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Same Graph Cross-Task Transfer in GNNs

Protocols and Predictors

When does reusing supervision across node classification and link prediction help on the same graph?

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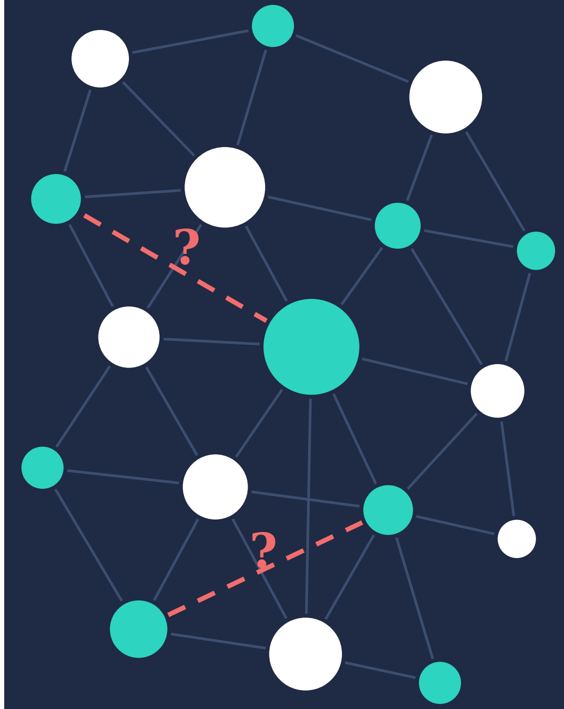

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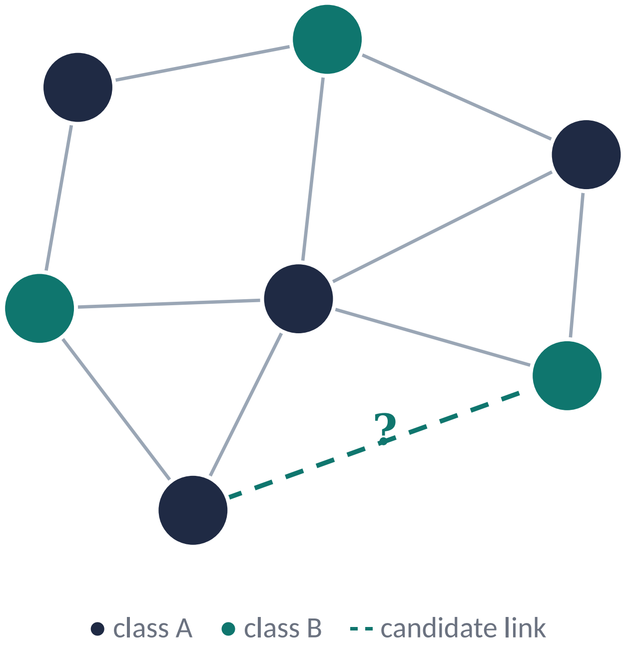
Multiple tasks on one graph

Real systems answer several questions over the same underlying graph. The supervision for both tasks already coexists in the data: node labels for **node classification (NC)** and observed edges for **link prediction (LP)**.

Example (social network). NC asks whether a node is a human user or a bot; LP suggests potential friendship connections.

Two practical needs. Can supervision from one task improve the other, and can a single shared encoder serve both to amortize training and serving cost?



Contributions

1. **Problem setting: same graph cross-task learning.** We formalize NC and LP reuse on one underlying graph and study both directions, NC→LP and LP→NC.

2. **Leakage-free evaluation protocol.** A standardized setup that fixes splits, observed-graph construction, and LP negatives, preventing leakage from evaluation edges.

3. **Systematic study across backbones and transfer strategies.** Five transfer strategies (WS, ET-Rep, ET-Concat, MV, Joint) over three backbones (GCN, GraphSAGE, GPS); a robust directional asymmetry across architectures.

