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Review

A Review of Link Prediction Algorithms in Dynamic Networks

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Abstract: Dynamic network link prediction refers to the prediction of possible future links or the identification of missing links on the basis of historical information of dynamic networks. Link prediction aids people in exploring and analyzing complex change patterns in the real world and it could be applied in personalized recommendation systems, intelligence analysis, anomaly detection, and other fields. This paper aims to provide a comprehensive review of dynamic network link prediction. Firstly, dynamic networks are categorized into dynamic univariate networks and dynamic multivariate networks according to the changes in their sets. Furthermore, dynamic network link prediction algorithms are classified into regular sampling and irregular sampling by the method of network sampling. After summarizing and comparing the common datasets and evaluation indicators for dynamic network link prediction, we briefly review classic related algorithms in recent years, and classify them according to the network changes, sampling methods, underlying principles of algorithms, and other classification methods. Meanwhile, the basic ideas, advantages, and disadvantages of these algorithms are discussed in detail. The application fields and challenges in this area are also summarized. In the final summary of the paper, the future research directions such as link prediction in dynamic heterogeneous weighted networks and the security issues brought about by link prediction are discussed.

Keywords: link prediction; dynamic network; complex network; time series forecasting

MSC: 68R10; 91D30



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1. Introduction

Complex systems that evolve over time in the real world are referred to as dynamic complex systems and can be abstracted as dynamic networks. Dynamic networks serve as an abstract model to describe various phenomena in the real world. It helps us understand the evaluation trends of dynamic systems for network structure optimization and systems design and control. In various fields, such as human society and biomedicine, social networks [1,2], gene networks, and communication networks [3] have become popular research tools [4]. The dynamic nature of networks is reflected in their changes over time. Nodes and edges, respectively, represent entities and the relationships between them [5]. For instance, in dynamic social platforms, nodes represent users, and the presence of edges between nodes indicates the existence of a relationship between users. A research hotspot in dynamic networks is dynamic network link prediction [6,7], which aims to predict the possibility of connections between unconnected node pairs according to the historical network topology, temporal information, and node attributes. As an important component of graph data mining, dynamic network link prediction is often used to mine

potential relationships between entities [8–10], with applications in areas like open-source intelligence mining and analysis.

Early research on link prediction tasks primarily focused on static networks, assuming that the network topology and node attributes would remain unchanged over a certain period. Chai et al. [11] proposed the LRNP algorithm for link prediction on static networks, using the adjacency matrix of a fully connected network as the base matrix for matrix low-rank representation to reveal the interactions between local structures of the fully connected network. They also proposed an optimized algorithm, OLRNP, which refines the observed network structure on account of the optimal interaction coefficient matrix. However, with the development of dynamic complex system theory in recent years, link prediction tasks are more aligned with the changing laws of the real world [12]. This paper, combining recent research achievements in dynamic link prediction, provides a comprehensive review of dynamic network link prediction algorithms.

The rest of this paper is organized as follows. In Section 2, we review relevant theories, common datasets, and evaluation indicators for dynamic link prediction tasks. In Sections 3 and 4, we introduce the classic dynamic link prediction algorithms from recent years and classify and analyze them according to their models. In Section 5, we summarize the related applications of dynamic link prediction. In Section 6, we discuss the existing problems and potential research directions of dynamic network link prediction tasks. Finally, we conclude our work in Section 7.

2. Preliminary Knowledge

This section describes the relevant background knowledge for dynamic network link prediction research. It provides a detailed introduction to the representation methods of dynamic networks and the classification of dynamic network link prediction, offering a general description of the related theories for better understanding. Additionally, this section also introduces common datasets and evaluation indicators.

2.1. Representation of Dynamic Network Data

Dynamic network structures change over time. From the perspective of network evolution, dynamic networks can be categorized into two types based on their changes:

Dynamic Univariate Networks. During the evolution of the network, the number of nodes and links will change over time, while the changes to the attribute set and other sets are ignored. In this case, a dynamic network can be defined as a triplet $G = \{V, E, T\}$, where $V = \{v_1, v_2, v_3, \ldots, v_N\}$ represents the node set, $E = \{e_{12}, e_{23}, e_{34}, \ldots, e_{k,k+1}\}$ represents the edge set, and $T = \{1, 2, 3, \ldots, t, t+1 \ldots\}$ represents the time set.

