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A Combined Deep-Learning and Transfer-Learning Approach for Supporting Social Influence Prediction

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Abstract

Social influence is a phenomenon describing the spread of opinions across the population. Nowadays, social influence analysis (SIA) has a great impact. For example, viral marketing and online content recommendation are applications of SIA. Hand-crafted features, as well as domain expert knowledge, are usually required in convention social influence analysis, but they incur high costs and are not scalable. Deep learning based approaches overcome these issues. For instance, a recently used approach learned latent features of users to predict social influence. In this paper, a teleport probability τ from the page rank domain is integrated into the graph convolution network model for further enhance the performance of such an approach. In addition, a combined personalized propagation of neural predictions (CPPNP) algorithm leads to an impressive prediction accuracy when comparing with existing methods. Evaluation results on three well-known datasets reveal that optimizing τ enhances the performance of CPPNP. Such a combined deep-learning and transfer-learning approach well supports the social influence prediction.

Keywords: emerging systems; deep learning; transfer learning; machine learning; social networks; social network analysis; predictive analytics

1. Introduction

The big data era is characterized by a very large volume of data generated in each instance [38]. Hence, making sense of these data (e.g., via data mining [26, 27, 29, 33], machine learning [13, 16, 30, 32]) is very important. Social

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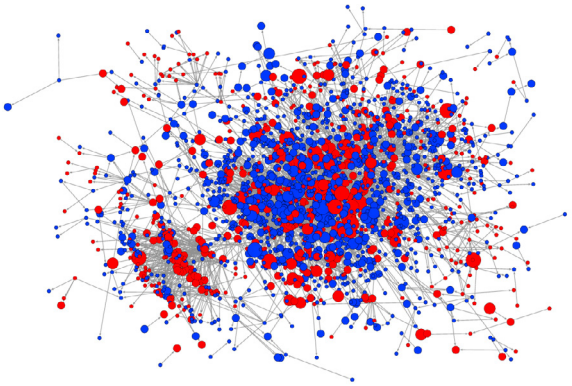

Fig. 1. Visualization of one of the sample batches in SNAP dataset.

networks are popular data sources, and they are growing [19, 34, 37, 47]. For example, as of July 2020, Facebook is the most popular social networks with more than 2.6 billion monthly active users. A rapid speed of growth in social networks is affecting the interaction between social network users. Gather those data and performing further analysis is then a challenging field of research. Social influence analysis [7, 11, 25, 28] is one possible branch. It describes the way people change their behaviours based on other people's influence. It can be observed everywhere around us and it is contained in many real-world applications as key components. Some examples include advertisement (e.g., [44]), recommendation systems (e.g., [1]), viral influence prediction (e.g., [43]).

In our society, social influence has become an emergent topic with the power to manipulate opinions and behaviors of people. This calls for demand for a better understanding and prediction on social influence.

Embedded relationships from input data can be approximated by deep neural network (DNN). The growing usage of convolution neural network (CNN) and DNN [23, 24] in computer vision have shown some success. While CNN deals well with videos and images (which can be summarized as Euclidean structure data), a great interest is devoted to apply similar techniques to non-Euclidean structure data (e.g., time dependent signal, geometric, and social network data [5]). Several applications can be created by the analysis of these data. However, the non-Euclidean nature and vector space structures lead to some ill-defined convolution operations. To overcome this difficulty, the *graph convolution network* (*GCN*) [17] has been introduced to demonstrate its effectiveness in applying convolution to graphs. It takes an average of the neighbourhood features. Furthermore, theoretical foundation of applying convolution operation on non-Euclidean structure data through the graph Fourier transform on spectral networks has been settled. A recent research on user level SIA [41] used deep learning. It has inspired the current work, which also deals with user-level prediction. With a user u and its neighbours v, an objective of the current paper is to predict the state of u at the end of the time interval given the statuses of its surrounding neighbours. Every node is either be *active* or *inactive*. Fig. 1 shows a visualization of the SNAP dataset (see [36] and Section 4 for more information). GCN also inspired both the *personalized propagation of neural predictions* (*PPNP*) *algorithm* and the *approximation to PPNP* (*APPNP*) *algorithm* [22].

