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Node quality-driven unsupervised cross-network node classification: a reinforcement transfer learning approach

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Data form the cornerstone of artificial intelligence (AI). The quality of data significantly influences the performance and generalization of AI models in real-world applications. Recent research [1] has shown that not all data samples contribute equally during model training. In deep neural networks (DNNs), the importance of individual data instances can vary substantially. As such, evaluating data quality and strategically incorporating high-quality samples into model training has become a topic of paramount importance in AI research.

In the context of unsupervised cross-network node classification (CNNC), the objective is to classify fully unlabeled nodes in a target network by transferring knowledge from a labeled source network. While transfer learning has demonstrated effectiveness in improving CNNC performance, its success is often limited by the presence of noisy or low-quality nodes within the source network. These low-quality nodes may arise from data acquisition errors, mislabeled instances, or hardware-induced anomalies [2]. Such imperfections can lead to negative transfer [3], wherein irrelevant or harmful prior knowledge from the source network adversely impacts classification performance in the target network.

Existing methods address this issue by reducing the distributional divergence between source and target domains [4] or by employing knowledge distillation techniques [5]. However, these methods do not resolve the problem by improving the quality of nodes. Therefore, identifying and leveraging high-quality, transferable nodes from the source network becomes critical for robust knowledge transfer. This gives rise to our first challenge in unsupervised CNNC. **CH1**: *How to effectively select high-quality nodes from the source network that are most relevant to the target network?*

Moreover, node information in network-structured data spans two primary dimensions: node attributes and structural/topological features. When selecting high-quality nodes, it is essential to determine which type of feature, i.e., attributes, topology, or a combination thereof, should be prioritized. Existing CNNC approaches often neglect this question, defaulting to topology-only representations or simplistic fusions of features, without considering how feature relevance varies across datasets. This leads to our second challenge. **CH2**: *Which type of node feature should be prioritized for high-quality node selection?*

Proposed framework. To tackle these challenges, we propose a novel framework called node quality-driven unsupervised CNNC (NQDU). This framework systematically exploits both attribute- and structure-level similarities between nodes in the source and target networks. Within NQDU, we develop an unsupervised CNNC method, and further contribute a new theoretical generalization bound for classification error in the target network. The overall design of NQDU comprises two core components (as illustrated in Figure 1): (1) high-quality node selection from the source network; (2) cross-network node classification, leveraging the selected nodes to learn network-invariant node representations.

High-quality node selection. As shown in Figure 1(a), to identify transferable nodes, we employ a node quality evaluator, implemented as a deep neural network, to estimate the likelihood of each source node being valuable for CNNC training. A reinforcement learning mechanism, guided by reward signals derived from the target network, is used to optimize the evaluator. The model samples node subsets based on their quality scores, and feedback from classification performance on the target network is used to iteratively refine node selection. This learning-to-select mechanism ensures that only the most relevant and informative nodes are retained for knowledge transfer.

Cross-network node classification. As shown in Figure 1(b), using the selected high-quality nodes, we propose a robust unsupervised CNNC method composed of three sub-modules: a network embedding module, which includes an attribute-level extractor, a topology-level extractor, a fusion (concatenation) layer, and a topological consistency constraint, to learn network-invariant representations; a classifier, designed to support both multi-class and multi-label classification tasks; a network discriminator, which aligns the latent feature distributions of the source and target networks through adversarial learning. The adversarial interaction between the network embedding module and the discriminator ensures the representations are domain-invariant, enabling effective transfer. For implementation details, refer to Appendix D.

Theoretical contributions. In addition to methodological advances, we derive a generalization bound for CNNC, grounded in the quality of selected source nodes and the alignment of their embeddings across domains. Our theoretical results establish con-

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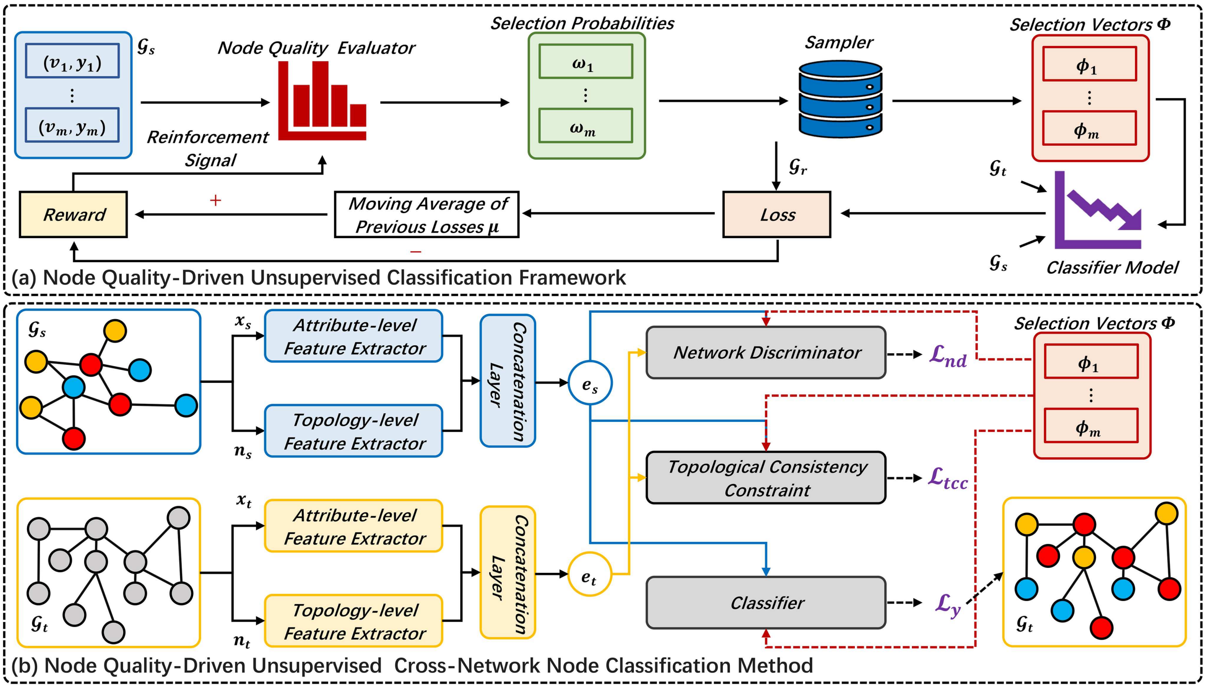

