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Introduction

1.1 Motivations

In defining the essence of professional teamwork, Hackman and Katz [41] stated that teams function as "purposive social systems," defined as people who are readily identifiable to each other by role and position and who work interdependently to accomplish one or more collective objectives. Teams are increasingly indispensable to achievement in any organization. This is perhaps most evident in multinational organizations where communication technology has transformed the geographically dispersed teams and networks. Business operations in large organizations now involve large, interactive, and layered networks of teams and personnel communicating across hierarchies and countries during the execution of complex and multifaceted international businesses. Despite the organizations' substantial dependency on teams, fundamental knowledge about the conduct of team-enabled operations is lacking, especially at the *social, cognitive*, and *information* level in relation to team performance and network dynamics. What do high-performing engineering/design/sale teams share in common with respect to their communication patterns? How can we predict a team's performance before it starts to work on the assigned project? How can we foster productive behavioral changes of team members and leaders in order to optimize performance?

1.2 Research Objectives and Key Challenges

Generally speaking, the **team performance** can be viewed as the **composite** of the following three aspects, including (1) its **users**, (2) **tasks** that the team performs, and (3) the **networks** that the team is embedded in or operates on, i.e.,

$$\text{team performance} = f(\text{users, tasks, networks}) \tag{1.1}$$

The goal of this book is to create new instruments to *predict*, *optimize*, and *explain* teams' performance in the context of composite networks (i.e., social-cognitive-information networks). This research objective involves a number of key challenges, many of which can be attributed to **the complexity of teams**. Specifically, the complexity of the teams comes from all the following five components of Eq. (1.1).

- *Challenge 1: the complexity of the users.* There are three basic types of users, including the individuals (e.g., team members), team leaders (e.g., project managers), and the "owners" of human resource (e.g., HR in an organization). While, in general, different types of users are collaborative in nature, their goals are not always consistent with each other. For certain tasks, the team members or its leader might have to make a decision within a short time period, with incomplete and partial knowledge of its embedded environment/networks, and possibly under great stress.
- *Challenge 2: the complexity of tasks.* Within an organization, there are often multiple teams for a variety of different types of tasks, such as engineering teams, support teams, business teams, planning teams, etc. Each type of team might have its own "secret recipe" for success. For example, a successful engineering team might heavily rely on its execution of plan, while a planning team might need more innovation. Some tasks might be collaborative, while others might be competitive with each other. How can an organization optimize the performance of a target team in the presence of an adversarial team? From an organization perspective, how can it strengthen an existing team (e.g., by expanding the team size) without hurting others?
- *Challenge 3: the complexity of networks.* The challenges come from the environment that the team is embedded in or operates on, i.e., the fact that such networks are often *big*, meaning that they are large in size (*volume*), highly volatile in dynamics (*velocity*), spreading over multiple channels/layers/platforms (*variety*), and noisy and incomplete (*veracity*). In the book, we assume the networks are undirected, but the methods presented can be easily extended to handle the directionality of networks.
- *Challenge 4: the complexity of performance.* There is no single performance measure of the team, but rather a set of intercorrelated metrics. For example, the impact metrics for research teams include citation-based number of citations, h-index, online usage based view counts, download counts, and network-based centrality, all of which might be correlated with each other [13].

- *Challenge 5: the complexity of composite (e.g., $f()$).* The composite itself, which composes different aspects/metrics into the performance measure(s), is far beyond a many-to-one linear process. Instead, it is likely to be a many (aspect) to many (performance measures) nonlinear process.

1.3 Research Tasks Overview

In this book, we take a multidisciplinary approach, consisting of machine learning, visualization, and optimization, to tackle three complementary research tasks.

Task 1: Team Performance Prediction. Understanding the dynamic mechanisms that drive the success of high-performing teams can provide the key insights into building the best teams and hence lift the productivity and profitability of the organizations. From the algorithmic perspective, the interesting problems are to forecast the long-term performance of teams (*point prediction*) as well as the pathway to impact (*trajectory prediction*). For research teams, early prediction of their performance has many important implications, ranging from personal career development and recruitment search, to the jurisdiction of research resources. The impact pathway often provides a good indicator of the shift of the research frontier and can also help trigger an early intervention should the impact trajectory step down in the near future. On the other hand, as the ancient Greek philosopher Aristotle articulated more than 2,000 years ago that "*the whole is more than the sum of its parts*," it is worthwhile to quantitatively examine the relationship between the team-level and individual-level performances and leverage that to build a joint predictive model.

Task 2: Team Performance Optimization. In this task, we focus on the problem of optimizing/enhancing an existing team. For example, if the team leader perceives the need to enhance certain expertise of the entire team, who shall we bring into the team (i.e., *team expansion*)? If we need to reduce the size of an existing team (e.g., for the purpose of cost reduction), who shall leave the team (i.e., *team shrinkage*) so that the remaining team is least impacted? If the team leader sees a conflict between certain team members, how shall we resolve it (i.e., *team conflict resolution*)? In case the desired team configuration changes over time, how can we reflect such dynamics in the team enhancement process (i.e., *team evolution*)? We solve all these enhancement scenarios based on a team member replacement algorithm we developed recently [58]. On the other hand, teams can be often viewed as a dynamic system. We present the solution to plan the sequential optimization actions to maximize the cumulative performance using reinforcement learning.

Task 3: Team Performance Explanation. The basics of team effectiveness were identified by J. Richard Hackman, who uncovered a groundbreaking insight: what matter most to collaboration are certain enabling conditions. Recent studies found that three of Hackman's conditions – a compelling direction, a strong structure, and a supportive context – continue to be particularly critical to team success [40]. In this task, we aim to reveal the "secret recipe" for success by developing an explanation model for the aforementioned team performance prediction models as well as the performance optimization models. Such explanations can provide insights to *why* some teams are predicted to be successful and *why* we should bring a certain member to the team. Understanding the reasons behind predictions and recommendations is critical in assessing *trust*, which is especially fundamental if decisions (e.g., funding allocations) need to be made based on a prediction.

As an emerging form of teams, human–agent teams promises a superior performance that would significantly surpass the best of both human-only teams as well as agent-only teams by having human and agent members focus on their best, often complementary, strength. At the end of the book, we have discussed the research tasks and open challenges in the recent trend of human agent teaming.

1.4 Impacts and Benefits

In the context of composite networks, this book will establish effective algorithms and tools for the performance prediction and optimization of teams along with explanations. The research presented in the book will help organizations make a better decision to perform certain tasks that need collaborative effort within a team. Based on our work in this book, we will build a system of team enhancement (i.e., prediction, optimization, explanation). The visualization component of this system can be used to track individual and team performance over time, and provide feedback to individuals to foster productive behavior change. To the best of our knowledge, this is the first comprehensive effort that integrates interactive visualization mechanisms, machine learning models, and advanced network analysis algorithms for optimizing teams. The preliminary results (e.g., publications, presentations, and prototype systems) are available at `team-net-work.org`.