Key contributions of this paper include the transfer of two algorithms PPNP and APPNP from the domains of page rank to social influence domain, as well as the combination of both PPNP and APPNP into a *combined PPNP* (*CPPNP*) *algorithm*. Evaluation results show that CPPNP outperforms existing models like APPNP, GCN, and PPNP.

2. Background and related work

From the point of view of deep learning, SIA belongs to the research branch of the graph neural network (GNN) related problems [42]. Other type of applications in the recommendation system domain (e.g., page rank prediction [40], collaborative filtering, etc.) has been successfully faced with GNN, thus getting inspiration from these applications is beneficial to our current research. As stated in Section 1, inspired by the GCN, two algorithms (namely, PPNP and APPNP) were developed [22]. In GCN, the influence of each node to its neighbours is the same. In other words, the probability to propagate its influence to its neighbours is the same for all the edges of the graph. We introduce a

teleport probability τ to adjust the information propagation and to let every node to have different influential power to its neighbours. In comparison to GCN (which takes the average influence over all its neighbours), the results shows that if $\tau \in [0.05, 0.2]$, PPNP and APPNP outperform the GNN used for baseline Four related approaches are briefly discussed in this section.

2.1. Graph convolution network

GCN [20] is a semi-supervised learning network handling graph-structured data. It exploits the information from graph Laplacian, Fourier transformation and eigen-decomposition. In particular, GCN considers a stack of layers, each using the following propagation rule $g(K^{(l)}, A) = \sigma(AK^{(l)}W^{(l)})$, where K is a prediction matrix from the previous layer, $K^{(0)}$ is the initial feature matrix Y, and A is an adjacency matrix taking advantage of the identity matrix to keep its self-loop in the graph. It is worth noting that the matrix A can be diagonalized as $A = \hat{D}^{-\frac{1}{2}}\hat{A}\hat{D}^{-\frac{1}{2}}$.

2.2. Personalized propagation of neural predictions

With the teleport vector θ_u of node u for preserving the node's local neighbourhood, the influence score $I(u, v)$ of node u on node v measures the v-th element of personalized page rank $p_{\text{ppr}}(\theta_u)$ in the PPNP algorithm [21]. The recurrent equation with teleport vector having the teleport probability $\tau \in (0, 1]$ is $\boldsymbol{p}_{\text{pr}}(\theta_u) = \tau(\boldsymbol{I}_n - (1-\tau)\hat{A})^{-1}\boldsymbol{\theta}_u$. Then, the prediction function can be expressed as

$$X_{\text{PPNP}} = \text{softmax}(\tau(\boldsymbol{I}_n - (1-\tau)\hat{\boldsymbol{A}})^{-1}\boldsymbol{K}) \tag{1}$$

where $\boldsymbol{K}_{i,s} = g_\tau(\boldsymbol{Y}_{i,s})$ for the feature matrix Y_i and the neural network g_τ with predictions $\boldsymbol{K} \in \mathbb{R}^{n\times c}$. This dense matrix requires $O(n^2)$ both in time and space complexity.

2.3. Approximation to personalized propagation of neural predictions

The APPNP algorithm [21] solves the aforementioned drawback. The greatest eigenvalue of a diagonalizable matrix can be computed linearly by using eigenvalue algorithms. By combing these approach with the PPNP approach, we obtain the APPNP approach, which can be expressed as:

$$X^{(0)}_{APPNP} = \boldsymbol{K} = g_\tau(\boldsymbol{Y}) \tag{2}$$

$$X^{(n+1)}_{APPNP} = (1-\tau)\hat{\boldsymbol{A}}X^{(n)} + \tau\boldsymbol{K} \tag{3}$$

$$X^{(N)}_{APPNP} = \text{softmax}((1-\tau)\hat{\boldsymbol{A}}X^{(N-1)} + \tau K) \tag{4}$$

where K is a prediction matrix, N is the number of power method steps that $n \in [0, N-2]$; and $X^{(N)}_{APPNP}$ is a teleport set for approximate predictions.

