text{co-NP-hard}}{\text{co-NP-hard}}$
- under (k, b)-disturbances PTIME.

Highlights

All three objectives:

• We are the first to consider all three objectives, i.e., the explanation structure.

<u>Hardness</u>

• Construct PTIME solution for both verification (NP-Hard) and generation problem (co-NP Hard).

Parallel Algorithm

• Proposed parallel version for both verification and generation problem for large graphs.

ALGORITHMS

A1-Verification of Witness

Factual Verification:

• Conduct the model inference to verify if the subgraph is a witness.

Counterfactual Verification:

• Conduct the model inference to verify if the subgraph is a counterfactual witness.

Robust Verification:

- For each "non-true" label (labels \neq prediction), verify if the subgraph remains a CW under k edge flips.
- For each node in the "fragile" area (remaining subgraph), select top-b edges that are most likely changing the node labels. (PageRank score)

EXPERIMENTS

Experiment Setting

<u>Datasets</u>

	Dataset	# nodes	# edges	# node features	# class
	BAHouse	300	1500	-	
	PPI	2,245	61,318	50	12
	CiteSeer	3,327	9,104	3,703	
	Reddit	232,965	114,615,892	602	4
3		•			

<u>Baselines</u>

Baselines	Counterfactual	Factual	Rol
CF-GNNExp (AISTATS 2022)	\checkmark		
CF ² (WWW 2022)	\checkmark	\checkmark	
RoboGExp	\checkmark	\checkmark	

<u>Metrics</u>

- normalized $\operatorname{GED}(G_w, G'_w) = \frac{\operatorname{GED}(G_w, G'_w)}{\max(|G_w|, |G'_w|)}$ Consistency
- $Fidelity + = \frac{1}{|V_T|} \sum_{v \in V_T} (\mathbb{1}(M(v, G) = l) \mathbb{1}(M(v, G \setminus G_s) = l))$ • Fidelity+
- Fidelity-Fidelity $- = \frac{1}{|V|} \sum (\mathbb{1}(M(v,G) = l) - \mathbb{1}(M(v,G_s) = l))$ $|V_T| \sum_{v \in V_T}$

ACKNOWLEDGE

- Dazhuo Qiu and Mengying Wang contributed equally.
- Qiu and Khan are supported by the Novo Nordisk Foundation grant NNF22OC0072415.
- Wang and Wu are supported in part by NSF under CNS-1932574, ECCS-1933279, CNS-2028748
- and OAC-2104007.



A A L B O R G U N I V E R S I T Y



A2-Generating k-RCW *Expand*: • Includes node pairs that

- most likely to change its label if "flipped". subgraph • Augment the
- (initialized with test nodes) with edges that minimize the worst-case margin.

<u>Verify</u>:

- Check if the expanded subgraph is RCW
- k-disturbance: • Under k edges that are most likely to change the prediction.

A3-Parallel Generation

Partition:

- fragment graph.
- redundant verification.

Union:

- local subgraph.







• Edge-cut based partition where each worker processes one

• Using a bitmap to record the verified k-disturbance to avoid

• Assemble a global subgraph from each worker with the

• In each worker expand and verify local subgraph, and maintain the local bitmap.





RoboGExp TEAM