Dynamic Association Rules Mining to Improve Intermediation Between User Multi-channel Interactions and Interactive e-Services

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Abstract. This paper deals with multi-channel interaction managing thru an intermediation between channels and Interactive e-Services (IeS). After work on modeling and theoretical framework, we implemented a platform: Ubi-Learn, which is able to manage this kind of interaction thru an intermediation middleware based on a Multi-Agents System (MAS): Jade. The issue addressed here is linked to the way you choose a channel depending on the user's task. First, we have encoded several ad hoc rules (tacit knowledge) into the system. In this paper, we present our new approach based on association rules mining approach which allows us to propose automatically several dynamic rules (explicit knowledge).

Keywords: Interactive e-Services, Intermediation, association rules mining.

1 Introduction

The rapid spreading of wireless phone and data devices and the development of intelligent communications networks and middleware enable emergence of ubiquitous computing. To manage this new concept, we work both on the designing of Interactive e-Services (IeS) and on the intermediation between these IeS and the channels for interaction with the users (customers, learners, etc.). Our works have driven us towards two directions for the design of future multi-channel flexible interactive e-Services: (1) The complex interactions allowed by the right combination of channels or/and interaction modalities (i.e. language vs. direct manipulation). The coupling of these elements is done dynamically, depending on the user contexts and organization rules [6]; (2) The use of such or such channel or also set of channels is depending on the task done by the user. Knowing if a channel is adapted to a task in a certain context is very complex. In this paper, we propose an adapted solution which is to use a data mining algorithm allowing to extract particular knowledge called explicit knowledge. Nowadays, experts can not tackle a large amount of data. So, data mining method can help them in order to discover new information.

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At a conceptual level, we worked on a theoretical model of communication between human and organizations through channels, and we have built a taxonomy allowing, amongst other things, to select the best channel to use according to the context of the interaction. Finally, this taxonomy has helped us to formulate a definition of a channel. This paper deals with our recent works as regards the determination of rules allowing to choose the best channel into a given situation[1]. Thus, we introduce a Data Mining Agent (called DMA) which generates the dynamic rules set. Our first proposition is based on Association Rules Mining (ARM) such as "If *Antecedent* Then *Conclusion*" which constitutes an adapted solution to solve it. This task is a major issue in Data Mining (DM) which is an active research domain to face the increasing number of large databases. A set of association rules is mainly generated depending on two user-specified metrics: *support* and *confidence*. These metrics allow us to judge rules quality in order to inject them in the process of Ubi-Learn. The main originality of our proposition is to generate dynamic rules from the context. According to the context, we can regenerate rules both at design time and at runtime. For instance, the following rule {if (*Age*<30 AND *Occupation*="Computer scientist" AND Service="e-mail access" AND …) then *AdequatChannel*="PDA"} indicates that the preferred channel of a computer scientist under thirty years old is the PDA for the service…, etc. Then, these rules are used by a software agent (Rules Agent), which manages several adaptation levels (see Fig. 3).

2 Theoretical Works Around Channels Properties

2.2 An Analyze and Predictive Model of Channels Properties

Our previous works [2], [13] led us to consider three points of view about multi-channel interaction: (1) A more "interactional" approach where the channels intervene into complex cognitive processes between two people engaged more or less directly into a joint activity; (2) An approach that we call "Theory of Information", where the channels are characterized by their intrinsic properties, such as their symbolic representation possibilities, the media richness, and the adequacy to the user's task;

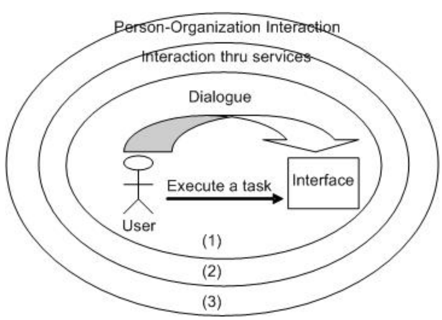

Fig 1. Different grains of an Interaction

[1] A situation is characterized by the contexts of interaction (user profile, rules of the organization, etc.) and the task(s) executed.