2.4. Graph attention network

Graph attention network (GAT) [50] applies self-attention technique in the propagation step for handling graph-structured data. The state of each node is computed by referencing its neighbors. In a GAT, single graph attention layers use attention coefficients. Attention coefficients τ_{uv} for neighbour node u to node v are computed by:

$$\tau_{uv} = \frac{\exp(\text{LeakyReLU}(\overrightarrow{\mathbf{b}}^T[\mathbf{W}\vec{h}_u \| \mathbf{W}\vec{h}_v]))}{\sum_{k\in N_u}\exp(\text{LeakyReLU}(\overrightarrow{\mathbf{b}}^T[\mathbf{W}\vec{h}_u \| \mathbf{W}\vec{h}_k]))} \tag{5}$$

where $\mathbf{b}^T$ is the transpose of weight vector $\mathbf{b}$ represented by the concatenation $[\mathbf{W}\vec{h}_u \| \mathbf{W}\vec{h}_v]$ of weight matrices applying to every node with $\mathbf{W} \in \mathbb{R}^{F' \times F}$. The output could be expressed as a linear combination of features: $\vec{a}'_u = \sigma(\sum_{v \in \mathcal{N}_u} \tau_{uv} \mathbf{W}\vec{a}_v)$. If N independent attention layers are used, the output can be generalised to become $\vec{a}'_u = \sigma(\frac{1}{K} \sum_{k=1}^{K} \sum_{v \in \mathcal{N}_u} \tau^k_{uv} \mathbf{W}^k \vec{h}_v)$.

3. Our combined personalized propagation of neural predictions

Recall that DeepInf is a end-to-end user level influence prediction model for discovering hidden patterns automatically, and PPNP is a personal propagation of neural predictions. These two techniques inspires us in combining the personalized page rank algorithm of PPNP and DeepInf architecture. In particular, the GAT/GCN network of the PPNP is replaced by personalized PageRank network model. The resulting algorithm is called combined-PPNP (CPPNP). By means of the experiments presented in Section 4, the CPPNP is shown to outperforms other algorithms.

The CPPNP approach uses the teleport probability τ to adjust the size of the neighborhood influences for both PPNP and APPNP approaches as in Eq. (6). The teleport vector enhanced recurrent equation is combined with a prediction function K and teleport probability τ as:

$$X_{\text{CPPNP}} = \text{softmax}(\tau(\boldsymbol{I}_n - (1-\tau)\hat{\boldsymbol{A}})^{-1}\boldsymbol{K} + \tau K) \tag{6}$$

where $\boldsymbol{K}_{i,i} = g_\tau(\boldsymbol{Y}_{i,s})$. The term τK on PPNP to reduce the linearity and provides more flexibility. This can be a reason for the better performance of CPPNP with respect to the other approaches.

4. Experimental assessment

4.1. Datasets

We used three test datasets coming from different domains:

- OAG [39] is an open academic graph that unifies 166,192,182 papers contained in the Microsoft Academic Graph (MAG) [46] and 154,771,162 papers in AMiner [48] databases.
- SNAP [35, 36] is a general purpose network analysis and graph mining library, which includes social networks, web graphs, road networks, internet networks, citation networks, collaboration networks, and communication networks. It contains more than 50 large network datasets from tens of thousands of nodes and edges to tens of millions of nodes and edges.
- Twitter dataset [12] contains data—in the form of networks with 456,626 nodes and 14,855,842 edges—collected by monitoring the spreading process of the discovery of the Higgs Boson on July 4, 2012.

