Data is More Than Knowledge

Implications of the Reversed Knowledge Hierarchy for Knowledge Management and Organizational Memory

Ilkka Tuomi

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Abstract

In knowledge management literature it is often pointed out that it is important to distinguish between data, information and knowledge. The generally accepted view sees data as simple facts that become information as data is combined into meaningful structures, which subsequently become knowledge as meaningful information is put into a context and when it can be used to make predictions. This view sees data as a prerequisite for information, and information as a prerequisite for knowledge. In this paper, I will explore the conceptual hierarchy of data, information and knowledge, showing that data emerges only after we have information, and that information emerges only after we already have knowledge. The reversed hierarchy of knowledge is shown to lead to a different approach in developing information systems that support knowledge management and organizational memory. It is also argued that this difference may have major implications for organizational flexibility and renewal.

Introduction

In knowledge management literature it has often been pointed out that the relation between knowledge, information and data is important, and often misunderstood. It has also been argued that this misunderstanding leads to problems in information system design. For example, Davenport and Prusak state that:

> "Knowledge is neither data nor information, though it is related to both, and the differences between these terms are often a matter of degree…Confusion about what data, information, and knowledge are—how they differ, what those words *mean*—has resulted in enormous expenditures on technology initiatives that rarely deliver what the firms spending the money needed or thought they were getting." [4]:1

Sometimes it is argued that the problems originate from our insufficient realization that there, indeed, exist considerable differences between data, information, and knowledge. For example, Sveiby maintains that:

> "Some of the present confusion concerning how to do business in the knowledge era would probably be eliminated if we had a better understanding of the ways in which information and knowledge are both similar and different. The widespread but largely unconscious assumption that information is equal to knowledge and that the relationship between a computer and information is equivalent to the relationship between a human brain and human knowledge can lead to dangerous and costly mistakes." [23]:24

In this paper, I will present a model that explicates the relationship between data, information, and knowledge. I will also show that the conventional view on this relationship requires rethinking, and that the traditional hierarchy of data, information, and knowledge needs to be reconsidered if we want to develop information system support for knowledge management and organizational memory. This reconsideration will also have important implications for the organizational information processing view that sees organization design as a problem of optimizing its information processing capacity.

The intuitive idea that knowledge is something more than information has lead many authors to make distinctions between raw data, information and knowledge. At first, these concepts look almost obvious to common sense, and yet—and maybe because of it—they have been a constant source of confusion. For example, according to some authors, data are understood to be symbols which have not yet been interpreted, information is data with meaning, and knowledge is what enables people to assign meaning and thereby generate information [21]:13. Or, data are simple observations of states of the world, information is data endowed with relevance and purpose, and knowledge is valuable information [3]:9. Or, information is meaningless, but becomes meaningful knowledge when it is interpreted [23]:42. Or, information consists of facts and data that are organized to describe a particular situation or condition whereas knowledge consists of truths and beliefs, perspectives and concepts, judgments and expectations, methodologies and know-how [30]:73. Or, information is a flow of meaningful messages to start with, but becomes knowledge when commitment and belief is created as a result of these messages [14]:58.

Underlying all these models of knowledge as a “higher form of information” is the idea that knowledge has to be extracted from its raw materials, and in the process, meaning has to be added to them. Organizational information processing literature and much of the organizational decision-making literature adopts basically the same view. The existence of “thorny epistemological issues” [13]:292 is recognized but not discussed, and references to relevant literature outside the cognitivistic tradition are rarely explicitly made.

If we assume that the object of our knowledge is an external reality that can be studied empirically to learn its structure and states, it is intuitively clear that first we need to observe some simple facts before we can create knowledge. It is however commonly known that raw data do not exist, and that even the most elementary perception is already influenced by potential uses, expectations, context, and theoretical constructs [e.g., 1; 8; 10; 11; 18]. This empirical model has during the last century been heavily criticized by several prominent philosophers of knowledge, for example, by Bergson, James, Husserl, Heidegger, Mead, Merleau-Ponty, and Polanyi [c.f. 27]. Although their criticisms have approached the problem of objectivistic and empiristic knowledge from somewhat different directions, they share the fundamental insight that the world as an object of human knowing exists only as an interpreted world that is completely infused with meaning. A human cognition cannot see simple facts without these facts being part of its current meaning structure.

Moreover, much of this meaning structure is unarticulated background against which articulation and explication happens. Therefore, organizational memory and knowledge management systems need also to address this unarticulated component of meaning.

This paper is conceptual and it gives practical implications for information system development. The paper is structured as follows:

First, I will discuss the conventional view on the hierarchical relationship between data, information, and knowledge. After showing that this conceptualization has important problems, I will show how an alternative view addresses these problems. I will then discuss the problem of interpersonal stocks of tacit knowledge, showing that the conventional view of seeing data as a raw material for information and knowledge is misleading in many practical situations. Finally, I will show that this creates major challenges for organizational memory and knowledge management system design, and argue that we need to use the model presented in the paper to design effective knowledge management and organizational memory systems.

The hierarchy of knowledge

Data has commonly been seen as simple facts that can be structured to become information. Information, in turn, becomes knowledge when it is interpreted, put into context, or when meaning is added to it. There are several variations of this widely adopted theme. The common idea is that data is something less than information, and information is less than knowledge. Moreover, it is assumed that we first need to have data before information can be created, and only when we have information, knowledge can emerge.

