

DLGMA'20
Workshop

Lagrangian Propagation Graph Neural Networks

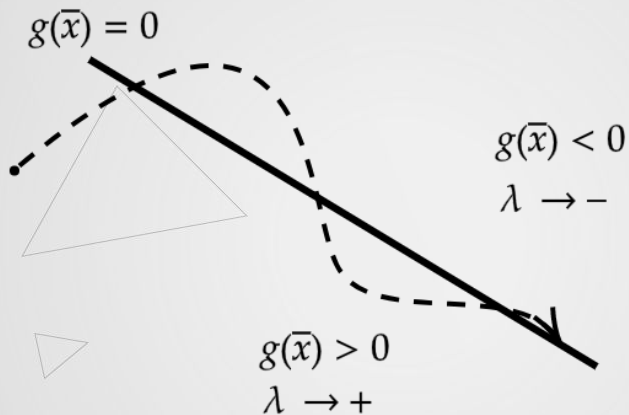


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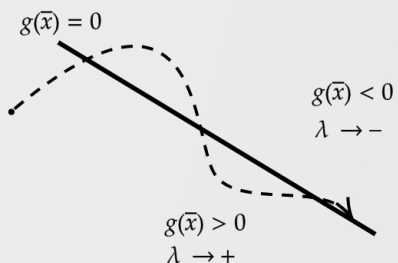


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Propose a novel constrained formulation approach to learning w.r.t. GNNs [Scarselli 2009]
Avoid epoch-wise fixed-point convergence, still take advantage of the multi-hop diffusion



$$\begin{aligned} \min \quad & \sum_{v \in S} L(g_w(x_{v, K-1}), y_v) \\ \text{s.t.} \quad & \mathcal{G}(x_{v, k} - f_{w, v}^k) = 0, \quad \forall v \in V, \forall k \in [0, K - 1] \end{aligned}$$

Cast it in the Lagrangian framework.

$$\min_{\theta_{f_w}, \theta_{g_w}, X} \max_{\Lambda} \mathcal{L}(\theta_{f_w}, \theta_{g_w}, X, \Lambda)$$

- Jointly optimize transition function and node state representation
- Diffusion as a differential optimization process, aimed at fulfilling the constraints
- Mixed strategy:
 - Still rely on BackPropagation to learn the transition and output functions
 - Exploit constraints to define the diffusion mechanism

