Effects of Strong and Weak Ties on Dynamic Link Prediction for Knowledge Diffusion in Disciplinary Citations: Postprint

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Date: 2023-04-01T16:02:52+00:00

Abstract

[Purpose/Significance] Strong and weak ties constitute one of the important factors influencing dynamic link prediction in interdisciplinary citation knowledge diffusion. Strong and weak citation ties in interdisciplinary knowledge diffusion mutually coordinate and influence each other, jointly promoting knowledge exchange, integration, and innovation among disciplines. The exploration of strong and weak tie effects in dynamic link prediction for interdisciplinary citation knowledge diffusion can provide theoretical and practical references for expanding the application scenarios of strong and weak tie theory, revealing the micro-evolutionary mechanisms of interdisciplinary citation knowledge diffusion behavior, and evaluating, designing, and optimizing dynamic link prediction algorithm metrics.

[Method/Process] Based on the concept of internal-external synergy, we construct a detection method for strong and weak tie effects in dynamic link prediction that combines external network structure regulation with internal micro-evolutionary mechanism analysis. From three dimensions—adjustment of interdisciplinary citation knowledge association weights, edge failure triggering, and strong and weak tie motif analysis—we investigate the strong and weak tie effects in dynamic link prediction for interdisciplinary citation knowledge diffusion based on common neighbor similarity.

[Results/Conclusions] Strong ties play a more important role in the evolution of interdisciplinary citation knowledge diffusion networks and the dynamic link prediction process. The strong and weak tie phenomena in link prediction are not only related to interdisciplinary citation association weights but are also influenced by the number of common neighbors and network micro-motif structures. The absorption and integration capacity of knowledge recipient disciplines demonstrates a more dominant role in the new link derivation process compared to the spillover and radiation capacity of knowledge source disciplines.

Full Text

Influence of Strong and Weak Ties on Dynamic Link Prediction in Disciplinary Citation Knowledge Diffusion Networks

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Abstract

[**Purpose/Significance**] Strong and weak ties represent a crucial factor affecting dynamic link prediction in disciplinary citation knowledge diffusion networks. Strong and weak citation ties in disciplinary knowledge diffusion interact synergistically and mutually influence each other, jointly promoting knowledge exchange, integration, and innovation across disciplines. Exploring the effects of strong and weak ties in dynamic link prediction for disciplinary citation knowledge diffusion can provide theoretical and practical references for expanding the application scenarios of strong/weak tie theory, revealing micro-evolutionary patterns of disciplinary citation knowledge diffusion behavior, and evaluating, designing, and optimizing dynamic link prediction algorithmic indicators.

[**Method/Process**] Grounded in the concept of internal-external synergy, this study constructs a detection method for strong and weak tie effects in dynamic link prediction that combines external network structure regulation with internal micro-evolution mechanism analysis. Specifically, the influence of strong and weak ties on dynamic link prediction of disciplinary citation knowledge diffusion is systematically examined from three dimensions: adjustment of disciplinary citation knowledge association weights, link failure triggering, and strong/weak tie motif analysis, all based on common neighbor similarity.

[**Results/Conclusions**] The research demonstrates that: (1) strong ties play a more important role in the evolution of disciplinary citation knowledge diffusion networks and dynamic link prediction processes; (2) the strong/weak tie phenomenon in link prediction is not only related to disciplinary citation association weights but also influenced by the number of common neighbors and network micro-motif structures; and (3) compared with the spillover radiation capacity of knowledge source disciplines, the absorption and integration capacity of knowledge destination disciplines assumes a more dominant position in the process of new link derivation.

