Experts2team: Task Relevance-Induced Team Formation by Combining Global Cohesion with Local Decoupling

Yue Kou[1], Yingxuan Du[1], Derong Shen[1], Xiangmin Zhou[2], Dong Li[3(✉)]
Tiezheng Nie[1], and Ge Yu[1]

[1] Northeastern University, Shenyang, Liaoning 110004, China
{kouyue,shenderong,nietiezheng,yuge}@cse.neu.edu.cn,2271973@stu.neu.edu.cn
[2] RMIT University, Melbourne, VIC 3000, Australia
xiangmin.zhou@rmit.edu.au
[3] Liaoning University, Shenyang, Liaoning 110036, China
dongli@lnu.edu.cn

Abstract. Effective teamwork is crucial for solving complex domain-specific problems, requiring expert teams tailored to task requirements. However, existing works overlook the diversity of expert collaboration types, tend to confine member selection within existing teams, and neglect the relevance between tasks. In this paper, we propose a task relevance-induced team formation framework by combining global cohesion with local decoupling (called Experts2team), ensuring the accuracy, diversity, and efficiency of team formation. Specifically, we first design a heterogeneous collaborative network (HCN) to more meticulously describe the collaborations among experts and propose a HCN-based method tailored for task-specific team division. Then we propose a comprehensive global-local approach to learning team representations, which effectively avoids the issue of scope limitation. We also propose a task relevance-induced team matching strategy to mitigate pseudo-failures during matching. We evaluate our method on four real-world datasets and the experimental results show the superiority of our method compared to state-of-the-art team formation methods.

Keywords: Team Formation · Global Cohesion · Local Decoupling · Task Relevance.

1 Introduction

As work becomes more collaborative and task demands diversify, team formation has gained attention. The main challenge is selecting experts who meet task requirements and cooperate effectively. Team formation is widely applicable across fields like research, project management, sports, and marketing.

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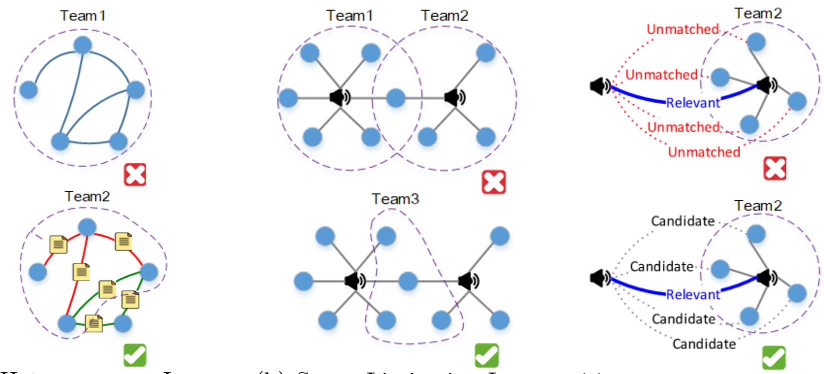
We focus on team formation, aiming to identify experts who meet task requirements and show strong collaboration potential based on their past cooperative relationships.For team formation, three key issues need to be addressed. (1) We need to more comprehensively capture the complex relationships among experts. Their collaboration patterns are diverse (such as varying collaborative themes). As shown in Fig.1(a), nodes represent experts, and edges represent their collaborative relationships. Red edges show collaborations in "social computing", while green edges indicate other collaborations like "data integration". If our goal is to form a "social psychology" team and we only consider collaborations without distinguishing types, we might form $Team1$, which has skilled experts with collaborative ties. However, $Team2$ aligns better with task requirements as their collaborations are closer to "social psychology". Therefore, a good team formation model should not only consider the experts' skills and the presence of collaboration, but also the collaboration types, ensuring a high degree of fit with the task requirements. (2) We need to break the limitation of scope to construct a more diversified team. As illustrated in Fig.1(b), $Team1$ tackles "social psychology", while $Team2$ focuses on "social computing". When forming a new team for "social analysis", we must avoid limiting member selection to existing teams, as this restricts diversity and innovation. Using traditional methods like random walk may restrict us to $Team1$ or $Team2$ itself, missing out on valuable combinations like $Team3$. Hence, an effective team formation model should consider both team internal composition and the potential for cross-team collaboration. (3) We must tackle the challenge of descriptive discrepancies between expert skills and task requirements, where despite unmatched ones in descriptions, there exists underlying semantic relevance. Relying solely on descriptive matches between expert skills and task requirements may overlook semantically related connections due to formulation differences, even if deeply linked. Considering task relevance can solve this issue. As shown in Fig.1(c), "team formation" in a new task requirement may not align with expert skills but is closely related to existing task requirements such as "social computing" (assuming it corresponds to $Team2$.). Then $Team2$ may become candidate teams. Thus, a good model should capture semantic task relevance for precise and efficient team formation.

Previous works on team formation are primarily categorized into subject-based [7–9, 19], text-based [3, 5, 16, 17, 20, 4], and graph-based [10–12, 2] methods. However, these methods overlook the diversity of expert collaboration types, tend to confine member selection within existing teams, and neglect the relevance between tasks. To overcome the above problems, we propose a task relevance-induced team formation framework by combining global cohesion with local decoupling (called Experts2team). This framework considers the heterogeneity of expert collaboration types, the potential for cross-team collaboration, and task relevance, thereby ensuring the accuracy, diversity, and efficiency of team formation. We summarise our contributions as follows:

- We design a heterogeneous collaborative network (HCN) to more meticulously describe the collaborations among experts, capable of capturing both the implicit semantics within text and the explicit structural relationships



(a) Heterogeneous Issue (b) Scope Limitation Issue (c) Pseudo-failures Issue

Fig. 1. Motivation Examples.

among experts simultaneously. Furthermore, we also propose a HCN-based team division method that is tailored to meet specific task requirements.

