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ON THE USE OF THE CHOQUET INTEGRAL FOR THE COLLABORATIVE CREATION OF LEARNING OBJECTS

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Abstract. Computer-supported collaborative knowledge creation is the continuous process of development of knowledge assets, where produced knowledge has to be assessed by the developers, taking into account a set of criteria that may keep some interdependencies. This work poses an approach for collaborative creation of learning objects in a Web-based, educational context, based upon a coordination protocol and an aggregation mechanism. The coordination protocol allows the continuous consolidation of opinions issued about the learning objects produced by a number of authors. During certain steps of the protocol, an aggregation process is performed that takes into account the inter-dependence among criteria. The results of using the Choquet integral as an aggregation operator are compared to the usual aggregation procedure based upon weighted arithmetic means.

Keywords: Collaborative work, multi-agent systems, fuzzy sets, aggregation operators, learning objects, choquet integral

1 INTRODUCTION

In the advocation for computer-supported knowledge creation [2], collaboration stands out as a tool to mediate, but not to eliminate, the differences between various views of the design of a system. Knowledge creation or production is considered the continuous development and certification of knowledge that is generated in a specific domain where a group of actors is participating, whose activities need to be coordinated. Especially, when the action of producers is asynchronous, coordination poses the features and issues of a distributed system [4]. Coordination is a key pattern of interaction that is needed to obtain knowledge that has been evaluated and validated by means of assessment and/or consensus in the group [5].

The e-learning arena provides a concrete example of that rather general issue of knowledge creation. The collaborative creation of instructional material is a distributed, multidisciplinary process, which can involve several roles (such as content providers, instructional designers, pedagogical advisors, teachers, and even students) with different points of view about how to build up a reusable learning object. During the process, their ideas and plans are exchanged, evaluated and eventually consolidated to form new consensus-based learning material, as the result of a continuous negotiation of proposals amongst them. Moreover, collaboration support is scarce in current authoring approaches for learning contents, which only provide individual views of the creation, edition and assessment processes. Most experiences on learning objects' collaborative development are based on discussions fora with online polls enclosed, where the negotiation process is manually managed in a store-and-retrieval basis. But when some degree of consensus is achieved, there are poorly automated ways to take results into the authoring tool [3]. Nevertheless, such feature is successfully supported by control version systems and software configuration management in the software development field [1].

A multiagent paradigm has been approached to develop a distributed knowledge creation system, where agents act as delegates of knowledge-producing actors. The multiagent architecture includes a protocol [6] that facilitates the coordination of assessments carried out during knowledge creation. In that architecture, agents are gathered around separate interaction groups, and hierarchical relationships are defined amongst them. Through the protocol, agents in a group achieve the *consolidation* of knowledge that is formulated such that it keeps up with a set of validation criteria. Consolidation is the establishment of produced knowledge as agreed by every agent in an interaction group, in such a way that every agent in the group eventually knows about it.

The consolidation process requires a distributed coordination mechanism or protocol, as well as some agreement on the assessment criteria used to validate objects that are created. Prior experience using assessment criteria in the protocol neglected the fact that these criteria in many cases interact with each other. In the search for a more convenient approach, the Choquet integral appeared as a candidate for weighted and correlated criteria.

This paper outlines a fuzzy aggregation-based evaluation approach for the validation of *learning objects* that are produced in a Web-based agent-supported collaborative system, and provides evidence about the appropriateness of the Choquet [15] integral as the aggregation procedure, comparing it with a simpler, more immediate technique.

Learning objects are independent, reusable elements of information that provide value to learning, education or training processes. In their digital version, every constituent element of a course can be viewed as learning objects, including two major facets. The first is the content of the learning object itself; the second is the metadata describing the learning object [7].

The rest of this paper is structured as follows. In Section 2, the proposed coordination protocol is described, without specifying a specific assessment criteria used by the agents to evaluate proposals. Section 3 describes the use of the Choquet integral to model the aggregation process, providing a comparison with arithmetic mean-based techniques. Finally, conclusions and future research directions are outlined in Section 4.