4.2. Predictive performance

Area under curve (AUC), precision, recall, and F_1 measures are used to quantify the predictive performance of the methods (the same performance indicators are for the DeepInf techniques). The comparison is done between CPPNP, APPNP, PPNP and using DeepInf as a baseline (DeepInf-GCN and DeepInf-GAT). The results *without* vs. *with* GAT are shown in Fig. 2 and Fig. 3, respectively. Fig. 2 shows that DeepInf-GCN has worse performance than the CPPNP model in almost all benchmark instance. Since the teleport probability τ deeply influence the performance of the method, we report its value in the name of the algorithm. In all the datasets, the best PPNP and APPNP model has worse performance than the CPPNP model. In Ref. [41], the best performance are reached by the GAT approach. In Fig. 3, note that CPPNP, APPNP, PPNP are still competitive when compared to GAT. In particular, in term of precision on the SNAP dataset CPPNP successfully outperforms DeepInf-GAT (72.38% vs 66.82%).

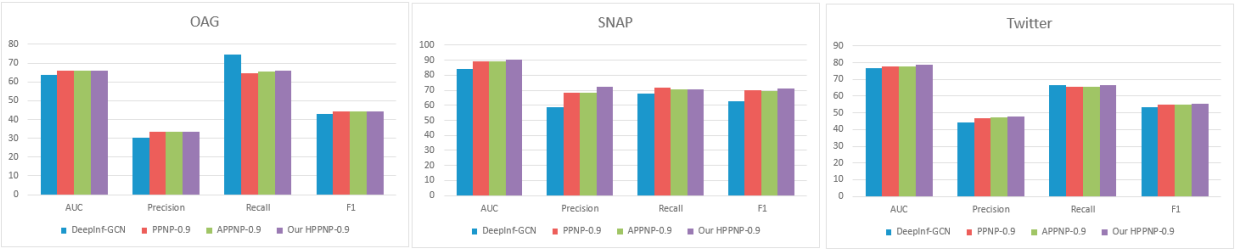

Fig. 2. Performances of different algorithms *without* GAT.

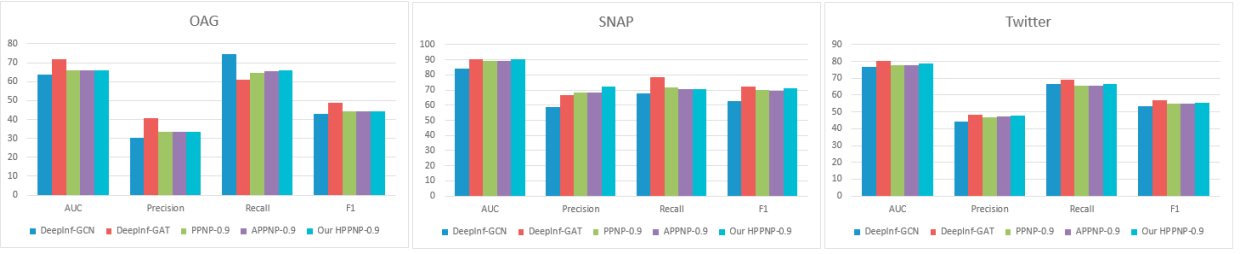

Fig. 3. Performances of different algorithms *with* GAT.

4.3. Parameter analysis

Our approach was compared directly to the DeepInf baseline by adjusting the teleport probability $\tau \in [0.2, 0.9]$. In the experiments, we used 500 epochs, 1024 mini batches, and a drop out rate of 0.2 to measure the effects of τ with respect to the five parameters.

4.3.1. Test loss

Observed from Fig. 4, the final test loss decreases when τ increases. Moreover, bigger τ leads to better performance, i.e., less data loss. The similarity of the performance of CPPNP and PPNP for small τ is due to the fact that CPPNP is built on PPNP. It is worth noting that CPPNP performs better than the other two models in all the considered datasets.

