

Optimising Congenial Teams

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Abstract. Effective teams are crucial for organisations, especially in environments that require teams to be constantly created and dismantled, such as software development, scientific experiments, crowd-sourcing, or the classroom. One of the key factors influencing team performance is the personality of team members. In this paper, we introduce a new algorithm to partition a group of individuals into gender and psychologically-balanced problem-solving teams. With this purpose, we got inspiration from Wildes post-Jungian theory for team formation. Personality traits of people are obtained through a quantitative transformation of the Myers-Briggs Type Indicator (MBTI). The algorithm uses a greedy technique to balance the psychological traits of the members of teams so that each team gets the full range of problem-solving capabilities. Finally, we present some preliminary empirical results comparing the quality of the teams obtained by our algorithm and those proposed by a teacher.

1 Introduction

Some tasks, due to their complexity, cannot be carried out by single individuals. They need the concurrence of sets of people forming teams. However, sometimes teams work less effectively than initially expected due to several reasons: a bad balance of their capacities, bad personal relations, or difficult social situations. Team formation is thus a problem that has attracted the interest of research groups all over the world, especially in the area of organizational psychology. The focus is on considering individuals characteristics and their context, when it comes to team creation. Those characteristics include skills and competences, experiences, age and gender as well as personality. Context is understood as organizational, cultural and, in general, social.

At individual level, research has proven that general mental ability is one of the best predictors of job success [22]. Moreover, with respect to teams, the stronger the competences of each member, the better the performance of the whole team [24]. Numerous studies [3, 14, 23, 26] underline the importance of personality traits or *types* in team formation. Other studies have focused on how team members should differ or converge in their characteristics, such as experience, personality, level of skill, or gender, among others [25]. Recent research findings [29, 27] suggest that both a diverse personality profile of team members and a balanced gender distribution, positively influence the effectiveness of a team. Here, effectiveness is understood as the probability of goal achievement while performing problem-solving tasks.

In the field of computer science, mainly in the area of multiagent systems, the focus is on which team and coalition structure maximizes social welfare, or minimizes the agents' incentive to leave their coalitions [19]. Team and coalition formation are key for many applications related to multiagent systems, such as RoboCup rescue teams [20], Unmanned Aerial Vehicles (UAVs) operations [11], or team formation in social networks [13], just to name a few. Rahwan et al. [18] propose the constrained coalition formation (CCF) framework, which allows to impose constraints on the coalition structures that can be formed, e.g. certain agents may be prohibited from being in the same coalition, or the coalition structure may be required to consist of coalitions of the same size. Recently, online teams consisting of qualified humans with the objective of balancing workload and coordination costs are automatically created [2]. The only model to our knowledge considering personality to form teams is [10]. They use the classical MBTI personality test while we use a modified version of it based on Post-Jungian Personality Theory [27]. Also, they look for the best possible team built around a selected leader while we look for the best partition of agents into multiple teams, without leaders, of a given size. We also differ in that we consider gender balance. Although [10] team formation considered real data, the resulting teams' performance was not validated in the real setting (Bayesian theory was used to predict the probability of success in various team composition conditions).

This paper makes the following contributions. First, we define the congenial team formation problem as the problem of partitioning a group of agents into teams with limited size so that each team counts on diverse and complementary personalities as well as gender balance. The teams are overall balanced across the partition in that the variance of congeniality of the different teams is small. We provide an approximate, local algorithm to solve our team formation problem. We empirically evaluate our algorithm using real data. Our preliminary results show that the teams generated by our algorithm are at least as good as the teams created by experts.

This paper is structured as follows. In Section 2 we give the background on personality measures. In Section 3 we formally describe the congenial team formation problem and in Section 4 we present our algorithm to solve the congenial team problem. Then, in Section 5 we describe an initial validation of our algorithm in the context of team formation in English learning classrooms. Finally, Section 6 discusses our approach and future work.

2 Personality

Personality determines people's behaviour, cognition and emotion. Different personality theorists present their own definitions of personality and different ways to measure it based on their theoretical positions.

