Patterns of Behaviour Mediated by Cognitive Scripts and Emotional Attitudes - Context-aware Engineering of Data Mining Systems

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Abstract
In this paper we outline a seven layer context-aware data mining architecture which combines context, sensemaking (cognitive and affective) and data mining technologies to design adaptive context-aware data mining systems. We particularly show how cognitive constructs and emotional attitudes of a user mediate in interpretation of meaning in hidden patterns. We illustrate the role of cognitive constructs in interpreting a CRM situation by a relationship manager in a banking and finance application. We also illustrate the role of emotional attitudes as an important factor in context-aware interpretation of mined behavioral patterns in a sales recruitment and benchmarking application.

Keywords –Data Mining, context, sensemaking, situation awareness, cognitive schema, affect model and emotions, knowledge management, decision optimization, user feedback layer architecture

1. Introduction

Data mining as the name suggests is the art and science of uncovering hidden patterns. Research in data mining has historically been driven by design and refinement of data and data web mining algorithms. More recently the focus has shifted towards design of more context centred and utility centred as against technology centered data mining approaches. Further data mining has its hurdles: the 'meanings' are not suggested by the data or the computers; they are imposed on data by human beings. This problem is further acerbated by the fact that data mining technologies are largely designed based on technology push models as against a strategy pull models driven by business managers. Business managers make sense of a new situation by constructing meaning or knowledge based on their cognitive constructs and adapt these cognitive constructs to the dynamics of the business situation. In the process of applying and adapting the cognitive constructs or schemas the managers may honor as well as reject pre specified meanings and outcomes mined using historical data (as is the case in a technology push model). The cognitive constructs also help to establish the semantic context in which data mining systems are used and interpreted. Most existing research in data mining has largely overlooked developing a social semantic and pragmatic context based approach while addressing algorithmic and technology issues towards design of data mining systems. From a social and pragmatic context people's interpretation of meaning and application of knowledge is not entirely based on their cold cognitive scripts or rules but are mediated by their emotional attitudes. Recent developments and focus of organizations in the area of emotional intelligence has established the role of emotions in human decision making.

Since the benefit of data mining models are perceived in terms of meaningful or applied knowledge one such approach which will allow us to bridge the gap between data mining technologies and meaningful knowledge outcomes is to support the user in the identification filtering and intelligent search of relevant knowledge in a context aware manner that assists the user. In this paper we focus on semantic and pragmatic contexts and the role of cognitive and affective characteristics of user in constructing and interpreting knowledge. The paper is structured as follows: Section 2 outlines the context model used for developing a context awareness data mining architecture. Section 3 describes the theoretical underpinnings of Semantic and Pragmatic context for data mining. Section 4 outlines the seven layers of the Context Aware Data Mining (CADM) architecture. Section 5 and 6 illustrate the application of the CADM architecture using a banking and finance and Behaviour profiling applications. Section 7 concludes the paper.

2. Context Model for Data Mining

Data when processed assumes an informational value. If applied within a particular context it becomes knowledge which is of value to an enterprise. Otherwise it may only be viewed as the accumulation of additional information and data. Knowledge is critical to the success of organizations today. It is said to account for 5% of GDP in OECD economies.

As in the work by Day and Abowd the term context is used in the broadest possible sense; it encompasses any information that might be useful for defining the user's situation. There are potentially many
more types of contextual information available than what is used to define a given situation.

The context is grouped into three main categories:

i) **Social Context**: This describes the varied social units that structure work and information organizations and teams communities and their distinctive social processes and practices.

ii) **Semantic context**: describes the individual interpretation of a situation based upon there existing system of cognitive frameworks and constructs goals and tasks; it represents the personal meaning or sense ascribed to information related to certain task or situation. It is also called sensemaking. This definition can also be extended to group interpretation with some provisos.

iii) **Pragmatic context**: The process of translating the personal interpretation or meaning into a specific behaviour or action is moderated by interaction of an individual’s rational with their affective (emotional characteristics). This includes also the need for adaptation and interpretation of meaning in terms of dynamic and evolving environment surrounding business situations and the spatio-temporal context (location and time) as applicable.

