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A knowledge management approach to data mining process for business intelligence

Hai Wang
Sobey School of Business, Saint Mary's University, Halifax, Canada, and
Shouhong Wang
Charlton College of Business, University of Massachusetts Dartmouth, Dartmouth, Massachusetts, USA

Abstract

Purpose – Data mining (DM) has been considered to be a tool of business intelligence (BI) for knowledge discovery. Recent discussions in this field state that DM does not contribute to business in a large-scale. The purpose of this paper is to discuss the importance of business insiders in the process of knowledge development to make DM more relevant to business.

Design/methodology/approach – This paper proposes a blog-based model of knowledge sharing system to support the DM process for effective BI.

Findings – Through an illustrative case study, the paper has demonstrated the usefulness of the model of knowledge sharing system for DM in the dynamic transformation of explicit and tacit knowledge for BI. DM can be an effective BI tool only when business insiders are involved and organizational knowledge sharing is implemented.

Practical implications – The structure of blog-based knowledge sharing systems for DM process can be practically applied to enterprises for BI.

Originality/value – The paper suggests that any significant DM process in the BI context must involve data miner centered DM cycle and business insider centered knowledge development cycle.

Keywords Data mining, Business intelligence, Knowledge management, Knowledge sharing, Blogs

Paper type Research paper

Introduction

Data mining (DM) is the process of trawling through data to find previously unknown relationships among the data that are interesting to the user of the data (Hand, 1998). DM has been an established field (Fayyad *et al.*, 1996; Chen and Liu, 2005; Wang, 2005). However, despite the maturity of DM, recent critiques state that DM does not contribute to business in a large-scale (Pechenizkiy *et al.*, 2005). For instance, research in this area continues to propose incremental refinements in association rules algorithms, but very few papers describe how the discovered association rules are used (Wu *et al.*, 2000). While DM has been perceived to be a potentially powerful tool, the real benefit of DM for business intelligence (BI) has not been fully recognized (Wang *et al.*, 2007).

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The information technology community has found that many organizations are continuing to view DM as a magic tool for easy and quick fix (Kaplan, 2007). For instance, an article in *InformationWeek* (Preston, 2006) criticized US Government agencies over-estimated the power of predictive DM in rooting out terrorists, and wasted much resources and time. In fact, DM techniques can be more hazardous than helpful if the frontline users do not fully understand how to apply those techniques in pertinent context (Hall, 2004; Violino, 2004; King, 2005). The key to successful applications of DM as a BI tool is collaboration and knowledge sharing among frontline users and technology experts in the organization (Foley, 2001; Reingruber and Knodson, 2008). This paper is to investigate the relationship between DM, BI, and knowledge management (KM). It proposes a knowledge sharing model for business knowledge workers to make DM more relevant to BI.

Links between DM, BI, and KM

Distinction between BI and KM

BI is a broad category of applications and technologies of gathering, accessing, and analyzing a large amount of data for the organization to make effective business decisions (Cook and Cook, 2000; Williams and Williams, 2006). Typical BI technologies include business rule modeling, data profiling, data warehousing and online analytical processing, and DM (Loshin, 2003). The central theme of BI is to fully utilize massive data to help organizations gain competitive advantages.

KM, on the other hand, is a set of practices of the creation, development, and application of knowledge to enhance performance of the organization (Wiig, 1999; Buckman, 2004; Feng and Chen, 2007; Lee and Change, 2007; Smoliar, 2007; Wu *et al.*, 2007; Paiva and Goncalo, 2008; Ramachandran *et al.*, 2008). Similar to BI, KM improves the use of information and knowledge available to the organization (Sun and Chen, 2008). However, KM is distinct from BI in many aspects. Generally, KM is concerned with human subjective knowledge, not data or objective information (Davenport and Seely, 2006). The majority of models used in the KM field, such as the tacit and explicit knowledge framework for a dynamic human process of justifying personal belief toward the truth (Nonaka, 1994; Nonaka and Takeuchi, 1995), are typically non-technology oriented. Although KM has not evolved out of a set of formal methodologies, KM competently deal with unstructured information and tacit knowledge which BI fails to address (Marwick, 2001).