(3) An approach of the "acceptance" of the media by the user, whatever his adaptation to the media is. These three points of view correspond to two distinct theoretical fields one related to "Media" and another related to the adequacy between the task done and the media used. Moreover, it is essential to distinguish several views (cf. **Fig 1**) of an interaction at a granularity level:

– At thin grain ((1) on **Fig 1**), the interaction is like a situation where the user executes a task thru an electronic media[2]. This is an "interactional" approach, where the channels characteristics will have an incidence on the interaction and where the "Theory of Information" will have an important role. In this framework, the task adequacy is also an important aspect. Modeling the interaction level means we will be able to do a qualitative measurement of the using of such or such media according to its properties and according to the user task.
– At a larger grain ((2) on **Fig 1**), there are more constraints to the interaction. Indeed, this one is into an intermediation between some channels and services. So, it is necessary to take care of all the channel's properties, such as the networks, hardware, etc., but also the interaction context[3]. In this case, this is at this level that the taxonomy presented in the next section will be relevant;
– At the higher grain ((3) on **Fig 1**), this is the case of a Person-Organization Interaction. Here, it is necessary to add organization rules and policies. In this field, this is the "acceptance" aspect that will be relevant[4].

According to us, it is necessary to study these three points of view in order to characterize Person-Organization Interactions well. This step will allow us to be able to predict the channel to use according to the user's task and according to the global interaction context. The complexity of the multi-channel interaction being huge, we established a theoretical framework. Then, we discuss about the main points allowing to propose this framework. More details about this could be found in [3].

2.2 The Cooperation Inside the Cognitive Interaction

Works in the field of the psycholinguistic led by Clark, Brennan, and other colleagues [9], [8]. Their major interrogation was around the main properties of the communication. Their conclusions show obviously that this act needs collaboration between the interlocutors: *"The lesson is that communication is a collective activity. It requires the coordinated action of all the participants. Grounding is crucial for keeping that coordination on track."* [8]. Clark evokes the concept of joint activity which as means it is necessary to have at least two persons for an interaction. According to him, a joint activity is defined like activities set which imply more than one participant. Moreover, the atomic component of the activity is the action: an activity progresses towards its objective thru several joint actions. In addition, for collaboration and coordination, participants need to share several information, Clark calls that the common ground. According to him, there are two kinds of common ground: the personal and the communal. This common ground must evolve during the

[2] There are the two first points at the beginning of this section.
[3] There is several definition of context. We will discuss about this point in another section.
[4] This is the third and last point at the beginning of this section.

different communications. These updates need a process in order to be efficient: the Grounding. Clark defines grounding as: *"…to ground a thing, is to establish it as a part of common ground well enough for current purposes".* That means the participants work together to reach a mutual knowledge. Clark and Brennan have studied grounding thru different media (phone, e-mail, etc.). It seems that the effort needed to communicate is different according to the media used. They have determined eight constraints or properties and eleven costs related to the different media. **Table 1** shows the different properties. In this paper we will not discuss about the costs that we do not use in the works presented here.

Table 1. Constraints related to a communication between two participants

Co-presence	A and B share the same physical environment
Visibility	A and B are visible to each other
Audibility	A and B use speaking to communicate
Co-temporality	B receives at roughly the same time as A produces
Simultaneity	A and B can send and receive at once and simultaneously
Sequentiality	A's and B's turns cannot get out of sequence
Reviewability	B can review A's messages
Revisability	A can revise messages for B

According to Clark, *it* is the Least Collaborative Effort, which helps two participants to choose the best media in a given situation. The persons choose the media that reduces more the collaborative effort [7]. According to him, this means that during a communication, each participant tries to minimize his/her collaboration effort – the work that the two participants do is done thru a mutual acceptation of the collaboration. Some works in HCI are also based on grounding, such as [15].