This work postulates that there exists a goal or problem in any situation. It would be futile to identify a situation unless there is some task connected to it no matter how mundane. This is most obvious when dealing with users where a situation implies that there is a problem that needs to be solved. In the rest of the paper, we focus on design of the semantic and pragmatic context associated with context-aware data mining.

3 Theoretical Underpinnings of Semantic and Pragmatic Context for Data Mining

As indicated in the preceding section, **Semantic context** describes the individual interpretation of a situation based upon there existing (or learnt) cognitive models, goals and tasks related to the situation; it represents the personal meaning or sense ascribed to information related to certain task or situation. This description is theoretically underpinned in the area of sensemaking and naturalistic decision making [34, 35, 3] which as the name suggests is about constructing (or interpreting meaning or making sense of a given situation). The process of making sense involves interplay of action and interpretation rather than the influence of evaluation on choice. Figure 1 shows the interplay between sensemaking, data information, and knowledge.

Knowledge acts as an interpretant to turn data into information. In a given situation, we may encounter familiar as well unfamiliar or new information. The new information causes some level of dissonance prompting the question “What’s the story here?” In the process of resolving this dissonance, we create knowledge. Knowledge is created through a sensemaking process. However, sensemaking process takes place in a context. Data to one person is someone else’s information. An investment banker might stare at a computer screen of numbers which would look to most people as raw data. To the investment banker, however, slight changes in the numbers convey messages which act as information they might convert to knowledge (via sensemaking and take action). Thus, context is a key ingredient acting as an underlay to all three concepts of data information and knowledge.

For purpose of interpreting, constructing meaning and resolving the dissonance, people engage in organised sensemaking which involves use of cognitive constructs for labeling and categorizing to stabilize the streaming of experience. The process of labeling and categorisation involves connecting abstract and impersonal concepts with concrete and personal concepts which are amenable to functional deployment. For example, functional deployment may involve diagnostic labels in medicine that suggest a plausible action or treatment or some decision-related labels like credit card approval which suggest plausible approval disapproval of a credit card application.

![Figure 1: Interplay between Context, Data, Information, Knowledge and Sensemaking](image-url)
disorder and change. Situation comprehension using cognitive constructs can also be also be seen as a way of identifying and retrieve these schemas in a cost effective (in terms of time and efficient (in terms of resources required). These constructs also help to determine the leverage points where intelligent data mining technologies may be applied.

The discussion in the preceding paragraphs establish a semantic (e.g., sensemaking based on cognitive constructs) and pragmatic (adaptation for embedding intelligent data mining) need for identifying hidden patterns in an adaptive organized sensemaking framework.

From another perspective, the recent emergence of the area of emotional intelligence has clearly established the role of affect or emotions in human decision making [33, 34]. In context of sensemaking, it has helped in clarifying questions like whether intra-organizational institutions are better portrayed as cold cognitive scripts built around rules or as hot emotional attitudes built around values [7]. Since sensemaking involves interplay between interpretation and action, action is mediated by the affective characteristics of an individual and thus should be factored into meaningful or context-based interpretation of knowledge. That is the same set of numbers may be interpreted by one investment banker somewhat differently than another investment banker depending on their emotional attitudes. In other words, personal meaning is mediated through affective characteristics of users. In the context of data mining, some preliminary work involving the role of emotions in music mining and recommendation systems has been recently reported [8, 25, 26].

Thus based on context-aware feedback (situational and affective of user), we intend to integrate or combine sensemaking and intelligent data mining technologies (and software artifacts like objects and agents) to design adaptive context-aware data mining systems. In the next section, semantic and pragmatic contexts are modeled in the context-aware data mining architecture.

