A Temporal Multi-Dimensional Scholar Recommendation System with Interest Drift Modeling

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Abstract—**The proliferation of social networking platforms has significantly facilitated connections among scholars with shared research interests, elevating scholar recommendation to a prominent research focus.Current scholar recommendation methods exhibit critical limitations, particularly concerning insufficient modeling of temporal dynamics and inadequate capture of evolving research interests.This paper introduces the Temporal Dynamic Features based Personalized Research Collaborator Recommendation approach, designated TD-PCR. This method transcends traditional static modeling by implementing a three-fold temporal dynamic mechanism.First, it segments scholars' research trajectories using a sliding time window, dynamically weighting recent academic outputs with a temporal decay factor to prioritize contemporary contributions. Second, it constructs a research interest trend similarity metric to quantitatively assess the alignment of evolutionary paths in scholars' research directions. Third, it designs a comprehensive multi-dimensional time-sensitive feature system incorporating dynamic text similarity, temporally attenuated collaboration networks, and evolutionary academic influence characteristics. Innovatively integrating time-aware Doc2Vec document encoding, weighted random walk algorithms, and attention-enhanced neural networks within its architecture, the approach achieves precise collaborator recommendation via a synthesized five-dimensional feature vector comprising text similarity, social relevance, average influence, trend similarity, and domain similarity.In the existing dataset, the accuracy rate of this method reaches 99%. Evaluation shows that this method offers higher recommendation accuracy and better interpretability at the same time.**

Index Terms—**Scholar recommendation; Temporal dynamic modeling; Research interest evolution; Attention mechanism; Doc2Vec; Academic collaboration network**

I. Introduction

THE emergence and proliferation of academic social platforms, including prominent networks like ResearchGate and specialized code-sharing repositories like GitHub, have fundamentally transformed scholarly communication. These platforms serve as vital hubs for researchers seeking potential collaborators, disseminating findings, and sharing critical resources. However, the exponential growth in user bases on these platforms presents a significant challenge: scholars increasingly struggle to efficiently and accurately identify suitable collaborators within vast, dynamic academic populations. This challenge underscores the critical importance and growing demand for sophisticated, personalized scholar recommendation systems.

Existing approaches to scholar recommendation predominantly rely on static feature analysis. Common methodologies include generating recommendations based on textual similarity of publications, utilizing techniques such as TF-IDF or Latent Dirichlet Allocation (LDA), or leveraging structural properties of co-authorship and social relationship networks. While beneficial, these prevailing methods suffer from three fundamental limitations that impede recommendation accuracy and timeliness:

- **Neglect of Interest Dynamics:** Scholars' research foci frequently shift over time, meaning their current interests may differ substantially from their past work. Treating a scholar's entire publication history as a static corpus inherently obscures these evolving trajectories.
- **Inadequate Temporal Modeling:** Traditional methods lack robust mechanisms for temporal decay effects. They often undervalue the greater relevance of recent collaborations, publications, and emerging trends over older activities, resulting in recommendations biased toward historical patterns rather than a scholar's current context and future direction.
- **Lack of Multi-Dimensional Integration:** Notably, they focus only on specific features and fail to integrate diverse characteristics across key dimensions—semantic content, social networks, scholarly influence, temporal trends. This fragmentation misses interactions between evolving research interests, collaboration patterns, etc.

To address the aforementioned issues, this paper proposes a time-sensitive multi-dimensional scholar recommendation system that integrates interest drift modeling. The core innovations of the system are as follows:

- **Dynamic Feature Capture and Interest Drift Modeling:** We partition scholars' publication histories via time windows, extracting evolving research keywords, domains, and semantic features over periods to quantify research interest trajectories. Crucially, we design a trend similarity metric measuring dynamic alignment of these trajectories between scholars, beyond static snapshot comparisons.
- **Multi-dimensional Temporal Weighting:** We integrate temporal decay mechanisms across key recommendation dimensions:Text Similarity: Employing a temporal-aware Doc2Vec model to weight recent publications more heavily.Social Relevance: Utilizing a time-weighted PageRank algorithm within collaboration networks to prioritize recent and active connections.Academic Influence: Incorporating recency-sensitive metrics for influence evaluation.