4. **Multi-objective model selection and predictors.** CoTask Score (CTS) summarizes joint NC+LP utility; homophily predicts NC→LP gains, while LP→NC gains concentrate in structure-dominant regimes.

Leakage-free evaluation protocol

A valid cross-task comparison must satisfy three requirements, applied identically to NC, LP, and transfer.

i **No edge leakage.** Edges evaluated for LP must not appear in the graph used for message passing.

ii **Fixed negatives.** LP uses fixed negative sets for train, validation, and test, reused across all methods.

iii **Fixed splits.** All methods use the same node split for NC and the same edge split for LP positives.

Setup. Observed adjacency $A_{obs} = \mathrm{Adj}(V, E_{+tr})$. Splits 60/20/20 (NC) and 80/10/10 (LP); negatives at 1:1, fixed seeds, reused across methods.

Cross-task transfer as optimization

For a fixed backbone, NC and LP define different losses over the same parameters. We study five lightweight regimes:

- **WS:** initialize the target encoder from a source-task solution.
- **ET-Rep / ET-Concat:** reuse frozen source embeddings as input (replace or concatenate).
- **MV:** two encoders trained jointly with cross-view alignment.
- **Joint:** one shared encoder, two heads, both losses.

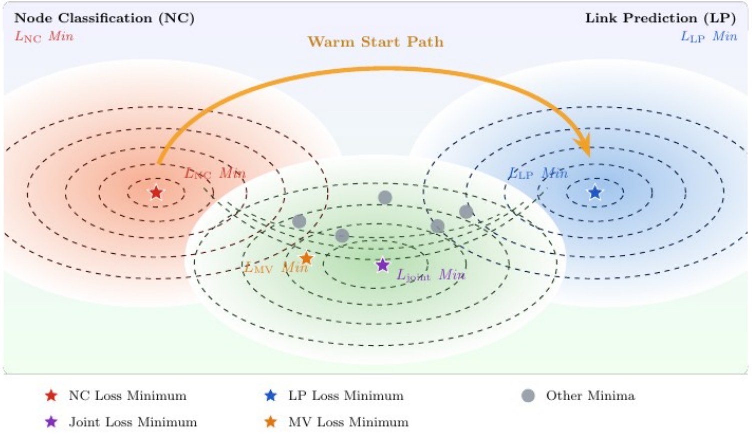


Figure 1. NC and LP are different losses over the same parameters, with possibly incompatible minima.

A directional asymmetry (GCN)

	NC→LP ΔAUC (pp)						LP→NC ΔAcc (pp)					
Dataset	Base	WS	ET-R	ET-C	MV	Joint	Base	WS	ET-R	ET-C	MV	Joint
Homophilic												
Cora	80.3	+9.4	+10.7	+9.8	+10.1	**+12.3**	85.3	**+0.6**	-12.7	+0.5	+0.5	+0.4
Citeseer	77.0	+11.9	+11.9	+11.1	+12.8	**+13.2**	71.6	+0.5	-16.8	+0.1	+0.3	**+3.5**
PubMed	89.8	**+5.9**	+4.1	+4.5	+5.0	+4.7	88.5	**+0.1**	-21.4	-1.0	-0.1	-0.5
Heterophilic												
Texas	67.0	+3.6	-0.3	-2.6	+4.7	**+7.1**	50.3	+2.6	+6.6	+1.6	-0.3	**+11.9**
Cornell	75.4	**+4.6**	-2.1	-1.3	+3.7	+2.3	51.6	**-0.3**	-11.1	-2.9	-2.4	-2.6
Wisconsin	75.1	+1.8	-0.2	-0.4	+2.3	**+3.7**	49.4	-0.2	-2.9	-1.6	-0.8	**+1.0**
Actor	80.4	-0.3	-1.6	-0.7	-0.3	**+1.2**	27.9	+0.5	-1.3	+1.0	+0.7	**+3.2**
Roman	73.8	**+0.1**	-10.6	-6.6	-0.1	-11.1	51.4	**+0.2**	-28.2	-0.4	0.0	-0.5
Structure-dominant												
USA	95.5	**+0.3**	+0.1	+0.3	+0.3	-0.6	54.6	-1.1	+5.8	**+7.8**	-0.2	+6.2
Europe	92.6	**+0.4**	-1.1	+0.1	+0.2	-2.3	53.7	-0.4	+2.6	+1.4	-1.0	**+2.8**
Brazil	90.4	**+3.1**	+0.1	+0.9	+1.3	+0.1	48.9	-0.4	**+15.2**	+6.7	+2.2	+13.7