DM is a bond between BI and KM

Owing to its strength, DM is known as a powerful BI tool for knowledge discovery (Chen and Liu, 2005). The process of DM is a KM process because it involves human knowledge (Brachman *et al.*, 1996). This view of DM naturally connects BI with KM. DM can be beneficial for KM in the following two major aspects:

(1) To share common understanding of the context of BI among data miners. For example, given a marketing survey database, the data miners share the scope of the database, the definitions of the data items, the meta-data of the database, and the a priori knowledge of DM techniques to be applied to the database.

(2) To use DM as a tool to extend human knowledge. For example, given a sales database, DM can reveal the consumers' purchase patterns previously unknown to the data miner.

Because of such overlaps between BI and KM, most managers do not fully understand the fundamental differences between BI and KM (Herschel and Jones, 2005).

Integration of BI and KM

There has been little doubt that BI and KM must be integrated in order to promote organizational learning and effective decision making, and the effectiveness of BI should be measured based on the knowledge improvement for the organization (Cook and Cook, 2000). Nevertheless, the visions of integration of BI and KM are diversified, and issues of whether KM should be viewed as a subset of BI or vice versa are still under debate in these two well established fields (Herschel and Jones, 2005). While both KM and BI are deeply influenced by the approaches of the research and practitioners' communities, the way of integration of KM and BI seems not unique.

There have been several models of integration of BI and KM reported in the literature. At the conceptual level, Malhotra (2004) has proposed general models of integration of KM and BI for routine structured information processing and non-routine unstructured sense making. White (2005) provides a flowchart model that articulates the use of BI in the KM context for decision making. The flowchart model illustrates the involvement of collaboration and interaction between the knowledge workers for socialization. These conceptual frameworks, however, need to be actualized for applications in great details. There have also been applications of integration of BI and KM reported in the literature (Cody *et al.*, 2002; Heinrichs and Lim, 2003). However, few reports on the implementation of knowledge sharing for DM process can be found in the literature.

DM cycle models

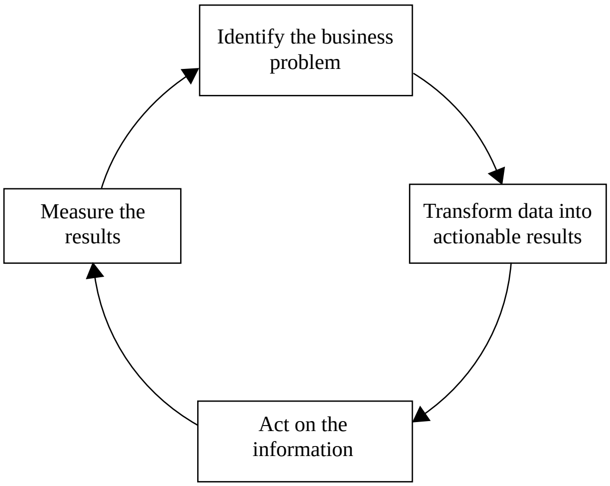
The traditional DM cycle model

DM is considered to be useful for business decision making, especially when the problem is well defined. Because of this, DM often gives people an illusion that one can acquire knowledge from computers through pushing buttons. The danger of this misperception lies in the over-emphasis on "knowledge discovery" in the DM field and de-emphasis on the role of user interaction with DM technologies in developing knowledge through learning.

Recently, efforts have been made to develop new research frameworks for DM (Pechenizkiy *et al.*, 2005). However, there still is a lack of attention on theories and models of DM for knowledge development in business. Conventional theories and models in this area ought to be re-examined and developed in such a way that a distinction is made between two important variables: DM centered information and business centered knowledge.

