Dimensions of Innovation: Knowledge-based Resource Mediation for Innovation Process Engineering

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Abstract: Innovation is a knowledge-intensive process whose success heavily relies on the composition of adequate teams. This paper presents a semi-automatic approach for teambuilding as a special case of knowledge-based mediation of innovation resources. The proposed solution relies on multidisciplinary findings from knowledge technology research as well as from organisational and social psychology. It is based on an extensible actor model for team members and systematically exploits taxonomies in the matchmaking process.

1. Introduction

Innovation is a knowledge-intensive process in which knowledge of different types is retrieved, applied and created. In innovation activities a wide variety of resources is required including people, services, tools and knowledge resources. One key to successful innovation lies in managing the most appropriate innovation resources for each activity. Knowledge-based resource mediation, thus, contributes to systematic innovation support.

Human resources are the most important type of innovation resources. Therefore, this paper focuses on knowledge-based support for the composition of innovation teams.

Teambuilding describes the process of “taking a collection of individuals with different needs, backgrounds, and expertise and transforming them into an integrated, effective work unit” (Thamhain & Wilemon 1997). The special challenges of teambuilding in innovation activities lie in the quickly changing team requirements (change is inherent to innovation), and in the high expectation to combine a high degree of creativity with efficient, market-driven and cost-effective performance.

Selecting team members with adequate skills is equally important as finding an appropriate composition of the team, since group dynamics have a strong influence on a group’s behaviour and efficiency

Our approach for semi-automatic teambuilding support is interdisciplinary: appropriate dimensions from the field of organisational and social psychology are selected to describe relevant characteristics that also can be captured efficiently in an organisational context. Knowledge-technology is used to model such resources characteristics in a flexible way building upon ontology-based user and task models. This paper suggests a heuristic of how corresponding descriptions of innovation tasks can be mapped against characteristics of individuals and teams in a knowledge-based way to increase the probability of a successful team performance.

The rest of the paper is structured as follows: Section 2 discusses related work in the area of teambuilding from organisational and social psychology and in the area of resource modelling and mediation. Our multidisciplinary approach for teambuilding is presented in section 3. Section 4 discusses challenges and impacts of applying our approach in an organizational context. The paper concludes with a summary of the paper's rationale and future work in this area.

2. Related Work

2.1 Prerequisites for a successful innovation team

Organisational and social psychology suggest many findings about factors for effective team work in innovation environments (cf. Katz 1997; West 1996). This literature focuses on determining factors of successful performance of existing teams from which conclusions can be drawn for successful teambuilding.

Team performance is influenced by various factors from the areas of organisational and social psychology. Organisational psychology describes which and how organisational variables influence the team performance. The factors of social psychology describe group variables regarding the individual, and the interaction between team members.

Organisational variables like e.g. reward systems, company organisation structure (Agrell & Gustafson 1996) or innovation culture (Paukert et al. 2004) have an impact on the team's performance. This paper focuses on the influence of the group variables on teambuilding. The following list is not exhaustive, but it provides an exemplary overview:

Individual – Individuals bring traits into a team which facilitate innovation. Creativity has to be mentioned next to creativity related traits like, desire for autonomy, social independence and anxiety level. Also, self-efficacy plays a role in innovative behaviour (Agrell & Gustafson 1996). Obviously, a person's capacity for teamwork is a prerequisite for efficient teamwork, consisting of a cluster of various variables, like e.g. readiness and ability to learn, positive attitude towards team work and mental flexibility (Bungard 2000).

Team – Team members are diverse in many attributes, with different effects on the team performance. With respect to skills and competences, diversity supports decision-making and problem-solving when team members have partly complementing, but overlapping, domains of expertise (Jackson 1997). Agrell and Gustafson (1996) point out that diversity in tenure supports creative problem solution. Whereas attributes like education and company tenure enhance innovation when there is high diversity, a team that's homogeneous with respect to attributes not directly related to the task perform better than diverse ones (Jackson 1997). Attributes of this category are socio-demographic variables like age, gender, martial status, cultural background but as well values, attitudes and hobbies. Such homogeneity is important for group stability, cooperation and positive discussion behaviour.

