

Learning from Counterfactual Links for Link Prediction

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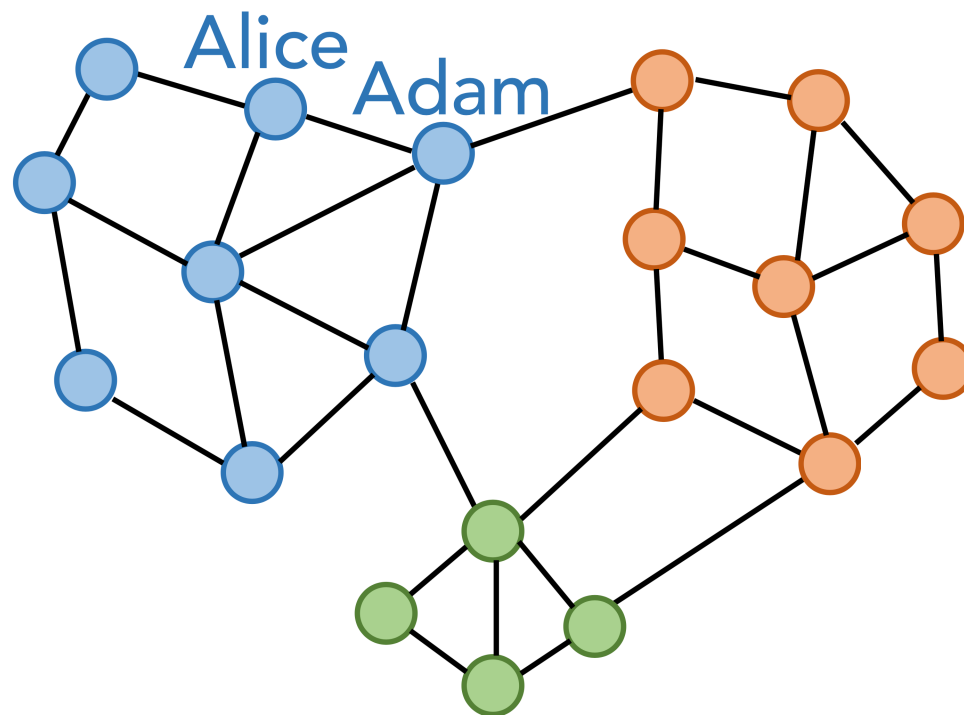
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Link Prediction

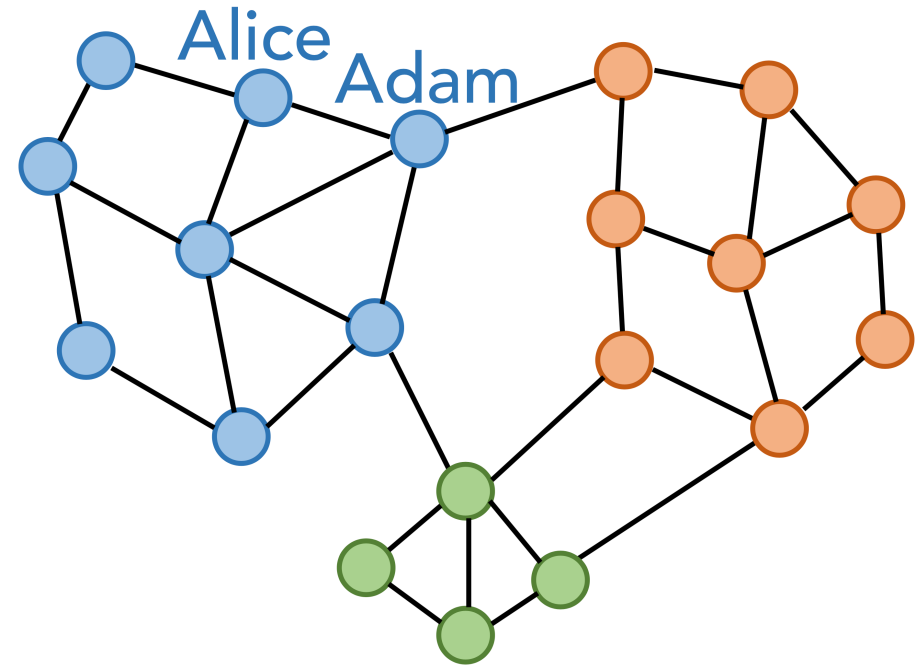
Given: a graph with adjacency matrix $\mathbf{A} \in \{0,1\}^{N \times N}$, raw node features $\mathbf{X} \in \mathbb{R}^{N \times F}$, and binary treatments $\mathbf{T} \in \{0,1\}^{N \times N}$ for each node pair.

Learn: low-dimensional node representations $\mathbf{Z} \in \mathbb{R}^{N \times H}$, which can be used for the prediction of link existences.