### 4. Context-aware Multilayer Multi-agent Data Mining Architecture

Jens Rasmussen has provided a very useful model that describes human information processing according to three levels of behaviour [37]. These are perception action level, procedural level, and construction level. Table 1 shows the correspondence between these three behaviour levels and corresponding situation awareness levels and inference mechanisms. Table 1 also shows the correspondence between the three behaviour levels and constructs layers agents of the Context-Aware Data Mining (CADM architecture) shown in Figure

<table>
<thead>
<tr>
<th>Behavioral level</th>
<th>Situation Awareness</th>
<th>Inference/Reasoning (cognitive function)</th>
<th>Corresponding CADM Constructs</th>
<th>Leveraging CADM Layer</th>
<th>Leveraging CADM Agents (some)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perception action level</td>
<td>Sensing</td>
<td>Reflex Reactive inference based on skills</td>
<td>Preprocessing</td>
<td>Reactive agent Layer</td>
<td>Data aggregation Data visualisation</td>
</tr>
<tr>
<td>Procedural level</td>
<td>Situation recognition as a pattern matching activity</td>
<td>Remembering a rule or procedure: If Situation then Algorithm of actions</td>
<td>Learnt patterns rules and associations</td>
<td>Intelligent Technology Agent Layer</td>
<td>Neural Network Clustering fuzzy neuro fusion agents</td>
</tr>
<tr>
<td>Constructive level</td>
<td>Situation construction</td>
<td>Formulating hypotheses and decision pathways that involve possible actions constraints and resources</td>
<td>Context Elitication Phase Context based Situation Interpretation Labeling Phase Situation action phase Situation Adaptation Phase</td>
<td>Sensemaking (cognitive Layer Adaptation Agent Layer Sensemaking (affective Layer</td>
<td>Situation Monitoring Situation Adaptation User Profiling Non verbal Affective agents</td>
</tr>
</tbody>
</table>

The various layers of the CADM architecture are outlined in the context of the three behaviour levels, namely perception, procedural, and constructive. At the perception action level, skills direct inference. There are hard-coded inference mechanisms that provide immediate responses to appropriate sensed information. They correspond to the need for urgency of action. In terms of the CADM architecture, this level is represented by the reactive layer. The reactive layer consists of agents which represent stimulus-response phenomenon in a user-defined environment. The agents in this layer may include data aggregation agents, data transformation agents, data visualization agents, which may not need learning.

At the procedural level, a set of rules or patterns direct inference. This set may be large but is always closed, i.e., it corresponds to pre-formed, pre-determined insights and...
learnt patterns of behaviour. In our CADM architecture this level is represented by the intelligent data mining technology layer. The intelligent technology layer contains data mining agents which involve learning to find patterns from data. This layer includes clustering (e.g., fuzzy neuro, GA and other agents) [9, 30].

At the constructive level, inference is a creative and constructive process based on an open world of actions, constraints, and resources. In the CADM architecture, this level is represented by three layers: namely, sensemaking (cognitive) layer, sensemaking (affective/emotion) layer, and situation-adaptation layer. Some of the agents related to these layers are shown in Figure 4. The situation-adaptation layer consists of situation monitoring agents which adapt the result of the action of the system on the user/environment in a given situation (e.g., acceptance/rejection of a recommendation prediction by the user/environment) and incorporate feedback to adapt the actions of the situation-action phase agents. An example in the next section will illustrate this aspect.

Overall, there are seven layers in the CADM architecture; five of which have been outlined above. The distribution and coordination layer in Figure 4 consists of agents who process data on behalf of agents in other layers in a parallel and distributed manner to meet the real-time and speed-up needs of the data mining process [1]. The coordination layer agents are used to coordinate communication between the user and the agents in the sensemaking (cognitive) and sensemaking (affective/emotion) layers of the architecture. The coordination layer agents are also used to coordinate communication between agents in the seven layers [1] and maintaining a blackboard type global system state representation.

Finally, the object layer is used to represent ontology of the domain objects which are manipulated by the sensemaking (cognitive) and sensemaking (affective/emotion) layers of the architecture. The object layer agents are also used to coordinate communication between agents in the seven layers [1] and maintaining a blackboard type global system state representation.

