Knowledge Service Platform with Live Knowledge Based System

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Abstract

Knowledge is essential for human life. Using it, we can make better decisions and thus perform correct actions. Therefore, it is important to manage it in appropriate manners. This paper presents a platform for knowledge service, which provides actionable live heuristic knowledge to the users. The platform consists of three layers - data, information and knowledge. In order to provide live knowledge service, all these layers require experiential knowledge, but they have not been well understood or well managed in conventional knowledge service approaches. Experiential knowledge is used to select better data analytic approaches, better transform data to information and to provide decision services to users. The heuristic knowledge used in the three layers is related to each other and should be managed seamlessly and maintained incrementally by experts in domains.

Keywords: Propositional knowledge, experiential knowledge, knowledge services, knowledge service technology, heuristic knowledge

1. Introduction

Entering the 21st century, our society is rapidly changing from the information society to the knowledge society. The information society only creates and disseminates the raw data [1]. In order to improve human condition, the knowledge society generates, processes, shares and makes knowledge available to all members [2]. Knowledge allows people to make effective decisions and actions. Many sociologists and economists have already predicted that it is inevitable that our society will change into the knowledge society and have suggested its characteristics in the 1970s [3, 4, 5, 6, 7].

In the knowledge society, ‘knowledge work’ is a central concept. Adelstein and Clegg [8] summaries its meaning as follows:

First, knowledge work is defined as a shift from manual to mental work involving problem identification and resolution through manipulating intangible ideas, symbols and images. Second, knowledge work is an organizational activity, whereby knowledge workers are organized and managed functionally to produce knowledge and disseminate it. Third, knowledge as work is achieved through formal accredited means that gives legitimacy to the work and those who perform it. Fourth,

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Received: Oct. 02, 2014, Revised: Nov. 02, 2014, Accepted: Jan. 06, 2015

knowledge work needs to be recorded and stored so that others, who may not be present at the time of articulation, can also access it.

Since the 1980s, Information and Communication Technology (ICT) has been rapidly developed and provided with critical opportunities that realize the conversion into the information society. The information society was triggered by the widespread use of Internet services since the 1980s and highlighted the necessity and importance of the transition to the knowledge society [9]. In this paper, the term knowledge service is used to represent ICT enabled service that supports knowledge work in an organisation.

Many people regard the knowledge society as the developmental concept of the information society, and try to provide knowledge service through ICT techniques used in the information society. However, this is not always the case. For example, the World Wide Web (WWW), which was designed to share information, successfully led the information society. The problem is that it is not appropriate for providing knowledge service. Therefore, it is necessary to review current ICT approaches in order to make the transition smooth.

This paper consists of the following content: Section 2 examines the concept of data, information and knowledge. Section 3 analyses the concept of different types of knowledge. Section 4 suggests the concept of live knowledge service based on the experiential learning cycle. Section 5 examines previous knowledge service technology from the concept of live knowledge service. Section 6 proposes a big data analysis platform, which is supported by live knowledge service. Section 7 concludes this paper by summarizing its contents.

2. Data, Information and Knowledge

Before one can begin to talk about knowledge service, one must start by clearly understanding the meaning of the words “data”, “information”, and “knowledge” [10, 11]. Data is the facts or figures in the forms of text, images, sounds and numbers collected through observation, experiments, measurement, investigation and automated data collection system (e.g., crawler).Data is not organised in any way and does not provide further information regarding pattern, context, etc. Information is contextualised, categorised, calculated and condensed data with relevance and purpose [12]. Essentially it is found “in answer to questions that begin with such words as who, what, where, when and how many” [13]. Information technology usually contributes to turning data into information. The human is mainly needed to assist in contextualization. Knowledge is information ‘combined with experience, context, interpretation and reflection’ [12]. Knowledge is objectively verified by scientific analysis and evaluation and systematically classified and formalised to be shared and disseminated among people. Therefore, the knowledge society is not fragmented information or data, but has an infrastructure for creating, sharing and using heuristic knowledge naturally [14].

