The Group Formation Problem: An Algorithmic Approach to Learning Group Formation

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Abstract. Fostering knowledge exchange among peers is important for learners' motivation, achievement of learning goals as well as improvement of problem solving competency. Still, the positive effects of such an exchange depend strongly on the suitability of the selected peers in a group.

A comparison of existing algorithmic solutions applicable for E-learning and CSCL scenarios reveals limited support for requirements derived from related work in pedagogical psychology. Therefore, the GroupAL algorithm is proposed. It supports the use of criteria that are either expected to be matched homogeneous or heterogeneous among participants while aiming for equally good group formation for all groups. A normed metric allows for comparison of different group formations and is robust against variations. Finally, the evaluation reveals the advantages and widespread applicability of GroupAL. Compared to existing solutions, it achieves a better group formation quality under the chosen conditions.

Keywords: Learning Group Formation, Algorithmic Optimization, Matching, CSCL.

1 Introduction and Motivation

The didactic concept of collaboration in small working groups is especially well suitable for tasks aiming for agency of problem solving competency [2]. For development of this increasingly important competency and a successful handling of open-format problems peers discuss their point of view and favored approaches to a problem. Open-format problems are characterized by missing pre-defined approaches or only single correct solutions. While working on such problems, peers can complement one another in learning style and benefit from advances in knowledge or skills. If this potential is used, peers act as an integrated group on analysis and solution of the problem at hand [3].

Fruitful cooperation in the group depends on group size, suitable open-format problems, and manifold other criteria which are related to capabilities and characteristics of the learners, as well as criteria concerning learning context and group constellation. If there is a misalignment within the group concerning

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these criteria, solo attempts as well as digression and missing motivation of individual group members occur [21]. Generally, in classroom scenarios (physical presence of learners) the pedagogue or seminar lecturer knows the learners and can build learning groups manually while considering the criteria. Studies revealed a strong, disadvantageous influence of friendship among the learners and contiguous seats in the moment of group allocation [22]. Thereby, the diverse preconditions of learners, as mentioned above, are not sufficiently considered in the group formation process that aims for maximizing knowledge gain of each individual and optimizing mutual assistance in problem analysis and solution development.

Motivation to develop a suitable, algorithm-based method providing assistance to lecturers for sophisticated learning group formation is further increased, if learners are spread over diverse locations and act as an inter-connected community. If such E-learning environments focus on support for self-regulated learning and do not enforce specific amounts of time invested or do not offer preset learning goals, diversity in preconditions and learning targets of participating learners are (more) diverse [11]. In case of unsupervised learning environments or in case of a higher number of participants that exceeds a certain (classroom typical) limit, manual group formation by lecturers is impractical and algorithmic solutions are not only of great support but strongly needed.

> *The challenge to optimize learning group formation from a given set of peers to match, while respecting homogeneously to match criteria simultaneously with heterogeneously to match criteria and aiming for a balanced quality of the build groups, is called the* Group Formation Problem*.*
> [17, p. 16]

None of the currently existing algorithmic solutions aiming for assistance in such learning group formation incorporates the mentioned aspects sufficiently (see section 2 below). As illustrated above, such a solution is expected to allow manifold criteria, with individual weighting and dimensionality. Additionally, flexibility is desired that allows combination of criteria which are matched homogeneously with criteria which are matched heterogeneously among learners of one group.

In the following, metrics are derived for evaluation of learning group formation quality allowing for the desired combination of criteria. The metrics are used as a basis for the proposed group formation algorithm GroupAL. The results of the conducted evaluation study prove the benefits and improved group formation quality compared to the existing solutions from related work under the chosen conditions.

The contribution at hand is a revised, condensed and translated overview based on earlier publications concerning GroupAL [18, 19, 17].

