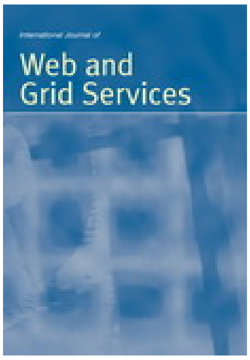

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C3D-LSTM: a novel convolution-3D-based LSTM for link prediction in dynamic social networks

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C3D-LSTM: a novel convolution-3D-based LSTM for link prediction in dynamic social networks

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Abstract: Recently, due to the surge in the use of social networks, link prediction has become an essential technique which could enable service providers to anticipate future friendships between users based on the network structure and personal data so as to enhance consumer loyalty and experience. Undoubtedly, link prediction analysis becomes increasingly difficult when social networks expand quickly, particularly in light of the major advancements in complex social network modelling. Prior studies which predicted social links based on static network settings may have ignored the dynamic variation of networks over time. In this research, an end-to-end model, convolution-3D-based long-short-term memory (abbreviated as C3D-LSTM), is developed to integrate the convolution neural network (CNN) and long-short-term memory (LSTM) network for effective link prediction. We employ 3D convolution to detect subtle patterns in social network snapshots, capturing short-term spatial-temporal features. LSTM layers then interpret these features to model the network's long-term temporal dynamics. To demonstrate its practicability, extensive experiments are conducted to show that C3D-LSTM surpasses current state-of-the-art techniques and delivers remarkable performance.

Keywords: deep learning; convolution neural network; CNN; link prediction; long-short-term memory network; LSTM; social network.

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1 Introduction

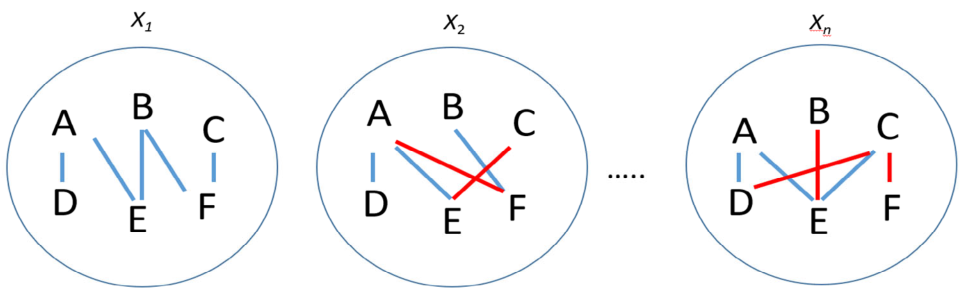
During the past few decades, information technology has evolved rapidly, and internet communication continues to change. Social network services including YouTube, Facebook, and Twitter, to name a few, have become the most popular and widely accepted platforms in recent years. Social networks are rapidly forming and evolving on the internet as a result of these new services, fostering the use of online tools by users to expand their networks, disseminate their messages, and engage in political campaigns. According to several studies (Adamic and Adar, 2003; Chen, 2018; Chen et al., 2021, 2012, 2014; Hvitfeldt and Silge, 2021; Pemantle, 2014; Zhang and Zhang, 2019), approximately 53.6% of the global population uses at least one social media platform, which could indicate the significance of social science. Social network analysis (SNA) focuses on the examination of connections between objects, which is consistent with the notion of data mining to depict the interaction between people, events, and occurrences in the field of data media.

Link prediction is an important technique in SNA which aims to predict potential connections or links between individuals or entities within a social network. Link prediction algorithms leverage the existing network structure and various attributes of nodes and edges to estimate the likelihood of future connections. Most prior studies (Yu et al., 2017; Mahmoudi et al., 2019; Bliss et al., 2014; Zhu and Cao, 2020; Li et al., 2014; Jheng et al., 2021) discussed prediction based on the static social network and the existing network topology and available node attributes. However, social networks are, in general, dynamic; i.e., the network varies with time. Some new users and relations might be created and established; likewise, some obsolete ones might be deleted as time passes. Obviously, dynamic networks are more complex, and predictions become more difficult and less accurate as the input changes over time. It is typical to use a number of graphs, each with fixed nodes and different links, to simulate a dynamic network. As a result of the inability to recognise patterns of evolution, static network link prediction techniques like similarity indices and network embedding algorithms have varying degrees of success. In addition, graph attention networks (GATs), graph convolution networks (GCNs), and other GNNs (Heidari and Iosifidis, 2021; Jasny et al., 2022; Murata and Moriyasu, 2007; Wang, 2022) have demonstrated their ability to handle large-dimensional graph-structured data; nevertheless, they can only perform static network analysis.

We use an example, shown in Figure 1, to illustrate the changes in dynamic networks over time, which could infer nodes and links constantly evolving and cause problems of precise prediction. In Figure 1, there are six users in each area, respectively A, B, C, D, E

and *F*. G_1, G_2 and G_n are social network graphics. In G_1, we can see that *A* has relationships with *D* and *E*, *B* has relationships with *E* and *F*, and *C* has a relationship with *F*. After some time, the graphic has changed. In G_2, *A* and *C* users start to get in touch with other users, and *B* has stopped contact with *E* with whom they had contact in G_1.