Dynamic Multivariate Networks. As time evolves, both the node set and the link set change, which could be the number of nodes and links, link weights, node attributes, or other features. According to the characteristics of nodes and edges, they can be divided into dynamic unweighted graphs, dynamic weighted graphs, and dynamic attributed graphs. At this point, a dynamic network can be defined as a quintuple $G = \{V, E, W, A, T\}$, where $V = \{v_1, v_2, v_3, \ldots, v_N\}$ represents the node set, $E = \{e_{12}, e_{23}, e_{34}, \ldots, e_{k,k+1}\}$ represents the edge set, $W = \{W_1, W_2, W_3, \ldots, W_k\}$ represents the edge weight set, $A = \{A_1, A_2, A_3, \ldots, A_N\}$ represents the node attribute set, and $T = \{1, 2, 3, \ldots, t, t+1 \ldots\}$ represents the time set. During the evolution of a dynamic network over the time set T, the node set V, edge set E, edge weight set W, and node attribute set A may all change.

In the actual processing of dynamic network data, because dynamic multivariable networks have more variations in their sets, the process of predicting and dealing with multivariable networks is more challenging compared to dynamic univariable networks. Previous researchers have classified link prediction into transductive and inductive in-

ference tasks, according to whether the node set changes or not. The transductive task aims to infer the connection between historical nodes, and the inductive task could predict relationships between new and existing nodes, as well as between new nodes. Clearly, inductive inference is more challenging to implement than transductive inference. An example of dynamic network evolution is shown in Figure 1.

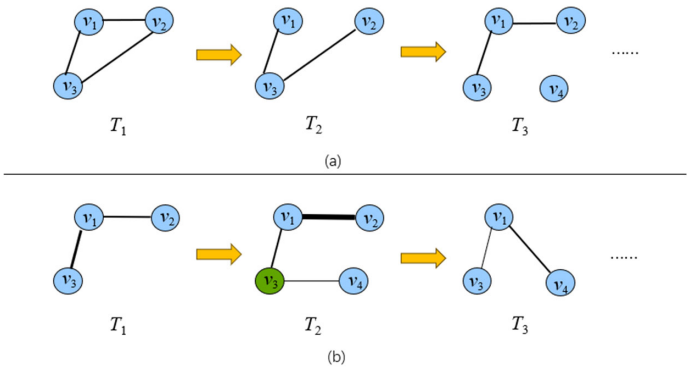


Figure 1. Example of dynamic network evolution. (**a**) is an example of a dynamic univariate network; (**b**) is an example of a dynamic multivariate network, where the thickness of the edges represents the weight of the links, with thicker edges indicating higher weight values; the color of the circle represents the attributes of the node.

2.2. Description of Dynamic Network Link Prediction

In a dynamic network $G = \{V, E, T\}$, let the set of edges Ω represent the collection of all possible links that could exist. And the set $N = \Omega - E$ represents the links that currently do not exist in the network. Dynamic link prediction, based on the known graph set, aims to predict whether node pairs $(i,j) \in N$ in a given period $1 \sim t$ will be connected at a specific moment $t + 1$. Each unconnected node pair (i,j) is going to be assigned a score, with higher scores indicating a greater likelihood of future connection [13]. Generally, a dynamic network is considered as a sequence of graphs, where each graph, also known as a snapshot, represents the network information at a specific moment in time. However, some researchers have pointed out that the segmentation of snapshots ignores the temporal continuity of dynamic networks, which can affect the implementation of various downstream tasks. Figure 2 illustrates the basic process of dynamic network link prediction.

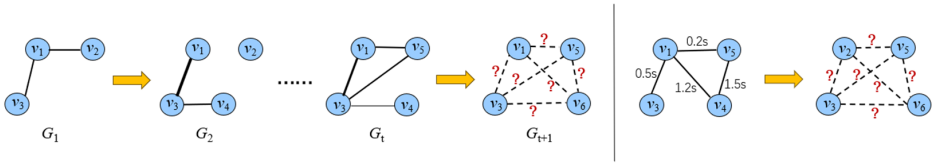


Figure 2. Illustration of the basic process for dynamic link prediction. This figure uses the sampling of a dynamic multivariate network as an example; the sampling of a dynamic univariate network follows the same principle.

The data sampling process in dynamic network link prediction can be roughly divided into two categories: regular sampling and irregular sampling.

a. Regular Sampling. As mentioned before, a dynamic graph consists of sequential snapshots. If the interval between successive shots is manually fixed, this process would be called regular sampling. In the case of multiple graph sequences, the time interval is usually set to the minimum duration of an interaction within the system. However, it could increase complexity [14].
b. Irregular Sampling. Rather than manually setting the interval, the modeling process could be based on new interaction, which is irregular. Continuous-time data sampling

can capture more precise network features for prediction, which helps improve prediction accuracy.