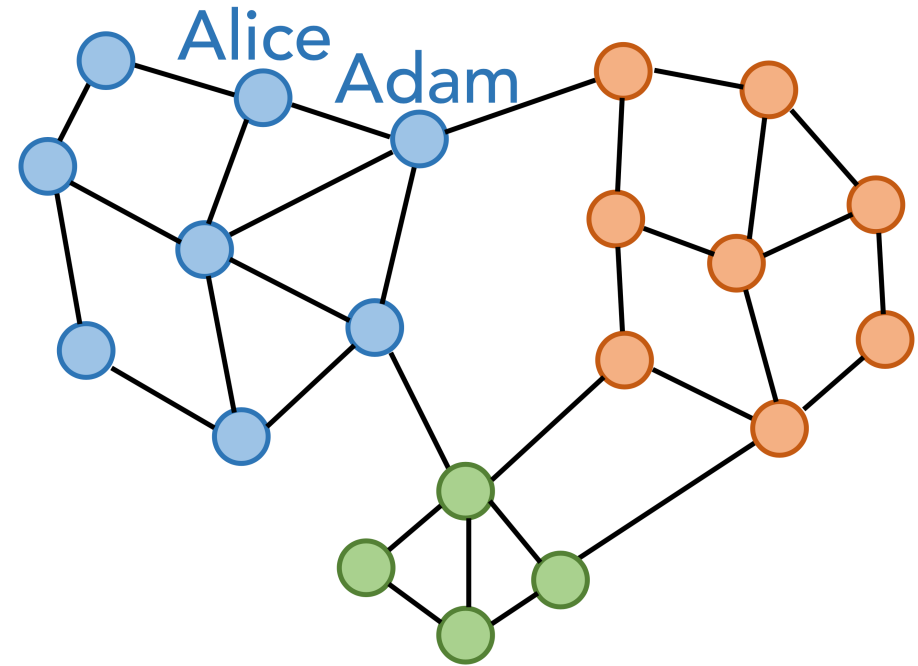
Counterfactual Outcomes to Balance Training Data

- Counterfactual question:
 - Would Alice and Adam still be friends if they were not living in the same neighborhood?

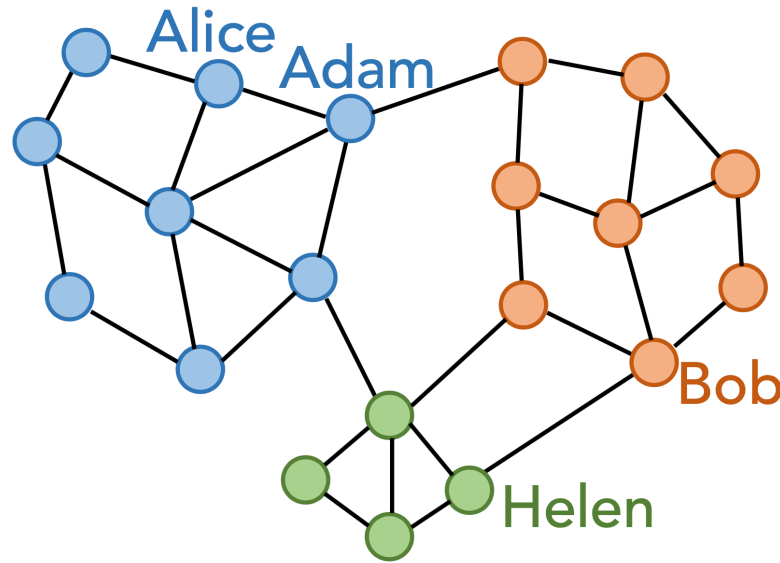


Counterfactual Outcomes to Balance Training Data

- Counterfactual question:
 - Would Alice and Adam still be friends if they were not living in the same neighborhood?
- Idea:
 - Generate *counterfactual links* to help the model learn better node representations for link prediction.



