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Network embedding architecture using laplace regularization-non-negative matrix factorization for virtualization

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ABSTRACT

While modeling the applications for a problem in cloud computing, researchers and scientists frequently use graphs as abstractions. Graphs provide structural models that make it possible to analyze and understand how many separate systems act together. The omnipresence in cloud computing systems is increasing information networks. The graph embedding algorithms preserve the microscopic structure over the cloud, and many of them miss the mesoscopic structure of the networks. In this paper, asymmetric non-negative Laplace regularization for cloud platform and matrix factorization is implemented for network embedding. The proposed algorithm preserves the mesoscopic structure in cloud computing, the learned model from the Laplace, and matrix factorization. The embedded cloud network can be used for link prediction, vertex recommendation, node clustering. It is a scalable algorithm for higher proximity preserving along with community structure. The correctness and convergence are measures as performance parameters in the network. Based factorization is used for updating the rules. The experimental study shows that the proposed system is well-organized compared to the existing process in structure preservation in cloud computing.

1. Introduction

The information network is increasing day-by-day; the network's size is growing large in the social network, citation network, etc. Representing the information network as the graph requires a considerable amount of resources. The network embedding maps the network into low dimensional space for conserving details of networks such as structure, distance, etc. The embedded network would preserve the structures and properties of the original network. The classical embedding algorithm usually preserves first and second-order proximity of given graphs. Preserving the mesoscopic ownership of the given graph is equally important. The mesoscopic features of the graph are useful for community incorporation. Graph embedding is an essential tool in the implementation of parallel algorithms and the simulation of interconnection networks. In the task interaction graph, the nodes are modeled to represent the graph's task, and direct communications between the functions are represented as edges between the nodes. To have the parallel computation of the significant process, the long process is decomposed into subprocess, and the sub-processes can be executed in parallel with one another, and the sub-processes can communicate with each other. The allocation of the sub-processes to the parallel processing can be done by modeling the structure in a graph embedding system. Graph embedding can also be employed in networks for embedding an extensive network into a smaller network.

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There are many criteria to measure the quality of graph embedding. In-network embedding the congestion is considered as one of the primary criteria for measuring the quality. While embedding for the network, many nodes present in the input graph are embedded in the resultant graph's single node. Where the probability of congestion occurrence has much higher while integrating an extensive network to a smaller network. The congestion in the network causes many problems such as noise, longer delay, loss of packets, etc. Reducing congestion is the most needed property to be considered while doing the graph embedding for the networks. The graph embedding also finds application in the design of the interconnection in the multiprocessor computers. The interconnection of the processor is usually designed as the symmetric graph. In the symmetric graph, the nodes denote processors, and edges show communication channels between the processors. While the desirable property for graph embedding for the interconnection network is smaller diameter, symmetry, scalability, enhancing the data flow, minimum congestion, efficient routing, fault tolerance, and robustness. The hypercube graph structure has considered the most desirable graph for the interconnection network because of its structural regularity, fault tolerance, and the possibility of exhibiting parallelism in the network. This work's primary motivation is to provide the maximum possibility of connection in networks to overcome various limitations like to improve scalability, data flow, reduce congestion, effective routing, etc.

2. Literature review

The graphs are usually represented as adjacency matrices, which are generally sparse and high dimensional. Many algorithms are proposed to learn the representation from the low dimensions, such as the Laplacian Eigen map and ISO Map [1]. These algorithms are best suited for small graphs, and scaling for large graphs is much complicated. Several algorithms are suggested, such as node2vec [2], Deep Walk [3], and LINE [4], which operate for large graphs. Deep Walk considers the nodes in the network to be "names" of artificial language, and it utilizes a random walk for creating "sentences" for it. Next, the representations for the nodes may be studied using the word2vec method. In their presentations, LINE attempts to capture both proximities of first and second order. Another algorithm that extends the work of DeepWalk is node2-vec . It adds the additional parameters to have a biased random walk that extends DeepWalk by adding factors to introduce a biased random walk.