2.3. Common Datasets for Dynamic Network Link Prediction Research

There are numerous dynamic network datasets [15], and in this paper, we present six classical datasets, which are sourced from various fields such as social interaction, communication, and financial transactions. Table 1 lists the basic information of these datasets. Researchers can use these datasets to validate the performance of their algorithms and compare the results with other methods using relevant evaluation indicators.

Table 1. Statistical characteristics of common datasets.

Datasets	$\|V\|$	$\|E\|$	Time Span
CollegeMsg [16]	1899	59,835	193 days
Wiki-Talk [16]	1,140,149	7,833,140	2320 days
MOOC User Action [2]	7047	411,749	seconds
Reddit-Hyperlink [17]	55,863	858,490	40 months
Bitcoin-OTC [18]	5881	35,592	seconds
Email-Eu-core [16]	986	332,334	803 days

CollegeMsg [16]. This network is composed of messages sent by users of the online social networking site at the University of California, Irvine. Users can search for and view each other's profiles to initiate conversations. A message sent by a user to another at a specific moment represents a link between the two nodes.

Wiki-Talk [16]. This network originates from Wikipedia, where users establish relationships by editing each other's discussion pages. Each link represents an instance that a user edited another user's discussion page at a particular moment.

MOOC User Action Dataset [2]. This dataset is derived from user actions on a MOOC platform. Nodes represent users or course activities, and links represent user actions on these activities. Different actions are timestamped in the network.

Bitcoin OTC [17]. This is a Bitcoin trading network, where nodes represent users who trade on Bitcoin websites. A link, with the timestamp, represents a transaction at that moment.

Reddit Hyperlink Network [18]. This network is extracted from posts that create hyperlinks, with each hyperlink connecting a post from the source community to a post in the target community. Each hyperlink carries a timestamp.

Email-Eu-core [16]. This network is generated from email data of a European research institution, containing only the email exchanges among core members of the institution. Nodes represent the members, and each link represents an email sent by a member to another at a specific moment.

2.4. Evaluation Metrics

AUC (Area Under the ROC Curve) [19]. AUC represents the probability that the score of a link in the test set is higher than a link in the collection of non-existent links. It is one of the most used metrics for dynamic network link prediction algorithms. For calculating, there are m times comparisons between the scores of links from the test set and non-existent links set, and the times of a greater score for a test set link is marked as $m\prime$, while m'' means the times for the equal. The details are in Equation (1):

$$AUC = \frac{m' + 0.5m''}{m} \tag{1}$$

Precision [20]. After link prediction, the scores of the predicted links are sorted. Precision is the proportion of correctly predicted links among the top M links in the prediction results. Precision provides a more intuitive indication of the algorithm's predictive per-

formance. If within the first K links, k links are predicted correctly, then the precision is calculated as follows:

$$precision = \frac{k}{K} \tag{2}$$

RS (ranking score). *RS* indicates the rank of the links in the test set within the sorted prediction results. For an irregular sampling graph, the *RS* metric can be influenced by the temporal information of the link flow. For any link q in the test set E^{test}, R_q represents its rank in the sorted results, and N represents the collection of non-existent links in the current network. The ranking score for q is then calculated as $RS_q = R_q/|N|$, and the overall ranking score is computed accordingly

$$RS = \frac{1}{|E^{test}|}\sum_{q \in E^{test}} RS_q = \frac{1}{|E^{test}|}\sum_{q \in E^{test}} \frac{R_q}{|N|} \tag{3}$$

RMSE (Root Mean Square Error) and MAE (Mean Absolute Error) are widely used metrics in weighted dynamic network link prediction. They are based on the Frobenius norm of the error matrix and l_1 norm, respectively, to measure the error between the predicted results $\widetilde{E}$ and the actual results E [21].

3. Unsupervised Learning Methods for Dynamic Network Link Prediction

In recent years, with the increasing complexity of dynamic networks, numerous algorithms have emerged to address the issue of dynamic network link prediction. Unsupervised learning algorithms generally achieve prediction tasks through the network topology and other unlabeled data. Clustering, dimensionality reduction, and some other common tasks belong to the domain of unsupervised learning.

3.1. Random Walk-Based Methods

The primary goal of random walk algorithms is to capture the topological structure information of nodes within the network and embed it into a low-dimensional vector space, without the need for labeled samples. DeepWalk [22] simulates random walks within the network to collect node sequences, which are then used to train the model for the embedded representations of the nodes. Therefore, random walk-based dynamic network link prediction algorithms are unsupervised in generating node embeddings [23].