- We propose a comprehensive global-local approach to learning team representations by combining global cohesion with local decoupling. It utilizes hypergraphs and folded graphs to capture the potential for cross-team collaborations from a global perspective. Subsequently, these global representations are mapped into internal expert representations through local decoupling. This approach not only leverages the internal composition of teams but also effectively avoids the issue of scope limitation.
- We propose a task relevance-induced team matching strategy. By analyzing the relevance between new tasks and historical tasks, this strategy selects appropriate candidate teams, effectively avoiding pseudo-failures during the matching process. The aim of this strategy is to enhance the accuracy and efficiency of team matching.
- We evaluate our method on four real-world datasets and the experimental results show the superiority of our method compared to state-of-the-art team formation methods.

2 Related Works

Subject-based Team Formation. Subject-based team formation aims to identify experts whose skills match specific topics by creating tasks based on research areas. Statistical language models are often utilized to identify experts relevant to the specified fields.Specifically, subject-conditioned probability models [9, 8] estimate expert-topic associations and rank the top-k experts.Other approaches enhance effectiveness by embedding topic semantics [19]. [7] proposes a model that uncovers topic-related author information by exploring high-order relationships in academic networks. Although these methods avoid challenges posed by large textual data, textual content may have semantic limitations.

Text-based Team Formation. To capture complex task requirements and meet user expectations, text-based team formation methods have been developed. For instance, [3, 5] use descriptive queries to identify top-k experts based on document similarity. [17, 16] analyze social network text to assess cooperation potential and team performance. [20] employs document embeddings to capture relationships within papers and locate the expert team. Solutions based on graph embeddings [4] leverage document relationships within a homogeneous graph to enhance the effectiveness of expert identification. However, text-based methods may fail to capture deep task semantics and overlook expert collaboration, and they also rely on high-quality data and may not scale well.

Graph-based Team Formation. Graph-based search techniques have been used to find expert teams from expert networks [11, 12, 10, 2]. Experts are represented as nodes in a graph, with edges signifying past collaborations. The challenge of team formation is to identify a subgraph that covers a specified set of skills while optimizing the objective function.[11] proposes approximate algorithms for assembling compact teams in attribute graphs. [10] explores group discovery in weighted node-labeled graphs using inter-node distance as a sorting criterion. [12] incorporates constraint pattern graphs to ensure effective team formation. However, these methods may struggle with incomplete graphs or insufficient information, leading to inaccurate team selection, and often involve high computational complexity, reducing efficiency for large-scale networks.

3 Framework of Our Solution

Let T=$\{t_i\}$ and E=$\{e_j\}$ be the set of tasks and experts, respectively. Each expert e_j is described by a set of skills s_j. Here both t_i and s_j are described by a set of keywords. E_i ($E_i \subseteq E$) is a team of experts which has been formed with respect to the task t_i ($t_i \in T$). Given a new task t_{new}, our goal is to form an expert team E_x ($E_x \subseteq E$) such that each member e_j ($e_j \in E_x$) meets the skill requirements of the task (i.e., $t_{new} \subseteq s_j$) while also having a close historical collaboration relationship with one another. To express the relationships between tasks and experts more clearly, we define a heterogeneous collaborative network.

Definition 3.1 (Heterogeneous Collaborative Network, HCN): The heterogeneous collaborative network is a weighted graph $G\,(\nu, \varepsilon, \kappa, \tau, \omega)$, where ν is the vertex set to denote tasks or experts (ν=$T \cup E$), $\varepsilon \subseteq T \times E$ is the edge set to denote the relationships between tasks and experts, κ is a function such that $\kappa(v)$ is a set of keywords to denote the requirements/skills of each node $v \in \nu$, τ is a function used to map nodes to node types (task type or expert type), and ω is a function such that $\omega(v, v')$ is the weight between v and v' ($(v, v') \in \varepsilon$).

In this work, we propose a task relevance-induced team formation framework by combining global cohesion with local decoupling (called Experts2team), as shown in Fig.2. It contains three components: **(a) HCN-based team division.** Based on HCN, teams are initially divided by identifying special paths, then refined based on constraints to form the final division, which is used to construct the hypergraph. **(b) Team representation learning: global-local approach.** Hypergraphs and folded graphs are used to capture cross-team collaboration potential, and these representations are transformed into expert representations via localized decoupling. **(c) Task relevance-induced team matching.** By calculating the relevance between the new task and historical tasks, the candidate teams are chosen and further used to determine the expert members involved. The details of these components are provided in Section 4.