The approaches to embedding the homogenous network for various applications show good results. The extended Deep Walk method is introduced for the heterogeneous networks, which uses meta path in the random walks. In the Deep extended walk, the meta path learning about heterogeneous network and importance is also given to selecting the meta-path [11]. Another network embedding process, SiNE, depends on concepts where the people always wish to be much closer to their friend next to the enemy. SiNE algorithm tries to reserve the global and local properties for heterogeneous network embedding [9]. The network embedding also has been done by considering the attributes in the nodes. The node will have characteristics; the attributed network embedding algorithm also preserves the attribute proximity and the first and even second level of closeness [5].

Various network embedding techniques are discussed in the surveys. (HongyunCai, Vincent W. Zheng, and Kevin Chen-Chuan Chang, 2018). As the node selection is highly crucial in the interconnection network. This graph algorithm will provide the mesoscopic structure for route selection while transmitting data. The graph embedding algorithm's objective is to preserve structures available in graphs and preserve the fundamental properties present in the graph [6]. Many network algorithms are proposed, which preserves the first and second-order proximities that have been presented among nodes [,]—the proposed a network embedding algorithm, which uses higher-order proximity. To preserve the microscopic and the mesoscopic structure, Laplace Regularization based Symmetric Non-negative factorization (LR-SNMF) based graph embedding algorithm is proposed in this paper. The microscopic structure is preserved using the non-negative symmetric matrix factorization, while the mesoscopic structure is preserved by detecting the communities and preserving it [10]. Incremental updating of rules is done, the correctness and the convergence of these rules is guaranteed. Non-negative matrix with Kullback-Leibler [7] Divergence is required for an estimator to satisfy the data sample's properties by using poison distribution. Using Laplace and non-negative matrix factorization is highly supported for theory-based game applications, which provides more accuracy in choosing path selection in wireless networks than the other algorithms.

3. Proposed methodology

3.1. Symmetric non-negative matrix factorization (SNMF)

The graph is denoted as Adjacency matrix A. The adjacency matrix is factorized, and the SNMF algorithm preserves the properties using the similarity measure concept. The SNMF works well for the embedding graph w to a lower dimension. In SNMF, the adjacency matrix A is factorized as HH^{T}. The objective function described below is the actual function of SNMF, which minimizes the square loss function, EQU (1).

$$O = \min_{H \geq 0} \| A - HH^{T} \|_{F}^{2} \tag{1}$$

Where $A \in R_{+}^{axb}, H \in R_{+}^{axk}, H \in R_{+}^{bxk}, R_{+}$ denotes a set of non-negative real numbers. Commonly $k < \min\{a,b\}$and typically k is assumed to be much smaller than a and b. The objective function has to minimize the square loss function, and factorization is reduced using the square of F-norm (Frobeniusnorm) of approximation error.

3.2. First order proximity

The first order of proximity $S^{(1)}$ gives direct connections or one-hop connections among the nodes. Suppose, if an edge exists among nodes '*i*' and '*j*,' then the first order proximity where positive; otherwise, it will be *0*. The first order of proximity is a simple and direct measure of similarity. It is essential to preserve the first order proximity of the graph while embedding. In real-world networks, the edges are sparse [11]. There may be nodes without edges between them, but it does not mean that there is no similarity. Considering only the first order proximity will leave crucial connections between the nodes. To overcome this, the familiar neighbors between the nodes need to be considered. Studying the common nodes to find the similarity measure gives rise to the next step of proximity measure known as second-order proximity.