The most popular approach is to determine personality through a set of questions. There have been several simplified schemes developed over the years to profile human personality. The most popular are the Five Factor Model (aka FFM or "Big Five") that uses five broad dimensions to describe human personality [8] and the Myers-Briggs Type Indicator (MBTI)

scheme designed to indicate psychological preferences in how people perceive the world and make decisions [7].

According to [17] FFM personality instruments fail to detect significant sex differences in personality structure. It is said also that the Big Five dimensions are too broad and heterogeneous, and lack the specificity to make accurate predictions in many real-life settings [5]. Johnson and Kreuger (2004) found that each domain was aetiologically complex, raising fundamental questions about the conceptual and empirical adequacy of the FFM.

On the other hand, the MBTI measure consists of four dimensions on a binary scale, e.g. either the person is Extroverted or Introverted. Within this approach every person falls into one of the sixteen possible combinations of the four letter codes, one letter representing one dimension. This approach is easy to interpret by non-psychologists, though reliance on dichotomous preference scores rather than continuous scores excessively restricts the level of statistical analysis [9].

Having considered the arguments above, we have decided to explore a novel method: the Post-Jungian Personality Theory, which is a modified version of the Myers-Briggs Type Indicator (MBTI), the “Step II” version of Quenk, Hammer and Majors [29]. The questionnaire is shorter, contains only 20 quick questions (compared to the 93 standard MBTI questions), which is very convenient for both experts wanting to design teams and individuals doing the test as completing the test takes just a few minutes. Douglass J. Wilde claims that it covers the same psychological territory as MBTI [27]. The main novelty of this approach is its use of the numerical data generated by the instrument [28]. The results of this method seem promising as within a decade this novel approach tripled the fraction of Stanford teams awarded national prizes by the Lincoln Foundation [27].

The test is based on the pioneering psychiatrist Carl Gustav Jung’s cognitive mode personality model. It has two sets of variable pairs called psychological functions:

- **Sensing / Intuition (SN)**: The sensing function S “includes all perceptions by means of the sense organs” [12], whereas the intuition function N “is perception by means of the unconscious” (ibid).

SN1	You prefer the:	(s) concrete	(n) abstract
SN2	You prefer:	(s) fact-finding	(n) speculating
SN3	You are more:	(s) practical	(n) conceptual
SN4	You are more:	(s) hands-on	(n) theoretical
SN5	You prefer the:	(s) traditional	(n) novel

Table 1. The part of the questionnaire to collect the SN dimension

- **Thinking / Feeling (TF)**: By the thinking function T Jung means “... intellectual cognition and the forming of logical conclusions,” whereas “feeling (F) is a function of subjective valuation” (ibid).
and psychological attitudes:

<i>TF1</i>	You prefer:	(t) logic	(f) empathy
<i>TF2</i>	You are more:	(t) truthful	(f) tactful
<i>TF3</i>	You are more:	(t) questioning	(f) accomodating
<i>TF4</i>	You are more:	(t) skeptical	(f) tolerant
<i>TF5</i>	Judges should be:	(t) impartial	(f) merciful

Table 2. The part of the questionnaire to collect the TF dimension

- **Perception / Judgment (PJ):** The attitude energy for information collection (P) is independent of and usually different from that for decision making (J) [12].

<i>PJ1</i>	You are more:	(p) casual	(j) systematic
<i>PJ2</i>	You prefer things:	(p) open-ended	(j) planned
<i>PJ3</i>	You work better	(p) pressured	(j) unpressured
<i>PJ4</i>	You prefer:	(p) variety	(j) routine
<i>PJ5</i>	You are more:	(p) improvised	(j) methodical

Table 3. The part of the questionnaire to collect the PJ dimension

- **Extroversion / Introversion (EI):** Extroversion is the flow of psychic energy outward toward the exterior world: “an outward turning of libido” [12], whereas introversion draws psychic energy towards ones interior psyche: “an inward turning of libido” [12].