- **Adaptive Feature Fusion:** We construct a neural network model enhanced with an attention mechanism. This architecture dynamically learns to fuse the extracted multi-dimensional temporal features (text similarity, trend similarity, temporally-weighted social relevance, and recency-adjusted influence) to generate personalized, accurate, and timely recommendations.

The subsequent structure of this paper is organized as follows: Section II reviews related work; Section III introduces the background knowledge and related theoretical foundations of the algorithm; Section IV elaborates on the framework and key algorithms of the recommendation system; Section V presents the experimental design and result analysis; Section VI summarizes the research and outlines future work.

II. Related Work

Scholar recommendation systems have evolved through several methodological paradigms, which we categorize and analyze below regarding their capabilities and limitations in modeling academic collaboration dynamics.Based on recent literature reviews, the recommendation algorithms applied in academic recommendation systems can be categorized into the following types, covering directions such as content - based features, collaborative filtering, hybrid strategies, and deep learning algorithms.[1]

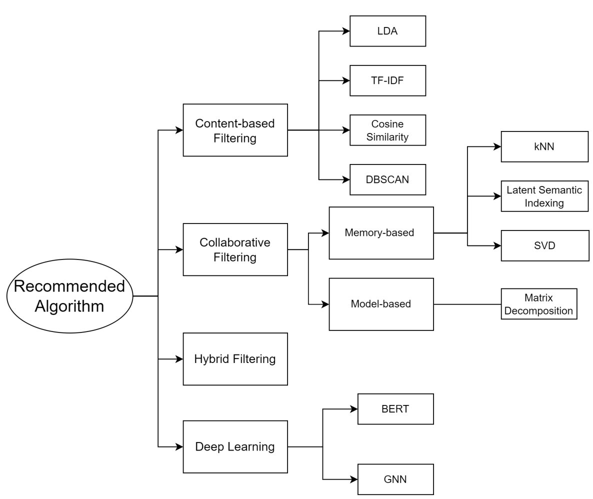

Fig. 1. Recommendation Algorithm

A. Content-Based Filtering (CBF) Approaches

CBF methods leverage textual features (e.g., keywords, topics) from publications to construct scholar profiles. User preferences are modeled through weighted vectors of item features derived from interaction logs. For instance, Hong et al. [2] recommended papers by profiling users with extracted keywords and computing cosine similarity between topics and publications.

Critical shortcomings: These methods treat publication histories as static corpora, inherently ignoring the temporal evolution of research interests (”interest drift”) and recency effects.

B. Collaborative Filtering (CF) Approach

CF methods fall into two categories: **Model-based approaches** utilize matrix factorization to infer user preferences via latent embedding factors. **Memory-based approaches** compute item-user affinities using arithmetic operations (e.g., cosine similarity, correlation coefficients), including kNN, LSI, and SVD variants. Pan and Li integrated LDA-based thematic similarity into item-based recommendations, while Ha et al. applied SVD for predicting interest in uncited papers.[3]

Critical shortcomings: CF methods predominantly rely on historical interaction patterns, lacking mechanisms to weight recent collaborations more heavily or capture shifting research trajectories. They also exhibit cold-start problems for new scholars.

C. Hybrid Recommendation Approach

Hybrid strategies combine CBF and CF through four primary schemes: Separate execution of CBF/CF with merged results. Incorporation of CBF features into CF frameworks. Integration of CF characteristics into CBF models.

Critical shortcomings: While hybridization improves robustness, extant implementations insufficiently address temporal dynamics—failing to model the decay of collaboration relevance over time or adapt to evolving research foci.

D. Graph Neural Network (GNN) Approach

Recent GNN-based methods model scholarly relationships through heterogeneous graph structures, achieving notable advances in structural-semantic fusion: Tao et al. [4] propose MGAT, leveraging modality-level gated attention to capture cross-modal user preferences, while Wang et al. [5] introduce HGNN-MAO, which aggregates low-order structural and high-order semantic neighborhoods via meta-path transformers to attain 3.1–14.5% accuracy gains over predecessors.

