Fuzzy Specializations and Aggregation Operator Design in Competence-Based Human Resource Processes

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Summary. The central component of most knowledge-based *Human Resource Management* (HRM) systems is a model of the actual or required knowledge and abilities of employees, applicants and job positions. The notion of *competence* has been used in many of them to describe levels of skills and knowledge as applied to concrete work situations. Nonetheless, the imprecise nature of relationships and interactions between competences has been neglected in existing approaches. In this paper, a model for imprecise *gen-spec* and composition relationships between competences is described, aimed at coming up with more detailed and realistic selection processes. A concrete case study is also described, illustrating how the `Hr-Xml` canonical format for competency definition and interchange can be extended to give support to those relationships.

Key words: human resource management, resemblance relationships, aggregation

1 Introduction

The technology of *Knowledge-based Systems* (KBS) can be applied to give support to [11] or complement [13] a wide range of *Human Resource Management* (HRM) activities, including human resource planning, recruitment, selection, and staff development. In consequence, application areas for artificial intelligence techniques range from strategic ones, like manpower planning

[6], to operational activities like performance appraisal or individualized training. Nonetheless, all of these application areas share a common requirement: the construction and maintenance of some form of knowledge base regarding *human resources* — both employees and job applicants —, with detailed and up-to-date information about the history, skills and abilities of each individual. Such kind of knowledge base requires a *epistemologically adequate* schema — in the sense given by McCarthy [12]— to properly represent the value of each individual, organized around a set of concepts describing difficult to characterize human traits like knowledge, abilities and attitudes. The notion of *competencies* — that form the basis of current industry proposed standards like `Hr-XML`[4] — can be used as the core structuring criterion for that purpose. Competence is understood as the relation between humans and work tasks in the context of concrete work *roles*, i.e. the concern is not about knowledge and skills in tehmselves, but about which knowledge and skills are required to perform a specific task in an efficient way [9]. Nonetheless, as competence can be considered as 'skills or knowledge applied to a concrete business objective', the three terms are in some cases used interchangeably. In the rest of this paper, we'll point the differences between the three concepts whenever it'd be relevant.

This competence-oriented view of human resources is considered to form the basis for organizations that are more responsive to its constituency [7]. As a consequence, a number of HRM-related systems have been built that organize its core model around the notion of competence or skill, some of them using ontologies for that purpose [21]. In all of them, some notion of relationship between competencies is used, but they do not capture the diverse forms of interaction between competences that are used by HR consultants in their everyday's work. For example, in `MASEL` the only relationship is that of competence grouping by company role [3], and in `CommOnCV` sector-specific competencies are grouped by position and activity [8] . Some systems use the concept of *skill tree* [20, 1], but the hierarchical relationship embodied in those trees is not clearly defined, and specializations are intermingled with composition relations, thus making difficult to aggregate and obtain overall realistic competence scores.

The focus of this paper is the fact that relationships between competencies or skills inside a HRM system are in many cases of an imprecise nature. For example, the 'developing dynamic Web page' skill subsumes more specific ones like 'developing `Jsp` pages' and 'developing `Php` pages' to some extent, and depending on the kind of HRM process being carried out, a given degree of specificity might be required. Another example is that of competencies that depend on each other like 'customer interaction' that may depend to some extent — or may be correlated in some way — with competencies like 'customer tracking' and 'customer value estimation'. These relationships are of a different nature than the more precise groupings found in `CommOnCV` since the

[4] http://www.hr-xml.org/

former are of a finer level of granularity. Nonetheless, selection services depend critically on these lower-level definitions, as they ultimately require numerical scores or sorting criteria for candidates that are computed from them. Possibility theory [2] has been applied elsewhere [15] to model compentences and competence matching, but limiting relationships between competences to boundary restrictions of possibility in specializations.

Given that imprecise relationships between competences have not been properly addressed in existing work, in this paper we aim at addressing at least some of them. Concretely, we approach the following two different kinds of relationships (they were identified by HR consultants in an informal analysis session):

i Generalization-specialization (*gen-spec*) relationships.
ii Aggregation-oriented relationships (compositions).