Figure 1 Example of dynamic relationships among friends on social networks (see online version for colours)



In this paper, we introduce a novel approach for link prediction in dynamic social networks through a framework we refer to as convolution-3D with long-short-term memory (C3D-LSTM). This framework is specifically designed to handle the complex spatio-temporal dynamics inherent in social network data. The core of our proposed method lies in the integration of 3D convolution with LSTM (Hvitfeldt and Silge, 2021) networks. The use of 3D convolution is pivotal in capturing the spatial relationships across different snapshots of the social network. Unlike traditional 2D convolution, which only considers spatial information in two dimensions, 3D convolution extends this capability by adding a third dimension, effectively allowing the model to learn from a series of network snapshots as if they were a continuous spatial-temporal block. This is particularly advantageous for understanding the evolution of links in a dynamic social network where spatial relationships can change over time. Following the 3D convolution layers, the LSTM component plays a crucial role. LSTMs are a type of recurrent neural network (RNN) (Xu et al., 2021) known for their ability to learn and remember long-term dependencies in sequential data. In the context of our model, the LSTM layers are employed to interpret the temporal features extracted by the preceding 3D convolution layers. The integration of LSTM is based on its gated mechanism, which effectively captures temporal dependencies and variations in the social network over time.

The architecture of C3D-LSTM is designed in a progressive stacking manner. Initially, the convolutional architecture processes the input data, extracting meaningful spatial features from multiple snapshots of the social network. Subsequently, these extracted features are fed into the LSTM layers, where the temporal dynamics are analysed. The rationale behind this architecture is to leverage the strength of convolutional networks in feature extraction from high-dimensional spatial data and to combine it with the prowess of LSTMs in handling temporal sequences. This synergistic combination allows C3D-LSTM to simultaneously learn and model both spatial and temporal features of dynamic social networks. To empirically validate our approach, we conducted in-depth tests using datasets from real-world businesses. The results demonstrate that our C3D-LSTM model significantly outperformed several state-of-the-art techniques, providing a robust solution for dynamic link prediction in social networks.

The following are the significant contributions of this paper.

- We present a unified model, C3D-LSTM, which exploits convolution feature fusion with LSTM for the link prediction of dynamic social networks. This model collects structural features from various snapshot networks using 3D-convolution and learns temporal structure using LSTM. In order to accurately anticipate the behaviour of dynamic networks, the model can successfully learn spatiotemporal properties.
- The majority of prior related approaches can only forecast newly added connections in the network. However, our method can predict all links that will come, vanish, or remain constant to provide precise predictions of the whole dynamic network evolution.
- We verify the effectiveness of C3D-LSTM on dynamic networks and compare it to alternative baseline techniques. Our model clearly outperforms state-of-the-art techniques on a number of measures, and it displays excellent generalisation and resilience in actual datasets with all mentioned metrics.

The organisation of the paper is as follows. Section 2 discusses the literature review and Section 3 presents the proposed methodology in details. We provide the experimental settings and results in a performance study in Section 4, and conclude the paper in Section 5.

2 Literature review

The evolution of linkages and nodes is becoming increasingly essential as social networks grow, and social network prediction is a popular topic of study. In order to make the problem simpler, dynamic networks are frequently represented as a series of graphs. Evidently, the forecast depends on many pictures in different ways. We now provide relevant findings on both traditional and deep learning link prediction techniques.

2.1 Conventional link prediction

The greater the resemblance, the more probable it is that two nodes will join. Many dynamic network and link prediction tools, including local and global structural similarity indices, use the network's topological information to determine how similar paired nodes are to one another.

For the purpose of abstracting social networks and the exogenous elements that support network structure, Adamic and Adar (2003) created a system for mining internet communications. It has potential uses in community discovery, community labelling, and automated real-world relationship inferencing. In order to forecast links in a series of dynamically changing networks, Yu et al. (2017) proposed a link prediction model with space and time conformity (LIST). LIST combines the spatial topology of the network in each timestamp with the temporal network evolution to characterise dynamic networks as time functions. In order to overcome the link prediction problem, Mahmoudi et al. (2019) proposed a novel approach based on time and user to forecast connections based on changes in user communities. To address the issue of short-term link prediction, Bliss et al. (2014) presented the covariance matrix adaptation evolution strategy (CMA-ES) technique for link prediction; 16 fields and node similarity indexes are combined using CMA-ES. Future linkages can be predicted using the semantic subgraphs and graph attention network (SESGAT) approach proposed by Zhu and Cao (2020). To determine the significance of various semantic subgraphs for link prediction, SESGAT uses various types of semantic information in various semantic subgraphs. Our strategy outperforms other cutting-edge algorithms in terms of prediction performance, according to experimental findings on actual social networks.

By combining temporal data, community structure, and node centrality in the network, Ibrahim and Chen (2014) presented a technique for link prediction in dynamic networks. The rationale for our proposal is the loss of some significant topological information in dynamic networks due to static graph prediction. Following the construction of a dynamic weighted social attribute network, Zeng et al. (2016) provided a technique for extracting various kinds of characteristics from the weighted social attribute network. The classifier for link prediction was trained using these characteristics. To address the drawbacks of the CNGF and KatzGF conventional link prediction algorithms, Dong et al. (2013) proposed two revised techniques. KatzGF is based on global information, whereas CNGF is based on local data. In order to forecast linkages, Yu et al. (2014) proposed a novel approach based on the random walk algorithm that constructs network topology and uses knowledge of enhanced node properties. The results demonstrate that the strategy we propose can increase prediction accuracy and those node properties will have an impact on connection formation. In order to provide a low-dimensional feature representation of the node-pair instances, Rahman and Hasan (2016) proposed the GRATFEL approach, which employs an unsupervised feature learning method based on short graphlet transition characteristics. To reduce the reconstruction error, GRATZEL models the feature learning problem as an optimisation encoding work. Using gradient descent, it resolves this optimisation problem. Jie described an approach for a dynamic multi-dimension network in Jie (2015). It creates a dynamic, multi-dimension network using a mobile social network model, and suggests a suitable connection prediction. Using metrics of the 'proximity' of nodes in a network, Liben-Nowell and Kleinberg (2003) defined the issue of "can we infer which new interactions among its members are likely to occur in the near future?" as the link prediction problem.

