### Linked Recurrent Neural Networks

**Extended Abstract**

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#### ABSTRACT

Recurrent Neural Networks (RNNs) have been proven to be effective in modeling sequential data and have been applied to boost a variety of tasks such as document classification, speech recognition and machine translation. Most of existing RNN models have been designed for sequences assumed to be identically and independently distributed (i.i.d). However, in many real-world applications, sequences are naturally linked. For example, web documents are connected by hyperlinks; and genes interact with each other. On the one hand, linked sequences are inherently not i.i.d., which poses tremendous challenges to existing RNN models. On the other hand, linked sequences offer link information in addition to the sequential information. We conduct experiments on real-world datasets from multiple domains and the experimental results validate the effectiveness of the proposed framework.

#### 1 INTRODUCTION

Recurrent Neural Networks (RNNs) have been proven to be powerful in learning a reusable parameters that produce hidden representations of sequences. They have been successfully applied to model sequential data and achieve state-of-the-art performance in numerous domains such as speech recognition [12, 29, 39], natural language processing [1, 19, 31, 33], healthcare [7, 18, 25], recommendations [14, 48, 50] and information retrieval [35].

The majority of existing RNN models have been designed for traditional sequences, which are assumed to be identically, independently distributed (i.i.d). However, many real-world applications generate linked sequences. For example, web documents, sequences of words, are connected via hyperlinks; genes, sequences of DNA or RNA, typically interact with each other. Figure 1 illustrates one toy example of linked sequences where there are four sequences – $S_1$, $S_2$, $S_3$ and $S_4$. These four sequences are linked via three links – $S_1$ is connected with $S_2$ and $S_3$, $S_2$ is connected with $S_1$ and $S_3$, and $S_3$ is linked with $S_2$ and $S_4$. On the one hand, these linked sequences are inherently related. For example, linked web documents are likely to be similar [10] and interacted genes tend to share similar functionalities [4]. Hence, linked sequences are not i.i.d., which presents immense challenges to traditional RNNs. On the other hand, linked sequences offer additional link information in addition to the sequential information. It is evident that link information can be exploited to boost various analytical tasks such as social recommendations [42], sentiment analysis [17, 46] and feature selection [43]. Thus, the availability of link information in linked sequences has the great potential to enable us to develop advanced Recurrent Neural Networks.

Now we have established that – (1) traditional RNNs are insufficient and dedicated efforts are needed for linked sequences; and (2) the availability of link information in linked sequences offer unprecedented opportunities to advance traditional RNNs. In this paper, we study the problem of modeling linked sequences via RNNs. In particular, we introduce a principled approach to capture link information and propose a linked Recurrent Neural Network (LinkedRNN), which models sequential and link information coherently. We conduct experiments on real-world datasets from multiple domains and the experimental results validate the effectiveness of the proposed framework.

#### CCS CONCEPTS

- Computer systems organization → Embedded systems; Redundancy; Robotics;  
- Networks → Network reliability;

#### KEYWORDS

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We validate the effectiveness of the proposed framework on real-world datasets across different domains. The rest of the paper is organized as follows. Section 2 gives a formal definition of the problem we aim to investigate. In Section 3, we motivate and detail the framework LinkedRNN. The experiment design, results and the datasets are described in Section 4. Section 5 and in Figure 2. It mainly consists of two layers. The RNN layer is to capture sequential information and how to combine sequential and link information coherently. To tackle these two challenges, we propose a novel Recurrent Neural Networks LinkedRNN. An illustrate of the proposed framework on the toy example of Figure 1 is demonstrated in Figure 2. It mainly consists of two layers. The RNN layer is to capture the sequential information. The output of the RNN layer is the input of the link layer where link information is captured. Next, we first detail each layer and then present the overall framework of LinkedRNN.

3 THE PROPOSED FRAMEWORK

In addition to sequential information, link information is available for linked sequences as shown in Figure 1. As aforementioned, the major challenges to model linked sequences are how to capture link information and how to combine sequential and link information coherently. To tackle these two challenges, we propose a novel Recurrent Neural Networks LinkedRNN. An illustrate of the proposed framework on the toy example of Figure 1 is demonstrated in Figure 2. It mainly consists of two layers. The RNN layer is to capture the sequential information. The output of the RNN layer is the input of the link layer where link information is captured. Next, we first detail each layer and then present the overall framework of LinkedRNN.