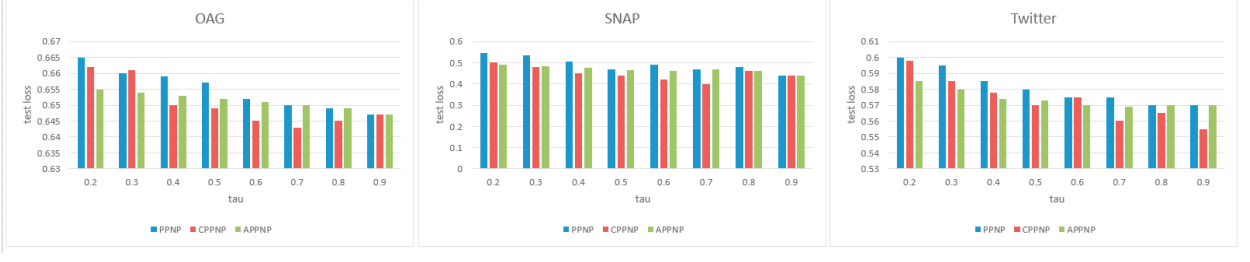

Fig. 4. *Test loss* on the datasets against $\tau \in [0.2, 0.9]$.

4.3.2. Area under curve (AUC)

By observing Fig. 5, it is possible to note that as τ increases, also the AUC increases. As for the test loss, CPPNP performs the best. Furthermore, the best value for τ is 0.8 or 0.9.

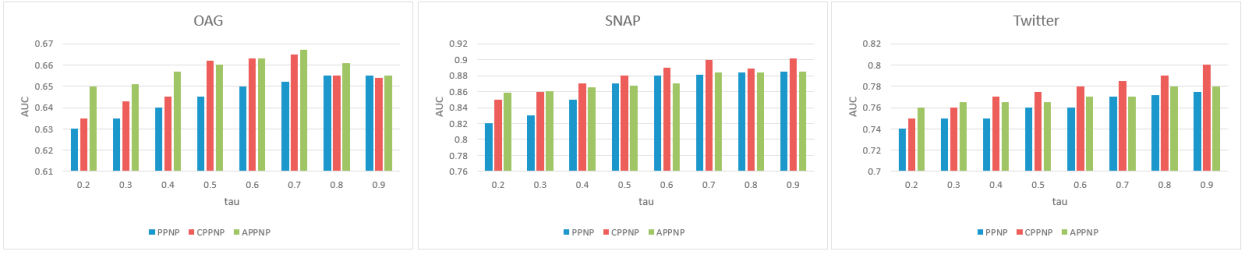

Fig. 5. *AUC* on the datasets against $\tau \in [0.2, 0.9]$.

4.3.3. *Precision*

Similarly to AUC, Fig. 6 shows that, as τ increases, precision increases. The dataset size influences the precision of different models. In fact. It is worth noting that CPPNP approach performs better than PPNP in the interval $\tau \in [0.2, 0.9]$.

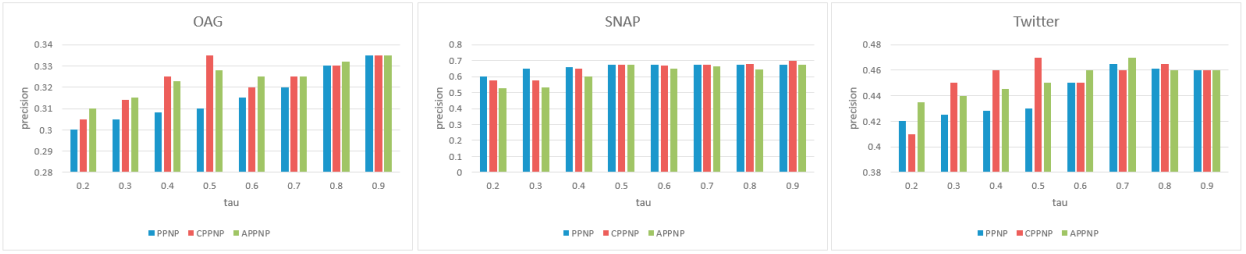

Fig. 6. *Precision* on the datasets against $\tau \in [0.2, 0.9]$.