Critical shortcomings: While modeling relational structures, these methods fail to adequately quantify longitudinal shifts in research interests and overlook the temporal weighting of academic interactions and outputs. Moreover, they universally neglect the temporal dynamics inherent in scholarly activities—such as the decay of collaborative relevance, recency-weighted academic influence, and longitudinal drifts in research focus.

E. Differentiation from Existing Work

Our Temporal Dynamic Personalized Research Collaborator Recommendation (TD-PCR) framework fundamentally transcends prior art by addressing three critical limitations:

Temporal modeling of interest evolution: Unlike static corpus aggregation (CBF/CF) or snapshot-based GNN approaches, TD-PCR partitions scholarly trajectories into biennial windows, quantifying interest drift via a research trend similarity metric that captures directional alignment in research evolution.

Multi-dimensional temporal decay: Whereas existing methods treat historical outputs uniformly, TD-PCR embeds decay mechanisms across text similarity (time-aware Doc2Vec weighting recent papers), social relevance (time-weighted PageRank), and academic influence (recency-adjusted impact factors/co-author contributions).

Adaptive feature fusion: While contemporary GNNs (e.g., MGAT, HGNN-MAO) optimize structural-semantic integration, TD-PCR uniquely synthesizes five temporal-dynamic features—text similarity, social relevance, academic influence, trend similarity, and domain similarity—through an attention-enhanced neural network, dynamically weighting dimensions based on predictive importance.

III. Preliminaries

A. Problem Formulation and Technical Foundations

The core task addressed in this work is **temporal-aware scholar recommendation**: given a target scholar s_t and their historical academic records, identify Top-N potential collaborators $\mathcal{R} = \{s_1, s_2, \ldots, s_N\}$ whose evolving research interests exhibit high compatibility with s_t's current trajectory. Input data comprises comprehensive scholarly footprints:

- **Papers records**: Papers $\mathcal{P} = \{p_1, p_2, \ldots, p_k\}$ with metadata (title, abstract, keywords, publication year, journal impact factor)
- **Collaboration networks**: Graph $G = (V, E)$ where scholars $v \in V$ are connected by edges $e_{ij} \in E$ weighted by collaboration frequency and recency
- **Research domain evolution**: Time-stamped field annotations $\mathcal{F} = \{f^{(t_1)}, f^{(t_2)}, \ldots, f^{(t_m)}\}$ per scholar

The objective is to learn a mapping function $\mathcal{M} : s_t \to \mathcal{R}$ that:

1) Quantifies interest drift through research trajectory alignment
2) Prioritizes recent academic activities via temporal decay mechanisms
3) Fuses multi-dimensional compatibility signals (textual, social, influential, evolutionary)

B. Text Representation Models

Doc2Vec[6] extends Word2Vec by learning fixed-length embeddings for variable-length texts. While Word2Vec generates word vectors $\boldsymbol{w} \in \mathbb{R}^d$ via context prediction:

$$\max \frac{1}{T} \sum_{t=k}^{T-k} \log p(w_t | w_{t-k}, \ldots, w_{t+k}) \tag{1}$$

Doc2Vec incorporates paragraph vectors $\boldsymbol{d} \in \mathbb{R}^d$ that capture document-level semantics:

$$p(w_t | \boldsymbol{d}, w_{t-k}, \ldots, w_{t+k}) \tag{2}$$

This enables robust similarity computation between scholarly publications essential for interest alignment quantification.

C. Random Walk Algorithms

For collaboration network $G = (V, E)$ with adjacency matrix $\boldsymbol{A}$ (where $A_{ij} = 1$ indicates collaboration), random walk simulates Markovian traversal:

$$\mathbb{P}(v_{t+1} = j \mid v_t = i) = \frac{A_{ij}}{\sum_k A_{ik}} \tag{3}$$

We compute node correlations through convergence probabilities:

$$P_i = \begin{cases} (1-\alpha) + \alpha \sum\limits_{j \in \mathcal{N}(i)} \frac{P_j}{|\mathcal{N}(j)|}, & \text{restart state} \\ \alpha \sum\limits_{j \in \mathcal{N}(i)} \frac{P_j}{|\mathcal{N}(j)|}, & \text{otherwise} \end{cases} \tag{4}$$

This models social relevance by weighting paths based on recency and connectivity.