3.1 Capturing sequential information

Given a sequence $S^i = \{x^1_i, x^2_i, \ldots, x^N_i\}$, the RNN layer aims to learn a representation vector that can capture its complex sequential patterns via Recurrent Neural Networks. In deep learning community, Recurrent Neural Networks (RNNs)[32, 36] have been very successful to capture sequential patterns in many fields[32, 40]. Specifically, RNN consists of recurrent units that take the previous state $h^i_{t-1}$ and current event $x^i_t$ as input and output a current state $h^i_t$ containing the sequential information seen so far as:

$$
 h^i_t = f(U h^i_{t-1} + W x^i_t) \tag{1}
$$

Where $U$ and $W$ are the learnable parameters and $f(\cdot)$ is a activation function which enables the non-linearity. However, one major limitation of the vanilla RNN in Equation 1 is that it suffers from gradients vanishing or exploding issues, which fail the learning procedure as it cannot capture the error signals during back-propagation process[5].
More advanced recurrent units such as long short-term memory (LSTM) model [15] and the Gated Recurrent Unit (GRU) [8] have been proposed to solve the gradient vanishing problem. Different from vanilla RNN, these variants employ gating mechanism to decide when and how much the state should be updated with the current information. In this work, due to its simplicity and effectiveness, we choose GRU as our RNN unit. Specifically, in the GRU, the current state $h^i_t$ is a linear interpolation between previous state $h^i_{t-1}$ and a candidate state $\tilde{h}^i_t$:

$$h^i_t = z^i_t \odot h^i_{t-1} + (1 - z^i_t) \odot \tilde{h}^i_t$$  \hspace{1cm} (2)

where $\odot$ is the element-wise multiplication and $z_t$ is called update gate which is introduced to control how much current state should be updated. It is obtained through the following equation:

$$z^i_t = \sigma(W_z x^i_t + U_z h^i_{t-1})$$  \hspace{1cm} (3)

Where $W_z$ and $U_z$ are the parameters and $\sigma(\cdot)$ is the sigmoid function, that is, $\sigma(x) = \frac{1}{1 + e^{-x}}$. In addition, the newly introduced candidate state $\tilde{h}^i_t$ is computed by the Equation 4:

$$\tilde{h}^i_t = g(W_r x^i_t + U_r h^i_{t-1})$$  \hspace{1cm} (4)

where $g(\cdot)$ is the tanh function that $g(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$ and $W$ and $U$ are model parameters. $r_t$ is the reset gate which determines the contribution of previous state to the candidate state and is obtained as follows:

$$r^i_t = \sigma(W_r x^i_t + U_r h^i_{t-1})$$  \hspace{1cm} (5)

The output of the RNN layer will be the input of the link layer. For a sequence $S^i$, the RNN layer will learn a sequence of latent representations $(h^i_1, h^i_2, \ldots, h^i_N)$. There are various ways to obtain the final output $h_i$ of $S^i$ from $(h^i_1, h^i_2, \ldots, h^i_N)$. In this work, we investigate two popular ways:

- As the last latent representation $h^i_{N_i}$ is able to capture information from previous states, we can just use it as the representation of the whole sequence. We denote this way of aggregation as $aggregation_{11}$. Specifically, we let $h_i = h^i_{N_i}$.
- The attention mechanism can help the model automatically focus on relevant parts of the sequence to better capture the long-range structure and it has shown effectiveness in many tasks [2, 9, 26]. Thus, we define our second way of aggregation based on the attention mechanism as follows:

$$h_i = \frac{\sum_{j=1}^{N_i} a_j h^i_j}{\sum_{m} e^{a(h^i_m)}} \hspace{1cm} (6)$$

where $a_j$ is the attention score, which can be obtained as

$$a_j = \frac{e^{a(h^i_j)}}{\sum_{m} e^{a(h^i_m)}} \hspace{1cm} (7)$$

where $a(h^i_j)$ is a feedforward layer:

$$a(h^i_j) = v^T_i \tanh(W_a h^i_j) \hspace{1cm} (8)$$

Note that different attention mechanisms can be used, we will leave it as one future work. We denote the aggregation way described above as $aggregation_{12}$.
3.2 Capturing link information
The RNN layer is able to capture the sequential information. However, in linked sequences, sequences are naturally related. The Homophily theory suggests that linked entities tend to have similar attributes [28], which have been validated in many real-world networks such as social networks [22], web networks [23], and biological networks [4]. As indicated by Homophily, a node is likely to share similar attributes and properties with nodes with connections. In other words, a node is similar to its neighbors. With this intuition, we propose the link layer to capture link information in linked sequences.