Time-based random walks on dynamic networks traverse edge sequences in the order of new edge appearance time, making these methods prioritize temporal features. The sequence of random walks represents a feasible route for information to pass through the dynamic network. Each step is based on a certain probability rule. By simulating the paths of random walks within the network, links can be predicted based on the frequency of path occurrence. Zhang et al. [23] proposed an algorithm based on random walks and time aggregation, which performs time-constrained random walks on networks to obtain node sequences. This algorithm does not need manual setting for snapshot intervals. Thereby, it avoids the issue of temporal information lost. After random walks, nearby nodes co-occur with the current node and are thus located within the same sliding window during training. Nguyen et al. [24] proposed a general framework for incorporating temporal dependencies into models based on random walks. It captures temporally valid interactions (such as information flow and disease spread) without any loss. Learning the transient network representation of continuous-time dynamic networks avoids the information loss in the process of approximating a series of discrete static snapshots. To integrate node identity, some researchers have proposed causal anonymous walks (CAWs) [25] for dynamic networks representation. CAWs extract temporal features of the network through time-based random walks, replace node identities with the hitting counts of the nodes based on walk sampling, and establish correlations between them. Random walk avoids the

time-consuming task of repeated sampling during training and ensures the reproducibility of results upon repeated training. One of the main challenges is how to effectively combine the information of the network structure with the rich attribute data of nodes.

3.2. Matrix Calculation-Based Methods

Matrix calculation-based prediction methods often represent the dynamic network as a matrix and then achieve dynamic network link prediction through processing methods such as matrix decomposition or matrix completion. The key to these methods lies in how to effectively utilize the information in the adjacency matrix for capturing the structural and temporal features of the network. In practical applications, preprocessing such as removing closed loops and normalizing the adjacency matrix is required to improve the accuracy and robustness of predictions.

NMF (Non-negative Matrix Factorization), which suits for processing non-negative data, is a classical matrix factorization method. Let A represent the adjacency matrix of the network, and the goal of NMF is to find a non-negative base matrix U and non-negative coefficient matrix V such that $A \approx UV^T$. An example of NMF is shown in Figure 3. Ahmed et al. [26] proposed an NMF-based algorithm for link prediction. This method utilizes novel iterative rules to construct matrix factors with important network features and the convergence and correctness of it is proved. Additionally, it demonstrates that the potential NMF features can effectively express the dynamics of the network, thus producing better performance. Ma et al. [27] addressed the relationship between algorithms based on matrix factorization by proving the equivalence between feature decomposition and NMF algorithms, which provides a theoretical basis for designing dynamic link prediction algorithms based on NMF. Based on this equivalence, a new NMF-based algorithm was proposed. This algorithm factorizes each network, uses graph communicability to obtain features, and then folds the feature matrix to predict links. Lei et al. [28] proposed a novel method, called Adaptive Multiple Non-negative Matrix Factorization (AM-NMF), from the perspective of network embedding. In the NMF framework, this method embeds dynamic networks into a low-dimensional space while preserving all features of different snapshots. It also introduces an adaptive parameter to the model, for automatically adjusting the contribution of different terms and effectively fusing hidden information from different time slices. Correspondingly, the inverse process of NMF in the shared space can generate predictions of future network topology. Ma et al. [29] proposed the Graph Regularized Non-negative Matrix Factorization (GrNMF) algorithm to capture the connections between network slices. GrNMF decomposes matrixes related to the network by setting the rest of the network as regularization, for better characterizing the topology of dynamic links. Predictive models based on matrix processing are widely used due to their solid mathematical foundation. For example, the application of matrix analysis methods in support vector machines, principal component analysis, and singular value decomposition has significantly improved the predictive performance of machine learning [27]. However, matrix computations are more susceptible to the increase in network scale, which could lead to a sharp rise in complexity.

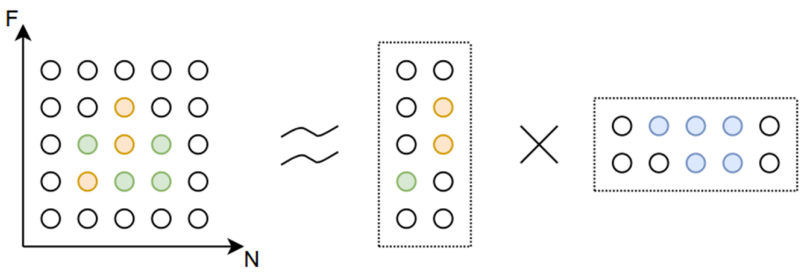


Figure 3. Example of Non-negative Matrix Factorization (NMF). The difference in color represents the difference in the value of the feature.