Keywords: disciplinary citation knowledge diffusion; strong and weak ties; weight adjustment; link failure; triad motif; dynamic link prediction

Classification Number: G250
DOI: 10.13266/j.issn.0252-3116.2021.13.007

1. Introduction

In 1973, American sociologist M.S. Granovetter proposed the weak tie theory [1]. In traditional societies, contact with one's closest associates represents a stable yet limited form of social cognition, termed the "strong tie" phenomenon, where strong tie relationships indicate high levels of interaction between actors. Simultaneously, a broader but relatively superficial form of social cognition exists—the "weak tie" phenomenon. Although less robust than strong ties, weak ties exhibit low-cost, high-efficiency transmission characteristics [1-2]. Strong ties maintain high-cohesion interactive associations within network communities, enabling bilateral actors to obtain stronger support more easily and effectively transmit complex information and tacit knowledge than weak ties [3]. However, strong ties may also lead to information redundancy and closure. In contrast, weak ties, while unstable, connect broader ranges and feature obvious resource heterogeneity among actors, enabling the transmission of non-redundant new knowledge and information across different communities. Weak ties play important roles in knowledge transfer, organizational innovation, and information flow [4-7].

In disciplinary citation knowledge diffusion networks, interaction strength and types between nodes also exhibit certain differences, manifesting as disciplinary citation strong ties and weak ties. Edges with larger citation frequencies (i.e., greater association weights) belong to strong ties, while those with smaller frequencies constitute weak ties. Strong and weak citation ties coordinate and influence each other, jointly promoting knowledge exchange, integration, and innovation among disciplines.

As disciplinary citation knowledge associations evolve continuously over time, a key challenge lies in how to accurately predict future citation links between disciplines based on current network information—namely, the dynamic link prediction problem in disciplinary citation knowledge diffusion. This capability provides powerful support for understanding disciplinary knowledge flow trends and assisting disciplinary knowledge management decisions. The core of predicting future links lies in grasping network evolution patterns, where changes in network micro-structures (especially strong/weak tie patterns) play crucial roles. Motifs, defined as frequently occurring local connection patterns in networks [8], serve as important micro-structures whose evolutionary characteristics can objectively reveal changes in network structural features [9]. Accurately understanding the evolutionary patterns of strong/weak tie micro-structures and analyzing micro-motif trends can more effectively predict overall network evolution directions, thereby facilitating link prediction algorithm design and improvement.

Existing research presents conflicting findings: some studies find that strong ties with larger weights play greater roles in link prediction (strong tie effect) [10], while others discover that weak ties with smaller weights play more important roles (weak tie effect) [11]. Previous research indicates that when predicting disciplinary citation knowledge diffusion evolution networks, some algorithmic indicators show improved prediction performance after considering weights, while others do not, suggesting the existence of strong/weak tie effects to varying degrees [12]. This demonstrates that strong and weak ties constitute an important factor influencing dynamic link prediction in disciplinary citation knowledge diffusion. Exploring these effects can expand application scenarios for strong/weak tie theory, reveal micro-evolutionary patterns of disciplinary citation knowledge diffusion behavior, and provide theoretical and practical references for evaluating, designing, and optimizing dynamic link prediction algorithmic indicators.

2. Literature Review

Current research on strong and weak ties in link prediction includes several notable contributions. T. Murata et al., based on the assumption that network topology and connection weights can better estimate node proximity, introduced an improved link prediction method using weighted proximity measures and validated its effectiveness on dense social networks [10]. L.Y. Lü et al. introduced adjustment parameters into weighted network link prediction indicators to explore the roles of strong and weak ties, providing semi-quantitative explanations through motif analysis [11]. H. Liu et al. proposed a link prediction model based on common neighbor centrality and weak ties, with empirical studies demonstrating its superiority over CN, AA, and RA algorithms [13]. N. Sett et al. examined the influence of connection weights on node proximity-based link prediction methods using additive, minimum-flow, and multiplicative models across ten different characteristic datasets, finding that model performance varied depending on the prediction method and dataset [14]. K.K. Shang et al. proposed a direct link prediction algorithm that improved accuracy on evolving networks, revealing that common neighbor count plays an important role in weak tie formation [15]. B. Liu et al. developed a general framework combining null models to quantify the effects of topology and weight distribution on link prediction in weighted networks [16]. K.J. Chen et al. designed a new link prediction method called iBridge that effectively identifies bridge connections, compensating for traditional methods' lower accuracy in predicting weak ties compared to strong ties [17].