As shown in Figure 2, to capture link information, for a node, the link layer not only includes information from its sequential information but also aggregates information from its neighbors. The link layer can contain multiple hidden layers. In other words, for one node, we can aggregate information from itself and its neighbors multiple times. Let \( \mathbf{v}_i^k \) be the high dimensional representations of the sequence \( S_i \) after \( k \) aggregations. To note that when \( k = 0 \), \( \mathbf{v}_i^0 \) is the input of the link layer, i.e., \( \mathbf{v}_i^0 = \mathbf{h}_i \). Then \( \mathbf{v}_i^{k+1} \) can be updated as:

\[
\mathbf{v}_i^{k+1} = \text{act}(\frac{1}{|\mathcal{N}(i)|} + \frac{1}{|\mathcal{N}(i)|} \sum_{j \in \mathcal{N}(i)} \mathbf{v}_j^k)
\]  

(9)

where \( \text{act}() \) is an element-wise activation function, \( \mathcal{N}(i) \) is the set of neighbors who are linked with \( S_i \), i.e., \( \mathcal{N}(i) = \{S_j | \mathcal{A}(i, j) = 1 \} \), and \( |\mathcal{N}(i)| \) is the number of neighbors of \( S_i \). We define \( \mathbf{v}_i^k = [\mathbf{v}_i^k, \mathbf{v}_i^k, \ldots, \mathbf{v}_i^k] \) as the matrix form of representations of all sequences at the \( k \)-th layer. We modify the original adjacency matrix \( \mathcal{A} \) by allowing \( \mathcal{A}(i, i) = 1 \). The aggregation in the Eq. (9) can be written in the matrix form as:

\[
\mathbf{v}_i^{k+1} = \text{act}(\mathbf{AD}^{-1}\mathbf{v}_i^k)
\]  

(10)

where \( \mathbf{v}_i^{k+1} \) is the embedding matrix after \( k + 1 \) step aggregation, and \( \mathbf{D} \) is the diagonal matrix where \( \mathbf{D}(i, i) \) is defined as:

\[
\mathbf{D}(i, i) = \sum_{j=1}^{\mathcal{N}(i)} \mathcal{A}(i, j)
\]  

(11)

3.3 Linked Recurrent Neural Networks
With the model components to capture sequential and link information, the procedure of the proposed framework LinkedRNN is presented below:

\[
(\mathbf{h}_i^1, \mathbf{h}_i^2, \ldots, \mathbf{h}_i^{\mathcal{N}(i)}) = \text{RNN}(S_i)
\]

\[
\mathbf{h}_i = \text{aggregation1}(\mathbf{h}_i^1, \mathbf{h}_i^2, \ldots, \mathbf{h}_i^{\mathcal{N}(i)})
\]

\[
\mathbf{v}_i^0 = \mathbf{h}_i
\]

\[
\mathbf{v}_i^{k+1} = \text{act}(\frac{1}{|\mathcal{N}(i)|} + \frac{1}{|\mathcal{N}(i)|} \sum_{j \in \mathcal{N}(i)} \mathbf{v}_j^k)
\]

\[
\mathbf{z}_i = \text{aggregation2}([\mathbf{v}_i^0, \mathbf{v}_i^1, \ldots, \mathbf{v}_i^{\mathcal{N}(i)}])
\]  

(12)

where the input of the RNN layer is the sequential information and the RNN layer will produce the sequence of latent representations \( (\mathbf{h}_i^1, \mathbf{h}_i^2, \ldots, \mathbf{h}_i^{\mathcal{N}(i)}) \). The sequence of latent representations will be aggregated to obtain the output of the RNN layer, which serves as the input of the Link layer. After \( M \) layers, link layer produces a sequence of latent representations \( (\mathbf{v}_i^0, \mathbf{v}_i^1, \ldots, \mathbf{v}_i^{M}) \), which will be aggregated to the final representation.