Roles - Roberts and Fusfeld (1997) point out five work roles – idea generating, entrepreneuring, project leading, gate keeping, and sponsoring - which have to be carried out by one or more individuals for an effective innovation process.

Communication –The ability of team members to communicate determines the success of an innovation team. Communication can be described formally in terms of company structures or with informal communication patterns (Johnson 1996). Another approach follows the communication abilities of individuals (Fittkau 2000).

The variables listed above represent a small but important selection of the variables influencing a team's performance. Considering these variables for teambuilding can enhance the performance with respect to the aspired goal.

2.2 Models, mediation and user modelling

Mediation in a decision making process incorporates matchmaking between the model of the resource needs and the model of the available resources, as well as it has to incorporate value-added processing for the decision making (Wiederhold & Genesereth 1997).

Task modelling is a required activity in different disciplines, from software engineering (Paternò 2000), to artificial intelligence (Georgeff et al. 1999), to business process modelling (Scheer 1998). A task model abstracts the process to reach a goal (a transition from an initial to a desired end-state). Models in all disciplines organise tasks in taxonomies of subtasks, where temporal relations, data and control flows between tasks augment the task taxonomy. Tasks can be further specified by the required inputs and pre-conditions on a domain model and the expected output and post-conditions. Additionally, modelling of potential or required agents to perform the tasks can be specified (persons, teams, services). Such agents can be modelled extensionally or intentionally by specifying requirements (e.g. the required skill or competence of an agent).

Modelling characteristics of persons, which is in the core of a teambuilding approach, is also found in other areas. A prominent example is user modelling in personalisation approaches, where user models are used to adapt system functionality to individual preferences and needs (Neuhold et al. 2003). User models in personalisation mainly refer to the cognitive patterns of a user (McTear 1993), like interests, preferences, or skills (c.f.. Wahlster & Kobsa 1989). More advanced models that also take into account user tasks are referred to as user context models (Goker & Myrhaug 2002). In teambuilding the relationship between persons and tasks is not the involvement of users in a task, but the attempt to assign persons to a task. A flexible user context model that is able to capture an extensible set of user model facets can be found in Niederée et al. (2004). This model is used as a starting point for actor modelling in our approach. Similarities between users are considered in collaborative filtering (see e.g. Bouthors 1999), and used as a basis for recommendations. In contrast to this, similarity between persons is used in teambuilding to estimate how well people can work together.

Expert finding is a significant example of mediation on human resources (Mattox et al. 1999, Yimam-Seid & Kobsa 2003), where models of the skills, knowledge, and competences of persons are used to support the process of finding the "right" expert.

Expert finding systems exploit information retrieval and data mining techniques on expertise indicator sources like authored documents, self-profiles, and organisational databases. Given a model of a person, its relationships to other resources are analysed in order to infer its indexing/classification in domain models (ontologies) of expertise. In order to match needs to resources, matchmaking operations on the resources model are implemented using exact or statistical/similarity matching, as well as inferencing on relations, concepts and expertise level match (Yimam-Seid & Kobsa 2003).

Another complex mediation scenario can be found in problem solving methods (PSM) sharing and reuse. PSM can be seen as resources which can be retrieved and integrated when developing ontology-based systems (Crubezy 2003). In PSM sharing and reuse, ontologies are used to define PSMs in terms of required input knowledge and expected output, and also in terms of assumptions on domain knowledge. Domain ontologies are used to state the knowledge to be processed, and task ontologies define PSM’s competence. A mediation component provides the mappings between task, domain and PSM ontologies, from which it retrieves, based on task competence and on assumption on domain knowledge.

From all the approaches the usefulness of ontologies (Gruber 1993) for the mediation of resource becomes clear. Ontologies provide the common vocabulary for modelling both resources needs and available resources in different collections in an interoperable way. Often, the notion of ontology is relaxed to that of taxonomies, i.e. a hierarchy of concepts related by subsumption relationships“(Guarino 1998).

Therefore, taxonomies implement the minimal ontological commitment underlying the mediation framework (Gruber, 1993). Further, taxonomies offer a consistent medium for summarising the results of matchmaking, like dynamic and multidimensional taxonomies computed from the categories associated with the resources in a result set (Niederée et al. 2002). Finally, analysis of taxonomic relationships can be performed on retrieved resources, providing value-added processing for the mediation on the available resources.