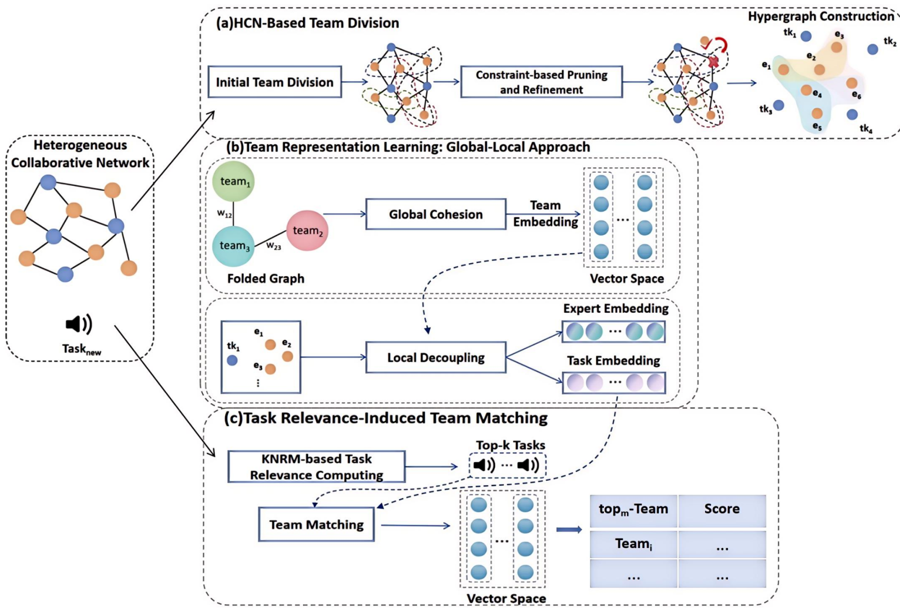


Fig. 2. An overview of our proposed Experts2team framework.

4 Our Proposed Model: Expert2team

4.1 HCN-based Team Division

Most existing team division methods rely solely on direct historical collaborations between experts, overlooking the diversity of collaboration types. To address this limitation, we construct a HCN and use special paths to uncover indirect relationships among experts, thereby capturing a broader and more nuanced perspective of their interactions. By integrating these indirect relationships with direct ones, we reorganize teams and construct a hypergraph, providing a more comprehensive representation of expert relationships.

Initial Team Division. We utilize a metapath to identify expert teams within the HCN. Taking metapath $\mathcal{P} = E - Q - E$ (common responder) as an example, we illustrate the strategy for selecting appropriate nodes to form hyperedges. Given a HCN G and a set of seed nodes ν_s, our objective is to construct highly cohesive teams that include the nodes in ν_s as hyperedges, with the team's cohesion quantified by the size N. First, we use the labeled search method to find every node connecting to ν_s. Starting from ν_s, we find all neighboring nodes along the path defined by $\mathcal{P}$ ($\mathcal{P}$-neighbor). Then, this process is repeated for all newly discovered nodes until no additional $\mathcal{P}$-neighbors can be identified. Finally, we get a set of initial teams.

Constraint-based Pruning and Refinement. For each node ν_s, we identify and record the $\mathcal{P}$-neighbour ($\mathcal{P}$-N) of all its two-hop neighbors. Nodes satisfying the $\mathcal{P}$-N constraint are retained for further expansion, and each qualifying neighbor is recorded. Conversely, nodes that fail to meet the $\mathcal{P}$-N constraint are excluded. This process involves iteratively removing all non-expanded nodes that fail to satisfy the $\mathcal{P}$-N constraint. The removal of node v may impact its neighboring nodes, so it is essential to verify whether each $\mathcal{P}$-neighbor of v continues to satisfy the $\mathcal{P}$-N constraint after v's removal. To relax the strict $\mathcal{P}$-N constraints, We incorporate all $\mathcal{P}$-neighbors of seed nodes ν_s that do not satisfy $\mathcal{P}$-N constraints into the team. Following the outlined steps, multiple expert teams can be identified using the HCN-based team division method, and the hypergraph is constructed by treating each team as a hyperedge. Subsequently, we demonstrate the specific application of the HCN-based team division method. Fig.3 illustrates the outcomes of four methods for constructing the HCN G, where $N = \{0, 1, 2, 3\}$ and $\mathcal{P} = E - Q - E$. The configuration $\mathcal{P}$-N-0 imposes the least restrictive, encompassing all expert nodes, including the independent expert e_{10}). As N increases, the teams exhibit progressively greater cohesion. Ultimately, $\mathcal{P}$-N-3 represents the most cohesive group of experts, where each expert in $\mathcal{P}$-N-3 has worked with three other experts.

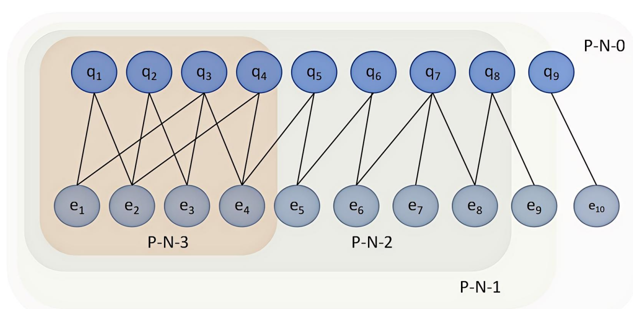


Fig. 3. Illustration of HCN-based Team Division

4.2 Team Representation Learning: Global-Local Approach.

Merely capturing the relationships between tasks and experts is insufficient for robust team identification, as experts capable of addressing the same task may lack prior collaborative experience. To address these limitations and enable the formation of more diverse and dynamic teams, we propose a team representation learning method that integrates global cohesion with local decoupling. This approach preserves the global team structure while capturing nuanced relationships between individual experts and tasks within an embedding space. Our method aims to break the boundaries of traditional team formation by utilizing hypergraph embeddings, a type of representation that models the global relationships among teams by representing each team as a hyperedge in a unified vector space. Additionally, it incorporates local information about individual experts and the tasks they address, embedding both into the same vector space. This dual-dimensional framework not only reflects the internal composition of teams but also highlights the potential for cross-team collaboration among experts.