<i>EI1</i>	You are more:	(e) sociable	(i) reserved
<i>EI2</i>	You are more:	(e) expressive	(i) contained
<i>EI3</i>	You prefer:	(e) groups	(i) individuals
<i>EI4</i>	You learn better by:	(e) listening	(i) reading
<i>EI5</i>	You are more:	(e) talkative	(i) quiet

Table 4. The part of the questionnaire to collect the EI dimension

Psychological functions and psychological attitudes compose together a personality. Every dimension of personality (EI, SN, TF, PJ) is tested by five questions as shown in tables 1–4. Each question can be answered in three different ways. Take for instance EI1 above (see table 4), a user can select “sociable”, “reserved” or both (see Figure 2). The numerical value of each dimension is calculated as follows. Take again the EI questionnaire (see table 4), we calculate the number of (e) answers (those at the left in the table), subtract from them the number of (i) answers and normalise by dividing by 5 which is the number of questions. The result is then a value in $[-1, 1]$. We repeat this procedure for each dimension to get a vector of four values $(EI, SN, TF, PJ) \in [-1, 1]^4$.

To construct teams, as we will see in Section 3, the psychological functions (SN and TF) will be the most influential ones.

3 The congenial team formation problem

Recent studies show that there is a trade-off between the creative productivity caused by “meta-cognitive conflict” and “harmony” — good feeling — on a team [6]. According to this view, effectiveness is generated by the conflict between people having different views of the world (associated with opposing personality and gender), whereas harmony comes from agreement between people with similar personalities [29]. Inspired by this theory, we will construct cognitively diverse teams using the psychological function pairs SN and TF, the psychological attitudes PJ and EI, and gender.

3.1 What are the qualities of an agent?

In our model, a number between -1 and 1 measures the personality of an agent in each dimension. For example for the Feeling-Thinking (TF) dimension, a value between -1 and 0 means that a person is of feeling type, and a value between 0 and 1 means she is of thinking type. Next, we formally define the notions of personality, agent, and team.

Definition 1 (Personality). *A personality is a vector of personality traits $\langle sn, tf, ei, pj \rangle \in [-1, 1]^4$ determining an agent’s behaviour.*

Definition 2 (Agent). *An agent is a pair $\langle g, p \rangle$ such that $g \in \{man, woman\}$ and p is a personality. We will note the set of agents as $A = \{a_1, \dots, a_n\}$.*

Definition 3 (Team). *We say that any non-empty subset of A is a team.*

Given a team S , we note by $w(S)$ and by $m(S)$ the number of women and men in the team respectively.

3.2 What is the best size of a team?

Among team scientists the size of a team is the most frequently studied parameter when analyzing team performance. [16] states that the right number of people in a team depends on the kind of tasks team members need to perform. She believes that for teams ranging from four to six, all the team members’ competences can be fully used, but for larger teams some members’ competences are under-used and this provokes that teams split up.

According to the studies of [4], the optimal number of members for problem-solving tasks is five. He states that there is a limit to the team size, which, if exceeded, causes the drop in the efficiency of the team. [4] says that in a case of a team containing more than six people there is a tendency to split the team into two, which brings about negative effects. The cause is twofold: high coordination cost and loss of motivation by team members [16].

Sometimes larger teams may be called for just to handle the amount of work. Bigger teams may also be needed when the staff is too small to supervise a high number of teams.

In these cases [29] advises to construct quintets and then put the remaining individuals on whichever teams strike their fancies, since their added presence will not improve the team composition anyway.

In conclusion, it appears that there is an inverse relationship between the size of the team and its effectiveness. According to the studies above, teams up to six members reach the highest efficiency to gradually decrease with adding new team members.

3.3 How to split agents in fixed sized teams?

We note by $n = |A|$ the number of agents in A , by $k \in \mathbb{N}$ the target number of agents in each team, and by m the minimum total number of teams, $m = \lfloor n/k \rfloor$.

The quantity distribution of agents in teams of a partition, noted $T : \mathbb{N} \times \mathbb{N} \rightarrow \mathbb{N} \times \mathbb{N} \cup (\mathbb{N} \times \mathbb{N})^2$, is defined as:

$$T(n, k) = \begin{cases} \{(m, k)\} & \text{if } n \geq k \text{ and } n \bmod k = 0 \\ \{(n \bmod k, k + 1), (m - (n \bmod k), k)\} & \text{if } n \geq k \text{ and } n \bmod k \leq m \\ \{(m, k), (1, n \bmod k)\} & \text{if } n \geq k \text{ and } n \bmod k > m \\ \{(0, k)\} & \text{otherwise} \end{cases} \quad (1)$$

Note that depending on the cardinality of set A and the desired team size, the number of agents in each team may vary by one individual.