Based on the concept hierarchy of data, information and knowledge, can we say that the knowledge society is really the advanced state of human society? Technologies may have different forms according to their application domains, but they have some common features. One of them is the fact that they try to maximise benefits by preventing unnecessary losses through rapid responses to the problem [15]. For example, a fire and ambulance service aims to reduce time between service request and response. This reduction allows us to accomplish our goal to minimise unnecessary losses. ICT is also related to this concept.

Then what makes ICT technology different from other technologies? What characteristics of ICT technology transform our society into the knowledge society? A compelling reason is that ICT technology is the first technology that converts intangible assets, such as information and knowledge, into tangible assets, and uses them to improve human productivity. The intangible assets used in computer can be divided into data, information and knowledge. The more these intangible assets are processed, the bigger the size of their value is created (Figure 1). In general, knowledge has greater value creation capacity compared to data and information. If there is no action, there is no value. The final action is decision making, which requires knowledge. For example, if the collected data is provided with anomaly detection knowledge (e.g. outlier or not), the user can rapidly discern anomaly status; otherwise the data has no meaning to the user. This does not mean that the data itself has low value; rather it means that the data value depends on knowledge utilisation.

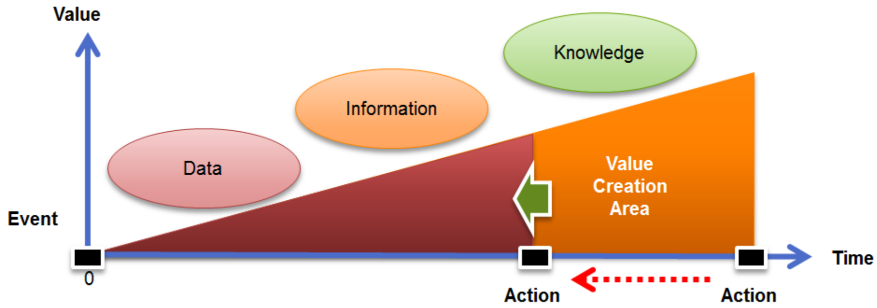

Figure 1. Value Creation Capacity

3. Theory of Knowledge

Within a theory of knowledge, there are three domains – propositional knowledge, practical knowledge and experiential knowledge. These three types of knowledge can stand on individually but complement each other [16].

Propositional knowledge is that which is constrained in theories or models. *'A person may build up a considerable volume of facts, theories and ideas about a subject, person or thing, without necessarily having direct experience of that subject, person or thing'* [17]. For example, a car mechanic can learn considerable propositional knowledge without seeing ta car engine. Propositional knowledge is synonymous with Ryle's concept of 'knowing that' [18] and Russell's 'descriptive knowledge' [19, 20, 21].

Practical knowledge is knowledge developed through the acquisition of skills. Making a bookcase or driving a car demonstrates practical knowledge. Practical knowledge is synonymous with Ryle's concept of 'knowing how' [18]. Practical knowledge does not necessarily require mastery of propositional knowledge. That is, a person may develop practical knowledge without necessarily developing the appropriate propositional knowledge. Practical knowledge can be combined with a sound knowledge base constructed by propositional knowledge, but it does not have to be the case [17].

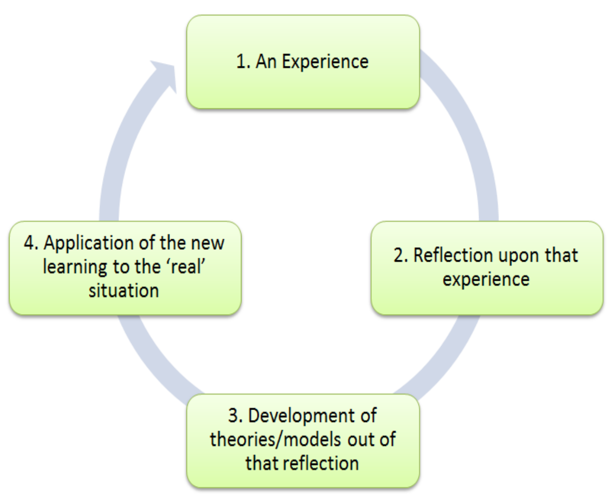

Figure 2. The Experiential Learning Model by Kolb [25]