5. Application of Situation Adaptation Layer in Banking and Finance

Figure 3 shows a sample implementation of the situation adaptation layer agents for credit card approval. Credit card approval process is to assess the credit level of customers based on their past commitments to the financial institution, economic ability, and demographic information. Fifteen variables are used to assess whether or not to approve a customer for a credit card. The fifteen independent variables are used at the procedural level for training a neural network (BP) prediction agent as shown in Figure 3. The situation adaptation agent is responsible for adapting the weight parameters NN credit card approval prediction agent for prediction. These parameters may be changed by the situation adaptation agent to improve the performance of the NN prediction agent. Predictions produced from the prediction agent are, of course, based on the data from the database of historical data. The prediction results in terms of their acceptance/rejection can be assessed manually (by the manager) or by the situation monitoring agent shown in Figure 3 (once it has been trained on Manager's feedback over time). The neural network in the situation monitoring agent compares the system's prediction with the human user/manager approval to learn the approval behaviour of the human counterpart in a CRM situation. Initially, the feedback is provided by the manager for training the network, and its acceptance/rejection by the relationship manager. Overtime, with enough training learning based on the manager's feedback, the situation monitoring agent's performance will be comparable to the human agent and takes over most of the situation assessment jobs from the human counterpart.
6. Application of Sensemaking (AfEmotion) Layer in Behaviour Profiling and Situation-action Affect Profiles

The purpose of this section is to illustrate i) how meaningful interpretation of mined patterns is mediated by the emotional or affective data and ii) development of situation action affect profiles in the CADM architecture.

6.1. Mediating Patterns with Affect

Recruitment and retention of employees has assumed strategic importance in organizations today. Turnover of salespersons and customer service personnel is among the highest in the industry. The authors have designed e-Sales Recruitment and Benchmarking System (e-SRBS) for behaviour profiling of salespersons [6]. e-SRBS is an intelligent system for determining the selling behaviour category and profile a sales candidate invited for a sales job interview. e-SRBS has been used by recruiting companies and sales managers in Australia for behaviour profiling and benchmarking of salespersons [6]. Table 2 shows a sequence of mined selling behaviour patterns of sales candidates and their predicted fuzzy selling behaviour category. The mined selling behaviour patterns and the fuzzy selling behaviour categories modeled are from data collected from e SRBS.

e SRBS combines deep knowledge in the form of a selling behavioral model (shown in Figure 5) and shallow knowledge in the form of knowledge and experience of the sales managers. The two dimensional behavioural model in Figure 5 is used to construct twelve fuzzy selling behaviour categories.
Table 2: Mined Selling Behaviour Patterns of Sales Candidates

<table>
<thead>
<tr>
<th>Sn</th>
<th>DH</th>
<th>SH</th>
<th>SW</th>
<th>DW</th>
<th>Fuzzy Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4</td>
<td>83</td>
<td></td>
<td></td>
<td>SW(Med)</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>83</td>
<td></td>
<td></td>
<td>SW(Med)</td>
</tr>
<tr>
<td>3</td>
<td>47</td>
<td>5</td>
<td></td>
<td></td>
<td>SH(Med)</td>
</tr>
<tr>
<td>4</td>
<td>98</td>
<td></td>
<td>4</td>
<td>4</td>
<td>SH(High)</td>
</tr>
<tr>
<td>5</td>
<td>38</td>
<td>59</td>
<td>4</td>
<td>4</td>
<td>SH(Med)</td>
</tr>
</tbody>
</table>

The fuzzy selling behaviour categories qualitatively provide information on the intensity (or extent to which a candidate’s behaviour belongs to one of the four (DH, DW, SH, and SW) selling behaviour quadrants shown in Figure 5.

Dominant-Hostile

The salesperson must impose their will on the customer by superior determination and strength. Selling is a struggle the salesperson must win.

Dominant-Warm

Sales are made when customers become convinced that they can satisfy a need by buying. The salesperson’s job is to demonstrate to the customer that their product would best satisfy the customer’s need.

Hostile

Customers buy only when they are ready to buy. Since persuasion does not work the salesperson’s job is to take their order when the customer is ready to give it.

Warm

People buy from salespersons they like. Once a prospect becomes a friend it is only reasonable that he should also become a customer.

Submissive-Hostile

Customers buy only when they are ready to buy. Since persuasion does not work the salesperson’s job is to take their order when the customer is ready to give it.

Submissive-Warm

People buy from salespersons they like. Once a prospect becomes a friend it is only reasonable that he should also become a customer.

In rest of this section we outline how a sales candidate’s emotional state feedback has been modeled using an affect space model (shown in Figure and facial expression analysis techniques using Gabor Wavelets [7]). We follow that with correlation of emotional responses with mined behavioural patterns and development of situation action and affect profiles of the sales candidates.

