Optimizing Team Formation in Educational Settings

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Abstract

Teamwork is a common aspect of higher education programs, offering various benefits such as enhancing interpersonal skills and improving learning outcomes. However, the current methods of team formation in project-based courses, including teacher-designed, student-led, and random approaches, have limitations and do not fully optimize the process. This paper introduces the educational Team Formation Problem (e-TFP) and proposes five strategies to optimize team formation. Preliminary results using a real-world university-level dataset demonstrate that these strategies outperform the heuristic human teacher solution and provide valuable insights for future team formation in educational settings.

1 Background and Related Work

Currently, most higher education programs include teamwork, offering benefits that range from enhanced interpersonal skills to better retention of information and improved learning outcomes. Universities typically employ three methods for forming teams: instructor-led, student-led, or random allocation. Each method has its own set of advantages and limitations.

Instructor-led team formation (Hilton and Phillips 2010; Rusticus and Justus 2019) enables instructors to decide which student will work with whom in a top-down manner, based on objectives such as skill alignment, project preferences, or personality. Yet this approach often leads to interpersonal conflicts and suboptimal outcomes due to the instructor's limited knowledge of individual students' preferences, as well as capacity constraints, especially in medium- or large-sized courses (Akbar, Gehringer, and Hu 2018).

In contrast, *student-led team formation* allows bottom-up team creation, often based on friendship or prior collaborative experiences. While this method reduces friction, it also has downsides. Student-led teams may foster good relationships but might lack the necessary skills to be successful in the specific course (Basta 2011; Chapman et al. 2006). Furthermore, this method could lead to "all-star" teams, where stronger students group together, leaving "weaker" members with subpar performance and unequal learning opportunities (Oakley et al. 2004). This approach also disadvantages students who lack strong networks or are pursuing non-popular elective curricula.

The third method, *random team selection*, involves a purely arbitrary process. It does not optimize teams, resulting in significant variations in team performance.

Various studies have explored *algorithmic team formation* optimization in business, crowdsourcing, and education. Many focus on the problem of expert selection, i.e., selecting team members to form one or more optimal teams (Bahargam et al. 2019; Bhowmik et al. 2014), without the requirement that every participant must belong to a team. These primarily address business scenarios. Looking into the exact problem parameters they focus on, some studies focus on *tie strength optimization*, where the ties represent relationship scores (Yaakob and Kawata 1999; Zhang and Zhang 2013), or communication costs (Lappas, Liu, and Terzi 2009) among the candidates, often combined with the optimization of other elements such as skill coverage for the given job (Lappas, Liu, and Terzi 2009). Other studies focus on team formation to optimize for *project preference matching* (Abraham, Irving, and Manlove 2003), and others center on *skill coverage*, occasionally combined with project preferences (Donndelinger et al. 2021) or workload (Vombatkere and Terzi 2023). However, to the best of our knowledge, no study so far has tackled team optimization in a setting where all participants must be included (typical in education), addressing both the participants' bottom-up teammate preferences and the teacher's top-down skill coverage requirements simultaneously.

In this paper, we formally model the educational Team Formation Problem (e-TFP) and propose five strategies for its optimization. We then evaluate the strategies using a real-world dataset from a medium-sized computer science course. Our results demonstrate that four out of the five proposed strategies outperform the heuristic solution employed by the course instructor in terms of skill coverage, student preference realization, and computational time. We conclude with a discussion of our findings, limitations, and suggestions for future research in team formation optimization for educational settings.

2 e-TFP problem modeling

The e-TFP problem model consists of a basic problem model, which can be extended with a number of objectives.

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The objectives can be added altogether or separately, transforming the basic e-TFP model into an optimization problem. This approach guarantees an initial feasible solution for the teacher can always exist, enabling the course to begin. The initial solution can then be improved based on the combination of input parameters and optimization objectives the teacher chooses to optimize for.