2 Related Work

Collaboration in small (learning) groups, work phases, and their beneficial conditions, are investigated in the field of pedagogical psychology since the Sixties

[30]. Since then, manifold research studies confirmed the positive effects of collaboration, group-based learning and knowledge exchange among peers. Therefore, Damon [7] concluded for the field of didactic that exchange among peers is a suitable amendment for any teaching scenario. One major prerequisite is the suitability of the problem definition to be addressed by multiple peers collaboratively. It this is not fulfilled, collaboration can still be achieved by knowledge exchange and mutual feedback which can be improved considerably by a structured moderation (of feedback) and preset interaction patterns [29].

After provision (by instructors) or selection (by learners) of problem definition, learning place(s) and interaction patterns, learning groups can be formed under consideration of the context. In case of differences in level of knowledge and abilities among learners, it appears obvious to elect some of them as tutors who pass on their knowledge advances to others in the group (or to a peer in learning tandems) [15, 31]. Even though *learning by teaching* appears to be advantageous likewise for the tutor, contrary argumentation exist. Based on Piaget's constructivist didactic, Damon [7, p. 334] argues mutual respect to be a basic requirement for social interaction and knowledge exchange among learners. But this respect is compromised by a too significant difference in the level of knowledge and abilities. This insight motivates the intention to match peers in learning groups that support mutual amendment based on diversity of knowledge while the level of knowledge is equal (*symmetry of knowledge*) [9, p. 7]. A suitable algorithmic representation model to map (part of) knowledge areas to learning problems and learning targets is given by the skill tree structure of the *knowledge spaces* proposed by Albert and Lukas [1]. Usage of such structures aims for coverage of all related skill tree areas by all learners after solving the provided learning problems. Beside criteria related to the knowledge (structures), learning style preferences are expected to be matched heterogeneously to allow group members to share their (different) views. The resulting cognitive dissonances lead to argumentation and exchange of diverging approaches and considerations, finally resulting in a more comprehensive work on the field of the provided learning problem and inter-relations [8]. Constitutional theories and models for evaluation of learning styles and subsequent group formation are proposed and evaluated by Felder and Silverman [10] or Kolb and Kolb [16]. Additional criteria related to the individual learner are age, gender, geo-location and intensity of work (working hours), which are generally matched homogeneously within a learning group.

Besides criteria related to the individual leaner, group-related criteria are also relevant. Most dominant aspect is the finding of the optimal size of a learning group. Even though the group size depends on learning problem characteristics and expected duration of collaboration within the group, studies identified the optimal group size between three to six learners [27].Such a size allows for adequate exchange and eventually desired heterogeneity of specific criteria within the group while avoiding emergence of sub-groups and redundancy which may lead to exclusion of group members in the end. In addition, attention to group roles and responsibility for parts of the addressed problem, is conducive for exchange within the learning group [20].

Extensive models for learning group formation emerged in the field of pedagogical psychology [6, 21, 26]. The related publications name further aspects and details concerning interplay of group members in learning groups. These aspects can be considered and weighted by users of GroupAL. Still, for the further algorithmic examination of the group formation problem these additional aspects are not discussed in detail here.

3 Goals for Algorithmic Learning Group Formation

In summary, the analysis of related work suggests the following four goals to be achieved by the desired method for algorithmic learning group formation:

G1 extendable modeling, exchangeability, and weighting of criteria used for group formation; due to the fact that no generally accepted list of criteria exists and criteria to be used depend on the context the groups are build for;

G2 support for the creation of homogeneous, heterogeneous and mixed learning groups in several criteria simultaneously; due to the beneficial influence of the *symmetry of knowledge* and mutual amendment;

G3 assessment and optimization of group formations based on a group formation metric that takes into consideration the constellation of group members; due to the targeted mutual exchange and avoidance of exclusion of members;

G4 minimization of the differences among the formed learning groups; due to acceptance by learners and fairness for all participants, e. g. in classroom scenarios.