Papadimitriou et al. (2012) proposed a buddy recommendation system that is both quicker and more accurate. The goal of Marjan et al. (2018) was the thorough assessment, analysis, discussion, and evaluation of cutting-edge link prediction techniques in dynamic social networks. Using weighted graph proximity metrics, Murata and Moriyasu (2007) proposed a technique which can enhance the social network's ability to forecast links. The outcome demonstrates that the suggested strategy is superior, particularly when the target social networks are quite dense. To enhance the effectiveness of the forecast, Tan and Pan (2019) proposed an approach that takes the dynamic topology of social networks into account. The methodology uses three metrics: the time-varying weight, the degree of common neighbour change, and the closeness of common neighbour relationships. Popescul and Ungar's (2007) comprehensive strategy proposed using statistical relational learning techniques to create link prediction models. Building regression models using relational database data involves creating prospective predictors through a systematic search of the query space, which are then evaluated to see if they should be included in the logistic regression. In order to increase the accuracy of link prediction, Zhang and Zhang (2019) proposed a weighted directed network link prediction algorithm based on user behaviour information, and investigated the possibility of using user interaction behaviour information as the weight of the weighted network edge.

The previous optimisation techniques, however, are computationally costly and have limitations due to the current similarity index. Traditional link prediction techniques, such as those based on similarity, commonly take advantage of the network topology's common traits and exhibit excellent generalisability. The time-varying qualities, nevertheless, place certain restrictions on them.

2.2 Machine learning-based link prediction

In addition to using traditional similarity-based prediction techniques, deep learning or machine learning are also used to determine the ideal similarity for accurate network link prediction. To anticipate dynamic linkages, Chen et al. (2021) created a unique encoder-LSTM-decoder (E-LSTM-D) deep learning model. This model can handle long-term prediction issues and is suitable for networks of various scales with well-tuned structures. Additionally, it has the ability to automatically learn both structural and temporal information in a single framework, allowing it to anticipate relationships that have never before appeared in the network. The conditional temporal restricted Boltzmann machine (ctRBM) is a brand-new approach to deep learning that Chen et al. (2012) proposed. This approach is based on the variability in individual transitions as well as the neighbourhood effect. Long-short-term memory (LSTM) is a brand-new, effective, gradient-based strategy that Hvitfeldt and Silge (2021) introduced to address the issue that learning to retain information over lengthy time intervals via recurrent backpropagation takes a very long time.

Shao et al. (2019) proposed an approach that combines machine learning and hierarchical representation learning for networks (HARP) to enhance link prediction. The rationale for the proposal is because Node2Vec will neglect the network structure. In order to increase prediction accuracy, Liu et al. (2020) suggested a link prediction technique for weighted dynamic networks that combines statistical modelling and supervised learning. In order to overcome the difficulties of predicting the future picture of the network and analysing the network by calculating all the necessary overall measures, Michalski et al. (2012) proposed a technique that makes use of machine learning technologies to forecast how specific network measures will change in the future.

In order to evaluate the Enron corpus, Klimt and Yang (2004) created a testing platform. Email is automatically categorised into the user's designated folders, and information is extracted from emails that have been arranged in time order. This study examined the relevance to email forecasting and offered a cutting-edge classifier. In order to exchange video input information, Ouyang et al. (2019) proposed a unique MTL architecture that first blends 3D convolution neural networks (CNNs) and LSTM with the MTL process. Their study broke down a movie into numerous pieces and used a hybrid 3D CNN and LSTM model to extract the sequential characteristics from these video snippets. For wireless network problems, Yao et al. (2016) proposed a model based on a hybrid CNN-LSTM prediction model network log (Selvarajah et al., 2020). With the use of fault prediction technology, staff members can plan ahead to rectify problems, speed up the process, and lessen the amount of damage that failures create. An approach called a weighted directed network link prediction is presented by Zhao and Zettsu (2018). The degree to which users engage with one another has a significant impact on link prediction accuracy. In order to weight the network, take into account the user's private information, and analyse their interests, we employ specific interactive behavioural features of social network users.

In the realm of dynamic link prediction, our proposed C3D-LSTM model distinguishes itself by adeptly capturing both structural and temporal dynamics of entire network snapshots, a capability not sufficiently addressed in most existing models. Unlike traditional methods that primarily rely on static similarity indices, C3D-LSTM innovatively integrates 3D convolution with LSTM to process complex spatio-temporal features, enabling a more nuanced understanding of network evolution. This model excels in discerning subtle spatial changes and patterns while capturing long-term temporal dependencies, overcoming the limitations of current models that focus either on static structural features or temporal aspects in isolation. The holistic approach of C3D-LSTM not only enhances prediction accuracy but also offers a comprehensive understanding of network dynamics, setting it apart in both effectiveness and robustness compared to state-of-the-art techniques in dynamic link prediction tasks.