D. Attention-Enhanced MLP

Our Multi-Layer Perceptron (MLP) with attention adaptively fuses input features $\boldsymbol{X} = \{\boldsymbol{x}_1, \ldots, \boldsymbol{x}_5\}$ (text, social, influence, trend, and domain similarity). The attention mechanism first computes relevance scores:

$$\alpha_i = \frac{\exp(\boldsymbol{q}^\top \boldsymbol{k}_i)}{\sum_j \exp(\boldsymbol{q}^\top \boldsymbol{k}_j)} \tag{5}$$

then generates weighted representations:

$$\boldsymbol{z} = \sum_i \alpha_i \boldsymbol{v}_i \tag{6}$$

where $\boldsymbol{q}, \boldsymbol{k}_i, \boldsymbol{v}_i$ are query, key, and value projections. This allows dynamic feature weighting for final recommendation scoring.

IV. The TD-PCR Approach

The workflow of Mul-RSR is outlined in Section A. The three steps of Mul-RSR are introduced in details in Sections B-D.

A. Overview of TD-PCR

The flow chart of Mul-RSR for personalized scholar recommendation framework is shown in Fig. 2. The framework is divided into three main steps: data collection and processing, multi-dimensional feature extraction, model training and recommendation. The specific implementation process is described as follows.

1) Data collection processing: The initial paper-centric dataset (3,000 publications) is restructured into scholar-centric profiles. Each scholar's publication history and collaboration records are segmented into biennial temporal windows to capture evolving research interests. This temporal structuring enables subsequent analysis of academic evolution across discrete career phases.

2) Multi-Dimensional Feature Extraction: We compute five core compatibility metrics from the processed scholar data:

- **Textual Similarity**: Doc2Vec embeddings of windowed abstracts with cosine similarity comparison
- **Social Relevance**: Collaboration network proximity via random walk, using time-decayed edge weights
- **Academic Influence**: Composite metric weighting publication recency, journal impact factor, and co-author contribution
- **Research Trend Similarity**: Alignment of field transitions across recent time windows
- **Domain Similarity**: Historical overlap of research fields across all publications

3) Model training and recommendation: The five-dimensional feature vectors serve as input to a multi-layer perceptron (MLP) enhanced with attention mechanisms. We initialize model parameters through greedy layer-wise pre-training, followed by end-to-end optimization via forward propagation and backpropagation with gradient descent. The attention component dynamically recalibrates feature importance during training, enhancing recommendation accuracy through adaptive weighting.

B. Data collection and processing

The preprocessing phase transforms raw publication records into temporal scholar profiles. Initial data, comprising metadata for 3,000 academic papers (including titles, authors, publication years, abstracts, keywords, journals, impact factors, and research fields), follows a paper-centric schema. To facilitate scholar-focused recommendation, we restructure this data into scholar-centric temporal profiles through three key operations:

Scholar-Centric Transformation: Aggregate all publications by individual researchers, creating comprehensive scholarly portfolios that track each academic's output trajectory over time.

Temporal Windowing: Partition each scholar's publication history into biennial segments ($\Delta t = 2$ years) aligned with academic cycles. Formally, for scholar s_i with publication set $\mathcal{P}_i$:

$$\mathcal{W}_k(s_i) = \{p \in \mathcal{P}_i \mid t_k \leq \text{year}(p) < t_k + 2\} \tag{7}$$

where t_k denotes window start year.

Dynamic Feature Initialization: Within each window, collate temporal attributes including: Publication vectors (titles/abstracts/keywords), Evolving collaboration networks, Research domain transitions

This structured temporal representation enables subsequent analysis of interest drift and academic evolution across consecutive career phases.