4 State of the Art in Algorithmic Learning Group Formation

The identified existing algorithmic solutions for learning group formation can generally be separated into two groups of approaches: *semantic matchmakers* and *non-linear optimization techniques.*

Semantic matchmakers utilize ontologies to calculate how well two (or more) learners match for optimal achievement of the set learning goals. Ontologies allow precise formulation for extensive boundary conditions to be respected during group formation [13]. However, application of ontology-based approaches becomes costly, if no suitable ontology exists or boundary conditions – as desired by lecturers – are not directly expressible. Moreover, semantic matchmakers unfortunately do not express the quality of created learning groups in a comparable value and do not include the desired equable distribution of learning group formation quality among all created groups. Still, semantic matchmakers are

Table 1. Approaches to algorithmic learning group formation; • agent system, evaluates suitability of candidates iteratively based on task solutions for a selected homogeneous or heterogeneous strategy, ° statement about restriction violations, * using a threshold, ⋆ using a heuristic.

System	Calculation of Group Formation Quality	Uniform Group Formation Quality	Infinite Number of Criteria	Criteria Weighting	Several Algorithms Available	Homogeneous Group Formation	Heterogeneous Group Formation	Mixed Group Formation
	Qualities							
Fits/CL [13]	-	+	-	-	-	+	+	+
GroupMe [23]	+°	-	+	+	-	+	+	+
I-minds [28]	-•	-	-	-	-	+	+	-•
GroupFormation [5]	-	-	-	-	-	+	+	-
Together [25]	+*	-	-	-	-	-	+	-
OmadoGenesis [12]	+	-	+	-	+	+	+	+
TeamMaker [4]	+⋆	-	+	+	-	+	+	+

well suited for large E-learning scenarios and for expressing complex dependencies to be considered for matchmaking. The benefits and drawbacks of semantic matchmakers and ontoloty-based group formation are derived from two semantic matchmakers whose characteristics are listed for comparison in the first rows of Table 1.

Non-linear optimization techniques use a representation of the desired person-criteria as an n-dimensional feature space (vector) for each learner. Group-related criteria are respected as boundary conditions or within the metric that is used to calculate the group formation quality (*objective quality function*). Based on the feature spaces as input, cluster analysis can be used to match similar learners in respect to the homogeneously to match criteria (similarity). Such an approach can be implemented, e. g. using Fuzzy-C-Means [25]. Unfortunately, this approach is limited in case both, heterogeneously and homogeneously to match criteria, need to be respected during group formation. Here heuristics and iterative optimization can be used as demonstrated by Cavanaugh and Ellis [4]. Only a limited number of solutions is based on algorithms which are specifically developed to address the stated requirements and go beyond classic optimization techniques. Generally, non-linear optimization techniques are used in smaller E-learning scenarios and web-based systems with a limited number of considerable criteria. The analyzed systems, based on non-linear optimization, are listed in the lower part of Table 1 for comparison.

The tabular disposition of existing approaches in Table 1 reveals the importance to focus the GroupAL development on support for homogeneously and heterogeneously to match criteria simultaneously, allow criteria weighting and calculation of a normed quality metric that allows comparison of several build group cohorts (see goals G1-G4).

For comparison the following sections focus on the non-linear optimization techniques which allow group formation with respect to only heterogeneously to match criteria or homogeneously and heterogeneously to match criteria simultaneously (GroupFormationTool [5], OmadoGenesis [12], Together [25], and TeamMaker [4]). Techniques focusing on support for homogeneous criteria only are primarily based on established clustering approaches and are covered in other publications [14]. Semantic matchmakers are not focused in the following as they are based on ontologies and thus applicability is less flexible in case criteria need to be easily exchangeable by end-users (e. g. instructors).

5 GroupAL Group Formation Algorithm

To achieve the four goals (G1-G4) as listed above, a metric will be defined in this section measuring the quality of a whole cohort of created learning groups in the interval $(0, 1)$. First, basic definitions will be introduced, then a metric to calculate the suitability of two participants is presented (*PairPerformanceIndex PPI*). It builds the basis to define a metric for one group (*GroupPerformanceIndex GPI*) and as a final step a metric for the cohort of all groups (*CohortPerformanceIndex CPI*). The CPI is calculated in order to ensure the minimization of differences between groups as described for goal G4.

Definitions are derived from Ounnas et al. [24] and are extended with a focus on the elements necessary for the definition of the group formation quality metric.