3.3. Second-order proximity

The Semi-supervised learning model for understanding the least possible squares is known as Laplace regularization, and it uses the regression model to perform regularization. The second-order proximity is needed among the nodes to classify the nodes among the shared neighbourhood nodes. The Second-order Proximity $S^{(2)}$ among the nodes N_i and N_j have given by $S^{(2)} = [S_{i,j}^{(2)}] \in R^{nxn}$ where R^{nxn} is the given graph. Consider the node N_i and define first-order proximity of a node N_i as $N_i = [S_{i,1}^{(1)}, \ldots, S_{i,n}^{(1)}]$ The second-order proximity is calculated among the nodes N_i and N_j. For finding second-order proximity among the node N_i, and N_j cosine likeness is considered, and it can be given as $S_{i,j}^{(2)} = \frac{N_i N_j}{\|N_i\| \|N_j\|}$, and $||X||$ is vector X in the norm. The similarity measure is calculated by using this formula. The similarity measure varies between 0 and 1. 0 being non-similar, and 1 indicates the high similarity of second-order proximity. A non-negative matrix $M \in R_{nxm}$ is introduced to find the second-order proximity in NMF (Nonnegative Matrix Factorization). The

microscopic properties are generally preserved in network embedding algorithms [12,13]. Preserving the mesoscopic property of the network, which is helpful for community embedding, is also essential. To order to maintain both the proximity of the first order and proximity of the second order, where it gets the final likeness matrix by using $S = S(1) + \eta S_{(2)}\eta > 0$ is the weight of proximity of the second-order, and it sets η=5 here consistently. The symmetric Non-negative Matrix Factorization (SNMF) model with Laplace joint representation is used. The Laplace's joint preserves geographic information. The Laplace - SNMF model preserves the mesoscopic and microscopic parameters. Then, in the NMF framework, we introduce a non-negative base matrix $\frac{A}{R_{nxm}}$, and a non-negative representation matrix $\frac{H}{R_{nxm}}$ where m represents dimension with I line of $H(H_i)$ represents node i. We expect to approximate the similarity matrix A with these two matrices, which result in the following objective function, EQU (2):

$$o = \min_{F^{2M}} \| A - HH^T \| \tag{2}$$

Where $H>0$ and $H^T > 0$. The model preserves the higher-order proximities, including the essential first and second-order proximities. Where maintained the third and fourth-order proximities. Similar to the algorithm proposed by Cao, Lu, and Xu , the proposed algorithm preserves the higher-order proximities in the A.

Liu et al. propose a multi-view clustering algorithm. [8], it is based on NMF and uses the clustering for embedding called Multi-NMF [14, 15]. The Multi-NMF algorithm captures the different views and combines the different consensus matrix of different perspectives to form a standard consensus matrix. It obtains a solution as a consensus solution gives the implicit clustering structure, which is present in the graph and shared by the different views. The Multi-NMF algorithms objective function with the multi-views is given in the following EQU (3).

$$o = \min\left(\sum_{v=1}^{n_v} \| V^v - W^v H^v \|_F^2 + \sum_{v=1}^{n_v} \gamma^v \| Q^v H^v - H^* \| \right) \tag{3}$$

Such that W^V, $H^V$and $H^* \geq 0$, where, n_v indicates the number of views present, γ^v indicates the V^{th} view's weight, which gives the importance of each view. Initially, all the views will have the same importance. The H^* provides the consensus matrix, and an auxiliary matrix Q^v is introduced to reduce the computation. The Q^v will reflect the implicit clustering feature present in the graph structure. According to the terminology (3), the coefficient matrices of different views are comparable and guarantee practical convergence of all views. Where A denotes the vector V^{th} of resemblance. The parameter V^{th} concept preserves the equilibrium between the SNMF reconstruction error and regularization to obtain improved efficiency by utilizing the SNMF factorization multi-view.