Counterfactual Links



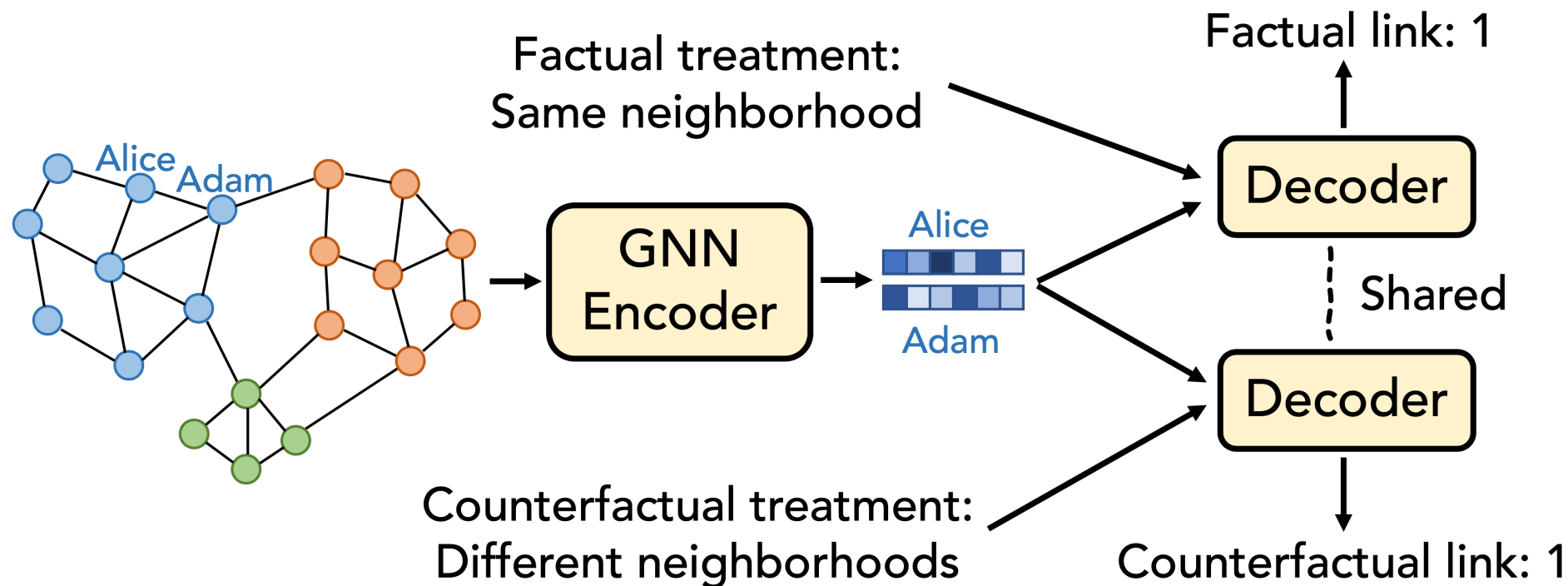
(Alice, Adam) $\xrightarrow{\text{Most similar with a different treatment}}$ (Helen, Bob)

Factual link: 1

Counterfactual link: 1



Learning from Counterfactual Links



Our proposed CFLP learns from both observed and counterfactual link existences.

Results 1

	CORA	CITESeer	PUBMED	FACEBOOK	OGB-DDI
Node2Vec	49.96 \pm 2.51	47.78 \pm 1.72	39.19 \pm 1.02	24.24 \pm 3.02	23.26 \pm 2.09
MVGRL	19.53 \pm 2.64	14.07 \pm 0.79	14.19 \pm 0.85	14.43 \pm 0.33	10.02 \pm 1.01
VGAE	45.91 \pm 3.38	44.04 \pm 4.86	23.73 \pm 1.61	37.01 \pm 0.63	11.71 \pm 1.96
SEAL	51.35 \pm 2.26	40.90 \pm 3.68	28.45 \pm 3.81	40.89 \pm 5.70	30.56 \pm 3.86
LGLP	<u>62.98</u> \pm 0.56	<u>57.43</u> \pm 3.71	–	37.86 \pm 2.13	–
GCN	49.06 \pm 1.72	55.56 \pm 1.32	21.84 \pm 3.87	<u>53.89</u> \pm 2.14	37.07 \pm 5.07
GSAGE	53.54 \pm 2.96	53.67 \pm 2.94	<u>39.13</u> \pm 4.41	45.51 \pm 3.22	53.90 \pm 4.74
JKNet	48.21 \pm 3.86	55.60 \pm 2.17	25.64 \pm 4.11	52.25 \pm 1.48	<u>60.56</u> \pm 8.69
Our proposed CFLP with different graph encoders					
CFLP w/ GCN	60.34 \pm 2.33	59.45 \pm 2.30	34.12 \pm 2.72	53.95 \pm 2.29	52.51 \pm 1.09
CFLP w/ GSAGE	57.33 \pm 1.73	53.05 \pm 2.07	43.07 \pm 2.36	47.28 \pm 3.00	75.49 \pm 4.33
CFLP w/ JKNet	65.57 \pm 1.05	68.09 \pm 1.49	44.90 \pm 2.00	55.22 \pm 1.29	86.08 \pm 1.98

Consistent improvement against baselines.



Results 2



Leaderboard for [ogbl-ddi](#)

The Hits@20 score on the test and validation sets. The higher, the better.

Package: >=1.2.1

Rank	Method	Ext. data	Test Hits@20	Validation Hits@20	Contact	References	#Params	Hardware	Date
1	PLNLP	No	0.9088 ± 0.0313	0.8242 ± 0.0253	Zhitao Wang (WeChat@Tencent)	Paper , Code	3,497,473	Tesla-P40(24GB GPU)	Dec 7, 2021
2	GraphSAGE + Edge Attr	No	0.8781 ± 0.0474	0.8044 ± 0.0404	Jing Yang	Paper , Code	3,761,665	Tesla V100 (32GB)	Aug 9, 2021
3	CFLP (w/ JKNet)	No	0.8608 ± 0.0198	0.8405 ± 0.0284	Tong Zhao	Paper , Code	837,635	GeForce RTX 2080 Ti (11GB GPU)	Nov 17, 2021



Thank you for listening!

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