5.1 Basic Definitions

Criteria. A criterion is defined as a vector $k \in \mathbb{R}^n$, which is considered to be used as a relevant parameter, variable or characteristic for group formation. The set K of criteria is finite. $K = \{\{k_1, k_2, \ldots, k_q\} | \forall j = 1, \ldots, q,\ k_j \in \mathbb{R}^n\}$.

Disjunctive Criteria Sets. A criterion has to be assigned explicitly to one of the following two disjunctive sets. A criterion is *homogeneous*, if the criterion's value should be preferably similar in a build group (K_{hom}). On the contrary, a *heterogeneous* criterion is expected to result in amendatory values among the group members (K_{het}). Because they are disjunctive, $K_{hom} \cap K_{het} = \varnothing \wedge K_{hom} \cup K_{het} = K$.

Participants. The finite set of participants is defined as $P = \{p_1, p_2, \ldots, p_M\}$. Each participant is characterized by a set of criteria $p \subseteq K$. The criteria used for comparison need to be equal for all participants. $M = |P| > 1$ is the number of participants.

Groups. A finite set of participants $p \in P$ is defined as a group g, if it has at least 2 elements $|g| > 1$ (minimal group). One element $p_i \in g$ is called a *member* of the group. $G_x \subseteq G$ is defined as the set of all groups with a fixed size X. Consequently, group cardinality is $\mathrm{N} = \frac{M}{X} \forall X \geq 1$.

Cohorts. A cohort C is a set of pairwise disjoint groups $g_1, g_2, \ldots, g_s$: $\forall p \in P \neg \exists g_1, g_2 \in G : p \in g_1 \wedge p \in g_2$. A cohort contains all participants. Additionally, a cohort only consists of groups with the same fixed size X.

5.2 Defining Pair Performance Index (PPI)

The PPI uses a weighted normalized distance function (wd) as a basis where each criterion can have an individual weight. The*normalized Manhattan distance* is used as underlying distance function (d) to calculate how similar two participants in the values of one criterion are (see Equation 1).

$$\begin{aligned} &wd : [0,1]^n \times [0,1]^n \times [0,1] \rightarrow [0,w], \\ &wd\left(k_p^1, k_p^2, w_p\right) = w_p * d\left(k_p^1, k_p^2\right), \end{aligned} \tag{1}$$

where k_p^1 and k_p^1 are criterion vectors for one criterion of two participants, n the dimensionality of k_p, w_p the weight for this criterion with $w_p \in [0,1]$ and the sum of all weights $\sum_{t=1}^{q} w_t = 1$. In contrast to e.g. the *Euclidean* distance, it is a linear function, appropriate to express how complete the dimension space of a criterion is covered by two participants. This is of particular importance for heterogeneously to match criteria (see Equation 2, *homSum* is calculated analogue for all $k_i \in K_{hom}$).

$$\begin{aligned} &hetSum : K \times K \times \{0,1\}^n \rightarrow \left[0, \sum\nolimits_{i=1}^{|K_{het}|} w_i\right] \in [0,1], \\ &hetSum\left(K_{het}^1, K_{het}^2, W\right) = \sum\nolimits_{i=1}^{|K_{het}|} wd\left(k_i^1, k_i^2, w_i\right), \end{aligned} \tag{2}$$

where $|K_{het}|$ is the set of heterogeneous criteria, and K_{het}^1 and K_{het}^2 are value vectors of the criteria for two participants.