Experiential knowledge is subjective and affective knowledge acquired through direct personal experience or relationship with a subject, person or a thing [22, 23]. This type of knowledge is synonymous with Polanyi's concept of 'personal knowledge' [24] and Russell's knowledge by acquaintance [19, 20, 21]. Sometimes experiential knowledge is regarded as 'professional knowledge' since it lies at the crux of individuals making wise professional judgments of action that is appropriate for the purpose of an occasion [23]. Experiential knowledge is drawn from multiple contextual cues and integrated by the expert into a problem solving process, which related to specific problem case. Experiential knowledge is necessarily personal and idiosyncratic [17]. Experiential knowledge is thus refined through the personal experience of synthesising facts, theories and intuition to problem in workplace [23].

Experiential knowledge is built up as people grow up and modifies it as people's experience of life develops and changes [23]. Experiential knowledge learning is defined as any learning activity which facilitates the development of experiential knowledge. Kolb [25] suggested the experiential learning model, where the expert continually learns experiential knowledge by reflecting upon new experience, by developing new theories/models out of that reflection and then by applying new experiential knowledge into a real situation (see Figure 2).

4. Descriptive Knowledge Based Systems

Knowledge management system (KMS) is an iconic system of descriptive knowledge based systems. KMS has been developed in many organisations since effective management of knowledge is regarded as a source of competitive advantage. There are also literatures that explain failures of KMS development projects [26, 27, 28, 29]. Using Knowledge Spiral Model, Nonaka explains how two different types of knowledge (explicit knowledge and implicit knowledge) interact together to share and create new knowledge [30]. Following Nonaka's suggestion, most KMSs have been developed, assuming that experiential knowledge can be indirectly acquired and maintained by managing descriptive knowledge. In this case, KMS only provides the space for sharing and storing propositional knowledge transformed from experiential knowledge. It is the users who create, store, retrieve and learn knowledge using KMS. This service assumes that descriptive knowledge transformed from experiential knowledge can be easily passed from knowledge providers to knowledge users. Most KMSs provide knowledge maps and search functions in order to help transferring knowledge. However, these functions do not work perfectly. In order to overcome the limitation of these kinds of services, recent KMSs are introducing online communities that can share experiential knowledge between members in an organisation. However, this approach aims to share knowledge without appropriate transformation of experiential knowledge into descriptive knowledge and thus causes problems related to long term knowledge storing, knowledge evolution and knowledge reuse. For example, the craftsmen's experiential knowledge for making the Korean celadon was not transformed into propositional knowledge, and thus could not be handed down their apprentices, and as a result have lost their techniques.

5. Live Knowledge Based Systems

A Live Knowledge Based System (LKBS) has the following characteristics: (1) Acquires experiential knowledge from human experts or data; (2) Has maintenance mechanism for experiential knowledge changes; and (3) Uses experiential knowledge for services. There are two conventional LKBS approaches – expert systems and machine learning. These two approaches will be examined in the following discussion.

A. Knowledge Acquistion

The two approaches used in experiential knowledge acquisition are significantly different. In expert systems, a knowledge engineer directly learns knowledge from human experts and embeds it into a knowledge base. Machine learning automatically learns knowledge through massive data analysis, which is based on mathematical models or statistical techniques [31]. While expert systems assume that knowledge engineers can understand knowledge thoroughly and implement a knowledge base within short time, machine learning assumes that there are large volume of data available for automated data analytics and can use knowledge learned by data analysis for knowledge base. Expert systems have been actively researched from1970s to

1990s. Various knowledge acquisition methods have been developed, but they heavily depend on the knowledge engineer and it is difficult to learn experiential knowledge within a short period of time. Knowledge acquisition methods (learning algorithms) for machine learning have significantly improved in the last few decades. However, it is very difficult to collect clean and appropriate data for learning experiential knowledge. In addition, it is not easy for machine learning methods to manage exceptional knowledge frequently found in the heuristic knowledge since these methods have been developed by using mathematical and statistical/probabilistic theory.