The final representation \( \mathbf{z}_i \) for the sequence \( S_i \) is to aggregate the sequence \( (\mathbf{v}_i^0, \mathbf{v}_i^1, \ldots, \mathbf{v}_i^{M}) \) from the link layer. In this work, we investigate several ways to obtain the final representation \( \mathbf{z}_i \) as:

- As \( \mathbf{v}_i^M \) is the output of the last layer, we can define the final representation as: \( \mathbf{z}_i = \mathbf{v}_i^M \); and we denote this way as \( \text{aggregation1} \).
- Although the new representation \( \mathbf{v}_i^M \) incorporates all the neighbor information, the signal in the representation of itself may be overwhelmed during the aggregation process. This is especially likely to happen when there are a large number of neighbors. Thus, to make the new representation to focus more on itself, we propose to use a feed forward neural network to perform the combination. We concatenate representations from the last two layers as the input of the feed forward network. We refer this aggregation method as \( \text{aggregation2} \).
- Each representation \( \mathbf{v}_i^k \) could contain its unique information, which cannot be carried in the later part. Thus, similarly, we use a feed forward neural network to perform the combination of \( (\mathbf{v}_i^0, \mathbf{v}_i^1, \ldots, \mathbf{v}_i^{M}) \). We refer this aggregation method as \( \text{aggregation3} \).

To learn the parameters of the proposed framework LinkedRNN, we need to define a loss function that depends on the specific task. In this work, we investigate LinkedRNN in two tasks—classification and regression.

**Classification.** The final output of a sequence \( S_i \) is \( \mathbf{z}_i \). We can consider \( \mathbf{z}_i \) as features and build the classifier. In particular, the predicted class labels can be obtained through a softmax function as:

\[
p^i = \text{softmax}(\mathbf{W}_c \mathbf{z}_i + b_c)
\]  

(13)

where \( \mathbf{W}_c \) and \( b_c \) are the coefficients and the bias parameters, respectively. \( p^i \) is the predicted label of the sequence \( S_i \). The corresponding loss function used in this paper is the cross-entropy loss.

**Regression.** For the regression problem, we choose linear regression in this work. In other words, the regression label of the sequence \( S_i \) is predicted as:

\[
p^i = \mathbf{W}_r \mathbf{z}_i + b_r
\]  

(14)

where \( \mathbf{W}_r \) and \( b_r \) are the regression coefficients and the bias parameters, respectively. Then square loss is adopted in this work as the loss function as:

\[
L = \frac{1}{K} \sum_{i=1}^{K} (y_i - p_i)^2
\]  

(15)

Note that there are other ways to define loss functions for classification and regression. We would like to leave the investigation of other formats of loss functions as one future work.
we firstly describe the datasets we used in the experiments and which is unseen in the given linked sequences. Then, we use Word2Vec [30] to embed each word into Euclidean space and for each sentence, we treat the mean of its word vectors as the sentence embedding. Thus, the abstract of each paper can be represented by a sequence of sentence embeddings. We will conduct the classification task on this dataset, i.e., paper classification.

To validate the effectiveness of the proposed framework, we construct three groups of representative baselines. The first group includes the state-of-the-art network embedding methods, i.e., node2vec [13] and GCN [20], which only capture the link information. The second group is the GRU RNN model [12], which is the basic model we used in our model to capture sequential information. Baselines in the third group is to combine models in the first and second perspective.

| Description                  | DBLP     | BOOHEE   |
|------------------------------|----------|----------|
| # of sequences               | 47,491   | 18,229   |
| Network density (%)          | 0.13     | 0.012    |
| Avg length of sequences      | 6.6      | 23.5     |
| Max length of sequences      | 20       | 29       |

Table 1: Statistics of the datasets.

**Prediction.** For an unlabeled sequence $S^l$ under the classification problem, its label is predicted as the one corresponding to the entity with the highest probability in softmax($W_c z_j + b_c$).

For an unlabeled sequence $S^l$ under the regression problem, its label is predicted as $W_r z_j + b_r$.

Although the framework is designed for transductive learning, it can be naturally used for inductive learning. For a sequence $S^K$, which is unseen in the given linked sequences $S$, according to its sequential and its neighbors $N(k)$, it is easy to obtain its representation $z_k$ via Eq. (12). Then based on $z_k$, its label can be predicted as the normal prediction step described above.