Global Cohesion-based Team Representation Learning. To establish hypergraph-embedded vector spaces that reflect the comprehensive interactions among teams, we first introduce the design of loss functions for hyperedge embeddings. Our approach represents teams and their interrelationships as hyperedges within a weighted folded graph. In this graph, each node corresponds to a team, and the edge's weight reflects the degree of association between the teams. This weight is computed as the proportion of shared experts. For example, consider $team1 = \{e_1, e_2, e_3\}$ and $team2 = \{e_3, e_4, e_5\}$. Since they share the expert e_3, the weight of the edge between them is $1/5$. In the folded graph, all teams are distinct, meaning no two teams have exactly the same set of members. Given such a weighted folded graph, our objective is to represent each team as a distinct region in a vector space. This representation is defined by a center vector and an offset, which together allow us to capture the team's unique characteristics and its relationships with other teams in a low-dimensional space. Each team Tm_i is represented in a D-dimensional embedding space as $Tm_i = \left(Cen^{(i)}, Off^{(i)}\right)$, where $Cen^{(i)}$ and $Off^{(i)}$ are the center vector and offset vector respectively.

$$Tm_i = \left\{\boldsymbol{v} \in R^d \mid dis\left(Cen^{(\mathrm{i})}, \boldsymbol{v}\right) \leq Off^{(\mathrm{i})}\right\} \tag{1}$$

Here $dis\left(Cen^{(\mathrm{i})}, \boldsymbol{v}\right)$ is used to measure the distance between vector $\boldsymbol{v}$ and $Cen^{(i)}$, and is calculated as follows:

$$dis\left(Cen^{(\mathrm{i})}, \boldsymbol{v}\right) = \sqrt{\sum_{j=1}^{d}\left(Cen_j^{(i)} - v_j\right)^2} \tag{2}$$

Here $Cen_j^{(i)}$ and v_j represent the j^{th} elements of $Cen^{(i)}$ and $\boldsymbol{v}$ respectively. In our method, the offset $Off^{(\mathrm{i})}$is a constant that is proportional to the team size, Meanwhile, the center vector $Cen^{(\mathrm{i})}$ is learned through negative sampling on the fold graph using Skip-gram. For teams i and j considered as positive training samples, and with $k = 1, 2, ..., K$ representing negative samples, we minimize the following loss function:

$$Loss_{team} = \left(dis\left(Cen^{(i)}, Cen^{(j)}\right) - d_{ij}\right)^2 + \frac{1}{k}\sum_{k=1}^{K} E_{Cen^{(k)} \sim P(Cen)} max\left[0, d_{ik} - dis\left(Cen^{(i)}, Cen^{(k)}\right)\right]^2 \quad (3)$$

Here $dis\left(Cen^{(i)}, Cen^{(j)}\right)$ is the distance between two center vectors, and d_{ij} is used to control the folding constants for the two teams. For any two nodes in the fold graph, $d_{ij} = (1 - w_{ij})\left(Off^{(i)} + Off^{(j)}\right)$, where w_{ij} denotes the weight of the edge connecting the adjacent nodes.

Local Decoupling-based Team Representation Learning. In this part, we provide a detailed explanation of how local relationships between experts and tasks are embedded. The loss functions for expert and task embeddings are defined as follows. Given all the nodes corresponding to tasks and expert types in graph G, we learn their D-dimensional latent representations, denoted as $X \in R^{N \times D}$, which capture both their semantic and structural relationships. The corresponding loss function is defined as:

$$Loss_{e,q} = argmax_{\theta} \sum_{v \in V} \sum_{t \in T'_v} \sum_{v_t \in N_t(v)} \log P(v_t \mid v; \theta) \quad (4)$$

Here $T'_v = \{experts, tasks\}$, and $N_t(v)$ refers to the neighbors of node v of type t. The term $P(v_t \mid v; \theta)$ represents the probability, which is defined as:

$$P(v_t \mid v; \theta) = \frac{exp(x_{v_t}, x_v)}{\sum_{\emptyset(u) \in T'_t}^{u \in \nu} exp(x_u, x_v)} \quad (5)$$

where $\emptyset$(u) : u $\rightarrow \tau(u)$ indicates the node type mapping for each node u and x_v represents the embedding vector of node v. To improve computational efficiency, we adopt the Skip-gram model with negative sampling to generate negative samples, thus facilitating faster and more scalable learning.

To summarize, by integrating the loss functions defined in Eq.(3) and Eq. (4), we obtain the overall loss function: $Loss_{overall} = Loss_{team} + Loss_{e,q}$. By learning the embeddings of experts, tasks, and teams, we can match experts to tasks in an efficient and semantically meaningful way.

4.3 Task Relevance-Induced Team Matching

To tackle the challenge of bridging the gap between expert skill descriptions and task requirements, we propose a task relevance-induced team matching strategy (as detailed in Fig. 4). We utilize an interactive neural network capable of capturing text similarity between the requirement descriptions of the new task and historical tasks. By leveraging text embedding techniques through deep learning, we precisely measure the semantic relevance between tasks. Therefore our strategy can effectively overcome the difficulties posed by descriptive mismatches, effectively avoiding pseudo-failures during the matching process. Thus it ensures the accuracy and efficiency of team formation.

KNRM-based Task Relevance Computing. Given the description of a new task $\kappa(t_{new})$ and the description of a historical task $\kappa(t_h)$, we use KNRM [21] to generate a ranking score $F(t_{new}, t_h)$ only using the keywords in $t_{new}=\{t_1^q, ..., t_n^q\}$ and the keywords in $t_h=\{t_1^d, ..., t_m^d\}$. Here KNRM is a kernel based neural ranking model for ad-hoc search. The model captures word-level interactions using word embeddings, and ranks documents (i.e., the historical tasks in our model) using a learning-to-rank layer. According to the ranking scores, we can determine the top-k historical tasks most relevant to t_{new}.