Relationships of type (i) essentially provide a mean to deal with competences at different levels of abstraction or specificity that are somewhat related by subsumption, i.e. they appear in the same work context and require related abilities or skills, and only specificity makes them different. For example, 'formal writing with word processors' is a general term that may subsume 'formal writing with Microsoft Word'. Relationships of type (ii) allow for the description of competences that are present whenever a combination of competences appear. Following the example, in a given context, 'formal writing' may be considered an aggregate of 'academic paper writing' and 'professional writing' (which in turn may be an aggregate of 'review writing' and 'report writing'). The differences between types (i) and (ii) are subtle in some cases, as will be detailed in the following sections.

The rest of this paper is structured as follows. In Section 2, a model for fuzzy relationships of type (i) is described. Section 3 deals with relationships of type (ii), assuming some form of HRM scenario involving aggregation of competencies modelled after the concepts described in the previous Section. Section 4 sketches some details about a concrete implementation case study that uses the proposed canonical model of competencies provided by the `Hr-XML` Consortium. Finally, conclusions and future research directions are provided in Section 5.

2 Modelling Vague Competence Specializations

In what follows, competences will be considered in the context of selection, which is one of the most common activities in HRM, necessary both in internal project group selection or assessments, skill gap analysis, recruitment and other tasks. It will be assumed also that HR consultants drive concrete selection activities.

In addition, a possibilistic approach following [15] is used, since it provides a realistic framework for modelling human traits, given that it provides a upper probability bound 'disconnected' with randomness, as described by Smithson [18]. The process of competence assessment can be summarized as follows: Initially, the score for each competence (in a set C of them) of a given individual is set as 'non applicable', indicating that the competence has not been assessed for that individual. After that, a consultant carries out an initial curriculum inspection, assigning a possibility distribution for some of the competencies. Then, subsequent analysis and selection processes will eventually lead to gather additional evidence about some competences, resulting in the progressive definition of the profile.

Following the usual notation, a measure space $(X, \mathcal{B}, \mu)$ is defined by a σ-field $\mathcal{B}$ of subsets of X and a (finite) measure μ defined on $\mathcal{B}$ such that $\mu(X) < \infty$. The function μ is said to be a *possibility measure* if $\mu(\emptyset) = 0$, $\mu(X) = 1$ and for any countable sequence of subsets S in $\mathcal{B}$, $\mu(\bigcup_{i \in S} s_i) = sup\{\mu(s_i) | i \in S\}$. It should be noted that a possibility measure Π such that $\Pi(A) = 1$ if $A \neq \emptyset$, and $\Pi(\emptyset) = 0$ describes the *least informative* possibility measure. Given a possibility measure Π a possibility distribution $\pi : X \rightarrow [0, 1]$ can be defined such that $\pi(x) = \Pi(\{x\})$.

Possibility distributions for a given individual $h \in H$, denoted by $\pi_{\tilde{c}}^{h}(x)$, $c \in C$ are defined following the usual conventions: (1) $\pi_{\tilde{c}}^{h}(x) = 0$ means that $\tilde{c} = x$ is impossible, and (2) $\pi_{\tilde{c}}^{h}(x) = 1$ means that $\tilde{c} = x$ is possible without any restriction. The domain of values of competencies is normalized in the [1,100] real interval.

Figure 1 depicts an example of possibility distribution for a given competence. The rationale in this case is that of assigning a score obtained from a self–assessment that yielded the value '3'. According to the function, it's granted complete possibility to values above that medium point, proceeding in this case in an optimistic way. The selection of the shape is competence and assessment method-dependant, and therefore, consultants are responsible for that decision. Possibility may be additionally restricted by certifications,

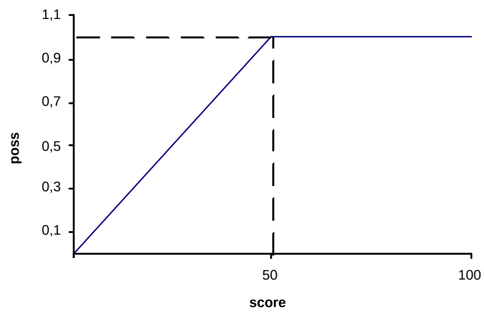

Fig. 1. Example possibility distribution.

grants or experience. For example, the presence of a certification in a programming language or technology can be used to give full possibility for related competences to a certain extent.