**4 EXPERIMENT**

In this section, we present experimental details to verify the effectiveness of the proposed framework. Specifically, we validate the proposed framework on datasets from two different domains. Next, we firstly describe the datasets we used in the experiments and then compare the performance of the proposed framework with representative baselines. Lastly, we analyze the key components of LinkedRNN.

**4.1 Datasets**

In this study, we collect two types of linked sequences. One is from DBLP where data contains textual sequences of papers. The other is from a weight loss website BOOHEE where data includes weight sequences of users. Some statistics of the datasets are demonstrated in Table 1. Next we introduce more details.

**DBLP dataset.** We constructed a paper citation network from the public available DBLP data set[45]. This dataset contains information for millions of paper from a variety of research fields. Specifically, each paper contains the following relevant information: paper id, publication venue, the id references of it and abstract. Following the similar practice in [44], we only select papers from conferences in 10 largest computer science domains including VCG, ACL, IP, TC, WC, CCS, CVP, PDS, NIPS, KDD, WWW, ICSE, Bioinformatics, TCS. We construct a sequence for each paper from their abstracts and regard their citation relationships as the link information between sequences. Specifically, we first split the abstract into sentences and tokenize each sentence using python NLTK package. Then, we use Word2Vec [30] to embed each word into Euclidean space and for each sentence, we treat the mean of its word vectors as the sentence embedding. Thus, the abstract of each paper can be represented by a sequence of sentence embeddings. We will conduct the classification task on this dataset, i.e., paper classification.

Thus, the label of each sequence is the corresponding publication venue.

**BOOHEE dataset.** This dataset is collected from one of the most popular weight management mobile applications, BOOHEE. It contains million of users who self-track their weights and interact with each other in the internal social network provided by the application. Specifically, they can follow friends, make comment to friends’ post and mention (@) friends in comments or posts. The recorded weights by users form sequences which contain the weight dynamic information and the social networking behaviors result in three networks that correspond to following, commenting, and mentioning interactions, respectively. Previous work [47] has shown a social correlation on the users’ weight loss. Thus, we use these social networks as the link information for the weight sequence data. We preprocess the dataset to filter out the sequences from suspicious spam users. Moreover, we change the time granularity of weight sequence from days to weeks to remove the daily fluctuation noise. Specifically, we compute the mean value of all the recorded weights in one week and use it as the weight for that week. For networks, we combine three networks into one by adding them together and filter out weak ties. In this dataset, we will conduct a regression task of weight prediction. We choose the most recent weight in a weight sequence as the weight we aim to predict (or the ground truth of the regression problem). Note that for a user, we remove all social interactions that form after the most recent weight where we want to avoid the issue of using future link information for weight prediction.

**4.2 Representative baselines**

To validate the effectiveness of the proposed framework, we construct three groups of representative baselines. The first group includes the state-of-the-art network embedding methods, i.e., node2vec [13] and GCN [20], which only capture the link information. The second group is the GRU RNN model [12], which is the basic model we used in our model to capture sequential information. Baselines in the third group is to combine models in the first and second groups, which captures both sequential and link information. Next, we present more details about these baselines.

- Node2vec [13]. Node2vec is one state-of-the-art network embedding method. It learns the representation of sequences only capturing the link information in a random-walk perspective.
- GCN [20] It is the traditional graph convolutional graph algorithm. It is trained with both link and label information. Hence, it is different from node2vec, which is learnt with only link information and is totally independent on the task.
- RNN [12] RNNs have been widely used for modeling sequential data and achieved great success in variety of domains. However, they tend to ignore the correlation between sequences and only focus on sequential information. We construct this baseline to show the importance of correlation information. To make the comparison fair, we employ the same recurrent unit (GRU) in both the proposed framework and this baseline.
### Table 2: Performance Comparison in the DBLP dataset