B. Knowledge Maintenance

As discussed in Section III and represented in Figure 2, maintaining a knowledge base is essential in LKBS since new cases (experiences) continually appear over time. When an expert system meets a new experience (case), human experts or knowledge engineers add new knowledge to the existing knowledge base. This rapidly increases maintenance cost as the volume of the knowledge base increases rapidly [32]. This phenomenon is called the 'knowledge acquisition bottleneck problem' [33]. This problem has been continually pointed out and substantial research has been conducted to solve it. However, the previous research was conducted without understanding the fact that experiential knowledge is provided not by the developers, but by the experts, and without considering cognitive psychological backgrounds of experiential knowledge[34]. Therefore, even though expert systems can provide live knowledge services using experiential knowledge and have lots of potential for implementing live knowledge services, they do not have practical roles in reality. In the machine learning area, the major focus is on the construction of initial experiential knowledge from data and thus less research was conducted on the maintenance issues. Therefore, in spite of researches on incremental learning algorithms [35, 36, 37], machine learning approaches are still difficult in responding rapidly to the changes of new experiences/cases[38, 39].

C. Knowledge Service

The ultimate goal of LKBS is to provide knowledge service using experiential knowledge. One of the critical issues is the location of experiential knowledge. First, experiential knowledge is embedded into all ICT software in some degree. Let us assume that a banking system processes transactions (e.g., savings, transfer, withdraw, etc.) requested via ATM, web or mobile internet. During the process, the system transforms the input data (e.g., amount of money, transaction type and receiver) into information and processes the requested operation. In this system, experiential knowledge of bank staff is transformed into a software program. The task processed by the bank staff using their experiential knowledge is now processed by this software program. The main disadvantage of this approach is that it is very difficult to maintain experiential knowledge. Secondly, knowledge bases constructed by expert systems or machine learning can be embedded into the program after acquiring experiential knowledge. This approach enables faster and efficient processing, but again it is very difficult to maintain the knowledge base over time. Finally, knowledge bases constructed by expert systems or machine learning approaches can be separated from the business logic and maintained separately. This approach allows the experts to maintain knowledge bases effectively.

D. Implementation Recommendations

LKBSs should acquire, maintain and serve experiential knowledge reflecting human experts' behaviours. In this view point, we suggest the basic implementation guidelines for LKBS as follows:

- In order to avoid knowledge errors caused by knowledge engineers, the system should learn experiential knowledge directly from the human experts.
- It is ideal that the system learns experiential knowledge when the experts use their knowledge in order to solve the current problem.
- The system should automatically perform verification and validation after adding or modifying knowledge.

- The system should incrementally learn the dynamically changing knowledge at real time.
- The system should learn using the problem cases since the human experts learn their knowledge using these cases.
- In order to take advantage of the machine learning approaches, it is necessary to use the hybrid method, which integrates manual knowledge acquisition approaches with machine learning approaches at the beginning of development.
- Since the data preparation is difficult to conduct without understanding about heuristic knowledge, it is necessary to have the means that verify the validity of the collected data.
- If there is available training data, it is recommended to learn experiential knowledge from both machine learning algorithms and the experts.

It would be impossible to develop an experiential knowledge service system that satisfies all guidelines discussed above. However, it is necessary to develop the system by analyzing individual domain requirements and by reflecting the guidelines discussed above.