3.4 How many partitions are there?

There are simply too many partitions! A set of n elements can be partitioned into k unordered subsets of r elements each, $kr = n$, in the following number of ways [21]:

$$\frac{1}{k!} \binom{n}{r, \dots, r} = \frac{n!}{k! \cdot r! \cdot \dots \cdot r!} = \frac{n!}{k! \cdot (r!)^k} \quad (2)$$

Consider now the case of different team sizes in each partition, where there are k subsets of r elements each and j subsets of t elements each ($kr + jt = n$). The number of unordered partitions in this case is given by the following expression [21]:

$$\frac{1}{k!j!} \binom{n}{t, t, \dots, t, r, \dots, r} = \frac{n!}{k! \cdot j! \cdot t! \cdot \dots \cdot t! \cdot r! \cdot \dots \cdot r!} = \frac{n!}{k! \cdot j! \cdot (r!)^k \cdot (t!)^j} \quad (3)$$

Example Let's say we have a classroom of $n = 30$ students, which is a typical Spanish secondary school classroom size. Our goal is to divide the classroom into duets. Hence, at the end of the procedure we want to have 15 pairs. According to equation 2, there are $6.19 \cdot 10^{15}$ partitions. In the case of a classroom with $n = 32$ students, we would need to consider $1.92 \cdot 10^{17}$ partitions, which is 31 times more.

Therefore, when performing team formation, considering all possible partitions is out of the question. Thus, hereafter we will focus on designing an approximate team formation algorithm that avoids exploring the whole search space.

3.5 Formalising the congenial team formation problem

Given a set of agents A , our goal is to split them into teams of a particular size that are balanced in personality and gender. This will lead us to define our team formation problem as a particular type of set partition problem. First, we will refer to any partition of A as a team partition. We are interested in the following team partitions.

Definition 4 (Size-constrained Team Partition). *Given a set of agents A we say that a team partition P_k is constrained by size k iff: (i) for every team $S_i \in P_k$ with size s_i , $|s_i - k| \leq 1$ holds; and (ii) for every pair of teams $S_i, S_j \in P_k$ with sizes s_i and s_j respectively, $|s_i - s_j| \leq 1$.*

We note by $\mathcal{P}_k(A)$ the set of all team partitions of A constrained by size k . Henceforth, we will focus on team partitions constrained by some size.

Now we want to find which is the most psychologically balanced team partition. We will base this optimisation problem on an evaluation function:

Definition 5. *Given the set of all team partitions of size k , $\mathcal{P}_k(A)$, a team evaluation function is any function f such that: $f : \mathcal{P}_k(A) \rightarrow \mathbb{R}$.*

The Bernoulli-Nash function product of individual utility is one of the most used methods for social welfare [15]. This function aims at a “fair” solution in which no one is especially penalised with a particular outcome. Here, the same idea applies when aiming at a balanced congeniality of the different teams in a partition. Hence, we will study the following function f in this paper, which henceforth we will refer to as the *congenial evaluation function*:

$$f(P) = \prod_{s \in P} h(S) \tag{4}$$

where P is a team partition. We will refer to $f(P)$ as the congenial value of team partition P . Inspired by the theory of Douglass J. Wilde [27] we will define the team utility function $h(S)$, such that:

- it values more teams whose SN and TF personality dimensions are as diverse as possible,
- it prefers teams with at least one agent with positive EI, TF dimensions and negative PJ dimension, namely an extrovert, thinking and judging agent (called ETJ personality),
- it values more teams with at least one introvert agent,
- it values the gender balance in a team.

Formally this utility function is defined as follows:

$$\begin{aligned}
h(S) = & \sigma_{SN}(S) \cdot \sigma_{TF}(S) + \max_{a_i \in S} ((0, \alpha, \alpha, \alpha) \cdot p_i, 0) \\
& + \max_{a_i \in S} ((0, 0, -\beta, 0) \cdot p_i, 0) + \gamma \cdot \sin \pi \cdot g(S)
\end{aligned} \tag{5}$$

where the different parameters are explained next.