The following property regarding *gen-spec* relations between competences must be true for any candidate profile. Given a pair of competencies a and b so that b is an specialization of a:

$$\forall x \ \ \pi^h_{\tilde{a}}(x) \geq \pi^h_{\tilde{b}}(x) \tag{1}$$

The rationale for (1) is that it's possible that for an individual the more specific competence is known to be not present at all (i.e. that $\pi^h_{\tilde{b}} \equiv 0$), but having that more specific competence entails that the more general one is also present. Despite this restriction, some specialized competences are less differentiated to some of its generalizations than others. This fact should be taken into account when using flexible approaches to selection, since in many practical situations, more specific competences can be *substituted* by more general ones, e.g. a selection searching for individuals with a given level of 'Oracle 6i Backup Administration' may also consider individuals with an appropriate level in 'Oracle Backup Administration', but not those having a more general competence like 'Relational database backup administration'. This leads to a concept of degree of substitutability between competences connected by *gen-spec* relations.

The approach to model this kind of imprecise relationships follows the resemblance-relation approach described in [14]. Concretely, we'll denote a generalization relationship between two competences in C as defined in (2).

$$a \succ^d b \quad a, b \in C \tag{2}$$

$$d = \{\phi_i(a, y) \mid a \succ^d y \ \wedge \ y \in C\} \tag{3}$$

A discriminator d determines the taxonomic criterion that justifies the relationship, and can be represented in the most general case by a set of predicates (3) – one for each direct specialization – that determines the specific properties of the instances of each subclass. Each of the predicates ϕi characterize one of the subclasses discriminated. Following the example, $product(X)$ and $version(X)$ could represent assertions discriminating backup competences like those mentioned above.

Given a competence, its direct subclasses are divided in disjoint sets (partitions), according to their discriminators. P denotes the set of (local) partitions.

$$P_a = \{p_{(d,a)} \mid a \in C\} \quad where \ p_{(d,a)} = \{c \mid c \in C \ \wedge \ a \succ^d c\} \tag{4}$$

Given a concrete $p_{(d,a)}$, a notion of *distance* from a to each of its specializations is required to model the concept of substitution mentioned above.

We have used *resemblance relations* to model that specialization distance. A resemblance relation R on a crisp domain D is a binary fuzzy relation (5).

$$R : D \times D \to [0,1] \tag{5}$$

which satisfies reflexive (6) and symmetric (7) properties.

$$R(x,x) = 1 \ \ \forall x \in D \tag{6}$$

$$R(x,y) = R(y,x) \ \ \forall x,y \in D \tag{7}$$

Given this definition, a separate partial resemblance relation R can be obtained locally for each partition of subclasses, so that we operate on a set of relations (8) in the form (9).

$$\Xi_D = \bigcup_{x \in P} R_x \tag{8}$$

$$R_x : p_{(d,c)} \cup \{c\} \times p_{(d,c)} \cup \{c\} \to [0,1] \tag{9}$$

Relations are labelled partial since they only contain competece–sub-competence relationships, that is, relations are really defined in the form $R_x : \{c\} \times p_{(d,c)} \to [0,1]$, i.e. from a specified competence to all its specializations that are discriminated by an specific d (although this could easily be extended to siblings). This enables a form of stepwise simple reasoning in which competences at hierarchy level i can be substituted with the closest competence in the $i \pm 1$ level traversing *gen-spec* relations through the different discriminators. The use of these resemblance relations in selection models the notion of substitution, as will be described in Section 4. The elicitation method for these relations was based on the techniques described in [14], using HR consultants as experts.