4. Supervised Learning Methods for Dynamic Network Link Prediction

Supervised learning involves using labeled samples for learning to predict the labels of unlabeled samples. Common supervised learning tasks include classification and regression [21], and supervised learning methods for dynamic network link prediction often use machine learning or deep learning models to determine the labels of unlabeled samples.

4.1. Traditional Machine Learning

Traditional machine learning methods such as logistic regression, support vector machines, and random forests have achieved good results in dynamic network link prediction tasks. They treat link prediction as a binary classification task, dividing it into two categories: links and no links. These methods typically extract features from the network, transform the original network data into high-dimensional feature vectors, and then use classification algorithms for link prediction. Liu et al. [30] modeled systems as dynamic networks to explore the potential relationships and evolution patterns between systems. They establish time series features of dynamic networks based on network topology features and link generation time and combine statistical models with supervised learning methods to predict links on a weighted dynamic network. Singh et al. [31] proposed a PILHNB method for dynamic social network link prediction based on Latent Dirichlet Allocation (LDA) and Hidden Naive Bayes (HNB). It considers behavioral control elements such as relationship network structure, node attributes, node location information, and node popularity, and learns the changing patterns of these factors of the network. Traditional machine learning methods have great generalizability and have been combined with dynamic network link prediction in various practical scenarios. Wen et al. [32] designed a random forest-based algorithm that can predict future vehicle trajectories based on historical traffic data and estimate road carbon emissions. The algorithm can help formulate and implement real-time traffic road management plans. Currently, traditional machine learning methods are relatively mature, providing many options for constructing complete prediction models and facilitating the assembly of various modules. However, they are susceptible to training data and typically require a large amount of labeled data.

4.2. Deep Learning Models

In recent years, deep learning has been widely applied in many fields. Graph Neural Networks (GNNs) [33], as one of the deep learning models, have also achieved remarkable performance in the field of dynamic network link prediction [34–36]. Applying GNNs to dynamic network link prediction tasks can effectively extract non-linear features and capture complex relationships in dynamic networks [37,38]. The concept of GNNs was initially outlined by Gori et al. [33] and further expanded by Scarselli et al. [39] and Gallicchio et al. [40]. To date, GNNs can be divided into four categories: Recurrent Graph Neural Networks (RecGNNs), Convolutional Graph Neural Networks (ConvGNNs), Graph Autoencoders (GAEs), and Spatio-Temporal Graph Neural Networks (STGNNs), with GAEs being an unsupervised deep learning model [41]. In practice, a complete dynamic network link prediction model is typically a combination of multiple GNN models.

GNNs have significant advantages in processing large-scale dynamic network data but are computationally complex. Jiao et al. [42] proposed a dynamic network embedding method that generates low-dimensional embedding vectors for nodes while preserving the non-linear features of dynamic networks. By combining attention mechanisms with RecGNNs, this method can update node representations and maintain the temporal dependence of vectors, which improves its accuracy and efficiency. Pham et al. [43] proposed a dynamic network link prediction method called ComGCN based on RecGNNs and ConvGNNs. ComGCN is a combination of micro-embedding (node-level) and meso-embedding

(community-level), capable of effectively handling link prediction problems in dynamic environments. Kumar et al. [44] developed a Graph Neural Simulator (GNS) hat can learn and predict the flow of systems. A GNS consists of three components: an encoder that embeds particle information into a latent graph, a processor that allows data propagation and calculates node interactions across steps, and a decoder that extracts relevant dynamics from the graph. A GNS updates the state with semi-implicit Euler integration according to predicted acceleration, and a GNS trained on trajectory data has good generalization capabilities. Zheng et al. [45] proposed a transition structure to adaptively personalize node modeling and capture node dynamics. This method constructs a two-layer graph structure: an explicit interaction graph and a sequential interaction graph of nodes. It encodes the transition structure through multi-step transition propagation and extracts effective information from the neighborhood with dual GNNs. The schematic diagram of ConvGNNs is shown in Figure 4.

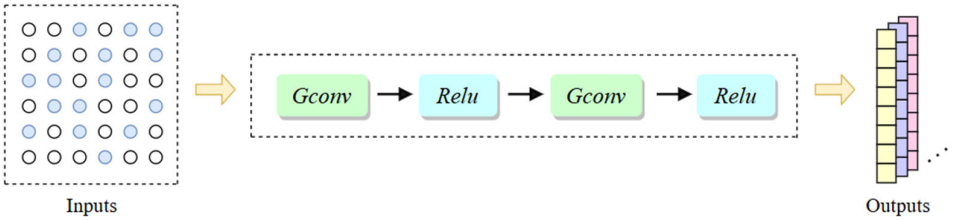


Figure 4. Schematic diagram of Convolutional Graph Neural Networks (ConvGNNs).