Hence, the PPI is calculated as the sum of distances for all heterogeneously to match criteria (*hetSum*) minus the sum of all distances of homogeneously to match criteria (*homSum*) as shown in Equation 3. Consequently, the PPI reaches its maximum in case distances for homogenous criteria is ideally zero and for heterogeneous criteria the whole n-dimensional space of each criterion is covered. As such, and with the possibility to weight criteria, the PPI fulfills goal G1 stated above and delivers a solutions for G2 (up to here, limited to group size of two participants).

$$\begin{aligned} &PPI : K \times K \times \{0,1\}^n \rightarrow \left[-\sum\nolimits_{i=1}^{|K_{hom}|} w_i, \sum\nolimits_{j=1}^{|K_{het}|} w_j\right] \in [-1,1], \\ &PPI\left(K^1, K^2, W\right) = hetSum\left(K_{het}^1, K_{het}^2, W\right) - homSum\left(K_{hom}^1, K_{hom}^2, W\right) \end{aligned} \tag{3}$$

For better usability in the following, PPI will be normalized as NPPI $\in [0, 1]$ by shifting the *PPI*-value by the maximum negative value (the maximum value of *homSum*) and division by the resulting maximum value (sum of maximal value of *homSum* plus maximum value of *hetSum*) which equals to $\sum_{t=1}^{|W|} w_i$ which equals to 1. Ideally, no division is necessary. The division is kept in Equation 4 to allow the GroupAL algorithm to cope with liberalization (sum of weights $\neq 1$).

$$\begin{aligned} &NPPI : K \times K \times \{0,1\}^n \to [0,1], \\ &NPPI\left(K^1, K^2, W\right) = \frac{PPI\left(K^1, K^2, W\right) + \sum_{i=1}^{|K_{hom}|} w_i}{\sum_{t=1}^{|W|} w_i} \end{aligned} \tag{4}$$

5.3 Defining Group Performance Index (GPI) and Cohort Performance Index (CPI)

Concerning goal G2 for arbitrary group size and to calculate a metric how well participants in a group match altogether, the mean value of all possible $\binom{X}{2}$ NPPIs in a group is calculated ($\overline{NPPI}$). A mean value is not sufficient to respect disadvantageous constellations, e. g. deviators. Consequently, GPI will as well take the normalized standard deviation of the group's NPPIs into account as shown in Equation 5. The fewer isolated individual participant in the group exist, the higher the overall GPI value is as requested with goal G3. The same approach is used to calculate the quality of a complete cohort of groups (CPI). It is the product of mean GPI ($\overline{GPI}$) multiplied with the normalized standard deviation of all GPIs in the cohort (see Equation 6). Consequently, if groups have dissimilar GPI values, it results in a low CPI as requested with goal G4. Beside normalized standard deviation other variation methods could have been taken into account as discussed by Konert [17, p. 79].

$$\begin{aligned} &GPI : G \to [0,1], \\ &GPI(g) = \overline{NPPI} * \left(\frac{1}{1 + \sigma_{NPPIs}}\right) \end{aligned} \tag{5}$$

$$\begin{aligned} &CPI : C \to [0,1], \\ &CPI(c) = \overline{GPI} * \left(\frac{1}{1 + \sigma_{GPIs}}\right) \end{aligned} \tag{6}$$

5.4 The GroupAL Matcher Algorithms

The matching algorithms use the defined metrics (PPI, GPI and CPI) to assign participants one by one to learning groups until all participants are assigned. Initially, N empty groups are created and all participants in set P are added to the group of not matched participants (*NMP*). Each group is assigned a random pivot element from *NGP*. Essentially, two different matching strategies where implemented for GroupAL as the matching approach can mainly influence the quality of achieved results.

Group-Centric Matcher. The *Group-Centric Matcher (GCM)* selects a random group first and then moves the one candidate from *NGP* into the group that increases the resulting *GPI* of the group the most on a percentage basis. This addition of the best candidate is continued until the group reaches it's targeted size of X members. The algorithm continues with the next group until all groups are processed or $NMP = \emptyset$. *GCM*'s behavior is expressed formally in Equation 7.

$$\left\{ g_{fix} \cup p \middle| \ \forall p \in NMP, g_{fix} \in G_x : |g_{fix}| < X \wedge max\left(\frac{GPI\left(g_{fix} \cup t\right)}{GPI\left(g_{fix}\right)}\right)\right\} \quad (7)$$