Figure 1 (Color online) The proposed NQDU framework and the NQDU CNCC method.

ditions under which effective knowledge transfer is possible.

Theorem 1 (Generalization bound for CNCC)**.** Let $\mathcal{H}_s^A$ and $\mathcal{H}_t^A$ denote hypothesis classes derived from a common hypothesis space A, corresponding to the source network G_s and the target network G_t, respectively. Let d_s^A and d_t^A be their representative VC-dimensions. Assume G_s and G_t consist of m_1 and m_2 unlabeled nodes sampled from distributions $\mathcal{D}_s$ and $\mathcal{D}_t$. A labeled set S of size m is constructed by sampling $\bar{\beta}m$ nodes from $\mathcal{D}_t$ and $(1-\bar{\beta})m$ nodes from $\mathcal{D}_s$, with labels given by f_s and f_t, respectively. Let $\hat{h} \in \mathcal{H}^A$ be the empirical minimizer of the convex combination of empirical risks: $\hat{\epsilon}_{\bar{\alpha}}(h^A) = \bar{\alpha}\hat{\epsilon}_t(h_t^A) + (1-\bar{\alpha})\hat{\epsilon}_s(h_s^A)$ and let $h_t^* = \min_{h \in \mathcal{H}^A} \epsilon_t(h^A)$ be the optimal hypothesis minimizing the true risk on the target network. Then, with probability at least $1-\theta$, the following generalization bound holds:

$$\begin{aligned}\epsilon_t(\hat{h}_t^A) \leqslant{}& \epsilon_t(h_t^*) \\ &+ \frac{2\sum_{j=1}^{k_t}(n_j-1)\delta_t(\varphi_j^t+\tau_t)+2\sum_{j=1}^{k_s}(n_j-1)\delta_s(\varphi_j^s+\tau_s)}{m} \\ &+4\sqrt{\frac{\bar{\alpha}^2}{\bar{\beta}}+\frac{(1-\bar{\alpha})^2}{1-\bar{\beta}}} \\ &\times\sqrt{\frac{2\log[(2(1-\bar{\beta})m)^{d_s^A}+(2\bar{\beta}m)^{d_t^A}]+2\log\frac{8}{\theta}}{2m}} \\ &+(1-\bar{\alpha})(\hat{d}_{\mathcal{A}\triangle\mathcal{A}}(G_s,G_t)) \\ &+4\sqrt{\frac{2d+\log[1+(2M)^{|2d_s^A-2d_t^A|}]+\log\frac{1}{\theta_1}}{M}}+\lambda,\end{aligned}$$

where $\hat{d}_{\mathcal{A}\triangle\mathcal{A}}(G_s, G_t)$ is the empirical $\mathcal{A}$-divergence between G_s and G_t, $M = \min\{\bar{\beta}m, (1-\bar{\beta})m\}$, $d = \min\{d_s^A, d_t^A\}$, λ is the joint optimal error of $\mathcal{H}^A$ on both domains, (δ, φ, τ) are correction terms arising from data selection and group imbalance. For proof details, refer to Appendix C.

Experimental validation. We validate our framework across three real-world datasets, i.e., social networks, citation networks, and protein-protein interaction networks, using four distinct types of node features. Experimental results consistently demonstrate the following. (1) Our NQDU method significantly outperforms SOTA CNNC approaches in classification accuracy. (2) When integrated with classical CNNC methods, the NQDU framework can improve the node classification accuracy of the corresponding method in the target network by at least 10% or more. (3) The choice of features for node quality evaluation has dataset-specific implications, revealing valuable insights into feature relevance.

Conclusion. This study presents a novel reinforcement learning-based NQDU framework for unsupervised CNNC, which intelligently identifies and leverages high-quality nodes to enhance cross-network transfer. By unifying data quality evaluation, feature selection, and adversarial representation learning, NQDU offers a comprehensive solution to the key limitations in current CNNC methods. In future work, we aim to extend NQDU to support multi-source and multi-modal CNNC, further expanding its applicability to diverse real-world settings.

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Supporting information Appendixes A–E. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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