2 MULTI-USER COORDINATION

The goal of knowledge creation is the consolidation of knowledge objects that are formulated in an agent-coordinated interaction environment. A knowledge-producing agent usually operates within the boundaries of an interaction domain that we call *mart*. Agent interaction in a mart complies with the rules of a coordination protocol, as described below. The interaction policy also fulfils the style of interaction that is pre-established between agents, which may be competitive or cooperative, or some of the sort [11].

The coordination mechanism can be borrowed from usual FIPA interaction protocols [9], like the contract net protocol or any auction protocol. Consider the case of a group of agents that are involved in making a decision about the value of a particular feature of a learning object. They can coordinate themselves by means of a contract net protocol, for instance. In that case, a special contractor agent takes control over the inquired feature during the process, and the rest of agents submit their proposed values. Then, the contractor plays a coordinator role and evaluates proposals against a set of previously agreed criteria, and eventually decides upon the chosen value for the object feature. Nevertheless, the contractor agent is playing a special role that is required in all interactions concerning the final decision, even though that special agent is not interested in taking part in the decision process. Moreover, if the contractor agent fails, the rest of agents in the market have to choose a new agent to play both coordinator and evaluator roles, needless to say what happens if the failure takes place during already started interactions.

The coordination issue is a topic in distributed systems' discipline, which provides techniques to solve common problems of synchronization, mutual exclusion, consensus, and fault-tolerance, among others, between a group of distributed processes. This scenario is rather similar to that of multi-agent systems, but only in the scope of the mentioned coordination problems. Most distributed algorithms in those systems use either de-centralized, peer-to-peer or replication approaches that prevent a single process to play any essential coordination role in the former, or replicate the same coordination role in the latter, to avoid the undesired effects of a failure in any process.

FIPA interaction protocols define asymmetric approaches to coordinate the creation of learning objects. The interaction protocol can be initiated by the agent that is submitting the object, or by other agent. If auction protocols are used, an initiator agent subjects its own proposals to bidding before getting them consolidated. However, in a contract net, the consolidation of an object is initiated by an agent (i.e., the *contractor*) that is different to the ones that can submit change proposals to it. To coordinate a group of knowledge-creating agents, you can also use a symmetric, peer-to-peer *consolidation protocol* [6], which permits any agent both to submit change proposals and start consolidation requests for an object. As well, it does not require any single agent to complete the protocol for the success of the consolidation process, since all agents play the same coordination role.

Interaction between agents is carried out by exchanging proposals containing FIPA-compliant communicative acts [8], and driven by participants' goals and needs. By *proposal* each formulation act of an agent is meant that intends to consolidate a given knowledge in its group. Since a proposal is intentional, we will not refer to it as fully produced knowledge until it becomes consolidated. Given a decision making process, the following types of messages can be used by agents executing the coordination protocol:

propose(k)**:** Agents send this message when they want a proposal k to be acknowledged by every agent in the mart, previous to its consolidation.

consolidate(k)**:** Agents send this message when they want to ratify a previously submitted proposal k as accepted by every agent in the mart. It can be identified with the FIPA *inform* declarative.

The consolidation protocol is a two-phase process, whose statechart is depicted in Figure 1, from the point of view of a particular agent. The *distribution* phase begins when an agent submits a change proposal by broadcasting a *propose* message in the market, also starting up a time-out t_0 to set its deadline. The rest of agents can either start the protocol and submit their own proposals, or reply with individual assessments over the received one. Once the deadline has expired, and other agents' proposals were not received or they had worse aggregate evaluations, the submitting agent begins the *consolidation* phase. The deadline for this phase is marked with a different time-out t_1, and starts by broadcasting *consolidate* messages about this occurrence. In this phase, only consolidate messages from other agents can stop the advancement of consolidation. In any stage, others' evaluations can come and contribute to the aggregate assessment. If an agent receives a propose or consolidate message carrying a proposal that is evaluated as preferred, timeout t_1 is initiated again to give it a chance. However, if the preferred proposal is not ratified eventually, then the agent will go on about its initial aim and will try again to consolidate its own proposal. Eventually, the protocol will finish whenever the aggregate assessment of a given proposal surpasses the rest during a period that goes on for $t_0 + t_1$ at least. This usually occurs in the long run, when the quality of formulated proposals is higher.