C. Multi-dimensional feature extraction

1) Textual Similarity Calculation: To quantify scholarly content alignment, we implement a temporal Doc2Vec framework that captures evolving research semantics. For each biennial window, abstracts are embedded using the Distributed Memory Model (PV-DM, $dm = 1$), which concatenates paragraph vectors with context words to predict target words, optimizing the objective:

$$\max \frac{1}{T} \sum_{t=k}^{T-k} \log p(w_t | \boldsymbol{d}, w_{t-k}, \ldots, w_{t+k}) \tag{8}$$

This generates scholar-representative vectors $\boldsymbol{d}_i^{(k)}$ per window. For pairwise comparison, we first chronologically align schol-

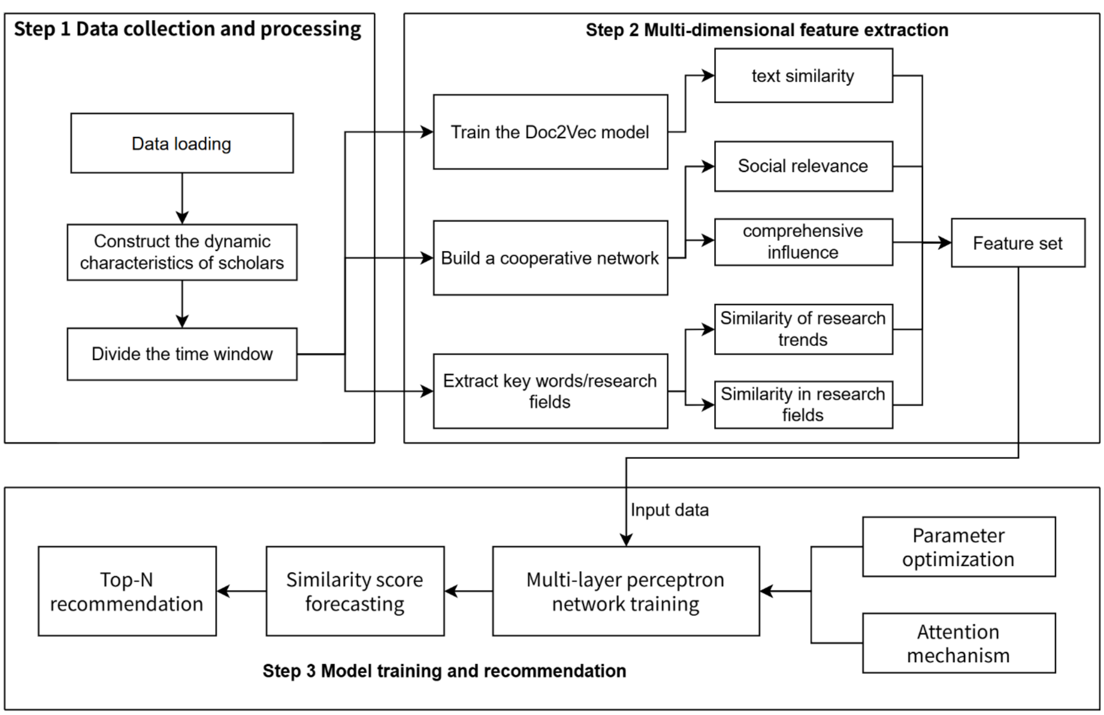

Fig. 2. Overview of TD-PCR

ars' temporal windows, then compute cosine similarity per aligned window pair:

$$\text{sim}_k(i,j) = \frac{\boldsymbol{d}_i^{(k)} \cdot \boldsymbol{d}_j^{(k)}}{\|\boldsymbol{d}_i^{(k)}\|\|\boldsymbol{d}_j^{(k)}\|} \tag{9}$$

A recency-weighted aggregation is applied across windows to prioritize recent research:

$$\text{sim}_{\text{text}}(i,j) = \frac{\sum_{k=1}^{K} \gamma^{(t_{\text{current}}-t_k)} \cdot \text{sim}_k(i,j)}{\sum_{k=1}^{K} \gamma^{(t_{\text{current}}-t_k)}} \quad (\gamma \in (0,1]) \tag{10}$$

yielding the final textual similarity matrix $\boldsymbol{M}_{n\times n}^{TS}$, where higher values indicate greater research content alignment.

2) Social Relevance Calculation: In this step, we use the graph-based random walk algorithm to calculate the socialrelevance between two scholars. A social relevance matrix $M_{n\times n}^{SR}$ will be constructed as the output of this step.