- $\sigma_{SN}(S)$ and $\sigma_{TF}(S)$: These variances are computed over SN and TF personality dimensions of the members of team S . As we want to maximise f we want these variances to be as large as possible. The larger the values of σ_{SN} and σ_{TF} the larger their product will be and hence, the team diversity.
- α : The maximum variance of any distribution over the interval $[a, b]$ corresponds to a distribution with the elements evenly situated at the extremes of the interval. The variance will always be $\sigma^2 \leq ((b - a)/2)^2$. In our case with $b = 1$ and $a = -1$ we have $\sigma \leq 1$. Then, To make the four factors equally important and given that the maximum value for p_i (the personality vector of agent a_i) would be $(1, 1, 1, 1)$ a maximum value for α would be $3\alpha = ((1 - (-1))/2)^2 = 1$, as we have the factor $\sigma_x \cdot \sigma_y$, so $\alpha \leq 0.33(3)$. For values situated in the middle of the interval the variance will be $\sigma^2 \leq \frac{(b-a)^2}{12}$, hence the reasonable value for α would be $\alpha = \frac{\sqrt{(1-(-1))^2/12}}{3} = 0.19$
- β : A similar reasoning shows that $\beta \leq 1$.
- γ is a parameter to weigh the importance of a gender balance and $g(S) = \frac{w(S)}{w(S)+m(S)}$. A perfectly gender balanced team with $w(S) = f(S)$ would give expression $\sin(\pi \cdot g(S)) = 1$. The higher the value of γ , the more important is that team S is gender balanced.

In summary, we will use a utility function h such that: $\alpha = \frac{\sigma_{SN}(S) \cdot \sigma_{TF}(S)}{3}$ and $\beta = 3 \cdot \alpha$. We can now formalise the congenial team formation problem as follows:

Definition 6. *Given a set of agents A and a team size k , the **congenial team formation problem (CTFP)** is the problem of finding a team partition constrained by size k whose congenial value is maximal. More specifically, the congenial team formation problem is the problem of finding $P_k^* \in \arg \max_{P \in \mathcal{P}_k(A)} f(P)$.*

Therefore, the CTFP can be regarded as a particular type of coalition structure generation problem such that: feasible coalition structures are those in $\mathcal{P}_k(A)$, and it employs the non-linear function h as characteristic function and the Bernoulli-Nash product defined by f to value coalition structures.

4 Solving the congenial team formation problem

In this section we detail an algorithm, the so-called *ConTeam*, which solves the congenial team formation problem described above. The algorithm proposed in this section,

ConTeam, is a greedy algorithm that quickly finds a first, local solution, to subsequently improve it, hoping to reach a global optimum.

Algorithm 1 is divided into two parts:

Algorithm 1. ConTeam	
Require: A	▷ The set of agents
Require: $T(A , k)$	▷ Quantitative team distribution
Require: $P_{best} = \emptyset$	▷ Initialize best partition
1: if $T(A , k) \neq (0, k)$ then	
2: for all $(numberOfTeams, size) \in T(A , k)$ do	
3: $C = Combinations(A, size)$	▷ We find combinations $\binom{ A }{size}$
4: for all $S \in C$ do Calculate team utility $h(S)$	▷ See section 3.5
5: $C_{sorted} = Sort(C)$ descending by team utility values	
6: $i = 0$	
7: $end = size(C_{sorted})$	
8: while $numberOfTeams \neq 0$ and $i \leq end$ do	
9: if $C_{sorted}[i] \cap P_{best} = \emptyset$ then	
10: $P_{best} = P_{best} \cup C'[i]$	
11: $numberOfTeams = numberOfTeams - 1$	
12: $i = i + 1$	
13: while not <i>termination_condition</i> do	
14: $(S_1, S_2) \leftarrow selectRandomTeams(P_{best})$	
15: $(P_{bestCandidate}, bestCandidateValue) \leftarrow (\emptyset, 0)$	
16: for all $P_{candidate} \in P_k(S_1 \cup S_2)$ do	
17: $candidateValue = f(P_{candidate})$	
18: if $candidateValue > bestCandidateValue$ then	
19: $P_{bestCandidate} = P_{candidate}$	
20: $bestCandidateValue = candidateValue$	
21: if $bestCandidateValue > h(S_1) \cdot h(S_2)$ then	
22: $P_{best} = replace(\{S_1, S_2\}, P_{bestCandidate})$	