In summary, while existing research has achieved considerable progress, several limitations remain: (1) Most discussions on strong/weak tie effects in link prediction focus on static networks such as aviation, collaboration, social, and neural networks, with few studies addressing dynamic, time-evolving disciplinary citation knowledge diffusion networks; (2) The examination of link prediction indicators is incomplete, with the impact of citation association strength on dynamic link prediction algorithm robustness remaining unclear; and (3) The relationship between strong/weak tie phenomena in link prediction and network micro-link evolution characteristics (especially in directed networks) is not well understood. Therefore, the influence of strong and weak ties on dynamic link prediction in disciplinary citation knowledge diffusion networks requires further investigation.

Based on these research gaps, this study addresses three key questions: What role does strengthening or suppressing disciplinary citation association weights play when using different algorithmic indicators for knowledge diffusion dynamic link prediction? How does the absence of citation ties with different weights affect prediction algorithm accuracy? What link tendencies exist between two disciplines with different strong/weak citation association patterns with neighbor disciplines? And what insights do evolutionary patterns of disciplinary citation knowledge diffusion behavior offer for evaluating, designing, and optimizing dynamic link prediction algorithmic indicators?

To address these questions, this paper constructs a detection method for strong and weak tie effects in dynamic link prediction based on internal-external synergy (dual-driven by internal causes and external manifestations). This method combines external network structure regulation with internal micro-evolution mechanism analysis, systematically examining strong/weak tie effects in disciplinary citation knowledge diffusion dynamic link prediction based on common neighbor similarity from three dimensions: weight adjustment, link failure triggering, and strong/weak tie motif analysis.

3. Research Design

The research framework for investigating strong and weak tie effects in disciplinary citation knowledge diffusion dynamic link prediction is illustrated in Figure 1 [Figure 1: see original paper]. The process is divided into two major modules across three stages: external network structure regulation and internal micro-evolution mechanism analysis. The external regulation module includes two stages—disciplinary citation knowledge association weight adjustment and link failure triggering analysis—while the internal analysis module corresponds to the strong/weak tie motif analysis stage. Specifically:

(1) **Weight Adjustment-Based Analysis**: Building upon common neighbor similarity link prediction indicators for directed weighted networks, parameter α is introduced to adjust disciplinary citation knowledge association weights, measuring how regulated strong/weak ties affect prediction effectiveness.

(2) **Link Failure-Based Analysis**: Employing a weight-differentiated link failure strategy, edges are selectively removed from disciplinary citation knowledge diffusion networks according to weight magnitude, revealing strong/weak tie effects on algorithm robustness from a deficiency perspective.

(3) **Temporal Evolution Network Motif Analysis**: Starting from micro-evolution in temporal networks, triad motif analysis is conducted to calcu-

late connection ratios of strong/weak tie transmission triad motifs, revealing fundamental mechanisms of disciplinary link formation under different weight influences to support algorithm evaluation and optimization.

3.1 Dynamic Link Prediction Process In disciplinary citation knowledge diffusion network G, nodes represent disciplines and edges represent citation knowledge connections between them. Over time, disciplines and their knowledge associations undergo dynamic changes. Using the network at time t (G) as the training network, a link prediction algorithm assigns a similarity value S to each discipline pair (x, y), representing the potential for future citation knowledge links. Larger S indicates higher likelihood of knowledge diffusion behavior through literature citation between the discipline pair [18]. Using the network at time t+1 (G $_1$) as the test network, the AUC evaluation metric for dynamic link prediction in disciplinary citation knowledge diffusion networks [12, 19] measures the probability that similarity values of newly added edges in G $_1$ (i.e., edges newly derived in G $_1$ that did not exist in G) are higher than those of any non-existent edge in G $_1$, thereby evaluating overall algorithmic performance. To ensure stability, iterative predictions are performed at one-year intervals for q iterations (from initial time t_0 to terminal time t_q), calculating precision values AUC_1, AUC_2, …, AUC_q and selecting appropriate statistical parameters based on their distribution characteristics [12].