Basic e-TFP problem model

Notations. We consider $0 \in \mathbb{N}$ and $\mathbb{N}^+ = \mathbb{N} \setminus \{0\}$. Let $[x, y] = \{i \in \mathbb{Z} \mid x \leq i \leq y\}$ for $x, y \in \mathbb{Z}$ with $x \leq y$, and $[x] = [0, x-1]$ for $x \in \mathbb{N}^+$. $\#A$ denotes the cardinality of any set A. We call a partition P an l-partition if $\#P = l$.

Input: Team data. A course consisting of $m \in \mathbb{N}^+$ *students* must be partitioned into $l \in \mathbb{N}^+$ *teams*. The additional *size bounds* $k_{min}, k_{max} \in \mathbb{N}$ restrict the size of each team. We assume $k_{min} \leq \frac{m}{l} \leq k_{max}$, otherwise no feasible l-partition of m students exists that respects the size bounds.

Preference data. Students rate each other numerically on a scale $[-d, d]$ with $d \in \mathbb{N}^+$, reflecting their desire to collaborate in a team. Higher values indicate higher preferences with 0 representing a neutral preference and negative values corresponding to an active desire to not wanting to work together. These ratings are categorized as "weak" teammate preferences. Students can also express a "strong" teammate preference when they specifically want to work with another student, indicated by some fixed value $X \in \mathbb{N} \setminus [-d, d]$. Such strong preferences are often based on previous collaborative experiences. Student evaluations create a *preference matrix* $P \in \mathbb{N}^{m \times m}$ containing values $p_{a,b} \in [-d, d] \cup \{X\}$ for students $a, b \in [m]$. This matrix includes both weak and strong preferences to maintain consistency in the input data and is generally not symmetric.

Skill data. The course employs a variety of $n \in \mathbb{N}^+$ *skills*. Skill levels are being measured in the range $[e]$ with $e \in \mathbb{N}^+$. Student skills form a *skill matrix* $S \in \mathbb{N}^{m \times n}$ with student $a \in [m]$ possessing the skill level $s_i^a \in [e]$ for skill $i \in [n]$. Given a *skill threshold* $v \in [e]$ provided by the teacher, a student a is considered to cover a skill i if $s_i^a \geq v$. This extends to teams, i.e. a team covers a skill if at least one of its members covers that skill. Additionally, the *minimal skill coverage* $c \in [n]$ indicates the minimal number of skills each team has to cover.

Solution. The basic problem solution is a partition of m students into l teams such that team sizes are respected and each team covers at least c skills. Thus, a feasible solution is a total function $f : [m] \to [l]$ such that $\forall j \in [l]$ $k_{min} \leq \#f^{-1}(j) \leq k_{max}$ (*team-size constraint*) and $\#\{i \in [n] \mid \exists a \in f^{-1}(j) : s_i^a \geq v\} \geq c$ (*team-skill constraint*). If $c = 0$, there always exists a trivial solution.

Extended e-TFP problem model

We now add to the basic e-TFP model objectives concerning the preferences, hence turning it into an optimization problem. Let $M = \{(a, b) \in [m]^2 \mid f(a) = f(b), a \neq b\}$ denote all pairs of students that are on the same team in some given feasible solution f. Furthermore, we call a preference $p_{a,b}$ *realized* if students a and b are assigned to the same team, i.e. $(a, b) \in M$.

- **O1 – Minimize teammate preference dissatisfaction.** Maximize the smallest realized preference, i.e. $\min_{(a,b) \in M} p_{a,b}$.
- **O2 – Maximize teammate preference satisfaction.** Maximize the sum of all realized preference values, i.e. $\sum_{(a,b) \in M} p_{a,b}$.
- **O3$_{p_0}^{+/-}$ – Maximize/minimize specific preferences.** Maximize $(+)$ or minimize $(-)$ the number of realized preferences with a value of p_0, i.e. $\#\{(a, b) \in M \mid p_{a,b} = p_0\}$.