2.3 The Social Aspect of the Channels

In this section, we will introduce the Media Richness Theory (MRT), and one of its critics led us to introduce the Theory of Media Synchronicity. The first assumption of this theory is that organizations process information to reduce uncertainty and equivocally [10]. Uncertainty is defined as *"the difference between the amount of information required to perform the task and the amount of information already possessed by the organization."* Equivocally is defined as the ambiguity of the task, caused by conflicting interpretations about a group situation or environment. Therefore, when equivocally is high, an individual does not know what questions to ask and when uncertainty is high the group knows the question but lacks the necessary information. In conclusion, as information increases, uncertainty and equivocally decrease. The second assumption of this theory is commonly used media in organizations works better for certain tasks than others. Specifically, [10] concluded that written media was preferred for unequivocal messages while face-to-face media was preferred for messages containing equivocally. They present a media richness hierarchy which incorporates four media classifications; face-to-face, telephone, addressed documents, and unaddressed documents. The richness of each media is based on four criteria shown in **Table 2**.

Table 2. Media properties from MRT

Feedback	Media capacity to support rapid bidirectional communication
Symbol variety	All signs allowing communication, verbal or not are likely to improve communication
Language variety	Using of different languages (scientist, etc.) allows to enrich the communication
Personal focus	Transcription of sentiments, emotions growth the medias richness

The richest communication medium is face-to-face meetings followed by telephone, e- mail, and memos and letters. But several points contradict that, let us take the example of e-mail and face-to-face: (1) in e-mail, we can add videos, pictures, files, etc.; (2) e-Mails become familiar (signature, personalization of the messages, etc.); (3) in e-Mail, the social presence is less strong, and this may be easier to talk with teachers, bosses, etc.

Moreover, this theory does not into account the context and the user's task. Dennis and Valacich [12] give some limitation of the MRT (Some empirical tests doing on the MRT show these limitations, in particular with recent electronic media), and propose some improvements. So they propose the Theory of Media Synchronicity. In this field, synchronicity means that two persons work together on a same activity at the same time and have a shared "concentration". They propose five media properties, characterizing the communication between these two people, and on the basis of the MRT. This is shown in **Table 3**.

Table 3. Media properties from the Theory of Media Synchronicity (TSM)

Feedback	Properties from MRT (the same signification)
Symbol variety	Properties from MRT (the same signification)
Concurrency	This is the number of communication at the same time (on the same media)
"Rehearsability"	Capacity to read again a message before send it
"Reprocessability"	Capacity re-examine the messages in the communication context

We can report that two interaction approaches, one like grounding from psycholinguistic, and the other from social psychology, present some analogies. The concepts of "concentration" and grounding have undoubtedly common roots.

2.4 Starting Point of Our Theoretical Framework

The study of these theories allows us to synthesize several channel properties that we have synthesized in **Table 4**. This tableau shows the relations which we highlighted between the different models, concepts and theories. Thus, for the moment, we proposed nine properties allowing to characterize a channel or a set of channels (Symbol variety, Feedback, Simultaneity, Sequentiality, Reviewability, Revisability, Personal focus, Language variety, Concurrency). Obviously, these properties are not enough to characterize a channel. To complement these works, we have built a taxonomy of the used channels inside a personalized interaction.

These works were already presented [5]. So our taxonomy includes our theoretical model with the different properties of the channels. For more details on this taxonomy see [3]. Thus, our theoretical framework, with the taxonomy allow us to characterize

Table 4. Relations between the different properties from the different models and theories

Grounding	MRT	TSM
Co-presence	Symbol variety	Symbol variety
Visibility		
Audibility		
Co-temporality	Feedback	Feedback
Simultaneity	*	*
“Sequentiality”	*	*
"Reviewability"	*	“Rehearsability”
"Revisability"	*	“Reprocessability”
Co-presence	Personal focus	*
*	*	Concurrency
Co-presence	Language variety	*
Visibility		*
Audibility		*

both a situation and the available channels, i.e. to do a given task, the user needs some properties, we can map these properties with the different channels properties, and choose the most adapted to the situation. Thus, we can be predictive concerning the channel to use in a given situation. Other models could help us in the future to improve this framework, such as the Task Acceptance Model (TAM) [11] and the Task-Technology Fit (TTF) [14]. TAM and FIT are often associated, and the strong idea, for us, here, is that the user must stay free, as far as possible, about the choice of the channels used to do his/her task. For the moment, we do not take into account these models in our modeling, but rather during the experimentation phases. Here, we are closer to a social approach. In the next section, we discuss this aspect. In the next section, we briefly present our platform Ubi-Learn, which manages the multi-channel interactions thru an intermediation between IeS and channels.