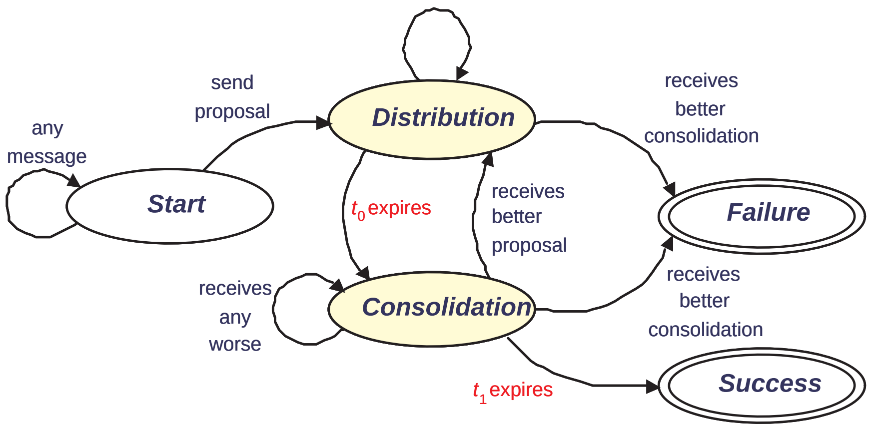

Fig. 1. State diagram of the coordination protocol

3 MULTI-CRITERIA AGGREGATION

Another task of agents during learning objects creation is to assist the assessment of other agents' proposals of change that may affect objects that fall under their concerns. Once again, the commitment of this task to a single agent is an unsafe decision, since the agent may fail half done. The sharing out of this duty may overcome the weakness if you have a mechanism to distribute evaluation tasks among involved agents, and then aggregate received assessments. Since agents play both source and evaluator roles of change proposals to a learning object, any agent can be asked for assessment of a learning object piece with respect to some criteria selected from a set of predefined ones.

The consolidation protocol provides two well-defined time points to ask questions to evaluators. They are located at the immediate beginning of distribution and consolidation phases, which coincide with each timeout startup. For simplicity, assessment messages are not depicted in Figure 1 but may occur during any timing phase. These timeouts define the allowed limits for receiving assessments. Any assessment message received out of such deadlines is ignored. Then, the aggregation process is started and its result determines whether a submitted proposal is preferred or not.

Collected assessments are expressed by selecting a linguistic label from a set of predefined ones defined over each decision criterion. We have a set of criteria $C = \{c_1, \ldots, c_m\}$ for the appropriateness of including a piece of the learning object, and a set of participants $P = \{p_1, \ldots, p_k\}$ in the collaborative creation process. Since several types of interaction between criteria can be defined, these have to be dealt with whilst the aggregation process is running. This section describes such a process and how the Choquet integral is useful to manage the inter-dependence of criteria.

3.1 Evaluation Criteria

In the e-learning arena, there is a need to facilitate search, evaluation, acquisition, and use of learning objects, for instance by learners or instructors or automated software processes. IEEE LOM standards [12] facilitates the sharing and exchange of learning objects, by enabling the development of catalogs and inventories while taking into account the diversity of contexts in which the learning objects are reused. In the collaborative settings described above, four major LOM metadata elements have been selected that apply as the assessment criteria of produced learning objects:

semantic density **(c_1):** the degree of conciseness of a learning object, estimated in terms of size, span or duration

difficulty **(c_2):** how hard it is to work with or through a learning object for the typical intended target audience

interactivity level **(c_3):** the degree to which the learner can influence the aspecto or behavior of a learning objetct.

cost **(c_4):** whether the use of a learning object requires payment and how much.