3.2 Weight Adjustment-Based Effect Analysis Previous research on the applicability of different link prediction indicators in disciplinary citation knowledge diffusion evolution networks showed that the LHN-I indicator performed worst with lowest stability, making it unsuitable for dynamic link prediction [12]; thus, it is excluded from this study. The parameterized weighted common neighbor similarity link prediction indicators for disciplinary citation knowledge diffusion networks are presented in Table 1 .

In Table 1, for disciplines x, y and their common neighbor z, Γ (x) represents the out-neighbor set of discipline x, and Γ (y) represents the in-neighbor set of discipline y. w (x,z) denotes the weight of knowledge diffusion connection from discipline x to z (i.e., citation frequency of x by z), w (z,y) denotes the weight from z to y, and w(x,y) denotes the weight from x to y. S (x) = Σ_{z Γ (x)} w (x,z)^α represents the sum of adjusted weights of knowledge diffusion connections from discipline x to its neighbors, S (y) = Σ_{z Γ (y)} w (z,y)^α represents the sum of adjusted weights from y's neighbors to y, and S (z) = Σ_{z Γ (x) Γ (y)} w (z)^α represents the sum of adjusted weights from common neighbor z to its neighbors.

When $\alpha = 0$, the indicators reduce to unweighted forms; when $\alpha = 1$, they become standard weighted forms. When $\alpha < 0$, weak ties play more important roles in link prediction; when $\alpha > 0$, strong ties are more important. Larger absolute values of α indicate more significant strong/weak tie effects.

3.3 Link Failure-Based Effect Analysis Disciplinary citation knowledge diffusion networks belong to the category of complex networks, where their heterogeneous topological structures determine that each knowledge diffusion link possesses varying degrees of importance. The failure of high-value links (with high knowledge load or high centrality) can cause connected disciplines to lose direction, altering network structure and knowledge transmission performance [20], thereby affecting the performance of dynamic link prediction algorithms that rely on topological information. This study employs a weight-differentiated link failure strategy to reveal strong/weak tie effects on prediction accuracy from a deficiency perspective, examining the ability to maintain predictive effectiveness.

Link failure refers to the selective removal of edges from disciplinary citation knowledge diffusion networks according to specific rules. Weight-differentiated link failure specifically involves removing edges based on weight magnitude. Two strategies are implemented:

(1) **Strong Tie Failure**: Edges are sorted by citation frequency (weight) from high to low and removed sequentially from strong to weak.

(2) **Weak Tie Failure**: Edges are sorted by citation frequency from low to high and removed sequentially from weak to strong.

For a selected link prediction algorithm, the same proportion of disciplinary citation edges (10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90%, 100%) is removed under both strategies, creating knowledge diffusion blocking networks G and G _w. These serve as training networks, with the complete disciplinary citation knowledge diffusion network G_1 as the test network. AUC values are calculated to compare performance differences caused by strong versus weak tie absence.

3.4 Temporal Evolution Network Motif Analysis Dynamic link prediction algorithms based on common neighbor similarity primarily depend on network topological information, with their effectiveness largely determined by whether algorithmic design captures target network structural features and evolution patterns [21]. Disciplinary citation knowledge diffusion networks change over time, reflected in citation patterns between disciplines and structural feature transformations. These structural features are mainly influenced by citation behaviors, which form certain micro-structures—triad motifs [8]. In disciplinary citation knowledge diffusion networks, 16 types of triad motifs are possible [22], as shown in Figure 2 [Figure 2: see original paper].

Each category is represented by 3-4 numbers/letters: the first digit indicates the number of reciprocal pairs in the triad motif; the second digit indicates the number of asymmetric pairs; the third digit indicates the number of null pairs; and the final letter (if needed) distinguishes similar motifs: "T" for transitive, "C" for cyclic, "D" for downward, and "U" for upward relationships [23].

For a triad motif composed of disciplines x, y, and z, if discipline z cites discipline x (i.e., knowledge from x flows to z through literature citation) and discipline y cites discipline z (i.e., knowledge from z diffuses to y through citation), regardless of whether disciplines x and y have direct citation association, it is termed a transitive triad motif. Transitive triad motifs form the prerequisite for dynamic link prediction using common neighbor similarity indicators.