Laplacian Regularization (LR) can preserve the initial data from local geometrical information [16]. Clustering performance may be improved by using LR to penalize the matrix coefficient H^*. Introduce LR in (3) Multi-SNMF and get a modified formula, EQU (4)

$$o = \min\left(\sum_{v=1}^{n_v} \| A^v - H^v \left(H^v\right)^T \|_F^2 + \sum_{v=1}^{n_v} \gamma^v \| Q^v H^v - H^* \|_F^2 \right) \tag{4}$$

Such that H^V and $H^* \geq 0$

By adding LR term with Mul-SNMF, the objective function of the joint symmetric non-negative matrix factorization (LJ-SNMF) is represented, EQU (5)

$$o = \min\left(\sum_{v=1}^{n_v} \| A^v - H^v \left(H^v\right)^T \|_F^2 + \sum_{v=1}^{n_v} \gamma^v \| Q^v H^v - H^* \|_F^2 + \beta tr\left(\left(H^*\right)^T L H^* \right) \right). \tag{5}$$

Such that H^V and $H^* \geq 0$,

The Laplacian matrix L is introduced in the objective function, and the tr(.) represents the trace of the matrix.

3.4. Embeddingbased unified network model

Here we aimed to join the above two models to add the community structure for guiding the representation matrix U learning process. The Community indicator matrix H provides direction for every node, and it expects UCT to be as exceptionally close as possible to H. Eventually, we have the following cumulative objective function, along with the objective function (1) and (5):

$$o = \min_{M,U,H} \left(\| A - HH^T \|_F^2 + \sum_{v=1}^{n_v} \| A^V - H^V \left(H^V\right)^T \|_F^2 \times \sum_{v=1}^{n_v} \gamma^V \| Q^V H^V - H^* \|_F^2 + \beta tr\left(\left(H^*\right)^T L H^* \right) \right). \tag{6}$$

s.t., $A \geq 0$, $H \geq 0$, tr(H^T H)=n, Where β and ÿ are the positive arguments for adjustment of the equivalent terms contribution. Node H representations are guarded by both microscopic structure (returned in the first term by S) and the mesoscopic community structure (returned from the third term by H). Thus H encloses more structural data and becomes most discriminatory.

3.5. Optimization

The objective function (6) is not convex, so we detach so iteratively refine the optimization of three sub-problems, ensuring each sub-problem converges to local minima [17,18].

3.5.1. M- Sub problem

M-Updating M with specific parameters in (6) and (7) set results in a typical NMF formulation (Lee and Seung 2001).

$$M = M \frac{AH}{MH^T H} \tag{7}$$

3.5.2. U- Sub Problem

Updating H with the other features in (6) fixed leads to a joint NMF problem (Akata et al. 2011), the updating rule (8) for which is

$$U = \frac{A^T M + \alpha H}{H\left(M^T M\right)} \tag{8}$$

3.5.3. H-Sub problem

We need to solve the following equation when updating H with specific parameters specified in (6):

$$o = \min_{H \geq 0} \left(\sum_{v=1}^{n_v} \| A^V - H^V \left(H^V\right)^T \|_F^2 + \sum_{v=1}^{n_v} \gamma^V \| Q^V H^V - H^* \|_F^2 + \beta tr\left(\left(H^*\right)^T L H^* \right) \right) \tag{9}$$

of the solution.

We should solve the optimization problem by the Lagrange approach to reduce objective function (9). By adding Multiplier Lagrange α, ψ, Lagrange

3.5.4. Lag is

$$Lag = \| A - HH^T \|_F^2 + \gamma \| QH - H^* \|_F^2 + \beta tr\left(\left(H^*\right)^T L H^* \right) + tr\left(\alpha H^T\right) + tr\left(\psi \left(H^*\right)^T\right) \tag{10}$$

3.5.5. Fixing

* H, updating H:

Lag's partial derivatives about the H are:

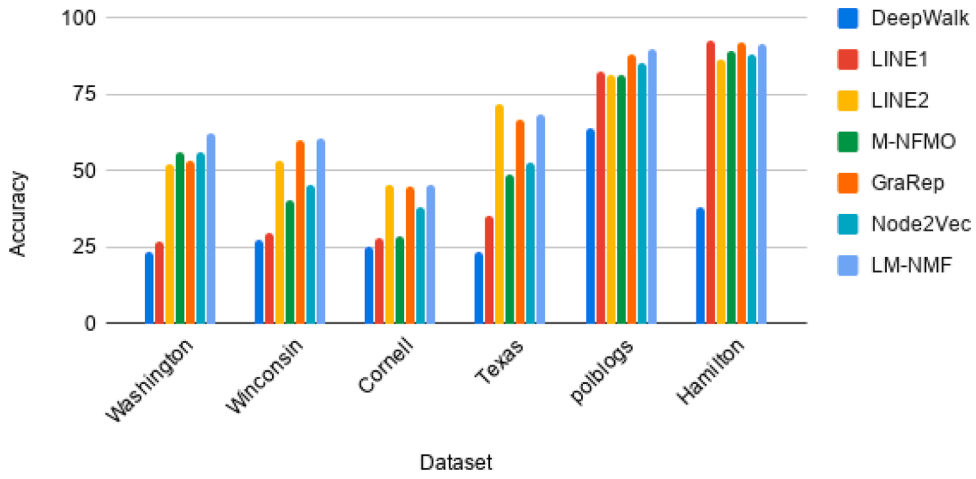

Fig. 1. Analysis of Parameter.

$$\frac{\partial Lag}{\partial H} = -2AH + 2HH^T H + 2(\beta LH^*) + \alpha + 2\gamma\left((HQ - H^*)Q^T\right). \tag{11}$$

Using the Kuhn-Tucker condition, the following result will be produced,

$$H_{ik} = H_{ik}\frac{(AH)_{ik} + \gamma\left(H^* Q^T\right)}{\left(HH^T H\right)_{ik} + \gamma\left(HQQ^T\right)_{ik}} \tag{12}$$

Fixing H, updating * H:

$$H^*_{ij} = H^*_{ij}\frac{\left(\sum_{v=1}^{n_v}\gamma_v H^v Q^v + \beta WH^*\right)_{ij}}{\left(\sum_{v=1}^{n_v}\gamma_v H^v Q^v + \beta DH^*\right)_{ij}} \tag{13}$$

4. Experimental evaluations

Regarding the tests, we hired the following actual networks. The sub-networks were gathered from four colleges, Cornell, Washington, Texas, and Wisconsin, respectively. The growing sub-network is split down into five populations. Blog of Political network (Polblogs) 4 (Adamic et al. 2005) (16,715 Edges, 1222Nodes) consists of blogs about US politics and web connections between them, recorded in 2005. We rendered the Hamilton social networks (2118 Nodes, 87,486 Borders, 15 Communities). M-NMF was compared with the following five network embedding algorithms: Node2Vec (Grover and Leskovec 2016), DeepWalk (Perozzi, Al-Rfou, and Skiena 2014), LINE (Tang et al., 2015), GraRep (Cao, Lu, and Xu 2015), and NMF0. Usually, it uses LINE1 to signify LINE preserving proximity to first order, and LINE2 to represents LINE maintaining proximity to second order. LM-NM is our proposed LM-NMF model that protects only the proximities of the first order and second orders. LM-NMF is used to validate the validity of Group system integration.

4.1. Node classification

M-NMF was compared to the following five network embedding algorithms: LINE (Tang et al. 2015), DeepWalk (Perozzi, Al-Rfou, and Skiena 2014), Node2Vec (Grover and Leskovec 2016), GraRep (Cao, Lu, and Xu 2015), and NMF0. Frequently, we use LINE1 to represent LINE, maintain proximity to the first order, and LINE2 for serving LINE to preserve proximity to the second request. LM-NM is our proposed LM-NMF model that preserves the proximity of the first order and second orders. LM-NMF is used to verify the effectiveness of incorporating the community structures we've seen; on eight of nine networks (except Texas), LM-NMF outperforms the other methods, which determines the effectiveness of the LM-NMF on classification tasks. Also, compared to Node2Vec, M-NMFO significantly improves the accuracy, which verifies the need to introduce a mesoscopic community structure for network embedding.