3 Designing Aggregation Schemes for Competencies

Weighted additive approaches like the percentage matching used in `OntoProper` [19] have been used for the process of selecting individuals given a desired profile for a task or job. But these approaches neglect the fact that the presence of one concrete skill or competence may be correlated or be interpreted as being covered by others. This and other forms of interaction between competencies point out that the problem of score aggregation for concrete selection processes require a careful examination of the nature of the skills involved in the process. Since relationships between competencies are seldom precisely defined, fuzzy integrals are good candidates for the design of flexible and interpretable aggregation schemes as described in [4]. Following the possibilistic framework described above, the aggregation of competence levels can be described as an aggregation of possibilities normalized in the [0,1] interval:

$$\Omega : I^n \to I \tag{10}$$

Our first attempt to model these forms of aggregation has been that of designing fuzzy measures that are used as capacities using the Choquet integral (11) as a concrete form of Ω operator.

$$\mathcal{C}_v(x) = \sum_{i=1}^{n} x_{(i)}[v(\{j|x_j \geq x_{(i)}\}) - v(\{j|x_j \geq x_{(i+1)}\})] \tag{11}$$

The fuzzy measure v is specific to each aggregated competence and should in the general case be specified by HR consultants (a sample process for the elicitation of those measures in other domain can be found in [16]). A fuzzy measure on a set X is a monotonic (i.e. $v(S) \leq v(T)$ whenever $S \subseteq T$) set function $v : 2^X \to [0,1], v(\emptyset) = 0, v(X) = 1$. A number of interactions between competences can be modelled by fuzzy measures, including substitutiveness, complementarity and preferential dependencies, as described by Marichal [10].

An example is given in Table 1, in which the value of the typical *soft* competence 'customer loyalty management' (clm) is obtained by aggregation of four competences[5], namely, 'Campaign eligibility criterion setting' (e), 'customer portfolio management' (m), 'customer segmentation analysis' (s) and 'customer loyalty program management' (l).

A positive correlation is assumed between e and s since they share a common collection of required skills to be attainable. This interaction, according to [10], expresses that the marginal contribution of s to every combination of criteria that contains e is strictly less than the marginal contribution of s to the same combination when e is excluded. In addition, m and l are considered as substitutive by the consultants (due to the fact that both reference a common collection of management skills), so that the presence of m or l produces almost the same effect than the presence of both.

Table 1. Example fuzzy measure $v(X)$

n = 1	n = 2	n = 3	n = 4
$\{e\} \to 0.4$	$\{e, s\} \to 0.5$	$\{e, m, s\} \to 0.6$	$\{e, m, s, l\} \to 1$
$\{m\} \to 0.15$	$\{e, m\} \to 0.55$	$\{e, s, l\} \to 0.65$	
$\{s\} \to 0.3$	$\{e, l\} \to 0.55$	$\{e, l, m\} \to 0.6$	
$\{l\} \to 0.15$	$\{m, s\} \to 0.45$	$\{m, l, s\} \to 0.5$	
	$\{s, l\} \to 0.45$		
	$\{l, m\} \to 0.2$		

It should be noted in Table 1 that the weight of $\{e, m\}$ is only slightly augmented when the substitutive competence l is added to the set, and the

5 The characterization of the competence is actually more complex, but a simplification is described for clarity

set of correlated competences $\{e, s\}$ has a weight of 0.5, which represents a difference of 0.2 from absolute additivity. In more complex cases, mathematical functions are required to model those relationships (and in presence of larger numbers of competences, *k-additivity* must be studied to be able to define v [5]). The requirement for two correlated criteria i and j is that they are sub-additive i.e., that $v(\{i,j\}) < v(\{i\}) + v(\{j\})$. Two substitutive competences are required to satisfy the relationship expressed in (12), so that the addition of a substitutive criterion have a small effect in the fuzzy measure (having no effect if the criterion are completely interchangeable).

$$v(T) < \left\{ \begin{matrix} v(T \cup i) \\ v(T \cup j) \end{matrix} \right\} \approx v(T \cup \{i,j\}) \ ; \ \ T \subseteq X - \{i,j\} \tag{12}$$

The results of the Choquet integral for the measure in Table 1 can be compared with those of a simple weighted mean ($\mathcal{W}$) to appreciate the differences (both expressed in a zero to three scale). For example, $\mathcal{C}(3,3,0,2) = 1.45$, while $\mathcal{W}(3,3,0,2) = 2.4$, showing how the second values overweights the correlated criteria (in addition, $\mathcal{C}(3,2,0,2) = 1.4$, so having a consistent small increment of 0.05, while the weighted mean delta is 0.3). In cases in which the participating criteria are independent, like $(0,2,2,0)$, $\mathcal{C}$ and $\mathcal{W}$ yield the same value.