Based on citation frequency, edges in transitive triad motifs can be divided into two categories: strong and weak ties. According to the weight distribution in disciplinary citation knowledge diffusion networks, a threshold m is established: edges with unidirectional citation counts $\geq$ m are strong ties, while those $<$ m are weak ties. Four types of strong/weak tie transitive triad motifs exist (ss, ww, sw, ws), as shown in Figure 3 [Figure 3: see original paper]. In the figure, thick lines between disciplines x→z and z→y represent strong ties, thin lines represent weak ties; dashed lines indicate possible connections; and solid lines from x→y represent actual knowledge spillover through citation.

These four motif types reflect citation knowledge associations between neighbor discipline z and source/destination disciplines x and y from a strong/weak tie perspective: (1) **ss** (strong-to-strong): intermediary discipline z has strong citation associations with both knowledge source x and destination y; (2) **ww** (weak-to-weak): z has weak associations with both x and y; (3) **sw** (strong-to-weak): source x has strong association with z, while z has weak association with destination y; (4) **ws** (weak-to-strong): source x has weak association with z, while z has strong association with destination y.

In dynamic link prediction, if strong ties are more important, then for ss-type motifs (two strong connections via z), disciplines x and y should have higher connection probability. Conversely, if weak ties dominate, ww-type motifs (two weak connections) should show higher connection probability. Based on this, P , P , P , and P represent the ratios of direct citation knowledge diffusion associations between disciplines with common neighbors under different strong/weak tie transitive triad motif types, measuring link tendencies under varying weight influences. Their meanings are summarized in Table 2 .

4. Data Processing and Results Analysis

Based on previous research on dynamic link prediction in disciplinary citation knowledge diffusion networks [12], this study selects the 2006-2016 social network domain disciplinary citation knowledge diffusion network as the research object, which demonstrated high prediction stability. In Web of Science, using the search strategy "TS='social network*'", 25,539 articles from SCI-EXPANDED and SSCI databases (2006-2016) were collected, deduplicated, and cleaned. Using the Journal Citation Reports (JCR) subject category mapping, disciplinary citation knowledge diffusion temporal evolution networks were extracted from journal citation data.

4.1 Weight Adjustment-Based Effect Analysis The variation of AUC values for weighted common neighbor similarity indicators with parameter α is shown in Figure 4 [Figure 4: see original paper]. All AUC values represent averages from 10 iterative dynamic link predictions at one-year intervals using the 2006-2016 temporal evolution networks [12].

As shown in Figure 4, except for the HDI indicator, the prediction effectiveness of the other seven indicators initially increases then decreases as α gradually increases, though the magnitude varies. CN, AA, and RA indicators rise rapidly to a peak then decline slowly; Salton and HPI indicators climb to a peak then drop rapidly; Jaccard and Sorenson indicators show similar patterns of slight initial increase followed by gradual decline. When $\alpha < 0$, HDI performance remains stable; when $\alpha > 0$, it shows fluctuating decline.

Table 3 presents AUC values under unweighted, weighted, and optimal parameter conditions. For disciplinary citation knowledge diffusion temporal evolution networks, all eight indicators achieve improved performance under optimal parameter adjustment compared to pure unweighted or weighted forms. The AA indicator performs best under optimal α (mean prediction accuracy reaching 0.77403), followed by CN and RA indicators, while HPI shows the lowest optimal mean accuracy at only 0.72315.

Table 4 shows optimal α values for different indicators. HDI's optimal parameter is negative, indicating that weak ties play more important roles when using this indicator for dynamic link prediction—enhancing weak citation ties while reducing strong tie weights yields better performance. The other seven indicators have positive optimal parameters, indicating that strong ties play more important roles. However, all optimal parameters are less than 1, suggesting that optimal dynamic link prediction is achieved when citation association strength is moderately attenuated ($0 < \alpha < 1$). This indicates that while strong ties are more important, their importance does not fully match their actual weights. CN, AA, and RA indicators have relatively larger optimal parameter values, suggesting their strong tie effects are more pronounced.