RecGNNs, as one of the models for processing sequential graph data, are often used to handle dynamic network data. Similar to RecGNNs are Long Short-Term Memory networks (LSTM) and Gated Recurrent Units (GRUs). Researchers frequently combine the structures of LSTM or GRUs with GNNs to form a new model for processing time series data with graph structures, which can significantly improve the accuracy of predictions. Chen et al. [46] proposed a deep learning model called Encoder–LSTM–Decoder (E-LSTM-D) for predicting dynamic links. This model can automatically learn structural and temporal features within a unified framework, enable the prediction of links that have never appeared before, and it is applicable to networks of different scales. Chen et al. [47] proposed GC-LSTM for dynamic network link prediction based on ConvGNNs and LSTM. LSTM serves as the main framework for learning the temporal features of all snapshots, while GCNN is used to capture the local structural attributes of nodes and their relationships for each snapshot. Spatial–Temporal Graph Neural Networks (STGNNs) combine the capabilities of GNNs and time series analysis to process spatial–temporal data [48]. Min et al. [49] designed a GNN framework called Spatio-Temporal Graph Social Network (STGSN), which models dynamic social networks from both spatial and temporal perspectives. It utilizes ConvGNNs to extract structural features of dynamic social networks and designs a method to analyze the distribution of temporal attention to capture temporal features of dynamic social networks through a temporal attention mechanism. The illustration of STGNNs is shown in Figure 5.

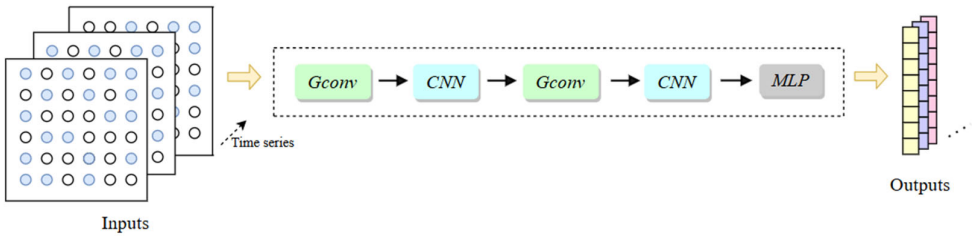


Figure 5. Illustration of Spatio-Temporal Graph Neural Networks (STGNNs).

One of the main challenges in modeling dynamic networks is how to effectively encode structural and temporal information into non-linear and continuous dynamic embeddings. To address this challenge, Chang et al. [50] proposed a model called Dynamic Message Passing Neural Network (TDIG-MPNN), which is for Temporal-Dependent Interaction Graphs (TDIGs). TDIG-MPNN captures fine-grained information of TDIGs and incorporates a selection mechanism composed of a co-attention mechanism and gating units to improve prediction performance. Yu et al. [51] proposed a Transformer-based method—DyGFormer. It learns from the first-order historical interactions of nodes in two ways: exploring neighbor co-occurrence encoding schemes based on the historical sequences of source and target nodes and dividing each sequence into multiple blocks and feeding them into the Transformer, which allows the model to benefit effectively from longer historical sequences. Wen et al. [52] designed a framework called TREND for dynamic network modeling, which integrates temporal events and dynamic nodes to capture local and global features, thereby improving the accuracy of dynamic modeling. It also combines the Hawkes process to capture the interplay between events.

In addition, many methods target more complex network data for link prediction [53,54], such as dynamic weighted networks and dynamic heterogeneous networks. Qin et al. [55] designed a new Inductive Dynamic Embedding Aggregation (IDEA) method. IDEA combines the traditional error minimization objective with the scale difference minimization objective to generate high-quality weighted snapshots that differentiate between large, small, and zero weights in the adjacency matrix. IDEA includes a generator and a discriminator that follow an encoder–decoder framework. Wei et al. [56] designed a Neighbor-Enhanced Representation Learning for Link Prediction in Dynamic Heterogeneous Attributed Networks (NeiDyHNE) method. NeiDyHNE learns information about common neighbors and neighbor interactions in dynamic heterogeneous networks to maintain the proximity of neighbors and common neighbors. NeiDyHNE consists of a hierarchical structural attention module and a convolutional temporal attention module. The hierarchical structural attention module captures the rich features and semantic structure of nodes, and the convolutional temporal attention module captures the evolutionary features of the network over time in dynamic heterogeneous networks, which encodes the attributes of nodes, neighborhood structure, and the evolutionary features of dynamic networks.