Other metadata defined in LOM standards are the language in which the learning object is described, the intended end user role, the typical age range, etc.; but for simplicity we do not consider all of them here.

Each alternative learning object l is associated with a profile $(x_1^l, \ldots, x_m^l) \in \mathbb{R}^n$, where, for any $i \in C$, x_i^l represents the partial score of l related to criterion c_i. We assume that all partial scores are defined according to the same interval scale.

Nevertheless, in many practical applications the decision criteria present some interaction or dependence degree. For instance, in learning objects evaluation, one can state that a *semantically dense* (highly scored for c_1) resource is probably *difficult* (highly scored for c_2) to work with. So far, we have studied two kinds of dependence, i.e. correlation and substitutiveness/complementarity, that are a major source of interaction between criteria.

3.1.1 Correlation

Two criteria $c_i, c_j \in C$ are positively correlated if one can observe a positive correlation between the partial scores related to c_i and those related to c_j. For example, consider the case of evaluating learning objects with respect to the four criteria described above, as expressed by every decision maker. Clearly, criteria c_1 and c_2 are correlated for the reason recently stated. Thus, these two criteria present some degree of redundancy.

3.1.2 Substitutiveness/Complementarity

Another type of dependence is that of substitutiveness between criteria. Consider again two criteria $c_i, c_j \in C$, and suppose that the decision maker demands that the satisfaction of only one criterion produces almost the same effect than the satisfaction of both. For example, it is important that learning objects be targeted to a given audience, but for children's education, the typical age range may be substitutive of the former criterion.

Alternatively, the decision maker can demand that the satisfaction of only one criterion produces a very weak effect compared with the satisfaction of both. We then speak about complementarity. That is the case of interactivity (c_3) and cost (c_4) criteria for learning objects, which, if improved together, will receive better evaluations.

3.2 Aggregation Processes

In each decision step of the previous coordination protocol, two kinds of aggregations are performed: (1) The most often used weighted arithmetic mean, and (2) our proposed approach based upon the Choquet integral. Both approaches were implemented in Java, and the experiments showed better results for the latter, which takes into account the interaction among several evaluation criteria.

3.2.1 Using the Weighted Mean

The weighted arithmetic mean operator used is of the form:

$$M_\omega(x) = \sum_{i=1}^{n} \omega_i x_i \tag{1}$$

with $\sum_i \omega_i = 1$ and $\omega_i \geq 0$ for all $i \in C$.

However, this operator is not able to model in any understandable way an interaction among criteria, since it can be used only in presence of independent criteria.

In order to have a flexible representation of complex interactions between criteria, it is useful to substitute the weight vector ω by a non-additive set function on C allowing to define a weight not only on each criterion, but also on each subset of criteria.

Suppose that criteria c_1 and c_2 are more important than the others, so that, with a weighted arithmetic mean, weights could be $(0.3, 0.3, 0.15, 0.15)$. Since the first two criteria somewhat overlap, the global evaluation will be overestimated (resp. underestimated) for dense and/or difficult learning objects.

3.2.2 Using the Choquet Integral

The discrete Choquet integral can be used as a generalization of the weighted arithmetic mean that accounts for interacting criteria [14].