3 Our Software Architecture

3.1 Overview

Fig 2 shows the intermediation between e-Services delivered by the organization and the user via the use of different channels synchronously or asynchronously. Ubi-Learn were already presented in [4]. In these works, we also presented the intermediation

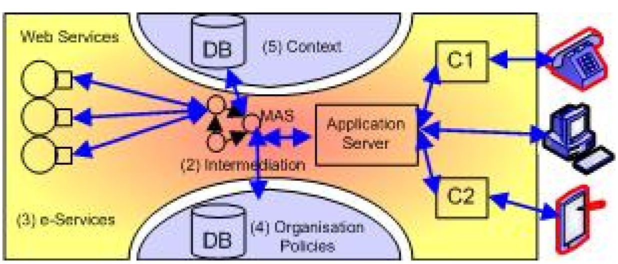

Fig 2. Simplified view of our software architecture (Ubi-Learn)

middleware implemented in Ubi-Learn, in the next section, we briefly remind it. In this figure, C1 and C2 represent the channel adaptation systems.

3.2 The Intermediation Middleware of Ubi-Learn

Fig. 3 shows that an intermediation uses several levels: the e-Service Composition; the Channel determination; the Quality of Service (QoS); the format that we call the Quality of Interaction (QoI) by analogy with the QoS; and finally the persistence of data. These different levels influence the intermediation and obviously, the composition and the adaptation of the e-Services, but also the capacity to choose the best channel for a particular IeS. It is important to notice that, in **Fig. 3**, all agents performing the actions are represented as a single agent whereas, to implement one agent of the figure, there could be a hierarchy of concrete Jade agents (e.g. a factory, a manager, etc.). In [4] we presented in details the four levels.

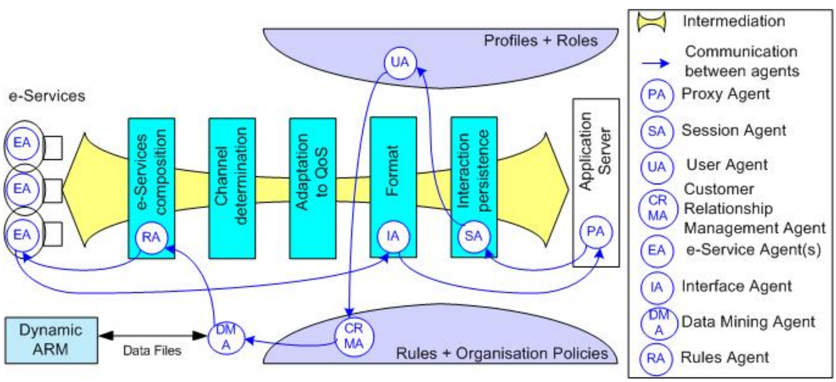

Fig. 3. Conceptual and technical view of our middleware

Here, briefly, and to summarize, we can describe the global running of the middleware from the **Fig. 3**: a customer accesses the Application Server through several channels. This server sends the user request to the *PA*. This agent creates a *SA* specific both to the user and the channel and is responsible for the persistence of each intermediation. Then, the request passes through *UA* (manages the user preferences, roles, etc.) and *CRMA* (manages the organization policies). These agents take the contexts into account. Afterwards, the *RA* executes a particular composition of the e-Services according to the channels in use. The *RA* sends a request to the appropriate *EA*, and the latter sends an XML flow (representing an abstract representation of the e-SI) to the *IA*. This agent sends the *ML flow (XHTML, WML or VoiceXML) to the *PA*, which sends these data back to the Application Server. And the latter transmits the *ML flow to the right channel. In the next section, we introduce our solution to generate rules (automatically and dynamically).