The virtuous cycle of DM is one of the widely circulated models in the DM field (Berry and Linoff, 2000). According to the virtuous cycle of DM (Figure 1), DM is a business process that goes through four phases: identify the business problem, transform data into actionable results, act on the information and measure the results.

The virtuous cycle of DM model shows the steps involved in a DM process, but tends to ignore the key element in DM: knowledge. The real problem with this model is not limited to its definition. Its primary limitation is in its limited real world application in two aspects. First, people often find that "knowledge" gained from DM does not always lead to an action in all situations, particularly when the piece of "knowledge" is



Source: Berry and Linoff (2000)

Figure 1.
The virtuous cycle of DM

hard to apply. In fact, this model overstates the role of DM in action, and in turn fails to recognize the roles of business insiders in developing their knowledge for coordination of actions for business. Second, this model mixes non-sequential processes into a single cycle, and de-emphasizes distinctive roles of different people involved in DM for BI.

A knowledge development cycles in DM

In the real management world, knowledge workers attend to do one type of work at their best performance and play roles of joint collaboration (Wang and Ariguzo, 2004). Practically, it is hard to find an expert of DM who is also an excellent business insider, and vice versa. In other words, knowledge workers involved in DM and its applications are usually divided into two groups: business insiders and data miners. A business insider is a CEO or middle level manager who possesses best knowledge in business problem solving and decision making. She or he must understand the concepts of DM, BI, and KM in the organization, although might not be familiar with detail DM techniques and procedures. A business insider's objective of taking part in conducting DM and the development of KM is to improve the business performance of her or his organization. A data miner, on the other hand, is an expert of DM, and best understands DM techniques in the organization. She or he must understand the nature of the business and be able to interpret DM results in the business context, but is not directly responsible for business actions. The collaboration of these two groups of people makes DM relevant to genuine BI.

The knowledge work done by business insiders can be generally described in the perspective of unstructured decision making (Simon, 1976). To be ready for action, a business insider searches appropriate information, evaluates alternative actions pertinent to this information, and choose the action that is best supported by the information. In the DM context, DM results can be a set of information for the business insider in making unstructured decisions. In using those DM results to evaluate alternatives, the business insider must recognize assumptions, biases, and uncertainty.

She or he keeps observing the outcomes of the execution of actions, and develop tacit knowledge through internalization.

In the DM community there have been "step-by-step data mining guides" (Lavrac *et al.*, 2004) that best describe how analytical work is done by data miners. Generally, the first step of a data miner in a DM project is to understand the problem owner's concerns. In the business field, the problem owner must be a business insider. The data miner then defines the problem using DM concepts in order to determine the goal of the DM project. The entire problem definition process may take the form of a "negotiation" between the data miner and the business insider. The defined problem should be solvable through the use of available DM techniques and tools. Next, the data miner must prepare data in a systematic way to make data adequate and clean. Once data are prepared, DM techniques and tools are applied to the data. Ideally, mining results that is interesting to the data miner would be obtained. To make the DM results actionable, the data miner must explain them to the business insider.

The interaction process between the business insiders and data miners is actually a knowledge-sharing process. In our view, the content of the entire interaction process (not just the DM results) is knowledge of the organization. It includes:

- linguistic standardization of DM terms and concepts;
- problem definitions;
- DM documents;
- DM resources; and
- actions and outcomes.

To articulate the complex interactions among knowledge workers in DM related activities, we explore the relationship between business insiders and data miners, the most important aspect of DM applications, using a two-cycle model. One is the DM development cycle and the other is the human knowledge development cycle, as shown in Figure 2. The intersection of these two cycles is known as the phase of knowledge sharing and planning.