| Measurement | Method      | Training ratio |
|-------------|-------------|----------------|
|             |             | 10% | 30% | 50% | 70% |
| Micro-F1    | node2vec 0.6641 | 0.6550 | 0.6688 | 0.6691 |
|             | GCN 0.7005  | 0.7093 | 0.7110 | 0.7180 |
|             | RNN 0.7686  | 0.7980 | 0.7978 | 0.8025 |
|             | RNN-node2vec 0.7940 | 0.8031 | 0.7933 | 0.8114 |
|             | RNN-GCN 0.7912  | 0.8230 | 0.8255 | 0.8284 |
|             | LinkedRNN 0.8146 | 0.8399 | 0.8463 | 0.8531 |
| Macro-F1    | node2vec 0.6514  | 0.6523 | 0.6513 | 0.6565 |
|             | GCN 0.6874  | 0.6992 | 0.7004 | 0.7095 |
|             | RNN 0.7452  | 0.7751 | 0.7754 | 0.7824 |
|             | RNN-node2vec 0.7734 | 0.7797 | 0.7702 | 0.7912 |
|             | RNN-GCN 0.7642  | 0.8014 | 0.8069 | 0.8104 |
|             | LinkedRNN 0.7970  | 0.8249 | 0.8331 | 0.8365 |

### Table 3: Performance Comparison in the BOOHEE dataset

| Method          | Training ratio |
|-----------------|----------------|
|                 | 10% | 30% | 50% | 70% |
| node2vec 8.8702 | 8.8517 | 7.4744 | 7.0390 |
| GCN 8.9347  | 8.6830 | 6.7949 | 6.7278 |
| RNN 8.6600  | 8.6048 | 7.0466 | 6.8033 |
| RNN-node2vec 8.4653 | 8.5944 | 7.0173 | 6.7796 |
| RNN-GCN 8.6286 | 8.5662 | 6.9967 | 6.7945 |
| LinkedRnn 7.1822 | 6.3882 | 6.8416 | 6.3517 |

- **RNN-node2vec.** The Node2vec method is able to learn representation from the link information and the RNN can do so from the sequential information. Thus, to obtain the representation of sequences that contains both link and sequential information, we concatenate the two sets of embeddings obtained from Node2vec and RNN via a feed forward neural network.

- **RNN-GCN.** RNN-GCN applies a similar strategy of combining RNN and node2vec to combine RNN and GCN.

There are several notes about the baselines. First, node2vec does not use label information and it is unsupervised, RNN and RNN-node2vec utilize label information and they are supervised, and GCN and RNN-GCN use both label information and unlabeled data and they are semi-supervised. Second, some sequences may not have link information and baselines only capture link information cannot learn representations for these sequences; hence, in this work, when representations from link information are unavailable, we will use the representations from the sequential information via RNN instead. Third, we do not choose LSTM and its variants as baselines since our current model is based on GRU and we also can choose LSTM and its variants as the base models.

### 4.3 Experimental settings

**Data split:** For both datasets, we randomly select 30% for test. Then we fix the test set and choose $x\%$ of the remaining 70% data for training and $1 - x\%$ for validation to select parameters for baselines and the proposed framework. In this work, we vary $x$ as $\{10, 30, 50, 70\}$.

**Parameter selection:** In our experiments, we set the dimension of representation vectors of sequences to 100. For Node2vec, we use the validation data to select the best value for $p$ and $q$ from $\{0.25, 0.50, 1, 2, 4\}$ as suggested by the authors [13] and use the default values for the remaining parameters. In addition, the learning rate for all of the methods are selected through validation set.

**Evaluation metrics:** Since we will perform classification in the DBLP data, we use Micro and Macro F1 scores as the metrics for DBLP, which are widely used for classification problems [13, 49]. The higher value means better performance. We perform the regression problem weight prediction in the BOOHEE data. Therefore the performance in BOOHEE data is evaluated by mean squared error (MSE) score. The lower value of MSE indicates higher prediction performance.
4.4 Experimental Results

We first present the results in DBLP data. The results are shown in Table 2. For the proposed framework, we choose \( M = 2 \) for the link layer and more details about discussions about the choices of its aggregation functions will be discussed in the following section. From the table, we make the following observations:

- As we can see in Table 2, in most cases, the performance tends to improve as the number of training samples increases.
- The random guess can obtain 0.1 for both micro-F1 and macro-F1. We note that the network embedding methods perform much better than the random guess, which clearly shows that the link information is indeed helpful for the prediction.
- GCN achieves much better performance than node2vec. As we mentioned before, GCN uses label information and the learnt representations are optimal for the given task. While node2vec learns representations independent on the given task, the representations may be not optimal.
- The RNN approach has higher performance than GCN. Both of them use the label information. This observation suggests that the content and sequential information is very helpful.
- Most of the time, RNN-node2vec and RNN-GCN outperform the individual models. This observation indicates that both sequential and link information are important and they contain complementary information.
- The proposed framework LinkedRNN consistently outperforms baselines. This strongly demonstrates the effectiveness of LinkedRNN. In addition, comparing to RNN-node2vec and RNN-GCN, the proposed framework is able to jointly capture the sequential and link information coherently, which leads to significant performance gain.

We present the performance on BOOHEE in Table 3. Overall, we make similar observations as these on DBLP as – (1) the performance improves with the increase of number of training samples; (2) the combined models outperform individual ones most of the time and (3) the proposed framework LinkedRNN obtains the best performance.

Via the comparison, we can conclude that both sequential and link information in the linked sequences are important and they contain complementary information. Meanwhile, the consistent impressive performance of LinkedRNN on datasets from different domains demonstrate its effectiveness in capturing the sequential and link information presented in the sequences.

4.5 Component Analysis

In the proposed framework LinkedRNN, we have investigate several ways to define the two aggregation functions. In this subsection, we investigate the impact of the aggregation functions on the performance of the proposed framework LinkedRNN by defining the following variants.

- LinkedRNN11: it is the variant which chooses \( aggregation_{11} \) and \( aggregation_{21} \)
- LinkedRNN12: we define the variant by using \( aggregation_{11} \) and \( aggregation_{22} \)
- LinkedRNN13: this variant is made by applying \( aggregation_{11} \) and \( aggregation_{23} \)
- LinkedRNN21: this variant utilizes \( aggregation_{12} \) and \( aggregation_{21} \)
- LinkedRNN22: it is the variant which chooses \( aggregation_{12} \) and \( aggregation_{22} \)
- LinkedRNN23: we construct the variant by adopting \( aggregation_{12} \) and \( aggregation_{23} \)

The results are demonstrated in Figure 3. Note that we only show results on DBLP with 50% as training since we can have similar observations with other settings. It can be observed:

- Generally, the variants of LinkedRNN with \( aggregation_{12} \) obtain better performance than \( aggregation_{11} \). It demonstrates that aggregating the sequence of the latent presentations with the help of the attention mechanism can boost the performance.
- Aggregating representations from more layers in the link layer typically can result in better performance.

![Figure 3: The impact of aggregation functions on the performance of the proposed framework.](image)

4.6 Parameter Analysis

LinkedRNN uses the link layer to capture link information. The link layer can have multiple layers. In this subsection, we study the impact of the number of layers on the performance of LinkedRNN. The performance changes with the number of layers are shown in Figure 4. Similar to the component analysis, we only report the results with one setting in DBLP since we have similar observations. In general, the performance first dramatically increases and then slowly decreases. One layer is not sufficient to capture the link information while more layers may result in overfitting.
Although it has been designed to model arbitrarily long sequences, RNNs have been proven to be powerful in modeling sequences in many domains. Most of existing RNN methods have been designed for sequences which are assumed to be i.i.d. However, in many real-world applications, sequences are inherently linked and linked sequences present both challenges and opportunities to existing RNN methods, which calls for novel RNN methods. In this paper, we study the problem of designing RNN models for linked sequences. Suggested by Homophily, we introduce a principled method to capture link information and propose a novel RNN framework LinkedRNN, which can jointly model sequential and link information. Experimental results on datasets from different domains demonstrate that (1) the proposed framework can outperform a variety of representative baselines; and (2) link information is helpful to boost the RNN performance.

There are several interesting directions to investigate in the future. First, our current model focuses on unweighted and undirected links and we will study weighted and directed links and the corresponding RNN models. Second, in current work, we focus on classification and regression problems with certain loss functions. We will investigate other types of loss functions to learn the parameters of the proposed framework and also investigate more applications of the proposed framework. Third, since our model can be naturally extended for inductive learning, we will further validate the effectiveness of the proposed framework for inductive learning. Finally, in some applications, the link information may be evolving; thus we plan to study RNN models, which can capture the dynamics of links as well.

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