In practical problems, many algorithms may integrate various methods based on the characteristics of different methods, the needs of the actual problem, and the features of datasets. Therefore, the design of dynamic network link prediction algorithms depends on various factors such as the specific application scenarios and network characteristics. A comparative classification of classic dynamic network link prediction algorithms is shown in Table 2.

Table 2. Comparison of classic dynamic network link prediction algorithms.

Algorithm Classification		Sample Type	Network Data	Literature Examples	Advantages	Disadvantages
Unsupervised	Random walk	irregular	Dynamic univariant network	[23,24]	(1) Great transferability; (2) Low computational complexity	Not suitable for large-scale networks, in which it will lead to unstable prediction accuracy
			Dynamic multivariant network	[25]		
	Matrix processing	regular	Dynamic univariant network	[26–29]	(1) Solid mathematical theoretical foundation; (2) Developed matrix calculation and easy programming	(1) Higher computational complexity; (2) Vulnerable to sparse matrix constraints

Table 2. *Cont.*

Supervised	Traditional machine learning	regular	Dynamic univariant network	[30]	(1) (2)	There are many machine learning methods and it is easy to combine complete prediction models; Some traditional machine learning models are highly interpretable	(1) (2)	Easily affected by training data; More data annotation needs
			Dynamic multivariant network	[31]				
	Deep learning model	regular	Dynamic univariant network	[43]	(1) (2) (3)	Ability to automatically learn complex features; End-to-end learning can be realized, and model construction is simpler; More adaptable to more complex network	(1) (2)	More computing resources needs; Poor interpretability of internal decision-making process
			Dynamic multivariant network	[46–48,52,53]				
		irregular	Dynamic univariant network	[42,50]				
			Dynamic multivariant network	[49,51]				

5. Applications

Dynamic network link prediction has been widely applied in various fields, even playing an indispensable role in some areas. This paper categorizes these applications into three types based on their purposes and motivations: traditional applications based on prediction, security applications based on the inverse process of prediction, and other interdisciplinary applications based on prediction.

5.1. Traditional Applications

Dynamic network link prediction is often used to predict user trajectories on online social platforms. One of the traditional applications based on prediction is the recommendation system. In recommendation systems, not only can explicit data provided directly by users (such as likes and ratings) be used, but also implicit access in the form of click data and behavioral pattern data can be obtained [57]. For online systems, users' historical behaviors, including habits and daily trajectories, could be the input of prediction models, and the output would be the personalized recommendations, such as products, videos, and articles, for the user [58,59]. In recent years, more research has been conducted on mining implicit data in recommendation systems based on dynamic network link prediction [60–62], analyzing and predicting user personalities and behaviors to understand their preferences. The advantage is that it can more quickly and accurately reflect changes in user preferences in recommendation systems [63].

5.2. Security Applications

Dynamic network link prediction has been widely used in many complex scenarios and is often employed to mine potentially valuable associations within networks [64]. However, it can also be used by malicious attackers to mine sensitive links in networks, leading to unnecessary losses, such as the leakage of users' privacy. Therefore, in recent years, research on the security of link prediction has attracted the attention of many researchers, and more researchers have begun to design privacy protection methods against link prediction attacks, which is also an important application of dynamic link prediction [65]. Privacy protection methods aim to reduce the predictive probability of sensitive links through techniques such as structural perturbation, K-anonymity, and differential privacy, thus achieving a certain level of security. Currently, research in this field can be roughly divided into three categories based on different research perspectives: privacy protection, robustness analysis, and anti-defense [66].

5.3. Other Interdisciplinary Applications

Most link prediction applications are based on the purpose of prediction [67]. However, there are some applications that can provide more practical value than just predicting links, one of which is anomaly detection [68]. Detection is the process of monitoring, identifying, and discovering hidden entities behind network structures. Anomaly detection is applicable

to dealing with security-related issues. For example, if the information provided by a user is maliciously fabricated, it could create fake accounts and pose security threats to the network and other users [69]. To ensure the security of dynamic social networks, researchers have proposed several methods based on link prediction to detect fake users in dynamic social networks. Kagan et al. [70] proposed an efficient fake profile detection algorithm that uses link prediction in dynamic social networks. The algorithm designs a two-layer meta-classifier that can detect abnormal vertices, using only features extracted from the network topology. It identifies abnormal vertices according to the reasoning hypothesis that vertices with more non-existent links are more likely to be abnormal. Teng et al. [71] achieved anomaly detection on dynamic attributed graphs by obtaining time features from time series data. Anomaly link detection still has much room for development and requires further research to resist other security issues.