E. Maintenable LKBS

As discussed above, two iconic LKBS – expert systems and machine learning systems –have limitations in their maintenance mechanism. There are two significant LKBS approaches that successfully support the maintenance mechanism. These approaches discussed below do not imply that they are superior to conventional expert systems or machine learning systems; rather they support maintenance mechanism. In the late 1980s, several significant methodologies were proposed to overcome the limitations of machine learning systems and expert systems based on new cognitive view point for experiential knowledge. Some researchers focused on the fact that experiential knowledge is the result of problem solving experience. Case Based Reasoning (CBR) was developed based on this view point [40]. If a problem is given, a CBR system suggests a solution by finding the most similar cases. The most important aspect of CBR is the fact that it stores the problem cases used for problem solving. CBR has been applied to many application areas, but has difficulty in finding similar cases [41, 42]. In order to find similar cases, it is necessary to find a way for indexing the cases and managing them continually. CBR usually uses the methods adopted from machine learning, but needs to find the way to solve this problem [43, 44, 45, 46]. Ripple-Down Rules (RDR) was initiated from the recognition of the conventional expert system development problems during the maintenance of a medical expert system, called Garvan-ES1 [39, 47]. RDR is based on the situated cognition, which proposed by Bill Clancy [48]. The situated cognition claims that knowledge is always changing and continually varying according to the problem context. Therefore, RDR excludes knowledge engineers from the knowledge acquisition process and allows domain experts to acquire knowledge by using the problem cases. During the knowledge acquisition process, the experts explain the reason for acquiring new knowledge to the system on a case-by-case basis, and the system updates the knowledge base based on the explanation. In particular, the RDR system does not cease the knowledge acquisition process at the early stage of the expert system development, but allows continual knowledge acquisition. In order to apply this approach, verification and validation process, costs for knowledge learning, should be simplified regardless the size and the complexity of knowledge base. RDR was applied to develop a pathology expert interpreting system at St. Vincent Hospital in Sydney, Australia. This system is used by about 30 % of pathology laboratories and accumulated over 16,000 rules [49, 50, 51]. It is rare that a knowledge system has been operated for such a long time with successful knowledge maintenance. RDR has also been applied to many other application areas, showing successful knowledge construction and maintenance [52]. However, RDR has limitations since it is mainly applied to classification and diagnosis problems. Therefore, it is necessary to investigate the limits of RDR and to conduct research for new methodology and new application domains.

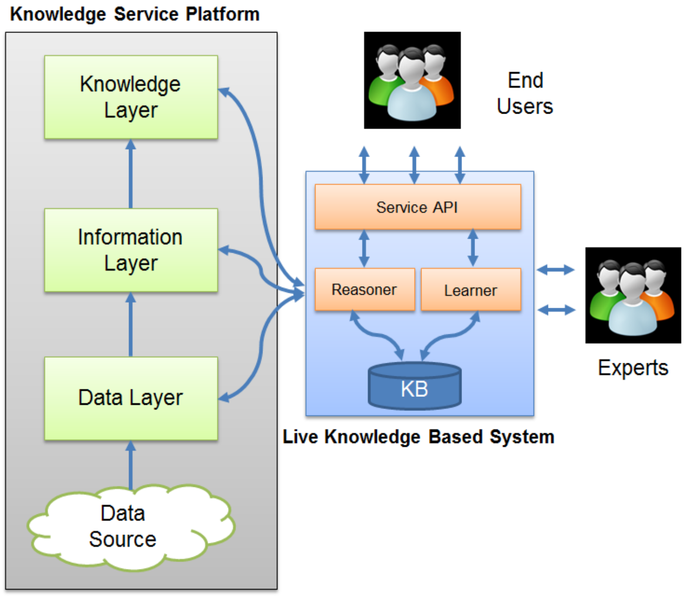

Figure 3. The Concept of Knowledge Service Platform [53]

6. Knowledge Service Platform

Figure 3 illustrates the concept of a knowledge service platform augmented by LKBS. The core of LKBS, depicted in the right side, has three major components – Reasoner, Learner, Knowledge Base (KB) and Service API. Learner initially acquires experiential knowledge from experts using knowledge engineering and/or machine learning techniques and incrementally adds new knowledge when LKBS meets new cases. Experiential knowledge is stored in knowledge base. Reasoner obtains a solution for the problem using experiential knowledge. LKBS provides its service via Service API. The left of Figure 3 represents various sub-systems required for a knowledge service platform. Each layer is correspondent with the concept hierarchy of data, information and knowledge discussed in Section II. Three layers (data layer, information layer and knowledge layer) depicted in any knowledge service consists of these three layers. The data layer consists of sub-systems for data processing such as data pre-processing, data integration, etc. The information layer consists of sub-systems for extracting information from data such as data analysis tools (e.g., R) and data mining/machine learning tools. The knowledge layer consists of sub-systems for acquiring domain knowledge. LKBS is essential sub-system in knowledge layer.