3. Teambuilding in the Innovation Process

The goal of teambuilding is to select a group of individuals for a specific task within the innovation process. This imposes the following main challenges:

- Actor modelling: models for representing persons as resources in the innovation process capturing aspects relevant for teambuilding;
- Task modelling: models for representing task characteristics that are relevant for assigning adequate persons to a task;
- Teambuilding methods: algorithm for selecting team members based on the task model, the actor models, and best-practice from team-building;
- Information collection: Methods for collecting and updating the information for the involved models;

This section focuses on the models and the methods. Section 4 covers aspects of information collection together with other aspects of teambuilding system adoption.

3.1 Task and Actor Modelling

Exploiting the aforementioned similarity with user modelling, we build our actor modelling on a flexible user context model that has been developed in our group, the Unified User Context Model (UUCM) (Niederée et al. 2004). Within the UUCM user context is modelled by a changeable set of facets that cover different aspects of the user and his context. The UUCM (see figure 1) rather forms a meta model that can be adapted by the selection of adequate facets. Each facet is associated with a facet qualifier, one or more facet values, a value qualifier, and a probability for the facet having the specified value. The facets used in a UUCM-based user model refer to one or more facet ontologies by facet qualifier. The value qualifier refers to the vocabulary the facet value is taken from. The explicit qualification of the facets and their values facilitates the use of such models in heterogeneous contexts.

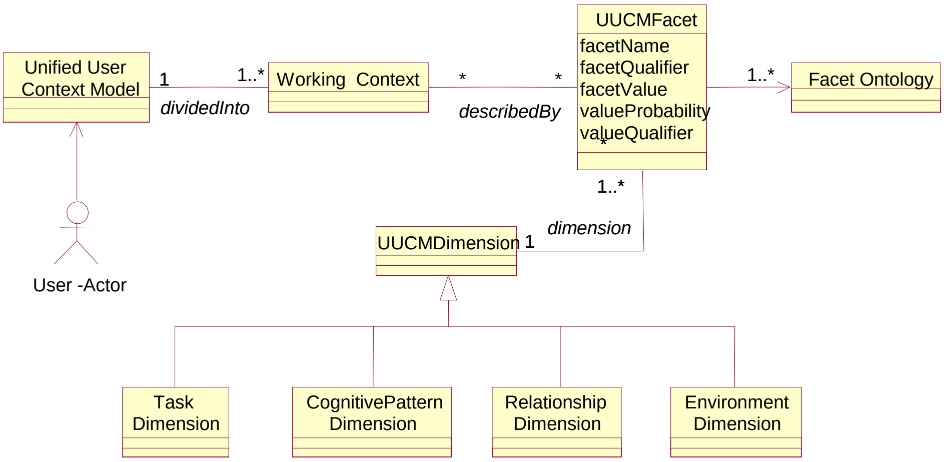

Figure 1: the Unified User Context Model

Analogously, we model an actor by a set of facets, which overlaps with the user modelling facet set, but is not identical; in fact, in actor modelling, attitudes of a person play a role, which is generally not taken into account for user modelling. The set of facets we consider for actor modelling is based on research in successful teambuilding (see section 3.2).

Different approaches to task modelling have been discussed in section 2. For teambuilding, skill requirements towards actors represent the most important aspect of the task model. Furthermore, the timeframe of a task is important for the assignment, in order to ensure availability of the assigned actors for the task. In our approach, the model of the required skills for a task is defined referring to the skills facets of the UUCM (figure 1).

3.2 Relevant Actor Modelling Facets

For semi-automatic support of teambuilding, a relevant subset of the factors discussed in section 2.1 has to be included into the actor model. The selection of factors is determined by their relevance for successful teambuilding as well as by the direct and indirect costs for capturing the respective summarizing knowledge (see section 4).

The values of skills and competences are structured into two parts: the *skill domain* which describes the type of skill like “Java Programming” and the *skill level* which captures the level a person has reached in this skill like “no usable knowledge”, “know”, etc. (see e.g. TSE 2004 for exemplary taxonomies).