In addition, dynamic network link prediction is widely used in fields such as gene regulatory network analysis and traffic flow analysis and can also be used for real-time network monitoring and early warning through prediction. Its application depends on the availability and type of network data as well as the accuracy and robustness of the prediction models. Applications are not limited to the aforementioned fields; in practical applications, dynamic link prediction models need to be designed in conjunction with specific domain issues and data to achieve the best application effects.

6. Challenges

Although current research based on dynamic networks has achieved many practical results [72–74], there are still many unresolved issues, and it faces many unresolved challenges. This paper discusses several urgent issues in this field from different perspectives.

Network Feature Fusion. With the widespread existence of the internet and various online platforms in human society, biomedicine, and other scenarios, the extracted network features are also increasing, such as dynamics, multi-layeredness, and heterogeneity. Although some researchers have proposed link prediction methods for dynamic multi-layer networks, dynamic heterogeneous networks, and dynamic attributed networks [75], there are still issues in these methods such as coarse fusion methods, unconsidered complexity, and room for improvement in accuracy. These issues are challenges that need to be faced and resolved in the next step.

Causal Relationships of Links. Causal inference on graphs can be used to assess the impact of advertisements on users' purchase decisions on online shopping platforms and to provide constructive advice for job seekers. The unique advantages of causal inference on graphs can enhance the understanding of causal relationships in complex networks [76]. In causal relationships, the cause leads to the effect, and the effect depends on the cause. Causal inference is the process of drawing conclusions about causality based on the conditions under which the effect occurs [77]. Knowledge graphs corresponding to the causal relationships between different factors can be constructed. Nowadays, due to their complex semantic structure, knowledge graphs are often used to study causal inference, helping to assess the risk level of cities, predict the occurrence of forest fires, and determine traffic congestion, all of which are closely related to the causal relationships established by links in dynamic networks. Pan et al. [78] proposed a dynamic network link prediction framework based on causal inference, CLIP, to address the limitations of existing methods in handling missing attributes, structural bias, and cross-network generalization. By eliminating structural bias and using sub-structural features as interventions, it predicts the potential future connections of unobserved nodes. However, challenges such as modeling and evaluation remain in this field, including the design of assumptions in causal models and the types of causal relationships, which require more comprehensive consideration.

Interpretability of Models. The application of deep learning has advanced the development of dynamic network link prediction, but the interpretability of deep learning models is not yet fully resolved. The lack of interpretability limits the understanding of their internal mechanisms. For example, there has been little research on explaining black box models in GNN architectures. Some researchers have attempted to explain the contribution of features to prediction accuracy based on game theory [79]. However, there is still no unified and comprehensive explanation or consensus on the impact of each feature on the prediction results. Rossi et al. [80] designed an interpretability framework that attempts to explain predictions by identifying combinations of facts that lead to predictions, extracting two complementary types of explanations: sufficient and necessary. Overcoming this challenge requires researchers to have a comprehensive knowledge system and thorough consideration.

Privacy and Information Security Issues. In recent years, the frequent exposure of privacy breaches reflects the neglect of sensitive information protection in the public network space [81]. The continuous improvement in dynamic network link prediction implies an increase in data mining capabilities. To ensure a safer and cleaner network space and prevent malicious attackers from disrupting the network environment, sensitive information in the network should be protected with emphasis [82]. Most researchers have developed defense strategies for static network link prediction [83–85], but there are few defense strategies for dynamic network link prediction attacks, although dynamic attacks tend to be more destructive and threatening to cyberspace.

Increasing Complexity. The gradual rise in network size presents new challenges in terms of time and space complexity for link prediction, especially in dynamic networks where the presence of time series inherently increases complexity. Then, the gradual increase in network size will further exacerbate the rise in complexity. Therefore, designing efficient prediction algorithms is one of the key tasks for researchers in this field, and scalability challenges demand efficient algorithms and interdisciplinary collaboration.

7. Conclusions

On the basis of previous research, this paper summarizes the recent advancements in dynamic network link prediction. We elaborate on the basic concepts and related theories of dynamic network link prediction and review the current classic methods and classifications of it from both unsupervised and supervised learning perspectives, analyze strengths and weaknesses of each algorithm, summarize common datasets and evaluation metrics, and discuss the applications and challenges of dynamic network link prediction. Dynamic network link prediction algorithms can facilitate deeper research into mining potential information in complex networks and analyzing network evolution mechanisms. However, due to the time-varying nature of complex systems in the real world, the complexity of dynamic networks continues to increase, presenting significant challenges for researchers. In future, it is necessary to research link prediction on more complex dynamic networks, such as dynamic heterogeneous weighted networks. The security issues brought about by dynamic network link prediction should receive more widespread attention that promotes further development in this field.

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