4 Dynamic Rules Generation

One drawback of the previous work is the static rules set which is fixed by experts. Consequently, these rules constitute the tacit knowledge of the expert. We wish to generate dynamically these rules set thanks to well-known data mining algorithms. In this case, the generated knowledge is explicit because it is the result of an algorithm. Among the current data mining methods, we wish to use the association rules mining (ARM) which is one of the possible solutions allowing to solve our problem by establishing logical relations between criteria. One of advantages is that the formalism is similar compared to current static rules.

4.1 Association Rules Generation

4.1.1 Motivations

In front of the increasing number of large databases, extracting useful information is a difficult and opened problem. This is the goal of an active research domain: Knowledge Discovery in Databases (KDD). KDD is a new hope for companies which use methods (e.g. statistical methods) that do not allow to tackle large amounts of data. We focus particularly on ARM such as "If *Antecedent* then *Conclusion*" [1]. This problem comes from basket market analysis in order to find implications between frequent database products. It is one possible solution to solve the problem and arises during data mining step. Currently, the rules set is generated depending on the tacit knowledge of an expert thanks to his personal experience. However, it is possible to find within database profiles, a new explicit knowledge which is not currently known by this same expert. Indeed, databases contain a significant quantity of knowledge which is hidden in meaningful masses. In order to generate dynamically the rules set, it is necessary to select some criteria according to our problem.

4.1.2 Definition

ARM [1] can be divided into two subproblems: the generation of the frequent itemsets lattice and the generation of association rules. Let $|I| = m$ the number of items, the search space to enumerate all possible frequent itemsets is equal to 2^m, and so exponential in m [1] and let $|T| = n$ the number of transactions. Let $I = \{a_1, a_2, \ldots, a_m\}$ be a set of items, and let $T = \{t_1, t_2, \ldots, t_n\}$ be a set of transactions establishing the database, where every transaction t_i is composed of a subset $X \subseteq I$ of items. A set of items $X \subseteq I$ is called *itemset*. A transaction t_i contains an itemset X in I, if $X \subseteq t_i$.

4.2 Methodology

In a first way, we realized a feasibility study in order to exploit existing tools. The Data Mining Agent (DMA) receives data (provided a binary matrix from the User Agent and the CRM Agent, thru data files). The DMA use an ARM algorithm (into Dynamic ARM[5] (DARM), see **Fig. 3**) to tackle these data files. When its task is finished, the Data Mining Agent retrieves rules from the DARM, and sort the right out the bad at a syntactic level (we keep only one channel in conclusion, etc.).

[5] DARM contains an ARM algorithms package.

Nevertheless, this agent should collaborate with a human being expert with the domain (this part is not show on the **Fig. 3**), which chooses the relevant rules at a semantic level. For each task, a rules set is generated by an ARM and for each of them, we selected one kind of rules such as “If *Customers' criteria* then *Channel”*. In these rules, *Customers' criteria* could be given by the context of interaction, the user's profile, etc. The quantity of these criteria can be easily infinite. Thus, it is difficult to generate these rules and sort them. These kinds of rules constitute the explicit knowledge which is relevant in this case. Consequently, they are inserted in the middleware, more precisely in the Rules Agent and the Data Mining Agent (see **Fig. 3**). After this task done, Data Mining Agent sends the selected rules to the Rules Agent thru a XML file. This agent update its knowledge base thanks to this rules set. The starting point of an ARM algorithm is a binary matrix ($m*n$). Intersection of a transaction (customer) and an item (criteria) is equal to 1 if the item is contained in the transaction. Criteria include customers' data and communication channels. Thanks to this matrix, it is possible to run an ARM which generates dynamically our rules set. Typical ARM is sufficient to obtain the rules set such as *apriori* [1].