The process begins with an embedding layer that maps each word t into an L-dimensional vector representation, denoted as $\boldsymbol{v}_t$. Based on this, a translation layer is employed to construct a translation matrix H. Each element in H represents the embedding similarity between a word in t_{new} and a word in t_h:

$$H_{ij} = \cos\left(\boldsymbol{v}_{t_i^q}, \boldsymbol{v}_{t_j^d}\right) \tag{6}$$

where $\boldsymbol{v}_{t_i^q}$ represents the embedding of the i-th word from $\kappa(t_{new})$, and $\boldsymbol{v}_{t_j^d}$ represents the embedding of the j-th word from $\kappa(t_h)$. Instead of attempting to learn a unique representation for each individual word pair, we leverage pre-trained word embeddings to represent words. This approach not only captures semantic relationships effectively but also significantly reduces the number of trainable parameters, making the model more efficient and scalable for large vocabularies. Then, we transform word-to-word interactions captured in the translation matrix H into task-solution ranking features $\phi(H)$:

$$\phi(H) = \sum_{i=1}^{n} \log \boldsymbol{K}\left(H_i\right) \tag{7}$$

$$\boldsymbol{K}\left(H_i\right) = \left\{K_1\left(H_i\right), \ldots, K_K\left(H_i\right)\right\} \tag{8}$$

$$K_k\left(H_i\right) = \sum_j \exp\left(-\frac{\left(H_{ij}-\mu_k\right)^2}{2\sigma_k^2}\right), k = 1, 2, ..., K \tag{9}$$

The function $\boldsymbol{K}\left(H_i\right)$ applies K kernels to the i-th word's row in the H, converting it into a K-dimensional feature vector. The log-sum of each word's feature vector generates the t_{new}-t_h ranking feature vector ϕ. The ranking features $\phi(H)$ are combined to generate the final ranking score:

$$F(t_{new}, t_h) = \tanh\left(w^T\phi(H) + b\right) \tag{10}$$

The parameters w and b are learned during the ranking process. The $tanh()$ function is utilized as the activation function, normalizing the range of ranking scores, to facilitate smoother convergence and enhance the stability of the learning process. By employing the task relevance computing strategy, the model is trained to automatically rank historical tasks based on relevance. Leveraging this ranking mechanism, the relevance $F(t_{new}, t_h)$ between t_{new} and each historical task t_h can be computed, enabling the identification of the top-k relevant historical task set T_h.

Team Matching. After identifying T_h, we will then map t_{new} into the same vector space as T_h. Then the embedding of t_{new} can be computed as follows:

$$\mathcal{G}_{embed}(t_{new}) = \sum_{t_h \in T_h} \left\{ \left(F(t_{new}, t_h) / \sum_{t \in T_h} F(t_{new}, t) \right) \times \mathcal{G}_{embed}(t_h) \right\} \tag{11}$$

In Section 4.2, we have already learned the embeddings of teams. Next, we will match the embedding of t_{new} with each of them. The distance between each potential team i and t_{new} is calculated as $dis\left(Cen^{(i)}, \mathcal{G}_{embed}(t_{new})\right)$, allowing us to select the top-k team that best matche t_{new}.

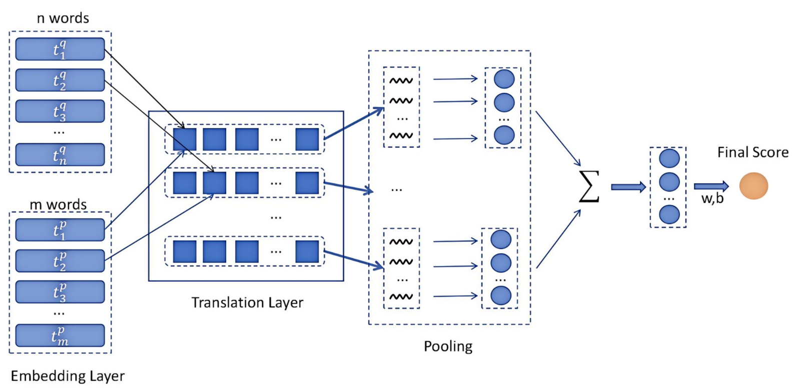


Fig. 4. Task Relevance-Induced Team Matching Strategy

5 Experiments

5.1 Experiments Setup

Datasets. The dataset utilized in this study comprises four authentic datasets from Stack Exchange: Android, History, DBA, and Physics. The properties of which are summarized in Table 1. In our research, we define the "gold standard" team as the ensemble of users who provide answers to a question. Our objective is to predict the team composition for each newly incoming question in the test dataset. For each dataset, we allocate 90% of questions for training, while the remaining 10% set aside for evaluating the performance of our approach.

Implement Details. In all the methods, We set the embedding dimension to 128 and maintain a batch size of 256. The embedding vectors of nodes are randomly initialized. The other parameters of the baseline methods remain as

Table 1. The statistics of datasets.