Attitudes are defined as a “…psychological tendency, which shows an enduring positive or negative assessment towards the object of the attitude (person, thing, group)” (Stahlberg & Frey 1997). In a working context, different kinds of attitudes are relevant like attitude towards team work (Delhees, 1994), towards projects, towards quality of results. Next to these, less obvious and less task-related attitudes play an important role, like attitude towards smoking (Lippa 1994) or towards political parties (Stahlberg & Frey 1997). Attitudes are usually quantified with a Likert scale or the semantic differential (Stahlberg & Frey 1997), providing a range of possible values for an attitude. To facilitate computation, the scales can be dichotomized; only if a person’s value on the scale is above a cut off point, the person is considered to have this attitude.

The marital status can be divided into single, married, widowed, divorced, and lifetime partnership.

The cultural background contains three subclasses: nationality, ethnicity and religion. The nationality ontology can be based on continents, continental regions and countries. Ethnic groups are defined e.g. in lexica. With respect to religion, five world religions can be distinguished; each of them dividable into several subgroups.

Roles model several activities (Roberts and Fusfeld 1997); to what degree a team member fills out what role can be e.g. identified by peer ratings. Roles can be described as follows:

Idea generating: analyzing and/or synthesizing information about markets, technologies, approaches, and procedures, from which an idea is generated.

Entrepreneuring: recognizing, proposing, pushing, and demonstrating innovative items for formal management approval.

Project leading: planning and coordinating the diverse sets of activities and people involved.

Gate keeping: collecting and channelling information about important changes in the internal and external environments.

Sponsoring: "behind-the-scene" support-generating function of the protector and advocate.

3.3 Teambuilding Methods

Our approach for teambuilding consists of three basic steps:

Step 1: Computation of candidate teams, where the combination of the team members' skills fulfils the skill requirements of the task

Step 2: Computation of a team quality value for each of the teams based on characteristics of the team members and best-practice in teambuilding

Step 3: Suggestion of most appropriate team combination for the considered task

The proposed approach relies on findings from organisational and social psychology on teambuilding and on a systematic exploitation of taxonomies.

3.3.1 Computation of Candidate Teams

For computing candidate teams, the skill requirements defined in the task model are matched with the skill profiles of the available actors' model, in order to determine groups of persons that cover all of the skills required for a task. In more detail, we consider skill profiles exactly matching the requirements as well as cases where the skill profile is similar. The degree of similarity with respect to the skill domain is captured by a similarity function *sim*

$$sim_{\tau}(sp.domain, sr.domain)$$

where *sp* is the skill profile and *sr* is the skill requirement of the task. The similarity between such domain concepts can be explicitly defined in the domain ontology or it can be approximated by considering the relative position of the two concepts in the defining skills domain taxonomy. We use the length of the path to the first common ancestor as a measure for the similarity. Starting with a similarity of 1 for equivalent concepts we apply a reduction factor γ (0<γ<1) for each step on the path. For categories c1 and c2 in the skill domain taxonomy the similarity is computed as:

$$sim(c1, c2) = \gamma^{|fca|(c1,c2)}(|\,r\,|(c1,c2) - |\,fca\,|(c1,c2) / |\,r\,|(c1,c2)) \qquad \text{[Eq. 3.1]}$$

where $|fca|$ $(c1,c2)$ is the average length of the path to the first common ancestor $fca(c1,c2)$ of the two concepts $c1$ and $c2$, and $|r|(c1,c2)$ is the average length of the paths of $c1$ and $c2$ to the root.

For the definition of the reduction factor γ different empirical measures can be applied. One approach would be to use filter measures (Weinstein & Birmingham 1999), determined by the expected probabilities that a member of the *fca* class is also a member of the considered child concept. In addition, a threshold τ is used to avoid the consideration of skill domain concepts that are too far away from each other.

For the skill level, the same or a higher level as the required one for the considered skill domain contributes with a factor 1 to the skill value, whereas a lower skill level contributes with a factor below 1. The computation of a skill value can, thus, be summarised to:

$$skillValue_\tau(sp, sr) = sim_\tau(sp.domain, sr.domain)(1 - \max(0, sr.level - sp.level)/n)$$

assuming that n is the number of skill levels, and that numeric values between 1 and n are assigned to the skill levels with increasing numbers for increasing skill levels.