4.3.4. *Recall*

Despite the previous results, recall do not show a trend with respect to τ; in Fig. 7 it is possible to note that it remains the same for all the values of τ. Furthermore, on the different datasets, all three models perform similarly.

4.3.5. *F_1 score*

As shown in Fig. 8, as τ increases, the F_1 score also increases. As for test loss, AUC and precision, the CPPNP achieved the best performances. If $\tau \to 1$, all the models have similar performance.

5. Conclusion and future work

The connection between people and social network is a field of fundamental importance. In particular, many research groups are analysing social influence. In this context, deep learning has been used. When considering GNN approaches, better results can be achieved. Inspired by the existing PPNP and APPNP approaches for predicting page rank, DeepInf is integrated with GNN to enhance the performance. In particular, GCN can be outperformed by both PPNP and APPNP in social influence analysis. Moreover, the combined algorithm CPPNP, which takes advantage of both PPNP and APPNP without increasing their computational complexity, has been described. In the experiments, CPPNP has been shown to perform better than existing PPNP and APPNP.

Future work will apply the same technique to other network settings such as smart grid, information from online analytical processing (OLAP) data [3, 4, 6, 9, 8, 52], social graphs [2, 10, 14, 18, 45, 49], social web [15, 31], wireless networks [53] and web intelligence [54] with our approach for supporting social influence prediction.

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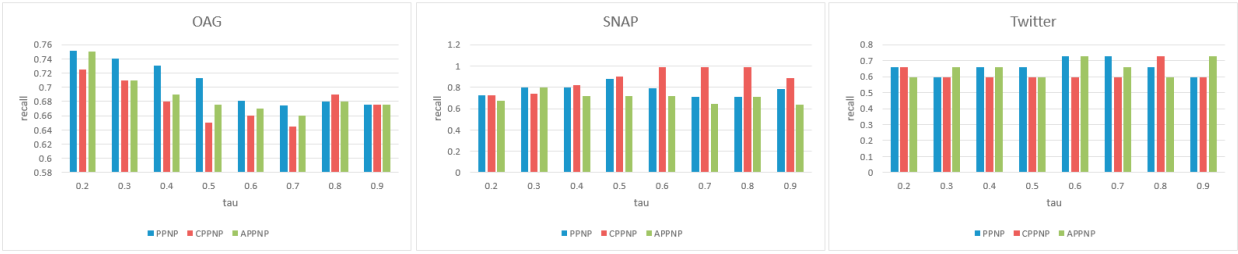

Fig. 7. *Recall* on the datasets against $\tau \in [0.2, 0.9]$.

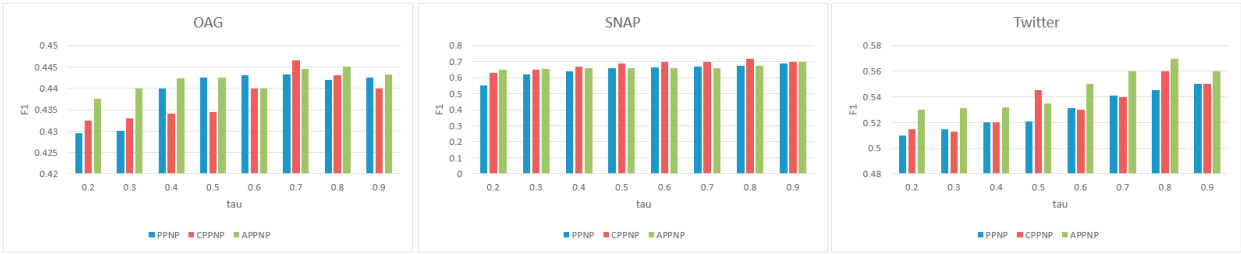

Fig. 8. F_1 *score* on the datasets against $\tau \in [0.2, 0.9]$.

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