Participant-Centric Matcher. In variation to *GCM*, the *Participant-Centric Matcher (PCM)* selects randomly candidate by candidate from the set *NMP* and moves them into the group whose *GPI* is increased the most by addition of this candidate on a percentage basis. The *PCM*'s behavior is expressed in Equation 8 for comparison.

$$\left\{ g \cup t_{fix} \middle| \ p_{fix} \in NMP, \forall g \in G_x : |g| < X \wedge max\left(\frac{GPI\left(g \cup p_{fix}\right)}{GPI(g)}\right)\right\} \quad (8)$$

6 Evaluation

To measure effectiveness in group formation, GroupAL Matchers (*GCM* and *PCM*) are compared to the solutions GroupFormation [5], Together [25], OmadoGenesis [12], and TeamMaker [4].

6.1 Study Design

The comparison of the matchers uses two different data setups, each providing the matching algorithms with generated data sets containing 500 participants. Setup α (Sα) contains for each participant 1 criterion $k_{het,1} \in K_{het} \mid dim(k_{het,1}) = 4$ and is used for comparison with the algorithms of related work that are only capable to process one criterion or support only a maximum of 4 dimensions (GroupFormation, Together, OmadoGenesis). Setup β (Sβ) contains for each participant 4 criteria $k_{het,1}, k_{het,2} \in K_{het} \wedge k_{hom,1}, k_{hom,2} \in K_{hom} \mid dim(k_i) = 4 \ \forall i \in [0, 1, \ldots, 4] \wedge k_i \in K$. This setup is used for comparison with TeamMaker whose capabilities come most close to GroupAL as it supports several homogeneous and heterogeneous criteria simultaneously, too.

Orthogonally, for setup α three variations of participants' criteria value distribution have been generated to investigate robustness regarding differences in value distribution (V1 even distribution, V2 normal distribution, V3 evenly distributed extreme values (only the values 0 and 1). As TeamMaker is designed for discrete criteria values, in setup β only even distribution of extreme values has been generated (V3).

To eliminate random effects, the four data sets (Sα V1-V3, Sβ V3) were generated 100 times and used for 100 runs of the matching algorithms. In each run the matchers were started three times to create group formatios with group sizes of 2,3, and 6 members.

6.2 Results and Interpretation

For setup α the average *CPI* values of all 100 runs for each value distribution variation (V1-V3), itemized for the three different targeted learning group sizes (2,3,6), is visualized in Figure 1.

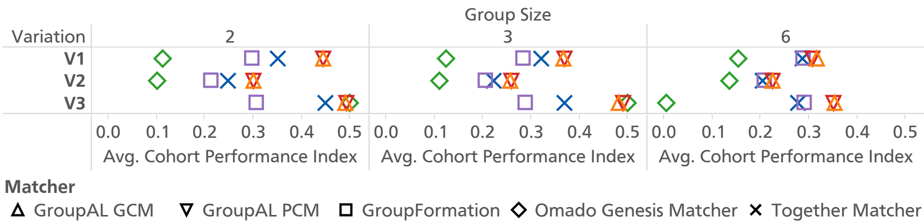

Fig. 1. Matcher differences in setup α

For setup β the average *CPI* and average *GPI* values of all 100 runs for the evenly distributed extreme values (V3), itemized for the three different targeted learning group sizes (2,3,6), is visualized in Figure 2. The plot shows two different calculation for *CPI* and *GPI*: on the left side based on the GroupAL quality metric as derived above and on the right side as defined and calculated by TeamMaker. This comparison allows to prove that GroupALs group formations are competitive even if the quality metric of TeamMaker is used. *GPI* and *CPI* calculations are not normalized by TeamMaker, resulting in negative values as the scale depends on the criteria and weights [4, p.8].

Interpretation. As clearly visible, in both setups the GroupAL matchers (*GCM* and *PCM*) achieve higher *CPI* values under the chosen conditions compared to the algorithms from related work which were compared here. Concerning the above stated goals G1-G4 and the derived quality metric for *GPI* and *CPI*, it is reasonable to conclude that GroupAL has a higher capability of matching participants with respect to diverse criteria combination while aiming for equated formation quality both, within groups (*GPI*), and of all groups within the resulting cohort (*CPI*).