The set $C_\tau(t)$ of candidates for a team performing task t will then be

$$C_\tau(t) = \{p \mid available(p,t) \wedge sp \in p.skill \wedge sr \in t.skill \wedge skillValue_\tau(sp.sr) \geq \tau\}$$

Note, that the formula takes into account availability of actors.

From members of C_τ (t), the set of possible teams of n members for a task t can be specified as:

$$CS_\tau(t,n) = \left\{ \begin{array}{l} \{p_1, p_2, ..., p_n\} \mid \forall i = 1..n \ \ p_i \in C_\tau(t) \wedge (\forall sr \in t.skill \exists p_i \exists sp \in p_i.skill \\ \wedge\, skillValue_\tau(sp, sr) \geq \tau) \end{array} \right\}$$

3.3.2 Computation of Team Quality

Successful teambuilding depends on various actor model facets that influence team quality in different ways. It's not true that team quality is best if team members are similar in all their facets. In some cases, teams profit from complementary characteristics. We use the term *compatibility* among team members to cover these two types of influence.

Instead of discussing the employed matchmaking methods for each considered facet separately, we push the exploitation of taxonomy one step further. The facets are classified by a taxonomy of principle matchmaking situations that we identified for teambuilding (see figure 2). All actor model facets that are classified in the same way can be handled by analogues matchmaking methods. By following this approach, the set of facets considered for teambuilding can be easily adapted and extended. Four types of distinctions are made within this taxonomy:

Value type (numeric value vs. atomic value): For the class *numeric value* the facet values are numeric or ordered and allow to compute similarity by a function f that only depends on the facet values (example: age difference); for the class *atomic value*, no similarity can be computed directly from the values: They are either equal or unequal.

Value range (single-valued vs. multi-valued): In the class *single-valued* facets are restricted to one value, whereas in the class *multi-valued* facets can have multiple values (example: hobbies, attitudes).

Value domain (value taxonomy vs. value set): For the class *value taxonomy*, a taxonomy underlying the facet values is considered in computing similarity, whereas in the case of *value set* no such taxonomy is considered.

Matchmaking method (similarity-based vs. complementing vs. max-coverage): This distinction is closely linked to the issue of compatibility raised above. It refers to the influence of the respective facet on teambuilding. With respect to some facets team members should be similar (*similarity-based*) and with respect to other facets they should complement each other (*complementing*). There is a third class where *maximal coverage* of the possible facet values is required.

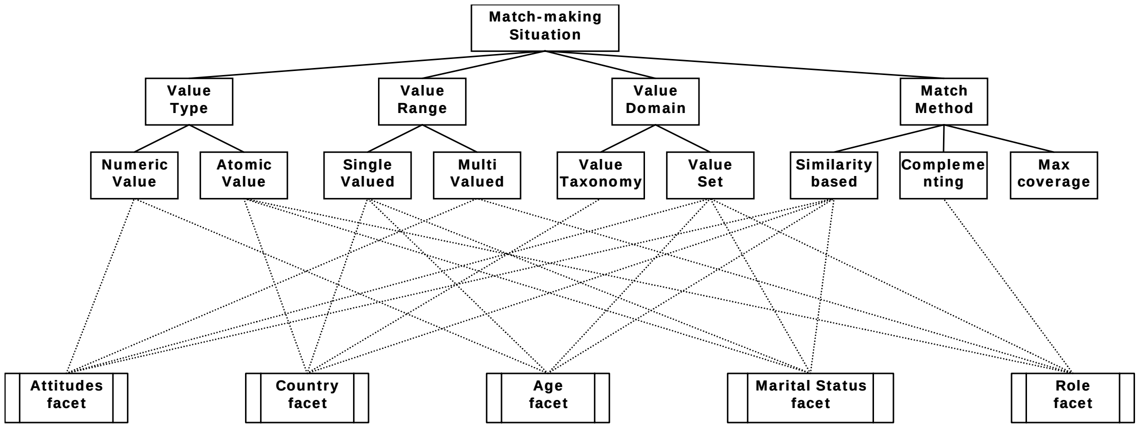

Figure 2: Taxonomy of matchmaking situations

From the analysis of the relevant modelling facets, clusters of frequent matchmaking situations have been identified that share the same classification under the taxonomy of matchmaking situations.