3 Proposed model: C3D-LSTM

In this section, we define the problem and discuss the detail of the C3D-LSTM model for forecasting dynamic network links. The proposed model has the ability to learn the structural and temporal characteristics of dynamic networks in advance of the upcoming addition and removal of links.

Definition 1 (dynamic network): Given a sequence of graphs, $\{G_1, \ldots, G_T\}$, where $G_k = (V, E_k)$ denotes the k^{th} snapshot of a dynamic network. Let U be the set of all users and E_k subset $V * V$. The adjacency matrix of G_k is denoted by A_k with the element $a_{k;i,j} = 1$ if there is a directed link from v_i to v_j and $a_{k;i,j} = 0$ otherwise.

Link prediction in static networks uses the observed distribution of edges to identify the real edges. During the inference phase, dynamic networks, on the other hand, have the ability to adaptively change their structure based on the input samples, giving them significant advantages over static networks. Link prediction in dynamic networks also fully utilises the data retrieved from earlier static networks to examine the network's evolutionary patterns, then uses the observed evolutionary patterns to forecast the network's future state. We utilise the adjacency matrix as the input and output of the prediction model since it is particularly successful at capturing the network topology. A dynamic network's network snapshots are all intimately connected to one another. However, employing a single snapshot G_T for prediction may have the issue of having insufficient data. As a result, we favour using many continuous social network snapshots for prediction. Our objective is to use 3D convolution to extract the structural characteristics of each snapshot network and LSTM to learn the temporal structure.

Definition 2 [dynamic network link prediction (DNLP)]: Given a sequence of graphs with length N, $S = \{G_{t-N}, \ldots, G_{t-1}\}$, DNLP aims to learn a function that maps the input sequence S to G_t. Dynamic networks evolve over time; as shown in Figure 2, new links may appear in the future, and old links may disappear. The main purpose of DNLP is to predict the node or link that will appear and disappear the next time. As an illustration, Figure 2 depicts the network's progression throughout time *T*. We can see that outdated links (1, 2), (3), and (5) vanish and new links (1, 3), (1, 4) arise, each of which is indicated by a red mark.

Figure 2 An example of the evolution of a social network (see online version for colours)

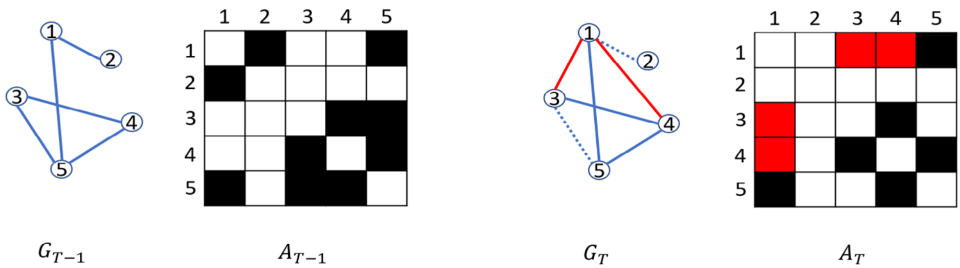
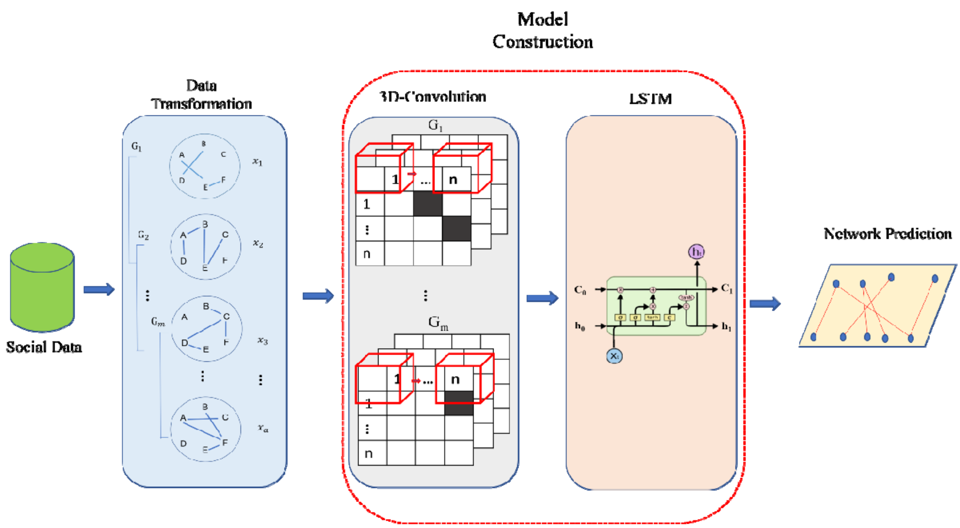


Figure 3 The system architecture of C3D-LSTM (see online version for colours)



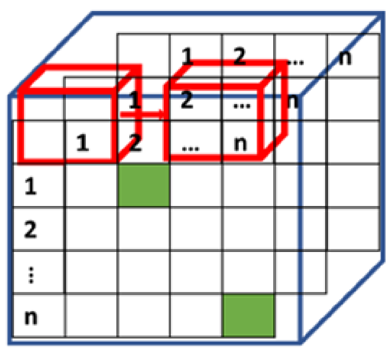
In this study, we propose a distinctive model C3D-LSTM. First, data are categorised using sliding windows, but because the most recent data contain too many zeros, the algorithm will not group each dataset with it. Following clustering, we add the data to the training model for training. There, we utilise 3D-convolution to extract data features for learning; 3D-convolution may extract more features to enhance the training outcome. Using LSTM in this case, we input the prediction region after 3D-convolution to forecast the data's accuracy, and output the AUC value. We did not select RNN since it lacks a gate to remember long-term values, which is why we output AUC to see it all. We discover that when Conv3D receives additional training data, the value will increase.