In the data miner centered DM cycle, there are five phases: communicating and planning, developing hypotheses, data preparation, selecting DM tools, and evaluating DM results. Most of the descriptions of these phases can be found in the DM literature (Berry and Linoff, 2000). Here, we give emphasis to the phase of developing hypotheses. Generally speaking, DM is to reveal interesting patterns in the data to verify a hypothesis or hypotheses for the data miners. A hypothesis mirrors a priori knowledge (or seed knowledge) for DM. A DM algorithm is designed to verify a specific type of hypothesis. Typical categories of DM algorithms, their corresponding general types of hypotheses for DM, and examples of seed knowledge are summarized in Table I. Hypotheses pertinent to business actions are always depending upon the knowledge sharing among data miners and business insiders.

In the business insider centered knowledge development cycle, there are four phases:

(1) *Knowledge sharing and planning*. In this phase, the business insiders understand the previous DM results, and help the data miners to set new DM tasks and objectives. The new DM tasks and objectives will serve as the base for the data miners to develop specific hypotheses for the next DM process.

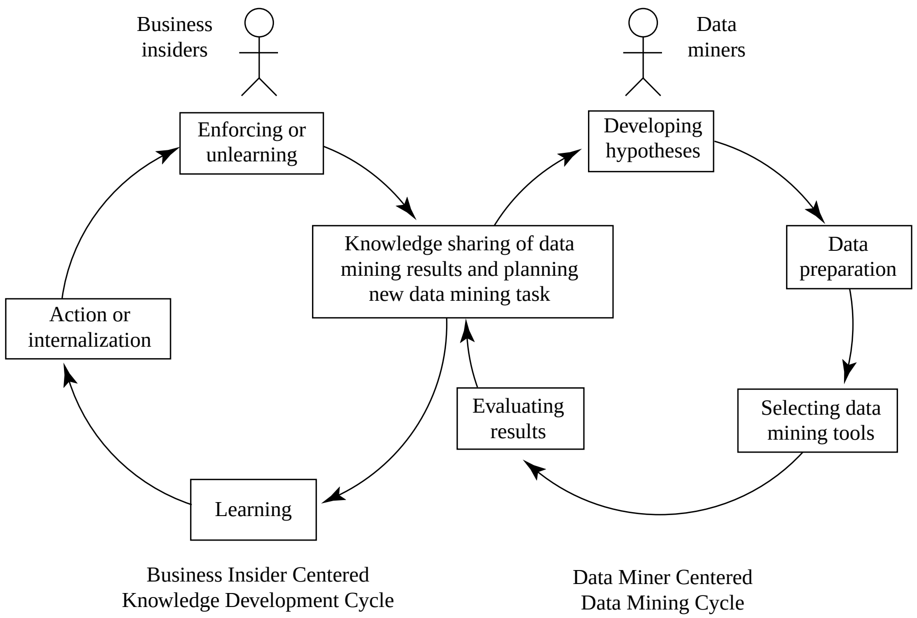


Figure 2.
Two cycles of knowledge development through DM

Table I.
DM algorithms and hypotheses

Categories of DM algorithms	Types of hypotheses for DM	Examples of seed knowledge
Classification	An observation with a certain set of attributes can be assigned to a class	A firm with certain attributes is likely to bankrupt
Cluster analysis	There are distinct segments in a given set of observations	Certain consumers form a market segment
Association rules	There are condition-outcome relationships among attribute/value pairs	If a consumer purchases A, then she/he is likely to purchase B
Regression	There is a certain function that can describe the relationship between the attributes of observations	The product sales are going down
Sequence analysis	There is a certain pattern of time-dependent events	An online shopper often search the correlated web sites
Deviation analysis	There is an abnormal observation in a set of observations	A competitor is taking an abnormal action

(2) *Learning*. Learning is vital for the business insiders' effective undertaking of the DM results. A learning process concludes how the DM results are useful for the business. The business insiders must understand the exact meaning of the pieces of information obtained from the DM process for a possible action.