GCN backbone. Gains in percentage points vs the single-task base (Base = base score). Bold = best of the five mechanisms per direction. ET-R = ET-Rep, ET-C = ET-Concat.

Homophily explains the asymmetry

NC→LP gains correlate with homophily (strongest for ET-Concat and ET-Rep), while LP→NC is not. NC training amplifies the cosine-similarity gap between linked and unlinked pairs, about 2.1x more on homophilic graphs **(r = +0.901).**

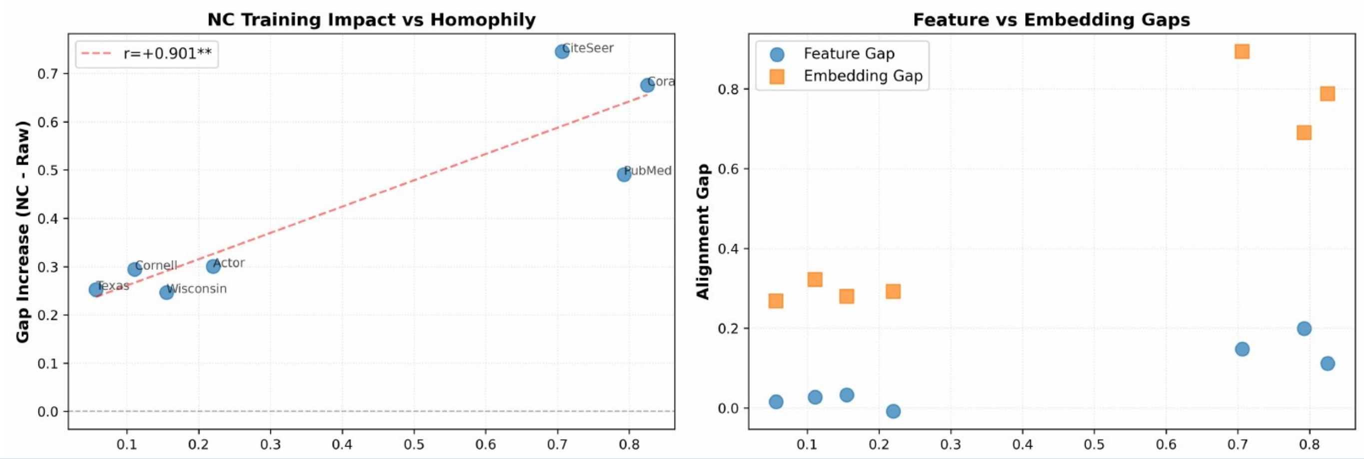


Figure 2. NC-training cosine-gap increase vs. node homophily (left); NC-trained embeddings vs. raw-feature gaps (right).

Conclusion

- Same graph cross-task transfer is strongly directional and predictable.
- NC→LP is reliably beneficial on homophilic graphs. LP→NC is less predictable and helps mainly in structure-dominant regimes.
- Coupled training (MV, Joint) is typically more stable than post hoc representation reuse.
- Homophily explains NC→LP gains more consistently than LP→NC.

Practical guidance. Homophilic graph: prefer NC→LP with a coupled objective (MV or Joint). Structure-dominant (LP easy, NC unsaturated): LP→NC can help. Avoid naive ET-Rep reuse.

Code & data: **github.com/avp-neelam/CrossTaskTransfer**