4.2 Link Failure-Based Effect Analysis Using Matlab to simulate dynamic link prediction performance changes under different link failure strategies, results are shown in Figure 5 [Figure 5: see original paper] (x-axis: proportion of edges removed sequentially from strong-to-weak/weak-to-strong; y-axis: AUC values from iterative dynamic link prediction using the reduced networks).

As Figure 5 shows, prediction accuracy declines to varying degrees as citation edges are removed. When all inter-disciplinary citation associations disappear (removal proportion = 100%), AUC values drop to 0.5, equivalent to random similarity value generation. For all eight indicators, accuracy declines more gradually under weak tie removal, with noticeable AUC decreases only after approximately 40% of weak ties are removed. This indicates weak tie failure has smaller impact on prediction effectiveness, demonstrating that disciplinary citation knowledge diffusion temporal evolution networks exhibit strong robustness against weak tie failure—i.e., substantial weak tie fault tolerance. Under strong tie failure, accuracy changes more sharply, indicating strong ties play more significant roles in maintaining prediction performance—the network's strong tie attack resistance is relatively low.

Differences between the two failure strategies vary across indicators: Salton and HPI indicators show the largest performance variation curves, followed by Jaccard, Sorenson, and HDI indicators, while CN, AA, and RA indicators show minimal differences. This suggests different indicators exhibit varying sensitivity to strong/weak tie (especially strong tie) absence—faster accuracy decay indicates higher sensitivity.

Notably, previous findings showed HDI's optimal weight adjustment parameter was negative (weak ties dominate), yet link failure strategies reveal strong ties have more obvious impact on HDI's performance maintenance. This apparent contradiction arises because link removal strategies change not only strong/weak tie weights but also the number of common neighbors and motif structure distribution, potentially altering prediction trends for the same indicator.

4.3 Temporal Evolution Network Motif Analysis In disciplinary citation knowledge diffusion temporal evolution networks, the relative ratios of 16 triad motif types are shown in Figure 6 [Figure 6: see original paper]. The 003 motif (three isolated nodes) accounts for the largest proportion, indicating many relatively isolated disciplines with sparse citation knowledge associations. The 012 and 102 motifs rank second, suggesting binary direct knowledge diffusion connections are more common than trilateral relationships, and unidirectional knowledge flow is more significant than bidirectional reciprocal fusion. Additionally, 021U motifs outnumber 021D motifs, indicating that for social network domain disciplines, when neighbor disciplines lack direct citation relationships, their co-citation knowledge convergence capacity exceeds their bibliographic coupling capacity.

Over time, the proportion of 003 motifs decreases while 102 motifs increase, indicating increasingly close citation knowledge exchange (especially bidirectional knowledge propagation) among social network domain disciplines, with steadily improving network connectivity that facilitates horizontal expansion and vertical penetration of knowledge across disciplines.

However, these motif types lack transitivity and thus are not transitive triad motifs—the prerequisite for common neighbor similarity-based dynamic link prediction. Figure 7 [Figure 7: see original paper] shows relative ratios of 11 transitive triad motif types in disciplinary citation knowledge diffusion temporal evolution networks. Among transitive motifs, 021C, 111D, 111U, and 201 motifs occupy large proportions, indicating that many discipline pairs connected through an intermediary discipline are not directly connected. Over time, increasing 210 and 300 motifs demonstrate growing bidirectional knowledge exchange associations and gradually improving reciprocal connectivity rates.

To clarify the temporal evolution essence from the perspective of citation association strength, P , P , P , and P are used to represent link ratios under different strong/weak tie transitive triad motif types, measuring link tendencies under varying weight influences. Six sub-networks were analyzed using interval sampling from the temporal evolution networks. Figure 8 [Figure 8: see original paper] shows strong/weak tie transitive triad motif link ratios (x-axis: rank order of non-redundant edge weights from small to large; y-axis: link ratios for ss, ww, sw, and ws motifs when using different weights as strong/weak tie thresholds).

Figure 8 reveals that in social network domain disciplinary citation knowledge diffusion networks, when two disciplines are connected via two strong tie paths, the probability of direct citation knowledge diffusion (P) far exceeds that via two weak tie paths (P). Especially when neighbor discipline z has very strong citation associations with both source discipline x and destination discipline y (i.e., both edge weights are large), the probability of direct knowledge spillover from x to y through citation can reach 100%. Overall, strong ties more effectively promote the formation of inter-disciplinary citation knowledge association links, playing more important roles in network evolution and dynamic link prediction.