3 e-TFP as a modular ILP problem

We formulate e-TFP as a modular *integer linear programming* (ILP) problem involving a base ILP model and extensions for the individual objectives. This allows us to explore multiple strategies by combining and optimizing different objectives in a hierarchical manner. We use the Gurobi solver version 10.0.1 for the implementation. To ease readability, we make use of indicator, min and logical constraints supported by Gurobi in the following ILP model.

Base model. The base model only deals with finding a feasible solution for the basic e-TFP problem. It defines the following variables: $x_{a,j} \in \{0, 1\}$ indicates whether student a is assigned to team j, $y_{j,i} \in \mathbb{N}$ counts how many members of team j cover the skill i, and $z_{j,i} \in \{0, 1\}$ indicates whether team j covers skill i. A feasible solution then respects the following constraints:

$$\sum_{j \in [l]} x_{a,j} = 1 \qquad \forall a \in [m] \qquad (1)$$

$$\sum_{a \in [m]} x_{a,j} \geq k_{min} \qquad \forall j \in [l] \qquad (2)$$

$$\sum_{a \in [m]} x_{a,j} \leq k_{max} \qquad \forall j \in [l] \qquad (3)$$

$$y_{j,i} = \sum_{a \in [m] : s_i^a \geq v} x_{a,j} \qquad \forall j \in [l], i \in [n] \qquad (4)$$

$$z_{j,i} = \min(1, y_{j,i}) \qquad \forall j \in [l], i \in [n] \qquad (5)$$

$$\sum_{i \in [n]} z_{j,i} \geq c \qquad \forall j \in [l] \qquad (6)$$

Constraint (1) ensures that each student a is assigned to exactly one team, while (2) and (3) keep each team's size within the specified bounds. The team skill constraint is modeled by constraints (4) through (6). Constraints (4) counts the members of team j covering skill i. This count is transformed into the binary indicator $z_{j,i}$ in constraint (5), which is then used in constraint (6) to ensure each team covers a minimum of c skills.

O1 – Minimize teammate preference dissatisfaction. With objective O1, we seek to avoid assigning two students who do not wish to work together to the same team. This requires the following additional variables: $q_{a,b} \in \{0,1\}$ indicates whether students a and b are assigned to the same team and $r \in \mathbb{R}$ models the lowest realized preference anywhere in the solution. The base model is then extended as follows: Maximize r subject to:

$$q_{a,b} = 1 \implies x_{a,j} = x_{b,j} \quad \forall a,b \in [m], j \in [l] \quad (7)$$
$$q_{a,b} = 0 \implies x_{a,j} + x_{b,j} \leq 1 \quad \forall a,b \in [m], j \in [l] \quad (8)$$
$$q_{a,b} = 1 \implies r \leq p_{a,b} \quad \forall a,b \in [m] \quad (9)$$

Constraints (7) and (8) ensure that indicator $q_{a,b}$ is set to 1 if and only if students a and b are assigned to the same team. Constraint (9) bounds r to the preference $p_{a,b}$ between a and b if they are assigned to the same team. Hence, maximizing r ensures optimal solutions avoid low-preference students on the same team whenever feasible.

O2 – Maximize teammate preference satisfaction. Objective O2 maximizes the sum of realized preferences. Variable $t_{a,b,j} \in \{0,1\}$ is introduced to indicate whether students a and b are both assigned to team j. This leads to the following base model extension:

$$\max \sum_{a,b \in [m], j \in [l]} t_{a,b,j} p_{a,b} \quad (10)$$
$$\text{s.t.} \quad t_{a,b,j} = x_{a,j} \wedge x_{b,j} \quad \forall a,b \in [m], j \in [l] \quad (11)$$

Constraint (11) ensures that $t_{a,b,j}$ is set to 1 if and only if both students a and b are assigned to team j. Objective (10) models all realized preferences. Note that the base model's constraints ensure that for each student pair (a,b) exactly one of the indicator variables $t_{a,b,j}$ is set to 1. Due to preliminary tests showing that certain modeling strategies significantly reduce the time Gurobi takes to solve these models, the indicator for two students being on the same team is modeled differently compared to objective O1.

