Node Masking

Leibniz-Institut
für Sozialwissenschaften

Reported by Chenghong Li

2022_WWW_GRAND+_Scalable Graph Random Neural Networks

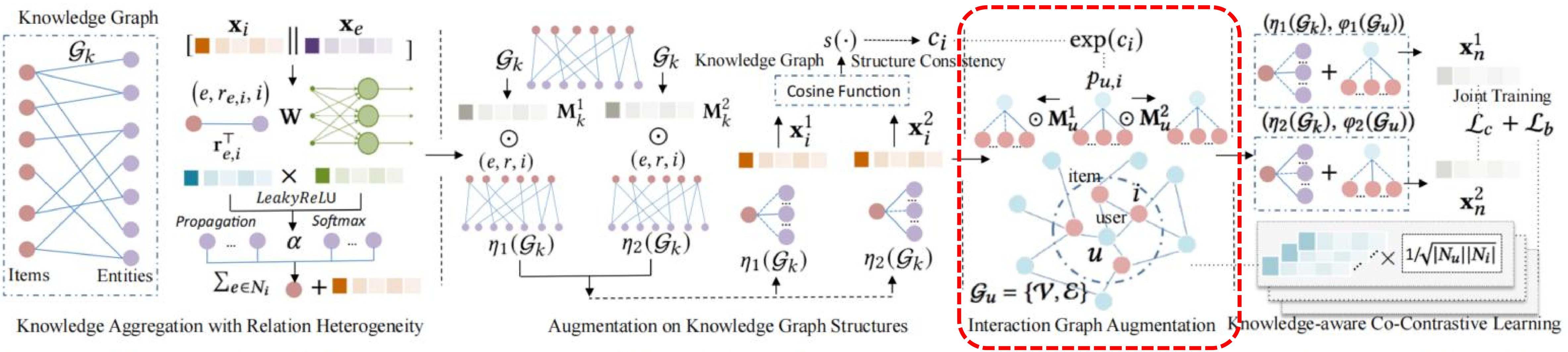

Figure 3: The overall architecture of our proposed KGCL. Knowledge-aware co-contrastive learning with augmentation functions on both knowledge graph $\eta(\cdot)$ and user-item interaction graph $\varphi(\cdot)$. Our contrastive objective $\mathcal{L}_c$ is jointly optimized with main embedding space shared by the knowledge graph aggregation and graph-based CF encoder.

$$w_{u,i} = \exp(c_i);\ p'_{u,i} = \max\left(\frac{w_{u,i} - w^{min}}{w^{max} - w^{min}}, p_\tau\right) \qquad (5)$$

$$p_{u,i} = p_a \cdot \mu_{p'} \cdot p'_{u,i}$$

$$\varphi(\mathcal{G}_u) = (\mathcal{V}, \mathbf{M}_u^1 \odot \mathcal{E}),\ \varphi(\mathcal{G}_u) = (\mathcal{V}, \mathbf{M}_u^2 \odot \mathcal{E}) \qquad (6)$$

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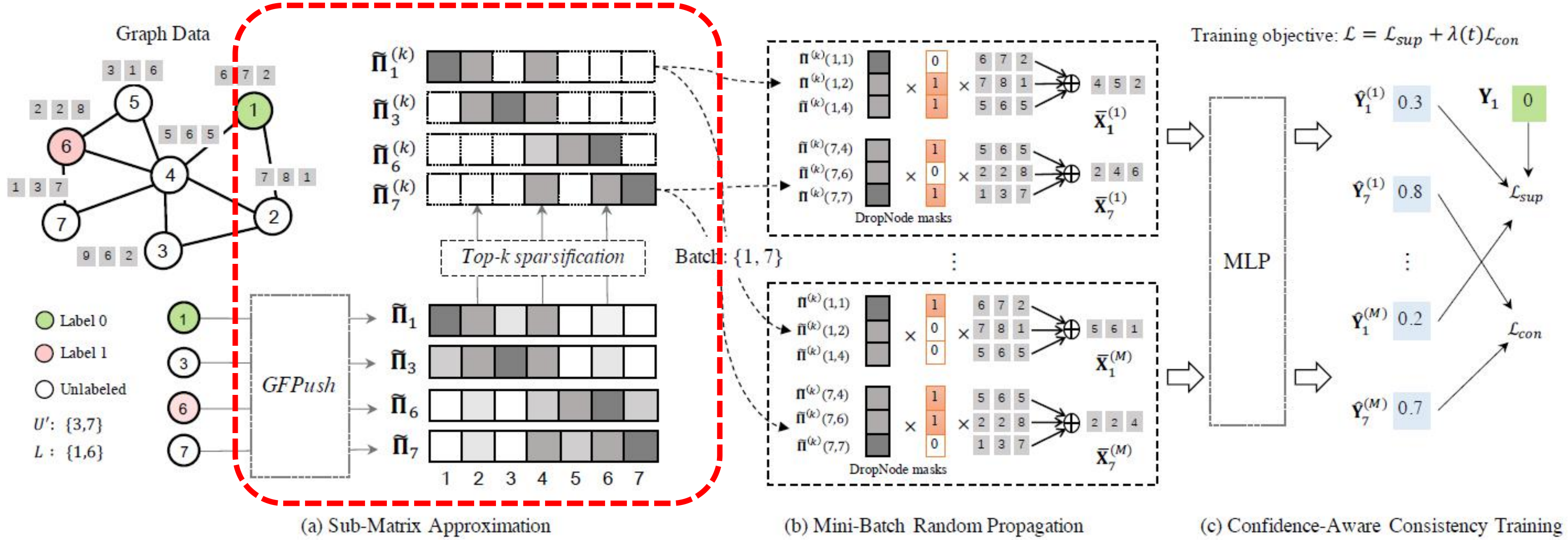