We tested the impact of LM-NMF's β and γ parameters on real networks. To some extent, the value of γ reflects the importance of the view. Here, we set the value of γ for every view will be the same. It proposes that the relative weight be determined based on the discrepancy between the individual view and consensus matrix. B represents the graph regularization parameter that reflects how much the need to constrain the result.

In this article, the value of γ differs from 0.001 to 0.1, and the value of β varies from 0.01 to 0.1. Because multiple networks' findings

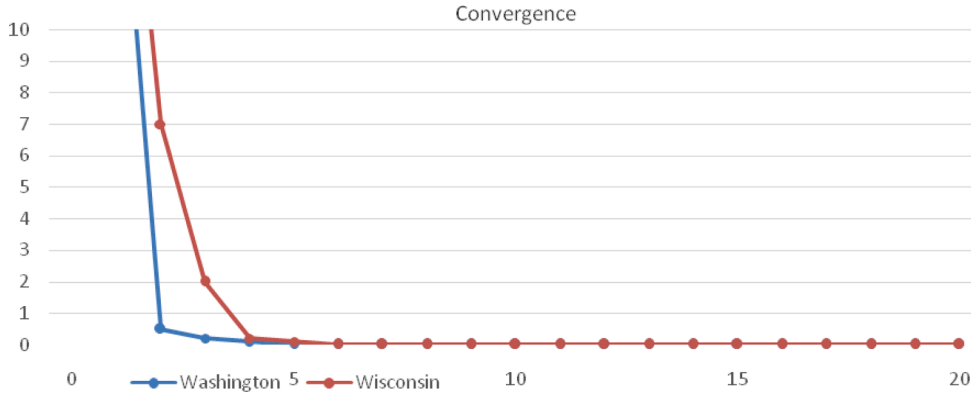

Fig. 2. The performances are relatively stable.

Table 1
Accuracy of classification.

Algorithm	Deep Walk	LINE 1	LINE 2	M-NFMO	GraRep	Node2Vec	LM-NMF
Washington	23.56	26.65	52.24	56.23	53.11	55.78	62.47
Winconsin	27.25	29.58	53.10	40.27	60.21	45.16	60.79
Cornell	25.23	27.94	45.26	28.31	44.98	38.21	45.26
Texas	23.18	35.29	71.60	48.54	66.85	52.91	68.49
Polblogs	63.88	82.28	81.12	81.36	88.25	85.51	89.94
Hamilton	38.27	92.78	86.57	89.23	91.91	87.8666	91.24

indicate similar patterns, we used only two networks (WisconsinandWashington) as examples here. We have shown the accuracy of the classification concerning β and Δ, respectively. The accuracy rates do not change too much, and the results are relatively constant, as seen in Fig. 1. We also noticed that LM-NMF still exhibits competitive performance on these two networks, even when the accuracies are relatively low. We may understand non-increasing objective function values, and it drops dramatically within the limited number of iterations (no. 5). Which is empirical shows the theory of convergence?

5. Conclusion and future work

New modeling has been proposed for network embedding in cloud computing based on the Laplacian regularization in non-negative matrix factorization. The Embedded based network model has a big future that creates exiting output for node selection in interconnection networks. This will supports wireless network applications. The first and second-order structures are preserved in cloud architecture for embedding. The direct computation is done in the matrix multiplication. The number of matrix multiplication for the proposed LM-NMF is the same as NMF; hence the complexity remains the same in-network. The accuracy of classification in network embedding of the proposed LM-NMF in the cloud environment is better than other algorithms for all 6 datasets. The algorithm also shows a rapid convergence rate. In the future, this graph embedded network design will be incorporated with real-time applications to control congestions while choosing the node at the network. It will be more helpful for theory-based game applications (Fig. 2) (Table 1).

Declaration of Competing Interest

None.

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