As the system architecture shows in Figure 3, the proposed C3D-LSTM uses 3D-convolution to learn the social structure of the cell state c and the hidden state h of any given snapshot, and uses LSTM to learn the temporal information of the state of each link. The proposed model is a 3D-convolutional embedded LSTM which translates the extracted feature mapping back to the original space. The projected network will be produced by C3D-LSTM, which will also execute network link prediction. The following section provides the details of the proposed model.

3.1 3D-convolution and LSTM modules of C3D-LSTM

The CNN is a popular model for identifying pictures. When we recognise a picture, we first take note of its structure and dissect it into several forms; CNN bases its model on this process. Convolution layer and pooling layer are two components of CNN that together may significantly lessen the neural network's training workload. In order to extract the features from a picture, the convolution layer divides it into many images after convolution. By doing this, the neural network is not required to receive the feature values of the entire image in order to classify the image, which lessens the burden on the network. Pooling layer is a technique for compressing photos while keeping crucial data. Max-pooling, a technique that employs sliding windows to take feature values and choose the highest value, decreases the amount of data that has to be calculated and the number of parameters that the system needs to compute.

Figure 4 3D-convolution operation of C3D-LSTM on dynamic social networks (see online version for colours)

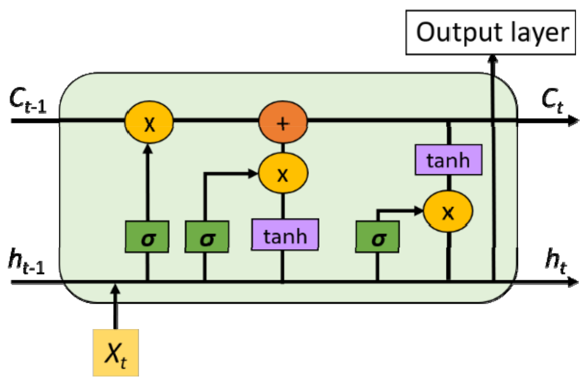


We propose the C3D-LSTM model, which is based on the same principle as the basic CNN but adds a third dimension, to enhance the prediction accuracy in dynamic networks. Convolution in the spatial dimension is known as Conv2D; in 3D-convolution, both space and time are involved. Figure 5 illustrates a convolution block for 3D-convolution. 3D-convolution can be utilised for training more data, extracting more features, and significantly enhancing prediction quality. Hence, C3D-LSTM adopts 3D convolutional filters to capture local features, encodes a list of things into a three-way tensor, and collects high-order interactions in a feedforward fashion. In particular, by adding the straightforward powerful convolution module, we enable interactions between non-adjacent snapshots.

According to the aforementioned system architecture shown in Figure 3, the C3D-LSTM model principally relies on two state values: the cell state *c*, which is used to store the long-term information, and the hidden state *h*, which is used to extract the short-term information of the last output. The key component of C3D-LSTM is that during the forward process, a cell state is present, resulting in a lengthy transmission of information across the cell state. We must take into account how neighbours' hidden states and neighbouring cells affect the hidden state of the node when performing the DNLP job. Since the hidden state and the cell state represent various types of information, respectively, we perform convolution operations on the cell layer state and the hidden layer state using 3D-convolutional models for the next phase.

Then, we introduce another critical module in C3D-LSTM, LSTM, as shown in Figure 3. The primary purpose of LSTM is to address the gradient disappearance and gradient explosion issues that arise during the training of lengthy sequences. The LSTM model can successfully capture long-term temporal correlations of any duration. Through the usage of three separate gates, input gate it, output gate o_t, and forget gate f_t, LSTM successfully maintains long-term dependence. The main unit of LSTM has a memory cell C_t, and the neuron input x_t and output h_t at time step t. We introduce each component and the learning process as follows.

Figure 5 LSTM operation of C3D-LSTM (see online version for colours)



A memory cell candidate and the current input are either added to long-term memory or not via the input gate. In order to write to a memory cell, a neuron's output must first travel through a gate known as the input gate. It is impossible to write content if the input gate is closed, and the neuron network learns when to close it:

$$i_t = \sigma\left(W_i h_{t-1} + U_i x_t + b_i\right) \tag{1}$$

The forget gate decides when to empty and forget the content of the memory cell and when to keep it in place. The preceding words will be filtered out by this valve, for instance, if the current word is a new subject or the opposite of the previous words. On the other hand, it may be preserved in memory, generally by the sigmoid function:

$$f_t = \sigma\left(W_f h_{t-1} + U_f x_t + b_i\right) \tag{2}$$

The output gate controls whether the value from the memory cell can be read by the outside world, and when it is closed, neither the value nor the content of the memory can be read. The new cell state is passed to the tanh function, which multiplies its output by the output of the sigmoid function to determine the information that the hidden state should contain. Finally, the hidden state is output as the current cell, and the new cell state and the new hidden state are transferred to the following time step:

$$o_t = \sigma\left(W_o h_{t-1} + U_o x_t + b_o\right) \tag{3}$$

A memory cell serves as a conduit for the delivery of pertinent information. The memory cell may always hold the message while processing the sequence. Older messages can thus be protected from the negative effects of recent memory:

$$c_t = f_t \circ c_{t-1} + i_t \circ \tilde{c}_t \tag{4}$$

In order to prevent the past output from being forgotten, LSTMs operate in a hidden state where they aggregate previous output, mix it with the current input to obtain the desired result, and then transmit the result to subsequent LSTMs:

$$h_t = o_t \circ \tanh(c_t) \tag{5}$$

3.2 C3D-LSTM model construction

For enhanced accuracy in DNLP, it is imperative to thoroughly train the C3D-LSTM model. This training is designed to align the output probability matrix closely with the adjacency matrix at time t. In regression prediction scenarios, the L_2 distance as shown in equation (6) is commonly used to gauge the similarity between the forecast and the true values:

$$L_2 = \sum_{i=0}^{N} \sum_{j=0}^{N} pow\left(P_t(i, j) - A_t * (i, j), 2\right) \tag{6}$$

$$L = L_2 + \beta L_{reg} \tag{7}$$

In this context, N represents the count of nodes in the snapshot at time t, A_t denotes the actual adjacency matrix at time t, and P_t symbolises the output probability matrix at the corresponding moment. Given the inherent sparsity of the network, relying exclusively on the L_2 distance as the loss function is likely to skew the expected results towards zero. Therefore, we also use a regularisation term called L_{reg} in order to prevent such overfitting to some extent. The whole training process loss is therefore defined as in equation (7) where the best will be discovered throughout the model training process, and is a parameter to trade-off the weighting of L_2 and L_{reg}. By computing the sum of squares of the ownership weight in the C3D-LSTM model, the regularisation loss L_{reg} is determined. We use Adam as our model's optimiser in order to minimise equation (7).

4 Experiments

In this section, we use five real datasets, Contact, Enroll, Radoslaw, Ford, and Toyota, collected by individual connection in real scenarios to evaluate the performance of the proposed C3D-LSTM model, and compare the effectiveness and robustness of the proposed methods with the state-of-the-art models. All real datasets are detailed as follows and are summarised in Table 1.

- Contact Dataset (http://konect.cc/networks/contact/) (Kunegis, 2013): This dynamic network dataset captures human contact through wireless devices, representing close physical interactions. Links between individuals are timestamped, recorded every 20 seconds, allowing multiple connections to be documented simultaneously. The high-frequency data collection in this dataset provides a unique challenge in handling temporal granularity, which is crucial for accurate link prediction in rapidly changing social dynamics.

- Radoslaw Dataset (https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/6Z3CGX) (Rossi and Ahmed, 2015): This is the internal email communication network between employees of a mid-sized manufacturing company. The network is directed and nodes represent employees. The left node represents the sender and the right node represents the recipient. Edges between two nodes are individual emails.
- Enron Dataset (https://www.cs.cmu.edu/~enron/) (Kessler, 2010): Representing an email network of a medium-sized corporation, each node corresponds to an employee, with links formed by email exchanges. The dataset exhibits temporal spikes in email activity, often extending over several days before a sudden drop, possibly due to holidays or weekends. This irregularity in communication patterns presents a challenge in understanding temporal dependencies and interpreting periods of inactivity, which are critical for predicting future links.
- Ford and Toyota Datasets (https://www.mobile01.com/) (Agarwal et al., 2020): Sourced from mobile01, a forum discussing vehicles, these datasets encapsulate user interactions in chat rooms over a decade from 2006 to 2016. We segmented Toyota into 36 time periods and Ford into 40, based on the observation that discussions often span several days. The extended interaction duration in these datasets provides a different temporal challenge, necessitating the model to capture long-term dependencies and changes in communication trends over time.

Table 1 Summarisation of real datasets

Dataset	*#User*	*#Edge*	*#Social graph*
Contact Dataset (http://konect.cc/networks/contact/)	274	391,969	583
Radoslaw Dataset (https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/6Z3CGX)	167	54,891	270
Enron Dataset (https://www.cs.cmu.edu/~enron/)	151	29,369	160
Ford Dataset (https://www.mobile01.com/)	4,042	4,596,824	36
Toyota Dataset (https://www.mobile01.com/)	3,435	2,656,328	40

Each dataset brings a unique set of characteristics that influence the model's performance. The Contact dataset, with its high temporal resolution, tests the model's ability to handle rapid changes in network structure. Enron, with its irregular communication patterns, challenges the model to differentiate between genuine disconnections and temporary inactivity. In contrast, the Ford and Toyota datasets require the model to understand prolonged interaction patterns, essential for predicting links in networks with extended discussions. These varied datasets ensure a comprehensive evaluation of the C3D-LSTM model, highlighting its adaptability and robustness across different real-world social network scenarios.

4.1 Data pre-processing and feature selection

In our study, we meticulously prepared five real-world datasets – Contact, Enroll, Radoslaw, Ford, and Toyota – for link prediction in social networks through comprehensive data preprocessing and feature selection. The pre-processing began with data cleaning to eliminate duplicates, correct inconsistencies, and handle missing values, followed by data transformation to standardise formats across the datasets. We also implemented min-max normalisation to address scale disparities among features, and conducted feature engineering to create new attributes reflective of the dynamic social network interactions. In the feature selection phase, we compare the optimal sequence length in the following experiments to ensure that our model was trained on high-quality, relevant data, enhancing its predictive accuracy and applicability to diverse real-world scenarios.