Cluster 1: similarity-based method on multi-valued-set facets of atomic values: For instance, an actor can be characterised by a number of attitudes or hobbies. Pairwise compatibility depends on the similarity of the two actors' respective set of facet values.

Cluster 2: similarity-based method on single-valued-set facets of atomic values: For instance, an actor can be characterised by being in a certain marital status or by gender. Actors are compatible if they share the same value.

Cluster 3: similarity-based method on single-valued-set facets of numeric values: Actors can be characterised by being of a certain age. Compatibility of actors depends on the difference between their respective values (i.e. age difference).

Cluster 4: similarity-based method on single-valued-facets with atomic values and modelling taxonomies: For instance, actors can be classified by a taxonomy of countries or by a taxonomy of skills. As in the computation of candidate teams, pairwise compatibility of actors depends on the similarity of the concepts in the taxonomy.

Cluster 5: similarity-based method on single-valued-facets with numeric values and modelling taxonomies: When experts enrich the age facet with a taxonomy of age groups. In this case, compatibility of actors has to consider two dimensions: the difference between numeric values (as in *cluster 3*) and the taxonomical structure in which the values are organised.

Cluster 6: complementing-based method on multi-valued-set facets of atomic values: Compatibility of actors depends on complementarity of the respective set of facet' values (e.g. roles facet). In other words, while in cluster 1 similarity is considered, here dissimilarity is considered valuable.

A method for the computation of the compatibility among team's candidates is defined for each of the clusters

Methods for the Matchmaking clusters

Once the set $CS_{\tau}(t,n)$ of candidate teams has been computed in step 1 of the approach, step 2 requires to compute team quality by examining the compatibility among the candidates *p1..pn* in $CS_{\tau}(t,n)$ along each of the modelling facets.

Given *p1,p2* $\in$ $CS_{\tau}(t,n)$ and the set of selected modelling facets *{f1,..fm}*, step 2 is systematically implemented by the following reasoning procedure:

- The facet *fi* is classified according to the taxonomy of matchmaking situations; from such classification, the proper cluster of matchmaking situation can be inferred.
- As the cluster is inferred, the basic method defined for this cluster can be applied on the set of facet values of *p1* and p2, and the compatibility *comp(p1,p2)* between *p1* and *p2* is estimated.
- The procedure is iterated for each of the selected *fi*.

Next, we formalise the basic methods that are applied for each of the identified clusters of matchmaking situation.

In *cluster 1* compatibility has to be computed considering both common and distinctive features (e.g. facet values a member possesses, but another does not). In literature, such an approach is known as "feature matching process", and expressed using set theory in the "ratio model" formula (Tversky 1977), where the semantic similarity among two object is a normalised value in function of the set of common features, the set of features possessed only by the first object, and the set of features possessed only by the second one.

In our case, the compatibility between *p1* and *p2* is given by the similarity of the respective set of facet values (how many values are (are not) in common). A "ratio model" value for the similarity of *p1* and *p2* along a facet *fi* is therefore computed by:

$$comp_{fi}(p1,p2) = sim_{fi}(p1,p2i) = \frac{|p1.fi \cap p2.fi|}{|p1.fi \cap p2.fi| + |p1.fi - p2.fi| + |p2.fi - p1.fi|} \qquad \text{[Eq. 3.2]}$$

where *p1.fi* and *p2.fi* are the set of values of *p1* and *p2* for facet *fi* respectively, *p1.fi*$\cap$*p2.fi* is the set of values *p1* and *p2* share, *p1.fi-p2.fi* is the set of values shown only by *p1*, *p2.fi-p1.fi* is the set of values of *p2* only. The value of the measure $sim_{fi}(p1,p2)$ is normalised in the range [0..1].

Cluster 2 can be considered a simplification of *cluster 1*, when assuming that both cardinality |*p1.fi*|=1 and cardinality |*p2.fi*|=1 (*single-valued-set facet*), and that $sim_{fi}(p1,p2)$ can assume either the value $sim_{fi}(p1,p2)=1$ or the value

$sim_{fi}(p1, p2) = 0$. In other words, the two candidates share or not share the same value in the facet (e.g. same or different gender, same or different marital status).