(3) *Action or internalization*. The ultimate objective of DM is to support actions of the business insiders. An action could be an activity related to decision making, or it could be an operation sequence. Frequently, information provided by the DM process is not sufficient for making any substantial action. In such a case,

the business insiders might be able to develop his/her tacit knowledge through internalization based on the DM results.

(4) *Enforcing or unlearning*. If the DM process does result in an action, the business insiders must observe the outcomes of the action after applying the DM results. The observations re-enforce the learning and understanding of the DM results. Whether any action is actually taken, the business insiders would further develop new DM tasks, and work with the data miners to set the objectives for a new DM cycle. Unlearning processes might also be required. Unlearning makes inappropriate information obtained from the DM process obsolete.

Knowledge sharing system for DM collaboration process

This section proposes a model of knowledge sharing systems for DM collaboration process in the knowledge sharing and planning phase which is the intersection between the DM centered cycle and business insider centered knowledge development cycle. The focus of this case study is on the general structure of such knowledge sharing systems. The tool to implement the present model of knowledge sharing systems is well-known techniques of blogs for collaboration (Lu and Hsiao, 2007).

The structure of blogs of knowledge sharing systems for DM

Blogs has been a popular tool of Web 2.0 for social networks, e-collaboration (Smith, 2007), and learning (Liao *et al.*, 2007). However, one of the issues of the use of blogs is the relevancy and usefulness (Glass, 2007). To facilitate knowledge sharing through blogs, a general structure of subjects of blogs must be applied (MacDougall, 2005; Vargo, 2006). This study proposes the following subjects for the knowledge sharing model for DM.

Task. A DM process is a task to discover interesting patterns of the data for the data miners. A task is formally described as a hierarchical structure of its sub-tasks. For instance, the task of marketing DM is to identify new segments of consumers. It can have two sub-tasks:

(1) to verify the old consumer segments; and

(2) to reveal new consumer segments.

Data. Data are the key resource in DM. Definitions of the data attributes and the proportion of the enterprise data warehouse used for the DM process are specified in this category of blogs.

DM tool. An instrument that can be used for the data miners for data retrieval, testing hypotheses, and deriving conclusions is called a DM tool. A DM tool could a statistical procedures, a DM algorithm, an artificial intelligence model (e.g. neural networks), or a non-definitional model (e.g. reasoning logic and search engine). A complex DM tool can be a set of structured procedures formalized by defining the sequence of DM operations (e.g. when) and instructions (e.g. how). The formal descriptions of procedures represent explicit expertise of DM.

Hypothesis. Hypotheses are powerful appliances to conceptualize the seed knowledge representations for DM. The goal of a DM task is to verify hypotheses which have been kept in the data miner's mind. For instance, common conjectures of association rules, such as "if a consumer purchases product A, then she/he also purchases product B" is a hypothesis. Profound DM requires sophisticated hypotheses in order to accomplish a non-trivial task.

DM result. A DM result is the outcome of the DM process that tests a hypothesis on the given data. Accordingly, a DM result summarizes the data used for the DM process, the hypothesis, the tool used for the DM process, the conclusion of the DM process, and the significance level of the conclusion.

Action. An action is a business decision and execution of the decision in response to a DM result. An action has a sponsor who is in charge of the action, a team of participants, and duration.

Action outcome. An action must have its outcome. An action outcome is the assessment of the business decision and its execution in terms of tangible and intangible costs and benefits. Metrics and measures of costs and benefits are shared by the organization.

Internalization. A DM result might not trigger an action, but can be learned by business insiders to develop tacit knowledge about the interesting patterns of data. Internalization is the process of transformation from a DM result to tacit knowledge. Free-format discussions in blogs related to a specific DM task comprise an internalization process. Internalization may not be applied to a specific DM directly, but could be useful for knowledge sharing in the organization.

DM planning. DM planning is a collaboration process of the development of new DM task. Using this category of blogs, the business insiders and the data miners set a new DM task. The objectives of the new DM task will serve the base for the data miners to develop specific hypotheses for the next DM process.