To show the performance, we compare the proposed C3D-LSTM with several baseline models on well-known evaluation metrics. All implementations are carried out with Python and executed on a workstation with Intel i7-9700 3.0 GHz, 32 GB main memory, and NVIDIA RTX 2080Ti 11 GB GPUs.

- LSTM: A special kind of RNN created to handle the gradient disappearance and explosion problems that might arise while training lengthy sequences. Longer sequences may benefit from LSTM's performance over ordinary RNN.
- Gate recurrent unit (GRU): A development of RNN, GRU is quite comparable to LSTM. The GRU structure gets rid of cell states and conveys information via hidden states. There are just two gate structures, the update gate and the reset gate.
- Conv2D+LSTM: We also employ 2D-convolutional layers along with LSTMs to extract features from input data to aid with sequence prediction. Conv2D-LSTM work focuses on applications that generate text descriptions from image sequences and visual time series prediction problems.

Table 2 Confusion matrix

Actual predict	*Fake (0)*	*Real (1)*
Fake (0)	True positive (TP)	False negative (FN)
Real (1)	False positive (FP)	True negative (TN)

Then, three well-known evaluation metrics are adopted to verify the performance. As the confusion matrix shown in Table 2, precision is the proportion of positive samples with accurate forecasts, whereas recall is the proportion of samples with true facts and those with accurate predictions. Based on Table 2, the precision and recall metrics are defined as equations (8) and (9), respectively:

$$Precision = \frac{TP}{TP + FP} \tag{8}$$

$$Recall = \frac{TP}{TP + FN} \tag{9}$$

For a link prediction method, it may produce scores for unidentified edges mixed with test data and edge sets that do not exist. The formula for calculating is described as:

$$AUC = \frac{n' + 0.5n''}{n} \tag{10}$$

The meaning of this formula is to choose one edge at random from the test set and an empty edge set in that order. Following *n* separate selections, *n* denotes the number of times the test edge's score exceeds that of the hypothetical edge, and *n* is the number of times the test edge's score is equal to the hypothetical edge. AUC for the random edge selection approach is obviously 0.5. As a result, whether or not the prediction algorithm's AUC is considerably more than 0.5 determines how accurate the algorithm is. In other words, AUC shows how well a link prediction algorithm performs in comparison to a random selection method.

4.2 Performance comparison

For the experiments, we assess AUC, precision, and recall for five datasets conducted on LSTM, GRU, Conv2D + LSTM, and C3D-LSTM, respectively. C3D-LSTM employs the kernel size ($3 \times 2 \times 2$, $5 \times 2 \times 2$, and $7 \times 2 \times 2$), where the first dimension represents depth in terms of the total number of snapshots, and the later dimensions are width and height.

In the presented results, as detailed in Table 3, the area under the curve (AUC) metric offers significant insights into the performance of various datasets. Notably, the dataset labelled 'Contact' boasts the highest AUC. This superior performance is attributed to the methodology employed: leveraging the most recent data to predict forthcoming data. An interesting observation is the high AUC for 'Contact' despite the low proportion of encounters.

On the other hand, the Enroll and Radoslaw datasets represent the company's email data. Their performance is influenced by the structured nature of corporate communication, with a set number of working days in a week. This regularity appears to be a limiting factor, causing them to underperform in comparison to Contact, subsequently leading to a reduced AUC. The Ford and Toyota datasets present another intriguing scenario. Despite having a substantial user base, their AUC is compromised. The primary reason for this is the sparsity of their datasets. A dense user population does not necessarily guarantee a high AUC, especially when the data distribution is sparse.

Expanding upon the precision and recall metrics, Tables 4 and 5 offer a comprehensive comparative analysis across the five real datasets. The variance in precision and recall values for Contact in relation to the other datasets is not just evident but also noteworthy. This disparity prompts a deeper dive into the underlying factors that contribute to such outcomes. Contact stands out, not merely due to its superior performance but also because of the inherent stability and consistency of its data. In the realm of data analysis, consistency often translates to predictability, which in turn can lead to better precision and recall. This is evident when comparing Contact with datasets that experience significant data fluctuations. Such datasets, despite their potential richness or volume, often grapple with the challenges posed by these fluctuations. Variability can introduce uncertainties, making predictions more challenging and thereby adversely affecting precision and recall.

Table 3 AUC performance on five real datasets

Dataset	*Contact*			*Enron*			*Radoslaw*			*Ford*			*Toyota*		
Seq. length	*3*	*5*	*7*	*3*	*5*	*7*	*3*	*5*	*7*	*3*	*5*	*7*	*3*	*5*	*7*
LSTM	0.9285	0.9707	0.9737	0.6191	0.7031	0.7098	0.7282	0.7865	0.7673	0.8268	0.8194	0.8105	0.5371	0.5842	0.5672
GRU	0.9341	0.9605	0.9668	0.6888	0.7064	0.7558	0.6147	0.6709	0.7405	0.7781	0.7891	0.8035	0.4870	0.5018	0.5024
Conv2D + LSTM	0.9554	0.9872	0.9881	0.7768	0.8194	0.8601	0.7639	0.7841	0.8265	0.8309	0.8689	0.8761	0.7234	0.7413	0.7395
C3D-LSTM	*0.9989*	*0.9990*	*0.9990*	*0.8164*	*0.8949*	*0.9096*	*0.8295*	*0.8798*	*0.9096*	*0.8815*	*0.8845*	*0.8896*	*0.7403*	*0.7520*	*0.7597*