Cluster 3 is a case represented by facets like age, where facet values are normally ordered in a one-dimensional space (e.g. integer values for age). Compatibility of candidates *p1* and *p2* is a normalised value of the distance between the numeric values they assume:

$$comp_{fi}(p1,p2) = sim_{fi}(p1,p2) = 1 - \frac{|p1.fi - p2.fi|}{n} \qquad \text{[Eq. 3.3]}$$

where *p1.fi* and *p2.fi* are the numeric values for *p1* and *p2* respectively, *n* the size of the range of possible values.

In the case of *cluster 4*, facet's atomic values are structured in a taxonomy (e.g., a taxonomy of countries). Compatibility of candidates can be computed on the similarity of the concepts classifying the respective facet's values. Assuming for example that *c1* and *c2* are used to classify the values of facet *fi* for *p1* and *p2*, respectively, [Eq. 3.1] can be applied (cf. section 3.3.1):

$$comp_{fi}(p1,p2) = sim(c1,c2)$$

C*luster 5* can be considered as a specialization of *cluster 3*, when numeric values are ordered in a semantic network rather than along a single dimension. For example, when supposing that the age facet is not just modelled as set of values, but as classes of age groups in a taxonomy, as in figure 3, the age facet will change its classification in the taxonomy of matchmaking situations from values set to value taxonomy (see figure 2).

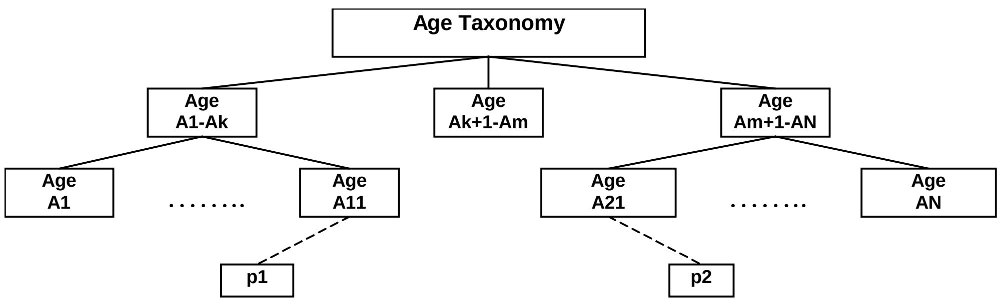

Figure 3: A Taxonomy of Age Groups

In this case, the method for computing the compatibility has to consider two aspects: similarity computed on the difference between numeric values, as in *cluster 3*, and a similarity factor from the taxonomical structure, as in *cluster 4*.

$$comp_{fi}(p1,p2) = sim_{fi}(p1,p2) = \gamma^{|fca|(p1.fi,p2.fi)}\left(1 - \frac{|p1.fi - p2.fi|}{n}\right) \qquad \text{[Eq. 3.4]}$$

where *p1.fi*, *p2.fi* are the numeric values for facet *fi* of *p1* and *p2* respectively, *n* the size of the values' range (see [Eq. 3.1]), and *c1* and *c2* are the concepts used for classifying *p1.fi* and *p2.fi* respectively; |*fca*| *(c1, c2)* and γ are defined as in equations [Eq. 3.3].

In the case of *cluster 6*, candidates show values from facets that express set of atomic values, as in *cluster 1*. Nevertheless, while in *cluster 1* similarity is considered, here dissimilarity is considered, as the team benefits from members showing complementary characteristics, like in the case of the role facets. Thus, [Eq. 3.2] can be adapted as follows:

$$comp_{fi}(p1,p2) = (1 - sim_{fi}(p1,p2)) = 1 - \frac{|p1.fi \cap p2.fi|}{|p1.fi \cap p2.fi| + |p1.fi - p2.fi| + |p2.fi - p1.fi|} \quad \text{[Eq. 3.5]}$$

Overall compatibility among team's candidates

Applying the described methods gives a measure for the compatibility among actors along each of the selected facets. However, goal of the second step is to compute an overall compatibility among actors.