The following relationships among scholars in social networks can be modeled as an undirected graph $G = (V, E)$, where the node set V corresponds to a group of scholars, and the edge set E represents the following connections between them.The core goal of random walk is to gauge the relevance between two nodes: the stronger the relevance, the higher the similarity between the two nodes (scholars). In the context of random walk, the relevance between node v_1 and node v_2 is shaped by the following four factors:

- **Factor 1:** The number of collaborations between node v_1 and node v_2 in the graph, as well as the year of their most recent collaboration. The greater the number of collaborations and the more recent the collaboration year (relative to the present), the higher the relevance. When the number of collaborations and the collaboration year are the same, Factor 2 shall be referenced.
- **Factor 2:** The quantity of paths through which node v_1 can reach node v_2 in the graph. A greater quantity of such paths corresponds to higher correlation. For instance, the correlation between (v_1, v_2) is stronger than that between (v_1, v_3) if there are more connecting paths between v_1 and v_2 than between v_1 and v_3. When the number of paths is identical, Factor 3 will be considered.
- **Factor 3:** The length of paths linking node v_1 to node v_2. Shorter path lengths indicate higher correlation. In scenarios where path lengths are the same, Factor 4 will be referenced.
- **Factor 4:** The total out-degree of all nodes in the paths that connect node v_1 to node v_2. Here, a node with a larger out-degree can be regarded as having higher visibility and more followers. The smaller the total out-degree of these nodes, the higher the correlation between v_1 and v_2.

The concept of random walk operates as follows: Given a graph G and an initial node v_1 within the graph, the walker has two choices: either stay at the starting node or move on to another node. In the latter case, the walker will randomly select and transition to a node v_2 that is connected to v_1. This process repeats iteratively until the access probability of each node converges to a fixed value.

In this context, all edge weights in graph G are assumed to be equal. After the random walk process reaches iterative convergence, the access probability of each scholar in the graph can be expressed by the following formula:

$$P_i = \begin{cases} (1-\alpha) + \alpha \sum_{j\in \text{set}(i)} \frac{P_j}{|\text{set}(j)|}, & r = 1 \\ \alpha \sum_{j\in \text{set}(i)} \frac{P_j}{|\text{set}(j)|}, & r = 0 \end{cases} \tag{11}$$

Here, T denotes the length of the training text sequence, k represents the size of the context window, and p stands for the probability of successfully predicting the central word W_t.

Taking Ai LiSha as an example, her collaboration network is illustrated in Fig. 3 . The yellow node represents the scholar himself, blue nodes stand for scholars who have direct collaborations with him, and green nodes denote indirect collaborators with high recommendation scores.

Fig. 3. Cooperation Network

3) Comprehensive influence: We use certain behavioral attributes here to represent scholars' contribution rate indicators, and construct a list L_{PCR}^{n} to store the comprehensive influence of each scholar. This is mainly divided into three contributions:

- **Time-decay score:** Recent papers are assigned higher weights in terms of their influence, which reflects the timeliness of academic achievements. It prioritizes the reflection of scholars' recent research activity and avoids excessive interference of outdated achievements on their current influence.
- **Impact factor score:** Papers published in journals with high impact factors are assigned higher weights, which reflects the academic quality of the achievements. It quantifies the academic influence of the publishing platforms for the achievements, with papers in higher-tier journals making more significant contributions.
- **Co-author score:** The fewer the authors of a paper, the higher the proportion of the scholar's independent contribution in that single paper, which avoids dilution due to collaboration. This score highlights scholars' independent contributions in collaborative research and prevents the inflation of influence caused by ”honorary authors” (i.e., authors listed without substantial contributions).

4) Similarity of research trends and research fields: Research trend similarity is designed to quantify the alignment of **temporal evolution patterns** in scholars' research interests, focusing on the most recent shifts to reflect their current directional changes. Its core premise is that a scholar's recent research adjustments—rather than long-past shifts—are more indicative of their emerging focus, making this metric critical for identifying collaborators with synchronized interest drifts.

Validity Check: First, we verify that a scholar has accumulated at least two time windows of research data. This ensures there is sufficient temporal granularity to observe a meaningful shift (e.g., from one 2-year period to the next).