Dataset	Questions	Answers	Experts	Teams
android	882	2136	1018	857
history	1697	4702	1164	1575
dba	2096	6976	1794	2554
physics	5010	12559	2938	4613

proposed by the authors. Our framework is implemented using PyTorch and executed on Intel(R) Xeon(R) Silver 4310 CPU 2.10GHz, a Nvidia A5000 GPU, and 251GB RAM. We use common ranking metrics: Gold Standard Team Match (GM), Match Set Count Level (CL), and Precision at N (PN), along with Skill Coverage (SC) and Expertise Level (EL) to assess team quality. GM measures the accuracy of team matching, CL estimates communication costs based on prior collaborations, and PN quantifies the percentage of experts correctly identified. SC evaluates the percentage of required skills covered by the team, while EL reflects the team's ability to solve the problem.The code and data are available at: https://github.com/ChangyeTange/e2t.

Baselines. We compared Experts2team to the following methods of team formation: CCR [13], SA-CA-CC [1], NCCO [10], TOSA [7], TAPG [20]. CCR focuses on team requirements and maximizing cooperation. NCCO and SA-CA-CC aim to enhance expertise and reduce communication costs. TOSA selects experts based on subject sensitivity, and TAPG optimizes expert team identification in large-scale data. We also compared Experts2team with state-of-the-art node embedding methods (NeRank [14] and Seq [18]), and the metapath2vec [6] method, to validate our embedding approach. NeRank and Seq predict suitable experts using network structure. NeRank uses both question titles and bodies, while Seq focuses on tags.

5.2 Overall Performance Comparison

In this section, we compare Experts2team to the team formation baseline:CCR [13], SA-CA-CC [1], NCCO [10], TOSA [7], TAPG [20]. According to the research focus of these various methods, we selected three evaluation indicators: SC, CL and PN. The results are presented in Fig.5-6, where it is evident that Experts2team demonstrates strong performance across all metrics. Below is an analysis of the experimental results.

(1) CCR, NCCO, and SCA (i.e. SA-CA-CC) exhibit shortcomings in terms of skill coverage, primarily due to their reliance on graph search techniques. These algorithms iteratively add members to the team until all necessary skills are met. However, this strategy readily traps the algorithms into local optimal solutions, leading to inadequate skill coverage.

(2) In terms of team communication costs(CL), it is observed that TOSA underperforms relative to other methods. This is attributed to the fact that the

main purpose of TOSA is to identify the appropriate expert based on subject sensitivity, rather than assembling a team of experts. So, TOSA considers more whether an expert has the necessary skills, which leads to its superior performance in skill coverage.

(3) In accuracy(PN), Expert2team and TAPG show comparable performance, as both methods incorporate textual information and account for collaborative relationships among experts in team formation. However, it is noteworthy that Expert2team, unlike TAPG which indirectly infers expert collaboration through their work, directly incorporates historical expert collaboration and inter-team relationships. This direct consideration of expert interactions contributes to Expert2team's superior performance on the communication cost metric.

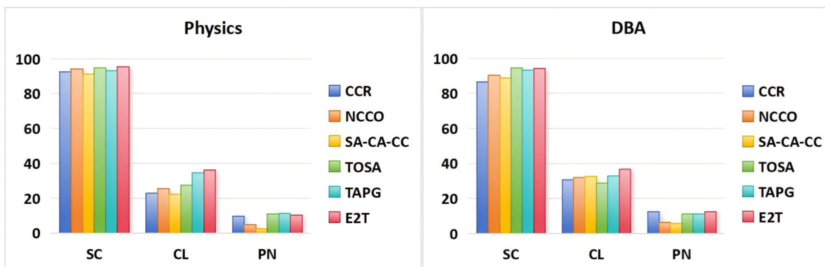


Fig. 5. Expert2team vs baselines in DBA and Physics

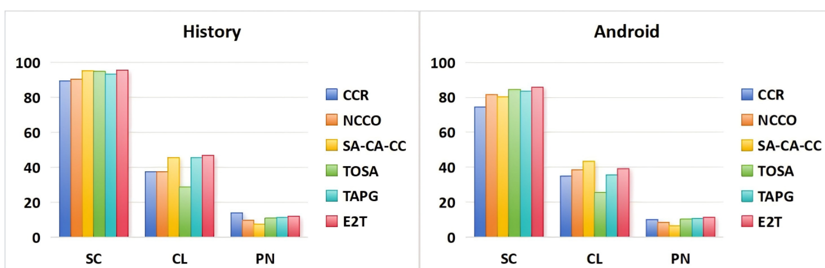


Fig. 6. Expert2team vs baselines in Android and History

5.3 Ablation Study

In this section, we substitute the embedding component of Experts2team with NeRank [14],Seq [18] and metapath2vec [6] to verify the effectiveness of our proposed embedding method. Across various datasets, we evaluate different sizes of expert teams formed using expert lookup methods.Due to space constraints within the article, we only show partial results.The performance metrics for these methods are shown in Fig.7-8. The experimental results show that Experts2team outperforms on SC, EL, CL and GM evaluation indicators for most datasets.The reasons for these observations are summarized as follows:

(1) Experts2team has a higher level of skill coverage (SC) compared to other methods. Because it uses not only the description of the question, but also the expert's answer to the question. In contrast, both NeRank and Seq ignored the responses provided by experts to existing questions. By taking into account both the content of the questions and the experts' replies, Experts2team is better equipped to explore potential relationships among experts, questions, and answers. Therefore, this approach enhances the effectiveness of identifying relevant experts for new issues.

(2) Experts2team outperforms other methods in terms of the expertise level (EL) of the retrieved teams. Similar to NeRank and Seq, it models questions, experts, and their relationships as a heterogeneous network. However, Experts2team incorporates answer scores as edge weights, which NeRank and Seq overlook. These scores reflect the expertise level of the experts and serve as a potential criterion for team member selection. This approach allows Experts2team to retrieve teams with a higher expertise level. As the team size increases, EL decreases slightly across all methods. This is due to the inclusion of more candidate experts, which may introduce irrelevant skills into the team, thereby lowering the EL.