The general expression of the integral given in 2 is a specific instance of the general form of a discrete aggregation operator on the real domain: $M_v : \mathbb{R}^n \to \mathbb{R}$, which takes as input a vector $x = (x_1, x_2, \ldots, x_n)$ and yields a single real value.

$$\mathcal{C}_v(x) = \sum_{i=1}^{n} x_{(i)}[v(\{j|x_j \geq x_{(i)}\}) - v(\{j|x_j \geq x_{(i+1)}\})] \tag{2}$$

In expression 2 we have that $x' = (x_{(1)}, x_{(2)}, \ldots, x_{(n)})$ is a non-decreasing permutation of the input n-tuple x, where $x'_{(n+1)} = \emptyset$ by convention. The integral is expressed in terms of a fuzzy measure (or Choquet capacity) v. A fuzzy measure on a set X is a monotonic (i.e. $v(S) \leq v(T)$ whenever $S \subseteq T$) set function $v : 2^X \to [0, 1]$. The fuzzy measure allows for the definition of weights not only on each criterion, but also on each subset of criteria.

The Choquet integral has been described elsewhere [14] as an aggregation operator enabling the explicit modelling of fuzzy interactions among criteria. Here, we will deal only with correlation and substitutiveness, since they are the two types of interactions identified in our domain of study.

The requirement for two correlated criteria i and j is that they are subadditive, as shown in (3):

$$v(\{i, j\}) < v(\{i\}) + v(\{j\}). \tag{3}$$

In addition, two substitutive criteria are required to satisfy the relationship expressed in (4), so that the addition of a substitutive criterion has a small effect in the fuzzy measure (having no effect if the criteria are completely interchangeable).

$$v(T) < \left\{ \begin{array}{c} v(T \cup i) \\ v(T \cup j) \end{array} \right\} \approx v(T \cup \{i, j\}) \; ; \;\; T \subseteq X - \{i, j\} \tag{4}$$

For our purposes, we have to build a fuzzy measure v reflecting the importance given to each of the criterion. Let us consider for our study that we have the measure described in Table 1, where the $a+$ symbol denotes presence and a blank denotes absence of criteria c_i in each set $S \in 2^X$.

c_1	+				+	+	+	
c_2		+			+			+
c_3			+			+		+
c_4				+			+	
$v(S)$	0.5	0.4	0.2	0.2	0.6	0.7	0.7	0.55

c_1			+	+	+		+
c_2	+		+	+		+	+
c_3		+	+		+	+	+
c_4	+	+		+	+	+	+
$v(S)$	0.45	0.6	0.65	0.65	0.9	0.8	1.0

Table 1. Fuzzy measure for the calculus of Choquet integral

Some points are worth to mention in this measure. First, the values for $v(S)$ when $|S| = 1$ (first four columns in Table 1) yield proportional weights to each single criteria with respect to those chosen for the weighted mean described above, holding also that $v(X) = 1$ (last column). Moreover, since c_3 and c_2 are complementary criteria, the contribution of both in a set S is higher than the contribution of only one of them, under the same set of remaining criteria.

3.3 Comparison of Both Approaches

When collaborators submit proposals for a given learning object, the coordination protocol is executed by every receiving author that is concerned about that object, until the proposal is eventually accepted, or substituted by a further elaborated one. This process continues until some degree of consensus on evaluation criteria is achieved. In each decision step of the protocol, an aggregation process is performed, based on the fuzzy operators described above. The values of the fuzzy measure used for the aggregation are obtained a priori by a process of collaborative inquiry as that described in [13], in which the participants in the group agree in an approximate definition. Of course, this direct elicitation approach is only feasible for decision problems with a small number of criteria, for which the number of mapping in the fuzzy measure is reasonably small.

Table 2 depicts an excerpt of the results from the weighted mean (*w-mean*) and Choquet integral (*c-int*) when the contribution of interactivity level (c_3) and cost (c_4) is void. Only integer values for inputs are shown, but in actual coordination processes they may come from estimation processes not necessarily constrained to a small and finite number of levels. When both semantic density (c_1) and difficulty (c_2) are high, the aggregation value yielded by w-mean is overestimated. However, this phenomenon, caused by the positive correlation between both criteria, does not occur with the Choquet integral.