5 Conclusions and Further Works

During a Person-Organization Interaction, choosing the best channel in a given situation is complex. All the different situations can not be exhaustively numbered. Indeed, these situations are too numerous (infinity) to be formalized. To solve this issue, we have worked on a theoretical framework to formalize the concept of channel and we have proposed both a taxonomy and a definition of the channel concept. This framework enables us to characterize all imaginable situations of Person-Organization Interaction, whatever the different contexts, the user, the task done, etc. and propose different rules allowing to choose best channel depending on the situation. In this paper, we argue the issue of the dynamic rules generation. According to us, the link we have made between two areas both Human Computer Interaction and Association Rules Mining for the purpose of the management of context-aware applications is original and relevant in this case. Indeed, these rules are as “If *Users criteria* then *channels*” where the users' criteria are given by the situation (context, task, etc.). Such we have said before, these criteria could be infinite. That is why we proposed to exploit a data mining solution to give some relevant rules to determine the best channel in a given situation. Currently, we work on a small sample of people to generate a compact rules set. However, our first experimentations show that the number of generated rules is large but results are encouraging because several rules are relevant. In order to refine the quality of generated rules, it is necessary to widen this sample. We can also see if the analysis of a large sample is possible in this area. To experiment it, we are realizing a form allowing to retrieve a consistent data set.

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References

1. Agrawal, R., Mannila, H., Srikan, R., Toivonen, H., Verkamo, A.I.: Fast discovery of association rules, Advances in knowledge discovery and data mining, American Association for Artificial Intelligence, pp. 307–328 (1996)
2. Bourguin, G., Derycke, A., Tarby, J.C.: Beyond the Interface: Co-Evolution inside Interactive Systems – A proposal founded on Activity Theory. In: Proceedings of IHM-HCI 2001 conference, Lille France, 10-14 september 2001, People and computer XV – Interaction without Frontiers, Blandford, Vanderdonckt, Gray. (eds) pp. 297–310. Springer, Heidelberg (2001)
3. Chevrin, V.: L'interaction Usagers/Services, multimodale et multicanale: une première proposition appliquée au domaine du e-Commerce. PhD in Computer Science. UST Lille. France (2006)
4. Chevrin, V., Sockeel, S., Derycke, A.: An Intermediation Middleware for supporting Ubiquitous Interaction in Mobile Commerce. In: ICPS'06, IEEE International Conference on Pervasive Services 2006 Lyon (2006)
5. Chevrin, V., Rouillard, J., Derycke, A.: Multi-channel and multi-modal interactions in E-marketing: Toward a generic architecture for integration and experimentation. In: HCI International conference, Las Vegas, Lawrence Erlbaum editors, 10 pages (June 2005)
6. Chevrin, V., Derycke, A., Rouillard, J.: Some issues for the Modelling of Interactive E-Services from the Customer Multi-Channel Interaction Perspectives, EEE 05 International. In: IEEE international conference on e-Technology, e-Commerce and e-Service, pp. 256–259. IEEE Press, Hong Kong (2005)
7. Clark, H.: Using Language. Cambridge University Press, Cambridge (1997)
8. Clark, H., Brennan, S.: Grounding in Communication. In: Resnick, L.B., Levine, J. M., Teasley, S.D. (eds.): Perspectives on Socially Shared Cognition (1991)
9. Clark, H., Schaefer, E.F.: Contributing to discourse. Cognitive Science 13, 259–294 (1989)
10. Daft, R.L., Lengel, R.H.: Information Richness: A New Approach to Managerial Behavior and Organization Design. In: Staw, B. M., Cummings, L. L. (eds.): Research in Organizational Behavior vol. 6, pp. 191–233 (1984)
11. Jr Davis, F.D.: A Technology Acceptance Model for Empirically Testing New End-User Systems: Theory and Results, Unpublished Doctoral Dissertation, Massachusetts Institute of Technology (1985)
12. Dennis, A.R., Valacich, J.S.: Rethinking Media Richness: Towards a Theory Of Media Synchronicity. In: Proceedings of the 32nd Hawaii International Conference on System Sciences (1999)
13. Derycke, A., Rouillard, J., Chevrin, V., Bayart, Y.: When Marketing meets HCI: Multi-channel customer relationships and multimodality in the personalization perspective. In: HCI International 2003 Heraklion, Crete, Greece, 2003, vol. 2 , pp. 626–630 (2003)
14. Goodhue, D.L.: Understanding User Evaluations of Information Systems, Management Science 41(12), 1827–1844 (1995)
15. Traum, D.R.: On Clark and Schaefer's Contribution Model and its applicability to Human-Computer Collaboration. In: proceedings of COOP'98 Workshop on Use of Clark's Models of Language for the design of Cooperative Systems (May 1998)