Facial expressions are an important physiological indicator of human emotions [9, 10]. An affect space model used by psychologists [11] is shown in Figure. The model involves three dimensions namely Valance (measured on a scale of pleasure (+) to displeasure (-)), Arousal (measured on scale of excited aroused (+) to sleepy (-)) and Stance (measured on a scale of high confidence (+) to low confidence (-)). Figure shows the affect space model with several labeled emotional states. The model can be divided into quadrants each quadrant being considered to represent a positive or negative emotional states as shown in Figure.

Like in everyday life, in human-computer interaction people’s emotions are characterized more by subtle variations or transient changes in facial emotional expressions (during the interaction rather than as prototypical emotional expressions [12, 13, 14, 15] like happy, angry, etc.).

The attempt here is to make use of the candidate’s emotional state to determine the correlation or commitment the candidate has to the entered response. A sample set of four questions in the area of success and failure is shown in Figure 7. In our case a positive change in emotional state of the candidate that coincides with the answering of a question may indicate a candidate’s higher commitment to the answer given and conversely.
a negative emotional state change indicates a reduced commitment of the candidate to the answer given.

6.2. Situation-Action Affect Profiling

The situation action affect profiles in this illustration relates to Question Answer Affect (emotional response sequence of the sales candidate).

<table>
<thead>
<tr>
<th>Question</th>
<th>Behavioral Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>I hate to lose or fail. I just don’t seem to be able to digest failure.</td>
<td>Cat: DW</td>
</tr>
<tr>
<td>Success matters most in life.</td>
<td></td>
</tr>
<tr>
<td>You take failures in stride. People are important up to a point.</td>
<td>Cat: SH</td>
</tr>
<tr>
<td>Success and progress is the ultimate goal.</td>
<td></td>
</tr>
<tr>
<td>You do your job. Failures mostly happen due to product and pricing policies of the company.</td>
<td>Cat: SW</td>
</tr>
<tr>
<td>It is more important to be associated with people than thinking of success or failure.</td>
<td></td>
</tr>
</tbody>
</table>

Figure 7: Sample Questions in the area of Success and Failure

Figure 8 shows an excerpt from the video sequence of a volunteer candidate answering questions from eSRBS. Figure 8 also shows the difference images and visualizations of the neural network classification. The sequence shown is taken at a time between a new question being presented to the candidate and the candidate answering that question. Gabor wavelet and neural network classifier are used for processing and classifying the negative positive and neutral emotional state of the sales candidate [16, 17]. The question was “You take failures in stride. People are important up to a point. Success and progress is the ultimate goal.” And the candidate answered: “To a large extent yes.” This question relates to the area of success or failure and the Dominate-Warm behavior category [6]. Figure 8 (a) was classified as a mix of roughly equal proportions of neutral and positive as indicated by the blue and green respectively and absence of red i.e. negative emotion change in the bottom half of the classification output and the cyan of the top half. Figure 8 (b) was classified as primarily neutral indicated by the diminished green in (b) and the shift from cyan to a more blue colour in the top half of the classification image with respect to (a) Figure 8 (c) classification image indicates a dominance of red (i.e. a negative emotional state).

Figure 9 shows the situation action affect profile of the candidate’s answers to questions in the area of success and failure. The situation action affect profile can be used to provide information not only in terms of the emotional state of the candidate but also in terms of emotional state intensity, emotion state duration and rate of change of emotional state over the profiling period in a context aware manner.

7. Conclusion

This paper defines and integrates the role of cognitive schemas and affect in a context aware manner in a multi-layered context aware data mining architecture. The paper outlines constructs related to seven layers of the CADM architecture namely reactive layer, intelligent technology layer, sensemaking (cognitive) layer, sensemaking (affective) layer, situation-adaptation layer, distribution and coordination layer and object layer. The paper illustrates application of CADM architecture and development of situation action affect profiles in areas like Customer Relationship Management and recruitment. The architecture also has implications in the area of knowledge management and decision making in critical event situations and process control situations.

References

Figure 9: Situation-action Affect Profile - Correlation of Emotional State Profile and Selling Behavior Profile