Extraction of Recent Fields: For scholars meeting the validity criterion, we extract the set of research fields from their two most recent time windows (denoted as $F_s^{(t)}$ and $F_s^{(t-1)}$ for scholar s, where t represents the latest window). These fields are typically derived from paper keywords, publication journals, or self-reported research domains, ensuring alignment with the scholar's most up-to-date outputs.

Jaccard Similarity Calculation: To measure the overlap between the two consecutive field sets, we compute their Jaccard similarity, defined as:

$$J(F_s^{(t)}, F_s^{(t-1)}) = \frac{|F_s^{(t)} \cap F_s^{(t-1)}|}{|F_s^{(t)} \cup F_s^{(t-1)}|} \tag{12}$$

This metric ranges from 0 (no overlap, indicating a complete shift in direction) to 1 (full overlap, indicating stable research focus). For example, if Scholar A shifted from "machine learning" to "deep learning" between two windows, the Jaccard score would reflect partial overlap (capturing the connection between the fields), whereas a shift from "physics" to "linguistics" would yield a near-zero score.

Dynamic Alignment Across Scholars: For each pair of scholars (s_i, s_j), we compare their individual trend shifts: if s_i's recent field transition aligns with s_j's (e.g., both moving from "computer vision" to "natural language processing"), their trend similarity score is elevated. Iterating this process across all scholars generates the dynamic field alignment matrix $M_{n\times n}^{RT}$, where each entry $M_{n\times n}^{RT}[i,j]$ quantifies the synchronicity of research direction shifts between scholar i and scholar j.

In contrast to trend similarity, research field similarity focuses on **cumulative alignment** across a scholar's entire research career, capturing the stability of their core interests.

Aggregation of All Fields: For each scholar, we compile a comprehensive set of research fields spanning all their time windows. This includes not only dominant fields but also niche areas explored in earlier or later stages, ensuring a holistic representation of their academic scope.

Jaccard Similarity for Global Overlap: For each pair of scholars (s_i, s_j), we compute the Jaccard similarity between their aggregated field sets $F_{s_i}^{all}$ and $F_{s_j}^{all}$:

$$J(F_{s_i}^{all}, F_{s_j}^{all}) = \frac{|F_{s_i}^{all} \cap F_{s_j}^{all}|}{|F_{s_i}^{all} \cup F_{s_j}^{all}|} \tag{13}$$

This score reflects the proportion of shared fields relative to the total unique fields across both scholars. For instance, two scholars with careers focused on "bioinformatics"—even if one recently shifted to "computational biology"—would score highly due to their extensive historical overlap.

Static Alignment Matrix: By iterating this global similarity calculation across all scholar pairs, we generate the static field alignment matrix $M_{n\times n}^{RF}$. Each entry $M_{n\times n}^{RF}[i,j]$ quantifies the long-term consistency of research interests between scholar i and scholar j, serving as a stable baseline for collaboration potential alongside the dynamic insights from $M_{n\times n}^{RT}$.

Together, these two metrics—trend similarity and field similarity—offer a dual perspective: capturing both the agility of recent research shifts and the depth of long-term specialization, thereby enriching the multi-dimensional feature set for personalized scholar recommendation.

D. Model training and recommendation

Based on the data processing in the previous section, we have obtained the textual similarity matrix $M_{TS}^{n\times n}$, social relevance matrix $M_{SR}^{n\times n}$, comprehensive influence list bL_{PCR}^{n}, dynamic research field alignment matrix $M_{RT}^{n\times n}$, and static research field alignment matrix $M_{RF}^{n\times n}$. Subsequently, using the scholars' collaboration network, we constructed a collaboration label matrix $M_{SL}^{n\times n}$ based on the collaborative relationships between scholars to store the true collaboration labels among them. I propose TD-PCR—a multi-feature-based dynamic scholar recommendation framework, which is built on the basis of Multi-Layer Perceptron (MLP) combined with an attention mechanism. The values of the feature matrices are used as input to the TD-PCR framework for training, and the output predicted similarity matrix $M_{PS}^{n\times n}$ represents the similarity scores among scholars.