- *Find a first team partition.* Given a set of agents A , we start by determining the quantitative distribution of individuals among teams of size k using function $T(|A|, k)$, as defined in section 3.3) (line 1). For each team size (line 2), we assess all possible teams of the given size (line 3), we compute their utilities (line 4), and we finally sort the teams by their utilities in descending order (line 5). Finally, starting from the top of the sorted list of possible teams, we greedily add teams to the team partition that we intend to build, P_{best} , considering the teams with the largest possible values (lines 8 to 12). When reaching line 13, P_{best} will contain a first disjoint subset of teams (a team partition). Intuitively, this first team partition is potentially a good solution because our algorithm builds the partition considering the teams with the largest utility values.

- *Improve the team partition.* The second part of the algorithm consists on continuously improving the current team partition. The idea is to obtain a better team partition by performing crossovers of two randomly selected teams to yield two better teams. This second part works as follows. First, we select two random teams, S_1 and S_2 , in the current team partition (line 14). Then we compute all team partitions of size k with agents in $S_1 \cup S_2$ (line 16), and we select the best candidate team partition, named $P_{bestcandidate}$ (lines 16 to 20). Finally, if the best candidate team partition utility is larger than the utility contribution of S_1 and S_2 to the current best partition P_{best} (line 21), then we replace teams S_1 and S_2 by the teams in the best candidate team partition (line 22). The algorithm continues until a termination condition is reached (line 13), be it after a number of iterations or when some time deadline is reached.

4.1 Analysing ConTeam

The purpose of this section is to pitch ConTeam against a complete, exhaustive search algorithm when solving the team formation problem. We will refer to this later algorithm as EPS (Exhaustive Partition Search).

Our comparison measures:

- the quality of the solutions produced by ConTeam (assessed as the *optimality ratio* of the solutions produced by ConTeam with respect to the optimal solution obtained by exhaustive search); and
- ConTeam’s time gain (as the time ratio between the time employed by ConTeam to produce solutions with respect to the time taken by exhaustive search to reach the optimum).

#agents	Team size on average	# partitions	Time ConTeam [s]	Time ConTeam St.Dev	Time EPS [s]	Optimality ratio	Time ratio
12	2	10395	0.03015	0.01171	14.34527	100.0%	0.210%
13	2	270270	0.06153	0.02729	205.21880	97.4%	0.030%
14	2	135135	0.00425	0.00346	428.66636	100.0%	0.001%
12	3	15400	0.05185	0.02382	9.42382	100.0%	0.550%
13	3	200200	0.08818	0.04102	96.36160	100.0%	0.092%
14	3	1051050	0.10422	0.06313	542.53701	100.0%	0.019%
15	3	1401400	0.09188	0.03403	2002.56047	98.5%	0.005%
13	4	45045	0.13395	0.06553	16.16449	100.0%	0.829%
14	4	126126	0.14734	0.08452	53.76786	99.6%	0.274%
15	4	2627625	0.25567	0.09486	55.22857	99.2%	0.463%
16	4	2627625	0.09327	0.05795	2083.84039	100.0%	0.004%
16	5	1009008	0.36315	0.14380	394.28547	100.0%	0.092%
17	5	2858856	1.01911	0.38031	1187.58897	100.0%	0.086%
18	6	2858856	1.16757	0.50153	1522.19960	99.8%	0.077%

Table 5. Comparison of ConTeam and EPS.

We perform our comparison as the number of agents grows and the size of teams grows. We considered team formation problems with up to 18 agents because of the obvious high cost of running EPS. Furthermore, based on our discussion on section 3.2 about team sizes in practice, we considered team sizes less or equal than 6 (namely $k \leq 6$). Regarding the termination conditions for ConTeam, this finished after either 90 seconds elapsed or 100 iterations of the loop between lines 14 and 22 took place without improving the current best solution. We run both ConTeam and EPS on a MacBook Pro, 2.6 GHz Intel Core i5, 8 GB 1600 MHz DDR3.