Additionally, since 2012, when two disciplines are connected via one strong and one weak tie path, if the knowledge destination's absorption/integration capacity exceeds the source's spillover radiation capacity, the probability of direct knowledge transfer is higher (P > P), regardless of the strong/weak tie threshold. This indicates that knowledge destination disciplines' capacity plays a more prominent role in new link derivation.

5. Conclusions

This study constructs a detection method for strong and weak tie effects in dynamic link prediction by combining external network structure regulation with internal micro-evolution mechanism analysis, based on the concept of internal-external synergy. From three dimensions—disciplinary citation knowledge association weight adjustment, link failure triggering, and strong/weak tie motif analysis—the research systematically explores strong/weak tie effects in disciplinary citation knowledge diffusion dynamic link prediction based on common neighbor similarity. This provides support for expanding strong/weak tie theory applications in directed weighted dynamic network link prediction, enriches and improves the methodological system for detecting strong/weak tie effects in dynamic link prediction, and offers theoretical and practical references for revealing micro-evolutionary patterns of disciplinary citation knowledge diffusion behavior and optimizing algorithmic indicators.

Key conclusions include:

(1) For different common neighbor similarity indicators, strong and weak tie

relationships exert varying degrees of influence on disciplinary citation knowledge diffusion dynamic link prediction. The "strong/weak tie effect" in link prediction is indicator-specific and does not fully represent the network's inherent link evolution characteristics. Overall, strong ties with larger weights contribute more to prediction accuracy improvement.

(2) From a deficiency perspective, strong ties play more significant roles in maintaining prediction performance; disciplinary citation knowledge diffusion temporal evolution networks exhibit strong robustness against weak tie failure, demonstrating substantial weak tie fault tolerance. Different indicators show varying sensitivity to strong/weak tie (especially strong tie) absence. Additionally, strong/weak tie phenomena in dynamic link prediction relate not only to citation association weights but also to common neighbor counts and network micro-motif structures.

(3) Over time, citation knowledge exchange among social network domain disciplines becomes increasingly close (especially bidirectional knowledge propagation), with steadily improving network connectivity providing favorable conditions for horizontal knowledge expansion and vertical penetration. Stronger citation associations between two disciplines and their neighbor disciplines lead to higher probabilities of direct knowledge transfer. Moreover, knowledge destination disciplines' absorption/integration capacity plays a more dominant role than source disciplines' spillover radiation capacity in new link derivation.

(4) Most common neighbor similarity-based link prediction indicators' design concepts align with link evolution patterns in disciplinary citation knowledge diffusion networks, though further improvement in considering strong/weak tie weight factors is needed. Overall, strong ties play more important roles in network evolution and dynamic link prediction, making them effective for enhancing prediction performance. However, while strong ties dominate, weak ties as a distinctive disciplinary interaction pattern also play non-negligible roles in knowledge propagation evolution. Disciplines with strong ties often exhibit high knowledge homogeneity, facilitating conventional development and incremental innovation in theories, techniques, and methods, while weak ties between disciplines with heterogeneous knowledge resources benefit the emergence of disruptive technological growth points, driving breakthrough innovations and leapfrog development. How to achieve organic integration of strong and weak ties in disciplinary knowledge diffusion dynamic link prediction represents an important future research direction.

Future work will optimize disciplinary citation knowledge diffusion temporal dynamic link prediction methods by deeply 挖掘 and accurately grasping the essential mechanisms of disciplinary citation knowledge diffusion behavior, reasonably utilizing strong/weak tie weight information from a micro-motif evolution perspective, and incorporating meso-level disciplinary community attribute information to improve prediction effectiveness.

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Author Contributions

Yue Zenghui: Research design, data analysis, and paper writing;
Xu Haiyun: Data processing and analysis;
Zhao Min: Paper revision.

Note: Figure translations are in progress. See original paper for figures.