ICNRL: An Initiative Framework Towards Information Centric Network Representation

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***Abstract*—The exponentially growing demand for computational resources prevents the Information Centric Networking (ICN) being deployed in practice due to the high dimensional sparse data computation. However, we argue that Network Representation Learning (NRL) can help to solve the problem by transforming the raw network information data into low-dimensional dense adjacency matrix representation. In this paper, we propose ICNRL, a novel task-based NRL scheme for ICN. Based on the adjacency matrix generated by NRL, ICNRL can calculate the index threshold value to support the networking decision making of content-store (CS), pending information table (PIT), and forwarding information base (FIB), and therefore improves the management and processing capabilities of ICN.**

I. Introduction

Effectively allocating interested information and contents in a vast scale interconnected network is a challenging task for the future Information-Centric Networking (ICN) design and operation. The conventional publish-subscribe service platforms, such as content delivery networks (CDN) and overlay networks, expose poor scalability, low cache utilization efficiency, and double-exponentially growth on computational demands when calculating high-dimensional sparse network characteristic data in large-scale heterogeneous networks [1].

In this work, we explore the feasibility of applying Network Representation Learning (NRL) to the conventional ICN paradigm. We propose *ICNRL*, a novel task-based NRL scheme for overcoming the weakness of current ICN. ICNRL tries to convert the network resource characteristic from high-dimensional sparse matrix to low-dimensional dense matrix, and can act as an index module to support caching, routing and forwarding tasks in content-store (CS), pending information table (PIT), and forwarding information base (FIB). Although ICNRL is still an initiative concept currently, our preliminary experiment results show that it can significantly reduce the memory usage and computational cost compared to the methods without NRL.

II. Background and related works

NRL is fundamentally an important method evolved from graph or network embedding methods. The existing solutions includes DeepWalk [7], LINE [8], word2Vec [1], node2Vec [2], and so on. However, these solutions are not designed for network problems, especially the ICN problems. The core idea of NRL is to extract the nodes with similar attributes from the original network, and then convert them to a hierarchical representation form (adjacency matrix). By utilizing this matrix, the original information can be transformed into a low-dimensional continuous adjacency matrix. Node topology information is retained and described in the newly constructed high-order low-dimensional matrix space after learning.

III. Proposed solution

In this work, we present *ICNRL*, an initiative conceptual task-based scheme that can exploit the advantages of NRL to improve the performance of ICN. ICNRL utilizes the low-dimensional dense adjacency matrix, and aims at acting as the index module for ICN to support caching, routing and forwarding tasks that run in CS, PIT, and FIB modules, respectively. ICNRL treats the task-related information content, but not the IP addressed terminal, as a node in the graph. The edges in the graph represent one or more relationships established based on the task goal. As a result, it is not necessary to calculate and optimize transmission path or allocate cache storage resources for all the network terminals.

Here we consider only the distributed symmetrical transmission scenario, and treat both the terminal nodes and the on-demand contents as vertices in the graph. Let $G = (V_n, V_c, E_{nn}, E_{nc})$ denote the ICN network, where $V_n = v_1, ..., v_n$ is the node set, $V_c = \{c \mid (u, c) \in C, u \in V_n\}$ is the content set, $E_{nn} \subseteq (v_n \cdot v_n)$ is the node to node edges set, and $E_{nc} \subseteq (v_n \cdot v_c)$ is the node to content edges set, as shown in Eq.1.

$$G(V_n, V_c, E_{nn}, E_{nc}) \rightarrow Network \begin{cases} E_{nn} \subseteq (v_n \cdot v_n) \\ E_{nc} \subseteq (v_n \cdot v_c) \end{cases} \quad (1)$$

The goal of network embedding is to allocate a low-dimensional real-valued vertices representation, denoted by $e_v \in R^d$ for each $v \in V$, where $d \ll \mid V \mid$. The set of embedded vertices that carries topological information in the latent space is denoted by $\theta = (e_1, e_2, ..., e_{|V|})$. The objective function in Eq.2 of ICNRL is to minimize E_{nn}. Here E_{nn}

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is the set of adjacent vertex pairs in the routes from content requester to the content source, and the first order network structural information will be recorded in this set. Let the joint probability of pair (u, v) in E_{nn} be $P(u, v; \theta)$. Let E_{nc} indicate the second order node-to-content relationship (i.e. all the terminals that are not directly connected to each other, but share the same requested contents), which has a joint probability $1P(u, v; \theta)$.

$$L_g = \sum_{(u,v)\in E_{nn}} \log P(v, u; \theta) + \sum_{(u,v)\in E_{nc}} \log (1 - P(v', u; \theta)). \tag{2}$$

The advantage of ICNRL is that each media source terminal [3], [4] in the ICN network can maintain a local adjacency matrix. This means that for each content-seeking task, we can only maintain the latent space for the possible node-to-content connections without traversing all known nodes in the network. As a result, ICNRL can reduce edge computation of data source connection through reducing the data sparsity, and therefore significantly reduces the memory usage and computational cost.