In setup α on extreme criteria values (V3), OmadoGenesis achieves slightly higher *CPIs* for small group sizes (2 and 3 members), but fails to match adequate candidates for groups with 6 members. In all other variations of setup α

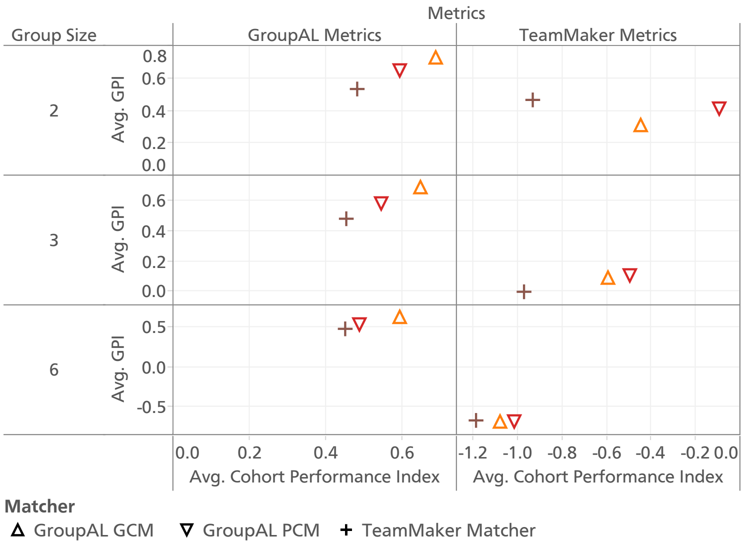

Fig. 2. Matcher differences in setup β

GroupAL's *GCM* and *PCM* deliver better results which are very close to each other. Only for groups with 6 members on evenly distributed criteria values (V1), GroupAL's *GCM* achieves slightly better results than GroupAL's *PCM*. Both GroupAL matchers appear to be quite robust against variations in criteria value distribution and requested group sizes.

In setup β the benefits of a normalized *GPI* and *CPI* can clearly be seen on the right side (GroupAL metrics). On the left side the results reveal that GroupAL matchers still achieve higher quality metric values even though *GPI* and *CPI* were calculated by the quality functions of TeamMaker.

7 Conclusion and Outlook

The discussion and revision of relevant criteria for group formation, as identified by related work from pedagogical psychology, lead to the conclusion that four goals need to be achieved by algorithmic learning group formation (G1-G4) in order to address the *group formation problem*. Beside other aspects, the demand for easy exchangeability of heterogeneously and homogeneously to match criteria or weights by instructors, the necessity to aim for evenly distributed group formation quality, and the objective to achieve beneficial exchange for all participants in a group, lead to the conclusion that non-linear optimization is preferable compared to semantic, ontology-based approaches.

After examination of existing algorithmic solutions and discussion of identified limitations, the GPI and CPI metrics of GroupAL were derived and defined formally, respecting the demanded goals G1-G4. The simulative evaluation of the two GroupAL matchers (*GCM* and *PCM*) revealed their capability to form learning groups that achieve significantly higher Group Performance (*GPI*) and Cohort Performance (*CPI*) results as the compared algorithms from related work under the chosen conditions.

The implementation of GroupAL matchers (*GCM* and *PCM*) and evaluation metrics (*PPI*, *GPI*, and *CPI*) will soon be released under an Open-Source license. As data sets for comparison of learning group formation algorithms are very limited, the generated data sets will be included. Interested parties are advised to search under the term 'GroupAL' regularly or visit the authors' websites for further information.

The advantages of GroupAL could further be corroborated by a field study to prove that learners indeed benefit significantly from peers in groups build based on GroupAL, i. e. *GPI* metric. Thus, future research includes the integration of GroupAL into E-learning environments like e. g. Moodle[1] to conduct long-term studies comparing on one side the effectivity based on achieved learning outcomes of participants in groups build by GroupAL and on the other side groups that are build randomly or by the participants themselves.

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