Multi-Class and Multi-Task Strategies for Neural Directed Link Prediction



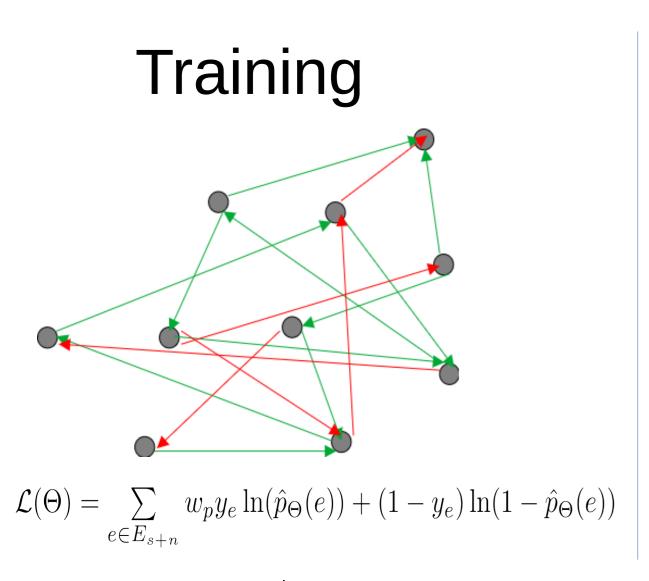
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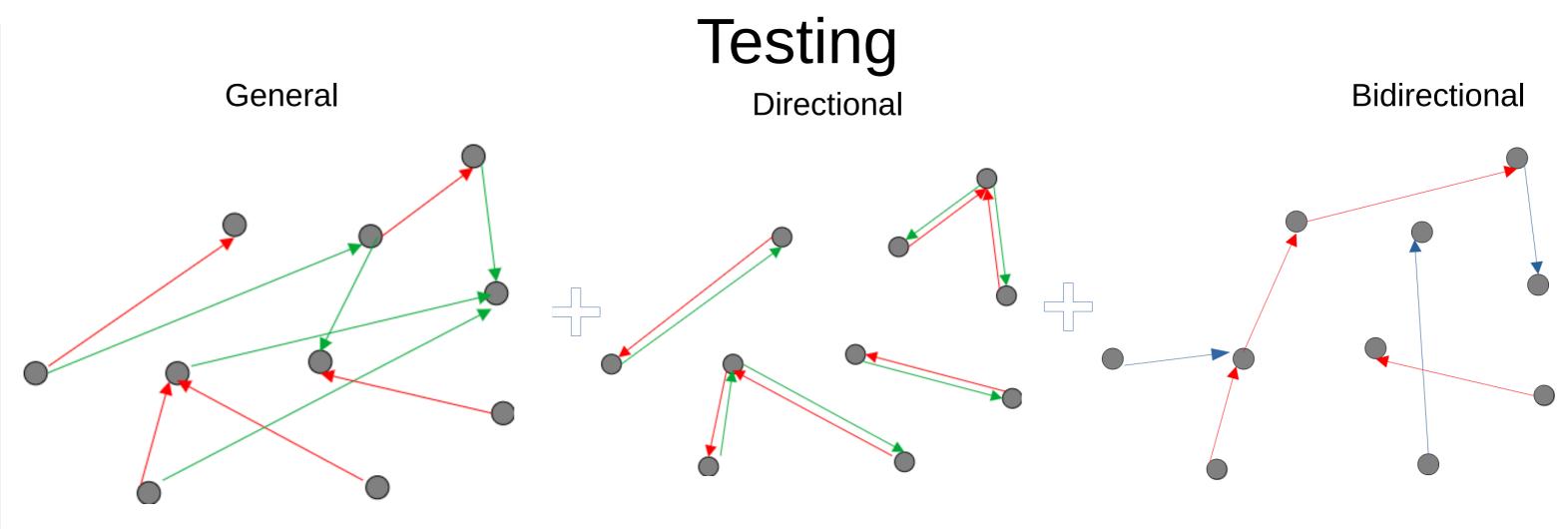
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(NAIVE) DIRECTED LINK PREDICTION



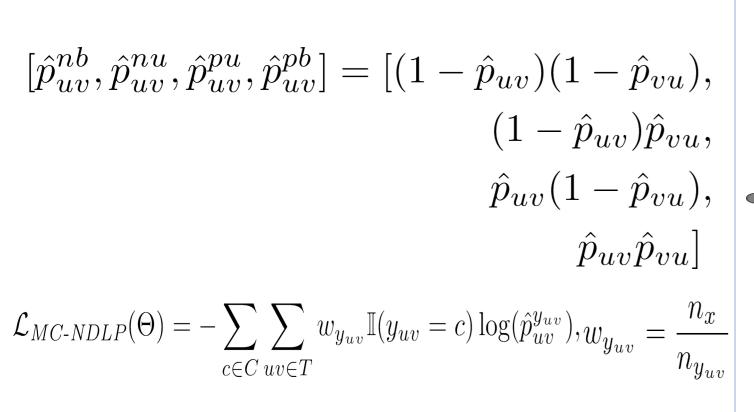


		GENERAL		DIRECTIONAL		BIDIRECTIONAL	
model	decoder	ROC-AUC	AUPRC	ROC-AUC	AUPRC	ROC-AUC	AUPRC
GAE	$ec{z}_i \cdot ec{z}_j$	84.6	88.6	50.0	50.0	$\boxed{62.4}$	64.0
GR-GAE	$\sigma(\vec{z}_v[0] - \lambda \ln(\vec{z}_u[1:] - \vec{z}_v[1:] _2^2))$	89.2	92.4	63.4	61.5	69.1	66.5
MLP-GAE	$\mathrm{MLP}(\overrightarrow{z}_v \overrightarrow{z}_u)$	77.1	78.2	90.7	90.7	69.9	69.7
MAGNET	MLP-like	75.2	77.8	90.4	89.8	71.9	70.4