Table 5 shows the results of our comparison. For each configuration (pair of number of agents and team size), we performed 50 runs of ConTeam. Our results show that the optimality ratio of ConTeam is consistently beyond 97.4%. Moreover, ConTeam reached optimality for 9 out of the 14 configurations that we considered. As to the time required by ConTeam we observe that it employs less than 1% of the time required by exhaustive search for the majority of configurations. Thus, ConTeam delivers high quality solutions at a low cost when compared to exhaustive search.

We studied the time needed to create triplets using ConTeam as we need them in the in the experiments of Section 5.2. We considered 150 agents and the calculation was done for 10 runs. After 100 iteration without solution improvement the ConTeam stops. The average time required is 59.44 seconds ($\sigma = 5.83$). Taking into account that team formation does not require real-time solutions, we consider this time as sufficiently good. As a conclusion of this analysis, we think that ConTeam can be effective also for commercial purposes, where employees need to be divided into teams.

5 Experimental Results

5.1 Grouping high school students

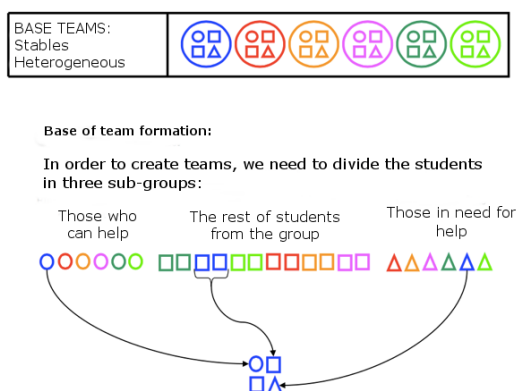


Fig. 1. Current practice on team formation (from [1]).

must be representative of the diversity of the whole class; their composition, therefore, must be heterogeneous.

To build teams, teachers currently distribute the students of a class into three rough sub groups (see Figure 1):

The term co-operative learning is often used to refer to learning procedures based on the organization of students into small heterogenous teams in which individual and team working are organized with the aim of getting both finished academic tasks and deep learning.

Co-operative learning is based on:

- The strength of interpersonal relationships,
- The effectiveness of socialization and integration values,
- The theories on learning steaming from disparity and sociocognitive conflict.

Having good student teams is key for successful co-operative learning. Groups should be small (3–4 students) and they

- students who are capable of helping others,
- students that are in need for help, and
- the rest of students from the group.

To distribute students teachers rely on their knowledge of students, as not only good grades have to be taken into consideration, also personality traits and affiliations are important, e.g. a student who has very good grades but is lacking teamwork skills will not be included in the first group, and a disruptive student with low grades student but with a good disposition to work on themes that really matter to him/her and/or with a strong leadership, can instead be included in the first group.

Each team should have one student of each sub-group at least, with only the sub-group “the rest of students” allowed to have two students in a team, see Figure 1.

5.2 Experiment design and results

English classrooms at Torras i Bages

“Institut Torras i Bages” is a state school near Barcelona. It has 500 students in ages varying from 11 to 18. Collaborative work has been implemented for 5 years in their final assignment (“Treball de Síntesi”) with a steady and significant increase in the scores and quality of the final product that students are asked to deliver.

The grouping system ConTeam has been used upon three groups of students: ‘3r ESO B’ (25 students), ‘3r ESO C’ (25 students) and ‘2n Batxillerat A’ (23 students). Using computers and/or mobile phones, students answered the questionnaire described in section 2. For the snapshot of the application used to collect answers, see Figure 2. Before answering the questions students were requested to: (i) focus on their inner self, (ii) answer truthfully, (iii) answer quickly with minimum over-thought, (iv) answer individually (not checking with friends), and (v) keep their answers private.

Post-Jung Personality Test

This information will be used in a scientific experiment to organise balanced teams of individuals taking into account the individual preferences and desires.

Please fill the form choosing the most suitable answer for you.

Based on your answers we will build your personality profile.

Select ‘Either way’ circle if you cannot choose one answer.

Your name

Your email

We need your e-mail in order to send you your customized personality results.