Assuming that in the TD-PCR model, the mapping function between the five-dimensional eigenvalues of scholars and similarity is F, the similarity score matrix is:

$$M_{PS}^{n\times n} = F\big(M_{TS}^{n\times n},\ M_{SR}^{n\times n},\ L_{PCR}^{n},\ M_{RT}^{n\times n},\ M_{RF}^{n\times n}\big) \tag{14}$$

According to the similarity score, Top-N recommendation is performed. The overall process is shown in Algorithm 1.

Algorithm 1 Personalized Scholar Recommendation

Require: Five-dimensional eigenvalues ($M_{TS}^{n\times n}$, $M_{SR}^{n\times n}$, L_{PCR}^{n}, $M_{RT}^{n\times n}$, $M_{RF}^{n\times n}$); Cooperation label matrix ($M_{SL}^{n\times n}$).
Ensure: Prediction matrix ($M_{PS}^{n\times n}$).

1: Initialize the model parameters
2: Forward propagation begins
3: Normalize the eigenvalues and input into the neural network
4: Fit the Cooperation label matrix
5: Output predicted value
6: Backpropagation begins
7: Update model parameters based on BP and SGD
8: Use attention mechanism to adjust the weights again
9: Output similarity score prediction value
10: Perform Top-N recommendation

TABLE I
SCHOLAR RECOMMENDATION RESULTS

Rank	Name	Recommended Score	Text Similarity	Trend Similarity	Domain Similarity
1	Jia Qingxuan	1.0000	0.6541	0.3333	0.4839
2	Fu Yingzhuo	1.0000	0.5568	0.0000	0.2805
3	Li Tong	1.0000	0.7295	0.2316	0.2222
4	Jia ShiYuan	1.0000	0.7333	0.0000	0.2317
5	Fei JunTing	0.9999	0.7487	0.1967	0.2073
6	Huang ZeYuan	0.9997	0.7256	0.1507	0.1702
7	Song JingZhc	0.9997	0.7087	0.2258	0.1739
8	Yuan Bonan	0.9994	0.6075	0.0000	0.1341
9	Jiang Tao	0.9994	0.4259	0.0000	0.1071
10	Duan JiaQi	0.9991	0.7194	0.0000	0.1463

V. EXPERIMENT AND RESULT ANALYSIS

We take scholar Chen Gang as an example to present the experimental results.

Among them, TABLE 1 shows the top 10 recommended scholars for Chen Gang, which contains similarity information across various dimensions. The recommended scores are ranked from high to low. Figu.4 presents the best recommended collaborative scholar for Chen Gang, displaying a radar chart of the five-dimensional features between this scholar and Chen Gang.

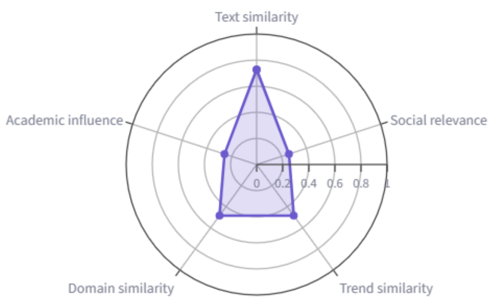

Fig. 4. Five-dimensional radar map

VI. CONCLUSIONS AND FUTURE WORK

Existing recommendation methods cannot meet the requirements of scholar recommendation for strong relevance, high accuracy, interpretability, and the dynamics of scholars' research interests. I propose a personalized dynamic scholar recommendation method based on multi-dimensional features, called TD-PCR. It first divides scholars' data structures by time windows and, in accordance with these time windows, explores the relevance between potential scholars from five aspects: textual similarity of published papers, social relevance, comprehensive influence, research trend similarity, and research field similarity. TD-PCR uses the Doc2Vec text model and random walk algorithm to measure the relevance between scholars. Based on Multi-Layer Perceptron (MLP) and attention mechanism, it can recommend Top-N scholars for each scholar.

Currently, the cold-start problem in the proposed TD-PCR method has not been effectively addressed. Specifically, for newly added scholars—i.e., those lacking sufficient historical data, such as researchers who have just entered the academic field, have not published enough papers, or have not formed a stable collaborative network—they lack adequate valid data across dimensions including textual features, social relations, comprehensive influence, research trends, and research fields. This makes it difficult for the model to accurately excavate their potential characteristics and research attributes through existing mechanisms. This will be a key focus of future work.

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