To each candidate member in a team there is a corresponding vector of facets' values (FV). For instance, if *pi.fk* is the value for the actor pi along the facet *fk*, then FVi=(*pi.f1, pi.f2, ... pi.fm*) is the vector of facets' values for the candidate pi according to the set of facets {*f1, f2, ... fm*}.

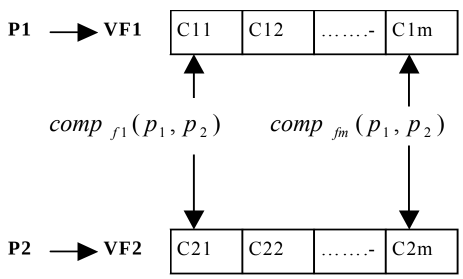

Figure 4: Vector of compatibility measures

Given the above definition, a team of actors can be represented by a n*m matrix, and the measure of the pairwise compatibility between actors be represented by the Euclidean distance between their vectors of facets' values (cf. Goldstone 1994). For instance, considering two candidate *p1* and *p2*, overall compatibility between *p1* and *p2* is measured by the Euclidean distance *comp(p1, p2)* between the respective vectors VF1 and VF2 in the m-dimensional space defined by the set of facets {*f1,..fm*}(see figure 4):

- $$comp(p1,p2) = \sqrt{\sum_{k=1}^{m} comp_{fk}(p_1,p_2)^2} \quad \text{[Eq. 3.6]}$$

where *compfk (p1,p2)* is the compatibility between *p1* and *p2* along the facet *fk* computed applying the basic method defined for the proper matchmaking cluster.

Based on [Eq. 3.6], the pairwise overall compatibility of actors can be computed. Overall team compatibility and a team quality value can be computed by summing up the pairwise overall compatibility for all the pairs within a candidate team.

4. Teambuilding Support in the Organisational Context

An elaborate teambuilding support tool unfolds its full advantages in large organisations with many members, in which managers do not know all employees personally.

However, the introduction of such semi-automatic teambuilding support within an organisation requires careful planning to ensure successful implementation and acceptance within the organisation.

The kind of data to be collected for the matchmaking methods is critical in an organisational context. The collection of personal data might be considered with suspicion and may raise fear of information misuse. In many countries the collection of such data is subject to special legal regulations. Therefore, it is important to ensure transparency and an open information policy with respect to data collection, the use of collected data, as well as to actively involve employees and representative bodies like work councils into the tool introduction process. For example, in Germany, the organisation's work council has to agree on the kind of stored data, access rights and possible data combinations.

Measuring the values for some of the discussed actor modelling facets might require considerable efforts and suffer a certain degree of subjectivity. Even the description of skills/competences requiring self-assessment or rating by managers is subjective. Especially the problems of measuring attitudes are well known (Stahlberg & Frey 1997). Relevant attitudes have to be selected with care and rating scales constructed to measure the attitudes. Generally, the problem of measuring in the social sciences has to be addressed (Bortz 1993). This issue is less critical for socio-demographic data like age, gender, nationality. The selection of facets depends on the organisational context. Some data may be available in one organisation but may not be available in another one. Therefore, a flexible teambuilding support has been developed that enables the adaptation of the facets considered for teambuilding.

A further aspect that has to be considered is to ensure that the information collected is regularly updated. This is required to reflect the evolution of persons in actor profiles. For this purpose, processes have to be set up for the regular update of the collected information. These can be mixed methods that combine automatic collection with manual entering, which can involve the potential team members themselves. Furthermore, the costs that are produced for keeping the personal data up-to-date have to be considered when semi-automatic teambuilding tools are introduced.

5. Conclusion and Future Work

This paper presented an approach for supporting the building of successful teams for tasks in the innovation process. The approach heavily relies on a flexible and extensible actor model to capture relevant characteristics of persons and on the systematic exploitation of taxonomies, which are used for structuring actor facet values as well as for the systematic development of matchmaking methods.

Currently we are working on a prototypical implementation of the proposed approach based on Semantic Web technology. Further activities planned to refine the approach are

- Developing methods for collecting and updating information for the actor models
- Validating the proposed method and the refining the methods; especially of the computation of the team quality based on user feedback

- Tranfering the developed methods to the matchmaking for other types of innovation resources, like e.g. information objects or services

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