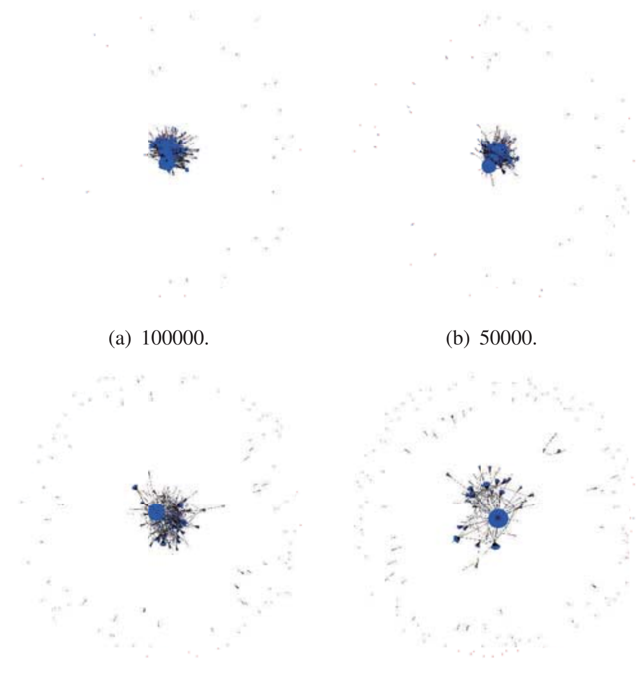
IV. Experiment results

We conduct experiments to demonstrate the viability of ICNRL framework. We apply our proposed methods to a dataset, which consists of more than 110k records that describe how mobile users visit the 202 types of Internet websites contents in their daily life within three days. To guarantee user's privacy, all the user related information is anonymised.

Fig. 1 shows the map of user/node to website content connections. The edges/links reflect the user-content relationship in the latent space adjacency matrix. When the whole network vertices (nodes and content) are considered as shown in Fig. 1(a), it takes around 5 hours to calculate the connected node-to-content edge pairs. But if we limit the plot scale to different degree of the adjacent hops for each node, the pairs are reduced accordingly. Fig.1(b) to 1(d) represent the total number of connected node-content edge pairs when the adjacent hops are limited to 6, 3, and 1 hops, respectively, corresponding to 50K, 30K, and 3K total edge pairs. The result shows that the proactive type of latent space adjacency matrix is more suitable for distributed terminals to establish a node-content map, and therefore can be applied to the local CS, PIT and FIB decision making for ICN terminals. In data center or servers with more computation power, a hybrid type of proactive and reactive node-content map is more practical to generate the global view map.

V. Conclusion

This paper presents ICNRL, a new task-based framework which generates low-dimensional dense adjacency matrix for ICN index model. With the terminal-content interconnection representation, ICNRL can support decision making for the CS, PIT and FIB computation and decision making. Our experiments show that the latent space adjacency matrix indicates possible connections for each content-seeking task



(a) 100000. (b) 50000. (c) 30000. (d) 3000.

Fig. 1: ICNRL adjacency matrix representation graph with different adjacency connections.

without traversing all known nodes in the network. As a result, ICNRL can calculate the latent space adjacency matrix for the task required scale instead of the whole network on each terminal, and therefore significantly reduce data source connection edge computation. Although ICNRL is still an initial attempt at integrating NRL into ICN currently, we believe that the asymmetrical transmission [5], [6] and higher order representation for different applications remain a worthy interesting study for the future.

References

[1] P. Cui, X. Wang, J. Pei, and W. Zhu. A survey on network embedding. arXiv:1711.08752 [cs.SI], 2017.
[2] A. Grover and J. Leskovec. Node2vec: Scalable feature learning for networks. In *Proc. ACM KDD*, 2016.
[3] Y. Lu, T. Hu, and X. Wang. Information centric networking media streaming experiment platform design. In *Proc. Smart Computing and Communication*, 2018.
[4] Y. Lu, W. Liu, and H. Cui. MSA vs. MVC: Future trends for big data processing platforms. In *Smart Computing and Communication*, 2018.
[5] Y. Lu, P. Mitchell, and D. Pearce. Performance evaluation of minimum impact routing for multi-hop wireless ad hoc network.
[6] Y. M. Lu, D. Grace, and P. D. Mitchell. Capacity evaluation of a multi-hop wireless ad hoc network using minimum impact routing. In *Proc. IEEE WiCOM*, 2006.
[7] B. Perozzi, R. Al-Rfou, and S. Skiena. DeepWalk: Online learning of social representations. In *Proc. ACM KDD*, 2014.
[8] J. Tang, M. Qu, M. Wang, M. Zhang, J. Yan, and Q. Mei. LINE: Large-scale information network embedding. In *Proc. WWW*, 2015.