Figure 1: Illustration of GRAND+. (a) GRAND+ adopts *Generalized Forward Push* (*GFPush*) and *Top-k sparsification* to approximate the corresponding rows of propagation matrix Π for nodes in $L \cup U'$. (b) The obtained sparsified row approximations are then used to perform mini-batch random propagation to generate augmentations for nodes in the batch. (c) Finally, the calculated feature augmentations are fed into an MLP to conduct confidence-aware consistency training, which employs both supervised loss $\mathcal{L}_{sup}$ and confidence-aware consistency loss $\mathcal{L}_{con}$ for model optimization.

2020_NeurIPS_Graph Random Neural Networks for Semi-Supervised Learning on Graphs

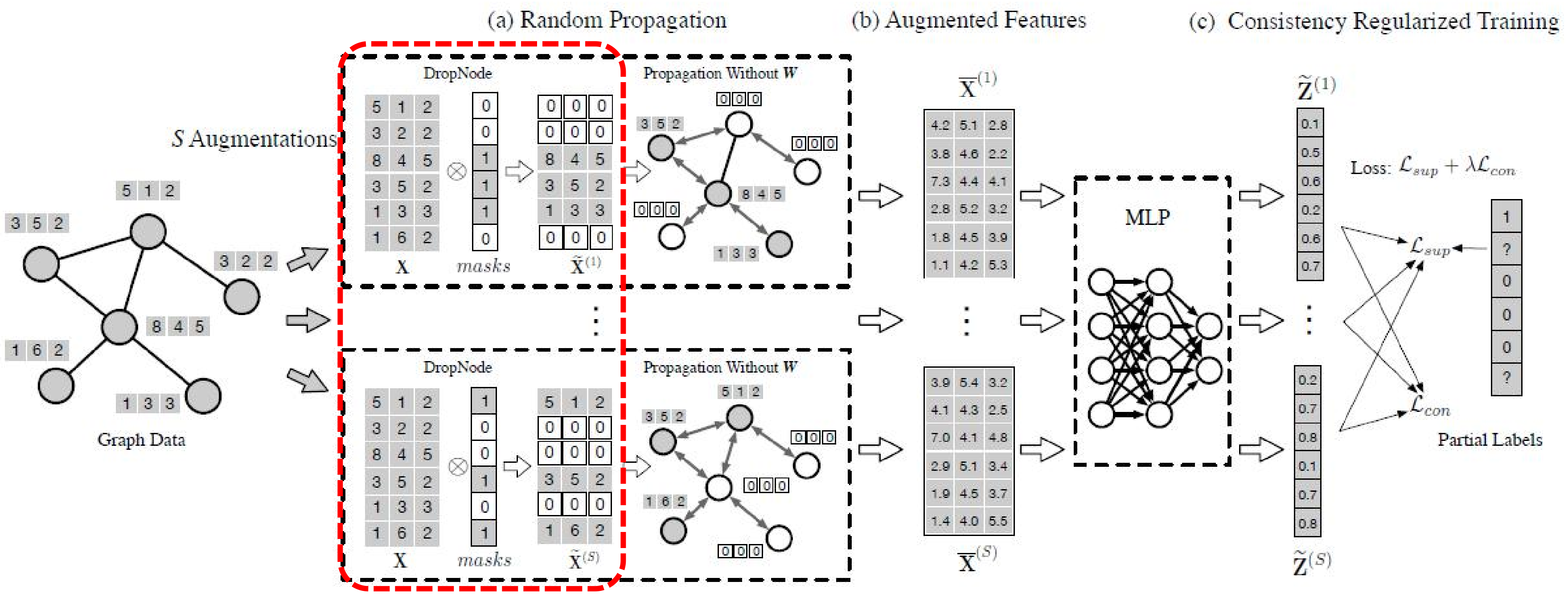

Figure 1: Illustration of GRAND with DropNode as the perturbation method. GRAND designs random propagation (a) to generate multiple graph data augmentations (b), which are further used as consistency regularization (c) for semi-supervised learning.