O3$_{p_0}^{+/-}$ – Maximize/minimize specific preferences. Objective O3 maximizes $(+)$ or minimizes $(-)$ the number of realized preferences with a value of p_0. Let $A = \{(a,b) \in [m]^2 \mid p_{a,b} = p_0\}$ be the set of student pairs with such preferences. Variable $t_{a,b,j} \in \{0,1\}$ is introduced only for all $(a,b) \in A$, indicating whether students a and b are both assigned to team j. The base model extension is as follows:

$$\text{max/min} \sum_{(a,b) \in A, j \in [l]} t_{a,b,j} \quad (12)$$
$$\text{s.t.} \quad t_{a,b,j} = x_{a,j} \wedge x_{b,j} \quad \forall (a,b) \in A, j \in [l] \quad (13)$$

Objective (12) maximizes or minimizes the number of student pairs of interest assigned to the same team. Constraint (13) is the same as (11).

4 Experimental results

We evaluate our approach using a real-world dataset from a university-level, project-based course. The course consisted of 60 students, split into groups of 4 to 6 people. We are provided with an anonymized skill matrix, denoting the skill level on a 0-5 scale of each student across 6 distinct skills, and a preference matrix with $d = 2$ and a value of $X = 4$ for strong preferences. A teacher's heuristic solution serves as a baseline for comparison (*greedy human solution*). We use two evaluation metrics: i) the number of realized strong and weak teammate preferences, and ii) the computational time of each solution. For this comparison, we set the skill threshold to $v = 4$ and the minimal skill coverage to $c = 4$.

Strategy	Realized preferences X	2	1	0	-1	-2	Time
greedy human solution	77	14	6	134	5	4	-
e-TFP(O1)	7	2	6	235	**0**	**0**	5s
e-TFP(O2)	106	**28**	**8**	103	2	1	4m 7s
e-TFP(O3$_X^+$)	**107**	22	6	104	3	6	12s
e-TFP(O1, O3$_X^+$)	103	19	4	122	**0**	**0**	5m 29s
e-TFP(O3$_{-2}^-$, O3$_{-1}^-$, O3$_X^+$)	103	19	4	124	**0**	**0**	45s

Table 1: Strategy comparison.

Strategy comparison. Table 1 summarizes the strategy performance and comparison results. Each strategy uses different objectives indicated by its name (e.g., e-TFP(O3$_X^+$) uses objective O3 to maximize the number of strong realized teammate preferences). Multiple objectives are optimized hierarchically from left to right.

Almost all strategies outperformed the heuristic teacher solution in minimizing student dissatisfaction from being in the same team with undesired teammates. Except e-TFP(O1), the human greedy solution had the fewest realized strong preferences (X), indicating its ineffectiveness in considering strong teammate preferences. As anticipated, e-TFP(O2) and e-TFP(O3$_X^+$) produced the best solution in terms of maximizing weak and strong teammate preferences. Additionally, e-TFP(O1, O3$_X^+$) and e-TFP(O3$_{-1}^-$, O3$_{-2}^-$, O3$_X^+$) had no realized preferences with values of -2 and -1, showcasing their effectiveness at avoiding undesired teammate preferences. All strategies were computationally efficient, taking seconds to a few minutes, while yielding optimal solutions based on their objectives. This renders them suitable for time-sensitive scenarios like online team formation. Finally, our strategy comparison indicates that a trade-off exists between minimizing student dissatisfaction and maximizing satisfaction (weak or strong).

5 Conclusion and Future work

This paper models the educational Team Formation Problem (e-TFP), addressing optimal student team composition by considering both bottom-up teammate preferences and top-down teacher skill coverage requirements. We propose five modular strategies to solve it, with results showcasing their superior performance over the human (teacher) greedy solution, while maintaining computational efficiency. Our findings also underscore the trade-offs teachers must consider based on course requirements. This study advances algorithmic team formation optimization, for better learning outcomes and higher student satisfaction. Future work includes testing larger inputs, varied skill coverage requirements, diverse teammate preference formats, and dynamic regrouping based on adaptations of the original solution.

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