Note that LKBS is used to manage experiential knowledge of all three layers. In particular, this approach is important in the following cases: First, LKBS can be used to manage experiential knowledge of the experts in data and information layers. For example, a data analyst has experiential knowledge on data analysis tools or machine learning tools. In this case, LKBS can be used to manage his experiential knowledge. In general, these tools are useless without experiential knowledge, but most data analytic tools do not provide mechanisms for managing experiential knowledge and for providing assistant services for novice users. These systems can improve the credibility of analysis in data analysis. Why are these aspects not considered in data analytic tools? It may simply be caused by technical difficulties, but it is more reasonable to think that they are not included in the tools because people do not have the experience for metadata management. That is, this problem is not caused by the absence of experiential knowledge management techniques, but it is caused by the fact that the big data analysis systems have been implemented by conversant techniques. However, experiential knowledge is not used in this stage only; rather it is used at all the stages including data collection and analysis and data transformation.

Second, LKBS can be used to manage meta-data or meta-information. It is inevitable to have metadata while storing, processing and analysing data and information. Metadata is important during data analysis and furthermore knowledge service. For example, prepositional knowledge is generally managed by a directory or knowledge map. In this case, the directory and knowledge map are meta-information and knowledge should be used to classify information into them. Data names and collection intervals are also representative examples of metadata. In data analysis, relationships between these metadata are totally managed by the experts using their experiential knowledge. Therefore LKBS can support meta-data and meta-information management in data and information layer.

7. Conclusions

Generally knowledge used for knowledge service is experiential knowledge. This means that knowledge service is ultimately diagnosis, recommendation and instruction provided by systems based on experiential knowledge. If experiential knowledge is embedded into knowledge service systems, it is used by the system and used for the system. This means that if experiential knowledge is embedded into a system, knowledge services can be provided to the users directly by the system. However, current knowledge services do not provide such services, whereas experiential knowledge is of the people and by the people. This means that experiential knowledge is stored in computers by the people and is shared through computers. Until now most knowledge service systems provided propositional knowledge service, because experience knowledge service technology was not developed. For this reason, people who have no experience in ICT concludes that there is no experiential knowledge service in current knowledge service. The most serious problem caused by the absence of this is that people conclude that this problem cannot be solved by technology in recent times; rather they believe that they can solve this problem only by non-technical approaches such as leadership, education, culture, etc.

As we already have experienced in knowledge management systems, if propositional knowledge becomes the status quo, it will be a major stream in knowledge service and corporate systems and society will stick to it. In other words, once propositional knowledge becomes the status quo, it will not change even though experiential knowledge service technology is significantly improved and its development cost is significantly decreased in the future. This is caused by the fact that ICT developers usually construct knowledge services using techniques with which they are familiar. However, misunderstanding the goal of knowledge service and the role of experiential knowledge is a more critical cause. This attitude transmits to professionals that have no experience in ICT and derives them to plan and design propositional knowledge service as a major knowledge service. We are not claiming that propositional knowledge service is useless. Instead, we wish to address that these two types of knowledge services should complement each other in order to provide a more complete service. For example, let assume that a computer system can diagnose its users using well-being related knowledge, provide consultation services with practical instructions, and provide propositional knowledge service related to the provided consulting (e.g., related documents). The knowledge service has value if the users can understand their health status and improve their health by using the consultation and propositional knowledge. In addition, when new research results are released and new findings contradict the existing knowledge, if the knowledge service system can learn new knowledge incrementally, experiential knowledge and propositional knowledge can be maintained harmoniously each other.

In this paper, we discussed how experiential knowledge service can be activated and can be used for knowledge service. It is important to develop techniques for learning and managing experiential knowledge because inequality between experiential knowledge services and propositional knowledge services can seriously impact on all areas of society. At the turning point of the information society to the knowledge society, correct understanding of experience knowledge services and developing related techniques will have a great impact on the competitiveness of our society.

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