Gender Male Female

Age 0-19 20-29 30-39 40-49 50-59 60+

Group

According to your affiliation, we will generate teams

Judges should be Merciful Impartial Either way

You prefer the Traditional Novel Either way

You prefer things Planned Open-ended Either way

You prefer Individuals Groups Either way

You are more Tolerant Skeptical Either way

You work better Unpressured Pressured Either way

You are more Methodical Improvised Either way

You are more Hands-on Theoretical Either way

Fig. 2. Snapshot of the web questionnaire used by students to obtain their personality profile.

Students knew that the purpose of the questions was to generate heterogeneous work groups, did the task well, and were happy with the ensuing personality report.

Groupings Once the psychological profile of all the students was obtained we have used the ConTeam algorithm to find teams of size three for each class. We have decided to generate two disparate groupings with ConTeam to check the robustness of the greedy approach.

The tutor of each team also generated teams according to the current grouping practice as illustrated in Figure 1 and described in section 5.1. The tutor not only knows their psychological profile from practice but she also knows the students’ social and cognitive capabilities.

Results Tutors have evaluated each team in each partition giving an integer value $v \in [1, 10]$ meaning their expectation of the performance of each team. Table 6 shows the average and standard deviation for each partition of the experiment.

Student Group	ConTeam 1st solution	ST.DEV ConTeam1	ConTeam 2nd solution	ST.DEV ConTeam2	Expert Ranking	ST.DEV Expert
2A	6.29	0.49	6.43	0.53	6.14	0.69
3B	7.00	2.56	7.38	0.92	7.13	0.99
3C	9.75	0.71	9.25	0.89	7.50	1.31

Table 6. Expert ranking of each partition - columns 1 - 4 present rankings with standard deviations of partitions created by ConTeam columns 5-6 present evaluations of partitions created by experts.

The results show that the partitions generated by ConTeam are as good as those generated by tutors. This means that even without knowing the students’ background, family situation, language level and social and cognitive capabilities, ConTeam is able to generate teams whose expected performance is very good.

It is important to note that sometimes the expert forms teams knowing that they are not going to perform too well simply because she has no computing capabilities to consider as many possible combinations of students as ConTeam can.

6 Discussion

In this paper we introduced ConTeam, an algorithm for partitioning groups of humans into gender and psychologically balanced problem-solving teams. The algorithm was tested on 3 student groups and the results were evaluated by a tutor that knew the students—their background, competences, social and cognitive capabilities. To our knowledge, ConTeam is the first computational model to build congenial teams based on personality diversity and

gender balance. This is a preliminary work, although first results show the efficacy of the algorithm.

The algorithm is potentially useful for any organisation that faces the need to optimise their problem solving teams (e.g. a class-room, a company, a research unit). Our next step will consist of evaluating the effectiveness of the algorithm by comparing the *actual* performance of teams created by an expert and ConTeam. We are planning to give each team in a partition a problem-solving, creative task and measure the quality of the outcome and the time spent. We will do this in the context of English learning tasks and in the context of projects within a software company. Another application in education we would like to explore is how to split large groups of students (e.g. 150 students) into classes (e.g. 6 classes of 25 students) that have congenial personality and congenial capabilities. This is a very large real combinatorial problem, not properly solved nowadays, that will require improvements in the current algorithm implementation.

We would also like to use a cluster or a supercomputer to scale up the solution and calculate the optimal partitions for a larger number of agents and compare it with the results of our greedy solution. Along this line, we will move from a centralised solution, as presented in this paper, to a distributed solution in which each person is represented by an agent that will search for possible crossovers in teams that are socially beneficial. In this way a faster concurrent search process can be implemented that can scale better over a cluster of computers.

There is also a need to consider richer and more sophisticated models to capture the various factors that influence the coalition formation process in the real world. We will consider how our problem relates to the constrained coalition formation framework [18]. This may help add constraints and preferences coming from experts that cannot be established by any algorithm, e.g. Ana cannot be in the same team with José as they used to have a romantic relationship.

Finally, this algorithm is an important milestone on our path to develop methods to build agent and human teams that balance not only personality, but also individual capabilities and trust on performing complex tasks.

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