(3) Experts2team demonstrates superior performance in the Match Set Count Level (CL) which is a metric used to evaluate the extent of common questions answered among team members. A higher CL indicates that team members have collaborated more frequently in the past to address problems, implying better communication and cooperation. We use the HCN-based team division method to identify hyperedges in the heterogeneous network graph as a team. Unlike other baselines that only consider direct cooperation for team formation, we consider the direct connection and indirect cooperation. As a result, Experts2team achieves a higher CL score and lower communication costs for teams compared to other methods.

(4) The match between the retrieved team members and the Gold Standard team members (GM). From the figure, we can see that the GM of Experts2team outperforms other methods. This indicates that Experts2team can more accurately retrieve the real team for the test question than existing methods.

5.4 Comparison with Gold Standard.

To further illustrate the superiority of Experts2team in Gold Standard Team Matching (GM), we conducted additional experiments to compare various methods under the condition of retrieving teams of the same size as the gold standard team. For a test question, these methods identify teams matching the actual number of respondents to the question. We calculated the average percentage overlap between the identified team and the gold standard team for each method. The results are presented in Fig. 9(a).

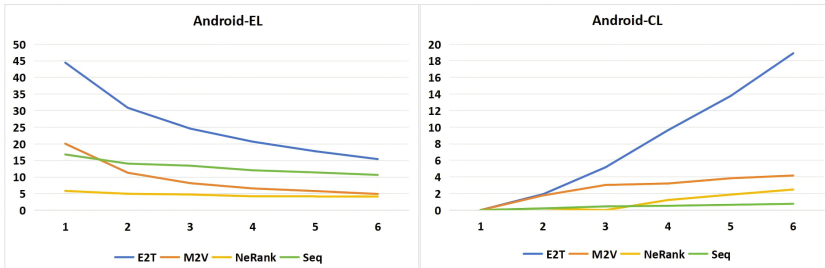


Fig. 7. Comparison of different methods based on CL and EL in Android

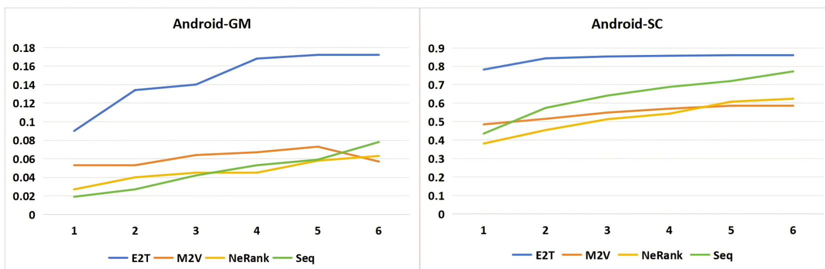


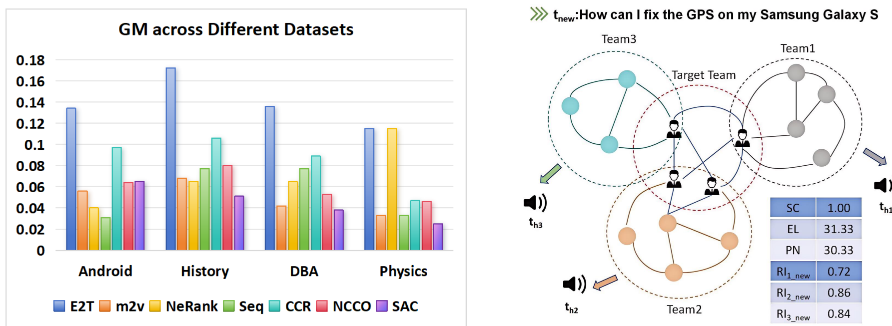
Fig. 8. Comparison of different methods based on GM and MC in Android

5.5 Case Study

To demonstrate the robust capabilities of Experts2team (E2T) in dynamic team formation, we analyze several real-world scenarios. As shown in Fig.9(b), for a new task t_{new} (e.g., "How can I fix the GPS on my Samsung Galaxy S?"), no direct matches are found among historical tasks. However, through their high relevance metric(RI), we identify several tasks $\{t_{h1}, t_{h2}, t_{h3}\}$ that are semantically related to t_{new}. Leveraging these relevant tasks, E2T successfully transcends the boundaries of existing teams, enabling it to select experts from different teams to dynamically form a new team (i.e., the target team) tailored to meet the requirements of t_{new}. This newly formed team ensures both the Skill Coverage (SC) necessary for completing t_{new} and the inclusion of experts with high Expertise Levels (EL).

6 Conclusion

In this paper, we propose a framework for forming teams called Experts2team, which combines global cohesion with local decoupling to enhance the accuracy, variety, and efficiency of team formation. First, we develop a team division approach using the heterogeneous collaborative network to provide a detailed description of expert collaborations. We also propose a method for learning team representations that integrates both global and local perspectives. Furthermore,



(a) The GM values of different teams when their sizes are the same as the gold standard team.

(b) Case study

Fig. 9. The result of GM comparison and case study

we propose a task relevance-induced team matching strategy to reduce the occurrence of mismatches during the process. For future work, we will incorporate the social relationships among experts to enhance effectivity. Beyond that, we will utilize the powerful understanding capabilities of large language models to enhance the explainability of the model.