The just described example illustrates the subtleties and context–dependency of competence composition in the general case, which calls for further studies on this kind of relationship. It should be noted that this form of relationship is different to that described in the previous section. For example, the presence of a given possible level x in competence s does not entail necessarily that the aggregated possible level in clm would be over that value.

4 Integrating Vague Relationships and Aggregation Schemes in Canonical Models

The just described competency relationships have been used to build a Web-based tool used as a support system in human resource selection. The tool allows a consultant to query for matching candidates for a given desired profile, and the tool uses the relationships described in Sections 2 and 3. The overall layout of the tool, showed in Figure 2 simply allows for the definition of a given required profile (a job profile), and returns the individuals in the database that better match the given profile.

Job positions are described by a set of competency scores that are associated to a specific selection process. A number of explicit scores is specified by the job seeker directly, that are considered as completely certain and *required* requirements. Other scores may be *desirable* but not mandatory requirements. In consequence, a job profile $p \in P$ for a given organization may be characterized as a set of scores:

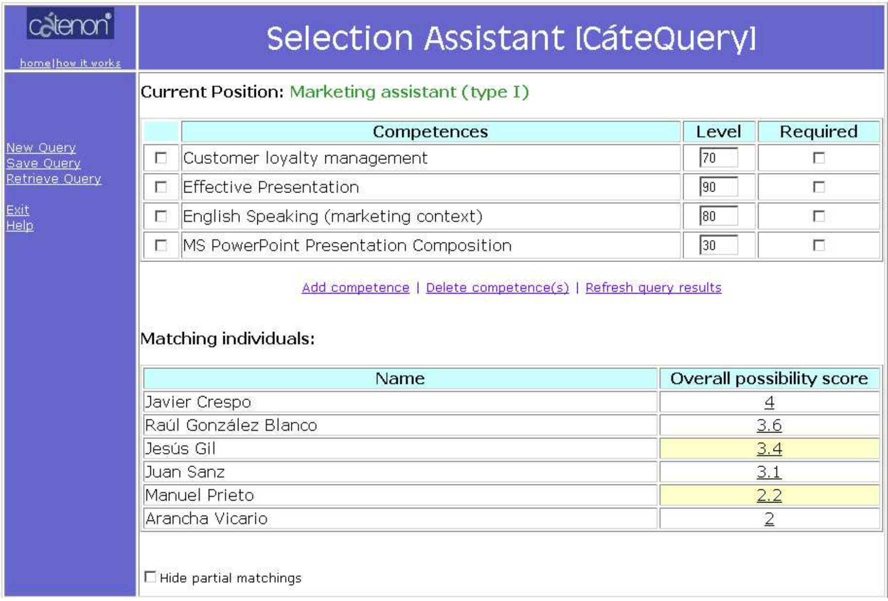

Fig. 2. Overall layout of the candidate–query Web tool.

$$p \equiv REQ_p \cup DES_p \tag{13}$$

$$p \equiv \{r_i\} \cup \{d_j\}, r_i, d_j \in (c, x), c \in C, x \in [1, 100] \tag{14}$$

The selection of the better subset of candidates for a given job position is carried out according to the following compatibility formula that represents the possibility of fit of the profile of candidate h to the job position p.

$$POSS_p^h = trunc(\prod_{(c_i,s_i) \in REQ_p} \pi_{c_i}^h(s_i)) \cdot \sum_{(c_i,s_i) \in DES_p} \pi_{c_i}^h(s_i) \tag{15}$$

The *trunc* function truncates the real value to an integer. This entails that if any of the required scores is below perfect possibility, the overall score becomes zero. Otherwise, the effect of that required competences is that of multiplying one by the rest of the formula. The $POSS$ value can be divided by $|DES_p|$ to have a normalized value for comparing degrees of matching in different selection processes.