Table 3 points out a second example of the power of the Choquet integral to smooth out the overrate of correlated criteria exposed by the weighted mean. In

c_1	c_2	c_3	c_4	*w-mean*	*c-int*
0	0	0	0	0.0	0.0
0	1	0	0	0.3	0.2
0	2	0	0	0.61	0.4
0	3	0	0	0.92	0.6
1	0	0	0	0.38	0.5
1	1	0	0	0.69	0.6
1	2	0	0	1.0	0.8
1	3	0	0	1.3	1.0
2	0	0	0	0.76	1.0
2	1	0	0	1.07	1.1
2	2	0	0	1.38	1.2
2	3	0	0	1.69	1.4
3	0	0	0	1.15	1.5
3	1	0	0	1.46	1.6
3	2	0	0	1.76	1.7
3	3	0	0	2.07	1.8

Table 2. Results from the weighted mean and Choquet integral aggregation operators for correlated criteria, particularized for $c_3 = 0$, $c_4 = 0$

this example, all discrete values of c_2 are shown for fixed values of $c_1 = 3$, $c_3 = 0$, and $c_4 = 1$. Since c_1 and c_2 are correlated, the values in the w-mean column are gradually increasing as the values of c_2 are higher, even becoming greater than those from c-int, mainly due to the overestimation introduced by the weighted mean, which the Choquet integral does not exhibit as intended.

c_1	c_2	c_3	c_4	*w-mean*	*c-int*
3	0	0	1	1.3	1.7
3	1	0	1	1.61	1.6
3	2	0	1	1.92	1.75
3	3	0	1	2.23	1.85

Table 3. Results from the weighted mean and Choquet integral aggregation operators for correlated criteria, particularized for $c_1 = 3$, $c_3 = 0$, $c_4 = 0$

A second source of interaction between criteria is complementarity. Table 4 depicts the aggregation values obtained when contribution from c_1 and c_2 is void, so we can check values for the complementary criteria. When only one of either c_3 or c_4 contributes, the value in w-mean is very similar to that raised by the contribution of both. Nevertheless, due to the contribution of both criteria the value in c-int is considerably higher than when only one applies, as desired.

c_1	c_2	c_3	c_4	*w-mean*	*c-int*
0	0	0	0	0.0	0.0
0	0	0	1	0.15	0.2
0	0	0	2	0.3	0.4
0	0	0	3	0.46	0.6
0	0	1	0	0.15	0.4
0	0	1	1	0.3	0.6
0	0	1	2	0.46	0.8
0	0	1	3	0.61	1.0
0	0	2	0	0.3	0.8
0	0	2	1	0.46	1.0
0	0	2	2	0.61	1.2
0	0	2	3	0.77	1.4
0	0	3	0	0.46	1.2
0	0	3	1	0.61	1.4
0	0	3	2	0.77	1.6
0	0	3	3	0.92	1.8

Table 4. Results from the weighted mean and Choquet integral aggregation operators for complementary criteria, particularized for $c_1 = 0$, $c_2 = 0$

4 CONCLUSIONS

This work poses an approach for collaborative creation of learning objects, where these have to be assessed by a group of developers to become consolidated. Participants in this process take into account a set of criteria that may be correlated or present some degree of interaction. This situation is considered as a multi-user, multi-criteria decision making scenario, where developers and decision makers are the same. The simultaneous, multi-user participation is coordinated by the execution of a protocol that allows the continuous consolidation of opinions simultaneously issued about the objects produced by authors.

During certain steps of the protocol, a multi-criteria aggregation process is performed. The use of the Choquet integral as an aggregation operator is compared to the usual aggregation procedure based upon a weighted arithmetic mean, turning out that the former performs better in the presence of criteria inter-dependence.

The approach described above is applied to the collaborative authoring of learning objects in an educational context, where the decision makers are instructional designers and the criteria are taken out from IEEE LTSC Learning Objects Metadata standards [12]. Nevertheless, relevant criteria for the assessment are modeled as *issues* and *values* that can change as the process progresses. This is not despite of more powerful, ontology-based representations for the same aspects [10], which are posed as a future work.

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