Practically, when organizing the blogs for knowledge sharing for DM, each blog has a label with the name of the DM task. A tentative DM task might be decided by the administrator of the blogs so that DM planning blogs can be related to the forthcoming DM task. The structural relationships between the nine categories of subjects of blogs of knowledge sharing systems for DM are shown in Figure 3.

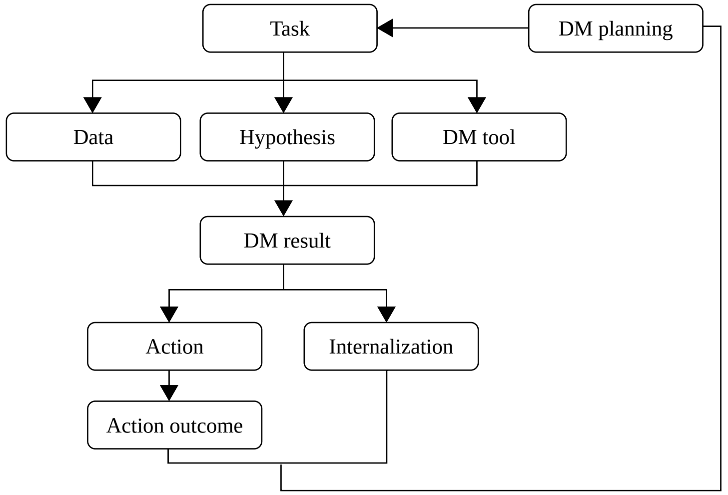


Figure 3.
Subjects and structure of blogs of knowledge sharing system for DM

An illustrative case study

The knowledge sharing model has been presented as an exemplar of the links between BI and KM to MBA students who were taking a BI course of one of the authors. The MBA students in the BI course used blogs (GoogleBlogger, 2008) to experience knowledge sharing for DM. The instructor acted as the data miner and interacted with the MBA students who acted as business insiders through the blogs.

This section illustrates the knowledge sharing model using a case study. This case is based on a well-known supermarket DM story that consumers who purchase beer are more likely to purchase diaper at the same time. This story sounds interesting because such a purchase pattern is unsuspected. Apparently, these consumers may not be the typical ones. This story was used in this case study as an example to demonstrate how DM through knowledge sharing could help the business to catch opportunities although such an unsuspected fact might be regional or short-lived.

The phases of the data miner centered DM cycle behind the DM case are fairly clear. The instructor posted blogs on the following subjects related to a mock DM process:

- The task of this DM process is to find an unusual customers' purchase pattern.
- The data used in this case are customers' purchase records of the last six months, including the merchandise items purchased by the customer each time.
- The hypothesis in this case is a type of association rule. Specifically, "customer who purchase product A is more likely to purchase product B, given that A and B are not known to be related to each other."
- The tool used for this DM case is a set of database SQL queries.
- The DM result shows that 36 percent customers who purchase beer also purchase diaper at the same time, and 95 percent of these customers use the superstore customer cards.

Since this story originally tended to impress the business community by showing how powerful DM could be and what "interesting knowledge" could be extracted from the data. Certainly, the story did not mention about the role of business insiders of the supermarket. Our assignment to the MBA students was to follow this scenario and examine a possible business insider centered knowledge development cycle, and post blogs to share knowledge. The MBA students learned the context of DM from the instructor's blogs, and generated several possible actions the business insiders might take:

- Placing beer and diaper together to make customers easier to access these two products together.
- Separating beer and diaper far away to encourage customers browse more merchandise items in the supermarket.
- Re-stocking beer and diaper at the same time.
- Printing coupons for beer and diaper and sending them together to consumers.
- Re-pricing beer and diaper by lowering one slightly and raising the other greatly in order to gain more profit.

The majority of these mock business insiders decided to increase the price of beer and decrease the price of diaper and expected to gain more profit. A made-up DM result was posted that, after two weeks trial, the sales of beer were going down and sales of diaper were going up, but the total profit on these two goods was insignificantly lower than the previous one.