When obtaining the possibility grades in expression (15), the relationships described in previous Sections are used in the following way:

i *Gen-spec* relationships are used to substitute more specific competences with direct generalizations both in REQ and DES, for individuals in whose profile the concrete competence is not present or does has a lower value than that of the generalized competence.

ii Aggregation operators associated to competences (as clm in the example of Section 3) are used whenever they appear in REQ or DES, computing the aggregated value from the partial values of sub–competences. This may occur recursively if more than one level of composition occurs.

In Figure 2, the column 'overall possibility score' is shadowed if a relationship of type (i) has been used as substitute. These scores are links that lead to a page providing details on the competences actually used in the computation of the score.

Competences involved in the described process can be described in standardized markup following the `Hr-Xml` conventions. But a number of extensions to the 'Competencies 1.0 (Measurable Characteristics)' recommendation are required to describe both resemblance relations and aggregation–oriented compositions:

- The recommendation states that 'competencies can be recursive', but a way to differentiate types of relationships is required.
- Each type or relationship must be accompanied by a collection of information elements describing the concrete characteristics of the relationship.

The following example fragment of extended markup illustrates a possible straightforward way of adding those required information items:

```
<?xml version="1.0"?> <Competency name="Communication Skills"
  xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance"
  xsi:noNamespaceSchemaLocation="http://ns.hr-xml.org/
                              Competencies-1_0/Competencies-1_0.xsd"
  xmlns:fuzzy="http://www.dei.inf.uc3m.es/hr/">
  <Competency name="Written Communication Skills">
          <CompetencyEvidence name="WRITTENTEST1-A"
                                 dateOfIncident="1995-01-01"
                                 lastUsed="2000-01-01">
                    <NumericValue minValue="3"
                              maxValue="5"
                             description="SEP-equivalent Skill-Level Range">5
                    </NumericValue>
          </CompetencyEvidence>
     <Competency name="Technical Writing Skills" fuzzy:type="specialization">
          <fuzzy:distance value="0.4"/>
          <fuzzy:discriminator name="Kind of writing"/>
          <CompetencyEvidence name="c1" >
          <!-- etc...-->
     </Competency>
 </Competency>
 <Competency name="Oral Communication Skills">
          <CompetencyEvidence name="ManagerObservation"
                       dateOfIncident="1996-01-01"
                       lastUsed="2000-01-01">
              <NumericValue minValue="1"
```

```
                         maxValue="5"
                         description="Company XYZ Skill Range">5</NumericValue>
        </CompetencyEvidence>
</Competency>

<!--  etc... -->

<fuzzy:AggregationScheme file="aggr1.xml" />
</Competency>
```

In the above fragment, extended elements and attributes are put into the `fuzzy` namespace. By default, competence nesting is interpreted as 'aggregation', and the `AggregationScheme` elements is provided an alternative for the official simple weighting scheme of `Hr-Xml`, and points to a separate file. Specialization relationships are marked explicitly by the `type` attribute, and elements `distance` and `discriminator` give details about the characteristics of the relationship.

5 Conclusions and Future Work

Imprecision is an inherent characteristic of both composition and generalization-specialization relationships in competence modelling, which makes necessary the development of richer and more realistic knowledge representations of contextually–situated competences. In this paper, we have proposed resemblance relations to model distance between competences and its specializations, and the use of the Choquet integral as a device to produce interpretable aggregations of competence levels considering interactions between them. Both relationships have also been integrated in a simple scoring possibilistic framework based on previous work [15], that has been used to develop a prototype tool that allows for querying for individuals that match a given job position. The resulting model provides a point of departure for further studies about the structure of competences that are more ambitious than current simple compensatory scoring models like the one described in [19].

The modelling constructs devised as part of our current competency model are fragmentary aspects of the problem of competency modelling, and in consequence, they need to be integrated in a comprehensive framework to give support to knowledge-based applications. Future work should focus on the specifics of each of the different kinds of competence relationships and their interactions to be able to develop a new generation of more realistic HRM tools. It should be noted that here we only deal with specific forms of imprecision, but other forms of imperfect information [17] are also inherent to most HRM systems. For example, *ambiguity* appears whenever they have to deal with conflicting information like assessments coming from peers and managers, and imprecision and uncertainty is also inherent to measurement instruments like questionnaires or indirect tests.

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