Table 4 Precision rate on five real datasets

Dataset	*Contact*			*Enron*			*Radoslaw*			*Ford*			*Toyota*		
Seq. length	*3*	*5*	*7*	*3*	*5*	*7*	*3*	*5*	*7*	*3*	*5*	*7*	*3*	*5*	*7*
LSTM	0.4882	0.4951	0.4906	0.1203	0.1741	0.2017	0.1329	0.1273	0.1255	0.0487	0.0381	0.0354	0.0125	0.0129	0.0150
GRU	0.4952	0.5240	0.5167	*0.4952*	*0.5240*	*0.5167*	0.0964	0.1231	0.1261	0.0382	0.0312	0.0220	0.0083	0.004	0.0051
Conv2D + LSTM	0.9682	0.9688	0.9653	0.2155	0.2301	0.2831	0.2318	0.2573	0.2573	0.2401	0.2125	0.1813	*0.0776*	*0.0655*	*0.0641*
C3D-LSTM	*0.9714*	*0.9733*	*0.9712*	0.2524	0.3008	0.3890	*0.3277*	*0.4032*	*0.4160*	*0.2827*	*0.2309*	*0.2895*	0.0644	0.0640	0.0632

Table 5 Recall rate on five real datasets

Dataset	*Contact*			*Enron*			*Radoslaw*			*Ford*			*Toyota*		
Seq. length	*3*	*5*	*7*	*3*	*5*	*7*	*3*	*5*	*7*	*3*	*5*	*7*	*3*	*5*	*7*
LSTM	0.2480	0.4893	0.5010	*0.2410*	*0.3040*	*0.0331*	0.1531	0.1548	0.1562	0.1346	0.1365	0.1201	0.0993	0.1019	0.1005
GRU	0.4949	0.5241	0.5171	0.4949	0.5241	0.5171	0.1458	0.1465	0.1485	0.1654	0.1244	0.1177	0.0893	0.0913	0.0921
Conv2D + LSTM	0.9637	0.9683	0.9716	0.2409	0.2533	0.2922	0.2602	0.2792	0.3305	0.1384	0.1407	0.1400	0.1024	0.1131	0.1166
C3D-LSTM	*0.9715*	*0.9737*	*0.9702*	0.2706	0.2850	0.2736	*0.2853*	*0.2928*	*0.3443*	*0.1657*	*0.1735*	*0.1771*	*0.1088*	*0.1263*	*0.1258*

Furthermore, it is essential to recognise that while a large user base, as seen in Ford and Toyota, might intuitively seem advantageous, it does not always correlate with better predictive outcomes. The sparsity of their datasets underscores an important lesson: the quality and distribution of data often outweigh sheer volume. A densely populated dataset, if not well-distributed, can lead to gaps in information, making predictions less reliable. In concluding our analysis, the findings significantly enrich the understanding of dynamic SNA by demonstrating the crucial role of data characteristics such as consistency, distribution, and quality in predictive modelling. The standout performance of the Contact dataset exemplifies the impact of stable and consistent data in enhancing predictability and accuracy in link prediction, challenging the traditional notion that larger datasets automatically yield better results. This is contrasted by the sparsity in Ford and Toyota, which highlights that a large user base is less effective if the data are unevenly distributed or sparse. Moreover, the structured nature of corporate communication datasets like Enroll and Radoslaw suggests that regular interaction patterns significantly influence model performance. These insights collectively underscore the necessity for tailored predictive modelling in dynamic social networks, advocating for approaches that adapt to the unique characteristics of each dataset rather than applying a one-size-fits-all model. This nuanced understanding not only advances the field of link prediction in social networks, but also provides a valuable framework for future research and practical applications, emphasising the importance of data quality and nuanced model adaptation in the evolving landscape of dynamic SNA.

5 Conclusions

In this paper, we introduce a novel model, C3D-LSTM, for predicting the social interaction in dynamic social networks. Particularly, there are two main components of C3D-LSTM:

1. We use a 3D-convolution feature fusion to elucidate hidden relationships and trends between consecutive social network snapshots. As a result, we could gather short-term spatial and temporal data for network representation.
2. We employ a LSTM-based model as the fundamental framework to learn the long-term temporal network representations of every snapshot of a dynamic network since C3D-LSTM can forecast both freshly formed and cancelled connections, unlike the majority of previous dynamic link prediction systems, which is more useful in real-world applications.

Extensive testing demonstrates that C3D-LSTM outperforms the most advanced methods currently available, and provides outstanding performance. The proposed model better comprehends the pattern of network evolution by capturing not only the time dependency between a series of snapshots but also the influence of the network structure. Finally, using a variety of dynamic network datasets, we ran several tests to compare our C3D-LSTM model against deep-learning network link prediction techniques. The outcomes confirm that our model performs better than the competition in terms of AUC, precision, and recall. In our future work, we aim to enhance the C3D-LSTM model for large-scale dynamic networks, focusing on computational optimisation and parallel processing. We also plan to expand its application to various network types like biological and transportation networks, and integrate advanced deep learning architectures such as transformer models. Additionally, adapting C3D-LSTM to leverage real-time streaming data is a key goal, aiming to improve its real-time predictive capabilities. These efforts will not only refine C3D-LSTM but also contribute significantly to the broader field of network analysis.

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