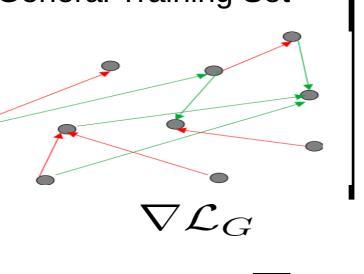
NEW TRAINING STRATEGIES

MGDA

Multi Class

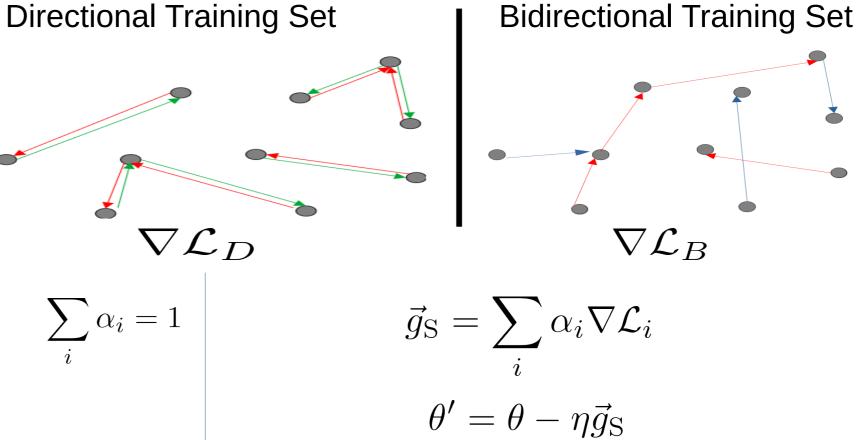






$$\vec{g}_{\text{MGDA}} = \min_{\substack{||\sum_{i} \alpha_{i} \nabla \mathcal{L}_{i}||_{2}^{2} \\ \theta' = \theta - \eta \vec{g}_{\text{MGDA}}}} \sum_{i} \alpha_{i} \nabla \mathcal{L}_{i} \quad \text{s.t.} \quad \sum_{i} \alpha_{i} = 1$$

Scalarization



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		GENERAL		DIRECTIONAL		BIDIRECTIONAL	
model	strategy	ROC-AUC	AUPRC	ROC-AUC	AUPRC	ROC-AUC	AUPRC
GR-GAE	BASELINE	89.2 ± 0.4	92.4 ± 0.2	63.4 ± 2.5	61.5 ± 2.7	69.1 ± 3.1	66.5 ± 3.3
	MO-NDLP	84.5 ± 1.1	86.3 ± 1.1	80.6 ± 0.7	80.2 ± 0.9	79.6 ± 4.3	84.6 ± 3.5
	MC-NDLP	88.6 ± 0.4	90.0 ± 0.4	82.1 ± 0.5	81.8 ± 0.7	77.3 ± 2.2	76.3 ± 1.7
	S-NDLP	87.8 ± 0.6	89.5 ± 0.5	82.3 ± 0.5	81.6 ± 0.4	89.6 ± 1.6	92.4 ± 1.1
$\overline{\mathrm{DiGAE}}$	BASELINE	80.4 ± 1.1	85.3 ± 0.8	57.5 ± 1.3	63.0 ± 1.4	70.4 ± 2.2	68.6 ± 1.2
	MO-NDLP	70.2 ± 3.8	72.6 ± 3.6	73.6 ± 5.4	76.0 ± 4.2	67.3 ± 4.6	69.6 ± 4.1
	MC-NDLP	75.4 ± 0.9	77.4 ± 1.0	84.3 ± 0.6	85.4 ± 0.8	68.9 ± 1.5	69.3 ± 1.1
	S- $NDLP$	72.5 ± 4.0	77.4 ± 4.4	61.6 ± 1.3	69.2 ± 1.4	72.1 ± 5.6	74.4 ± 5.7
$\overline{ ext{MLP-GAE}}$	BASELINE	77.1 ± 0.9	78.2 ± 0.6	90.7 ± 0.6	90.7 ± 0.6	69.9 ± 3.2	69.7 ± 3.7
	MO-NDLP	76.0 ± 0.8	76.4 ± 0.7	93.4 ± 0.6	93.5 ± 0.6	80.7 ± 1.6	79.2 ± 2.4
	MC-NDLP	74.5 ± 0.7	75.6 ± 0.7	94.3 ± 0.6	94.4 ± 0.5	71.7 ± 2.4	65.7 ± 1.8
	S-NDLP	74.7 ± 1.0	74.9 ± 0.9	90.5 ± 0.7	90.0 ± 0.9	72.0 ± 2.6	70.5 ± 2.9
MAGNET	BASELINE	75.2 ± 1.4	77.8 ± 1.0	90.4 ± 0.9	89.8 ± 0.8	71.9 ± 2.3	70.4 ± 2.8
	MO-NDLP	74.4 ± 1.4	77.4 ± 1.1	91.3 ± 1.0	90.9 ± 1.0	70.6 ± 2.7	68.6 ± 2.7
	MC-NDLP	74.4 ± 1.0	77.4 ± 1.0	92.1 ± 0.7	91.6 ± 0.7	71.8 ± 2.6	70.0 ± 2.6
	S-NDLP	74.6 ± 1.3	77.5 ± 1.1	91.0 ± 1.0	90.4 ± 1.0	71.8 ± 2.8	70.2 ± 2.9

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