References

1. An, A., Golab, L., Kargar, M., Szlichta, J.e.a.: Authority-based team discovery in social networks. arXiv preprint arXiv:1611.02992 (2016)
2. Apostolou, S., Tsaparas, P., Terzi, E.: Template-driven team formation. In: 2020 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM). pp. 258–265. IEEE (2020)
3. Berger, M., Zavrel, J., Groth, P.: Effective distributed representations for academic expert search. arXiv preprint arXiv:2010.08269 (2020)
4. Brochier, R., Gourru, A., Guille, A., Velcin, J.: New datasets and a benchmark of document network embedding methods for scientific expert finding. arXiv preprint arXiv:2004.03621 (2020)
5. Brochier, R., Guille, A., Rothan, B., Velcin, J.: Impact of the query set on the evaluation of expert finding systems. arXiv preprint arXiv:1806.10813 (2018)
6. Dong, Y., Chawla, N.V., Swami, A.: metapath2vec: Scalable representation learning for heterogeneous networks. In: Proceedings of the 23rd ACM SIGKDD international conference on knowledge discovery and data mining. pp. 135–144 (2017)
7. Gao, X., Wu, S., Xia, D., Xiong, H.: Topic-sensitive expert finding based solely on heterogeneous academic networks. Expert Systems with Applications **213**, 119241 (2023)
8. Hamidi Rad, R., Bagheri, E., Kargar, M., Srivastava, D., Szlichta, J.: Retrieving skill-based teams from collaboration networks. In: Proceedings of the 44th international ACM SIGIR conference on research and development in information retrieval. pp. 2015–2019 (2021)

9. Hamidi Rad, R., Fani, H., Bagheri, E., Kargar, M., Srivastava, D., Szlichta, J.: A variational neural architecture for skill-based team formation. ACM Transactions on Information Systems **42**(1), 1–28 (2023)
10. Kargar, M., Golab, L., Srivastava, D., Szlichta, J., Zihayat, M.: Effective keyword search over weighted graphs. IEEE Transactions on Knowledge and Data Engineering **34**(2), 601–616 (2020)
11. Khan, A., Golab, L., Kargar, M., Szlichta, J., Zihayat, M.: Compact group discovery in attributed graphs and social networks. Information Processing & Management **57**(2), 102054 (2020)
12. Kou, Y., Shen, D., Snell, Q., Li, D., Nie, T., Yu, G., Ma, S.: Efficient team formation in social networks based on constrained pattern graph. In: 2020 IEEE 36th International Conference on Data Engineering (ICDE). pp. 889–900. IEEE (2020)
13. Lappas, T., Liu, K., Terzi, E.: Finding a team of experts in social networks p. 467–476 (2009). https://doi.org/10.1145/1557019.1557074
14. Li, Z., Jiang, J.Y., Sun, Y., Wang, W.: Personalized question routing via heterogeneous network embedding. In: Proceedings of the AAAI conference on artificial intelligence. vol. 33, pp. 192–199 (2019)
15. Nikolaou, I., Terzi, E.: Team formation amidst conflicts. In: Proceedings of the ACM on Web Conference 2024. pp. 2417–2428 (2024)
16. Reimers, N.: Sentence-bert: Sentence embeddings using siamese bert-networks. arXiv preprint arXiv:1908.10084 (2019)
17. Rostami, P., Shakery, A.: A deep learning-based expert finding method to retrieve agile software teams from cqas. Information Processing Management **60**(2), 103144 (2023). https://doi.org/https://doi.org/10.1016/j.ipm.2022.103144, https://www.sciencedirect.com/science/article/pii/S030645732200245X
18. Sun, J., Zhao, J., Sun, H., Parthasarathy, S.: Endcold: An end-to-end framework for cold question routing in community question answering services. In: Proceedings of the twenty-ninth international conference on international joint conferences on artificial intelligence. pp. 3244–3250 (2021)
19. Gui, H., Zhu, Q., Liu, L., Zhang, A., Han, J.: Expert finding in heterogeneous bibliographic networks with locally-trained embeddings. arXiv preprint arXiv:1803.03370 (2018)
20. Xu, X., Liu, J., Wang, Y., Ke, X.: Academic expert finding via (k,P)-core based embedding over heterogeneous graphs. In: 2022 IEEE 38th International Conference on Data Engineering (ICDE). pp. 338–351. IEEE (2022)
21. Xiong, C., Dai, Z., Callan, J., Liu, Z., Power, R.: End-to-end neural ad-hoc ranking with kernel pooling. In: Proceedings of SIGIR. pp. 55–64 (2017)
22. Xuan, H., Li, B.: Temporal-aware multi-behavior contrastive recommendation. In: Database Systems for Advanced Applications. pp. 269–285. Springer Nature Switzerland, Cham (2023)
23. Zhang, Y., Zhang, J., Xu, F., Chen, L., Li, B., Guo, L., Yin, H.: Preference prototype-aware learning for universal cross-domain recommendation. In: Proceedings of the 33rd ACM International Conference on Information and Knowledge Management. p. 3290–3299. CIKM '24, Association for Computing Machinery, New York, NY, USA (2024). https://doi.org/10.1145/3627673.3679774
24. Zhang, Y., Zhang, J., Xu, F., Chen, L., Li, B., Guo, L., Yin, H.: Preference prototype-aware learning for universal cross-domain recommendation. In: Proceedings of the 33rd ACM International Conference on Information and Knowledge Management. p. 3290–3299. CIKM '24, Association for Computing Machinery, New York, NY, USA (2024). https://doi.org/10.1145/3627673.3679774, https://doi.org/10.1145/3627673.3679774