These mock business insiders then generated several candidate new DM tasks after reviewing basic tasks listed in the textbook (Loshin, 2003). They found that the DM planning part was difficult but interesting to them.

A user interface example of posting blogs is shown in Figure 4. Note the title and the labels of this blog which implement the structure of blogs and can be used for search. The blogs-based system contains general knowledge of DM, including DM objectives, data, DM tools, and a variety of hypotheses. The business insiders are allowed to interact with the blogs system to initiate actions, share action outcomes, and develop tacit knowledge about DM. Our experience was that the structured blogs system was very useful for knowledge sharing to make DM meaningful for BI.

Conclusion

The mainstream DM research has been emphasizing techniques and algorithms. Little research into how DM can be more relevant to business has been done. To become a genuine BI tool for comprehensive knowledge discovery, DM must be integrated with KM for knowledge improvement in the organization.

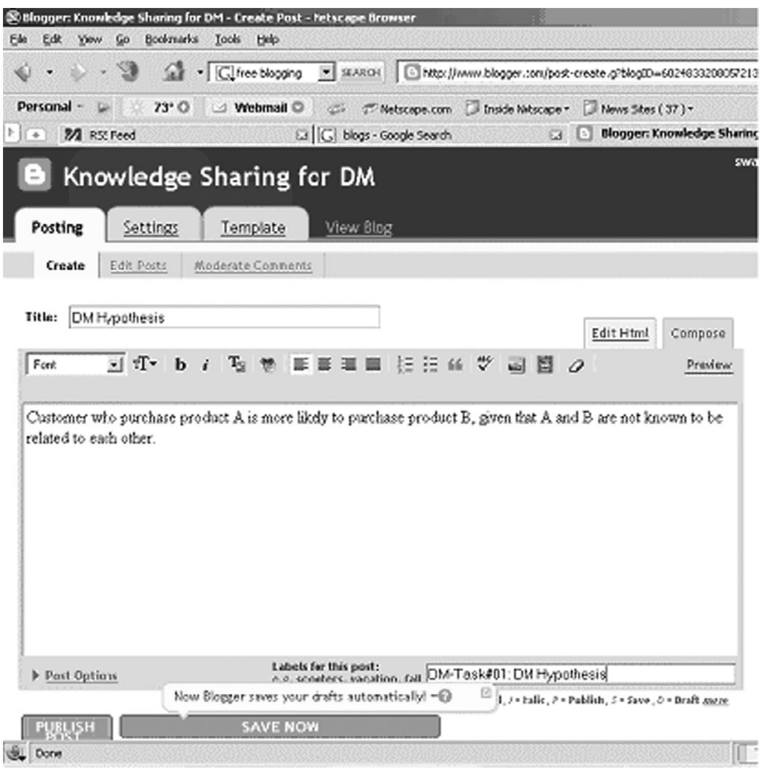


Figure 4.
Example of blogs for knowledge sharing for DM

The paper has proposed a model of knowledge development through DM. This model adds a crucial business insider centered knowledge development cycle to the conventional virtuous cycle of DM. The involvement of collaboration between knowledge workers can make DM more relevant to BI. The paper has further proposed a model of knowledge sharing system that facilitates collaboration between business insiders and data miners. Through an illustrative case study, the paper has demonstrated the usefulness of the model of knowledge sharing system for DM in the dynamic transformation of explicit knowledge and tacit knowledge for KM.

We believe that one of the most important aspects of effective DM for BI is the knowledge sharing and planning phase that connects business insiders and data miners in the organization. A greater understanding of context of DM and DM results will help business insiders to search actions. Similarly, a greater understanding of business context and outcomes of actions will help data miners to develop meaningful DM process for the business.

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Corresponding author
Shouhong Wang can be contacted at: swang@umassd.edu