A representation of this view is shown in Figure 1. This figure adds intelligence and wisdom as two further types of knowledge.[1]

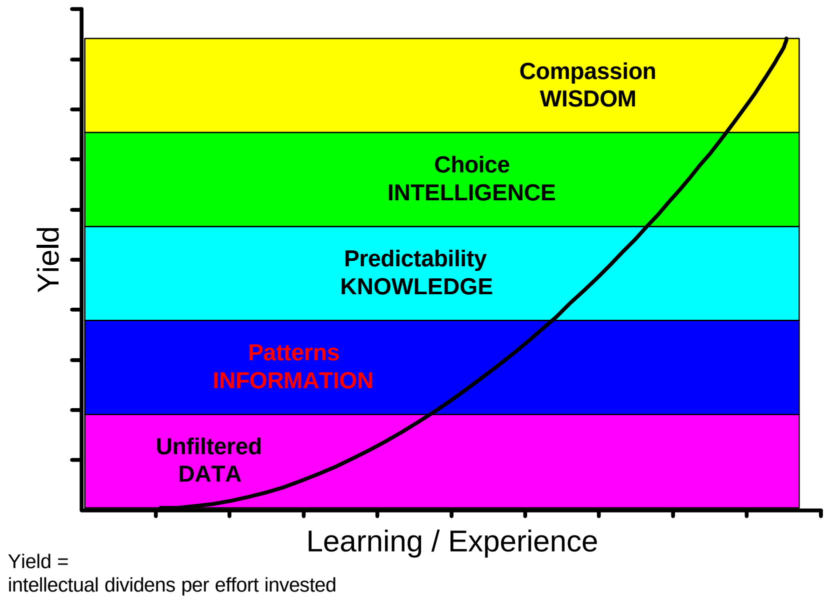

Figure 1. The conventional view on the knowledge hierarchy.

In Figure 1, data are assumed to be simple isolated facts. When such facts are put into a context, and combined within a structure, information emerges. When information is given meaning by interpreting it, information becomes knowledge. At this point, facts exist within a mental structure that consciousness can process, for example, to predict future consequences, or to make inferences. As the human mind uses this knowledge to choose between alternatives, behavior becomes intelligent. Finally, when values and commitment guide intelligent behavior, behavior may be said to be based on wisdom. The underlying view sees the construction of knowledge somewhat similar to using letters as atoms for building words that are subsequently combined to meaningful sentences. The symbolic curve in Figure 1 is intended to make the point that the value of the various forms of data-information-knowledge increases through learning. In this process data is increasingly "refined."

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[1] This representation of the relation between learning and yield comes originally from George Pór, c.f. http://www.co-i-l.com/coil/knowledge-garden/.

Most authors share this view, although the details differ. For example, Davenport and Prusak state that:

> "Data is a set of discrete, objective facts about events…Data describes only a part of what happened; it provides no judgment or interpretation and no sustainable basis of action…Data says nothing about its own importance or relevance." [4]:2-3

According to Davenport and Prusak, however, data turns into information as soon as it is given meaning. Information must inform: "it's data that makes a difference…Unlike data, information has meaning …Data becomes information when its creator adds meaning" [4]:3-4.

Although there seems to exist a broad consensus about the idea that knowledge is more than information, there are several different views on their exact relation. One of the more detailed descriptions of the conceptual hierarchy of knowledge has been given by Earl [6]. It differs from most extant hierarchies, as the distinguishing character of knowledge is its social acceptance. This reflects the idea that knowledge has to be interpersonal or objective. According to Earl, there are actually four levels of knowledge needed to understand organizational information, each level representing an increasing amount of structure, certainty and validation. First, organizational events are represented, collected and processed to generate data. Data are further manipulated, presented and interpreted to generate information. Information then leads to knowledge as it is tested, validated and codified [6]:59. Earl emphasizes the idea that knowledge emerges through inter-personal validation. The underlying conception, however, is still based on viewing data as the raw material from which knowledge is created.

The reversed hierarchy

Given the discussion above, it should not be difficult to recognize that the hierarchy of data-information-knowledge should be turned the other way around. Data emerges last—only after there is knowledge and information available. There are no "isolated pieces of simple facts" unless someone has created them using his or her knowledge. Data can emerge only if a meaning structure, or semantics, is first fixed and then used to represent information. This happens, for example, when information is stored in a semantically well defined computer database. In that special case, we have to de-contextualize knowledge, and structure it according to pre-defined semantics into “isolated” and independent database entries. Ideally, the data so produced can be completely detached from any meaning, so that it can be automatically processed using a computer program.

Data, therefore, exists as a solution to a practical problem: how to dissect information into two forms, data and data structure, that can be modeled, represented, and processed separately. As the computer does not have access to the meaning of the content it processes, computer programmers have to represent meaning in a way that makes automatic processing possible. This also explains why database architects have believed that it is important that database structure has well-defined semantics. Indeed, as Rosen [19] has shown, conventional digital computers generate a rather unique division between semantics and syntax as a result of their design as systems that comprise both hardware and software.

The reversed hierarchy is depicted in Figure 2. The meaning structure that underlies knowledge for an individual is articulated through cognitive effort to become focal and structured. If the meaning is articulated within a linguistic and conceptual context, it can become verbal and textual. At that point we conventionally call it information. It can be represented in a document, and put into a file, for example.

When such articulated knowledge is stored in computer memory for automatic manipulation, the meaning of information must be represented. In effect, information has to be split into “atoms” that have no meaning that would need to be taken into account in automatic processing. At this point we have created data. To arrive at this point, a lot of cognitive effort and design work is needed. In most cases, there also has to be negotiations among all interested parties, where the specific way the meaning is fixed is discussed. In practice, this happens, for example, by defining a conceptual model for a database. For example, a specific location or data field in the structure is used to indicate “an individual person,” and another “a city.” The value of the field may change, indicating a different individual or city, but the meaning of the content is fixed. In such an ideal computer system, there are no “exceptions.”

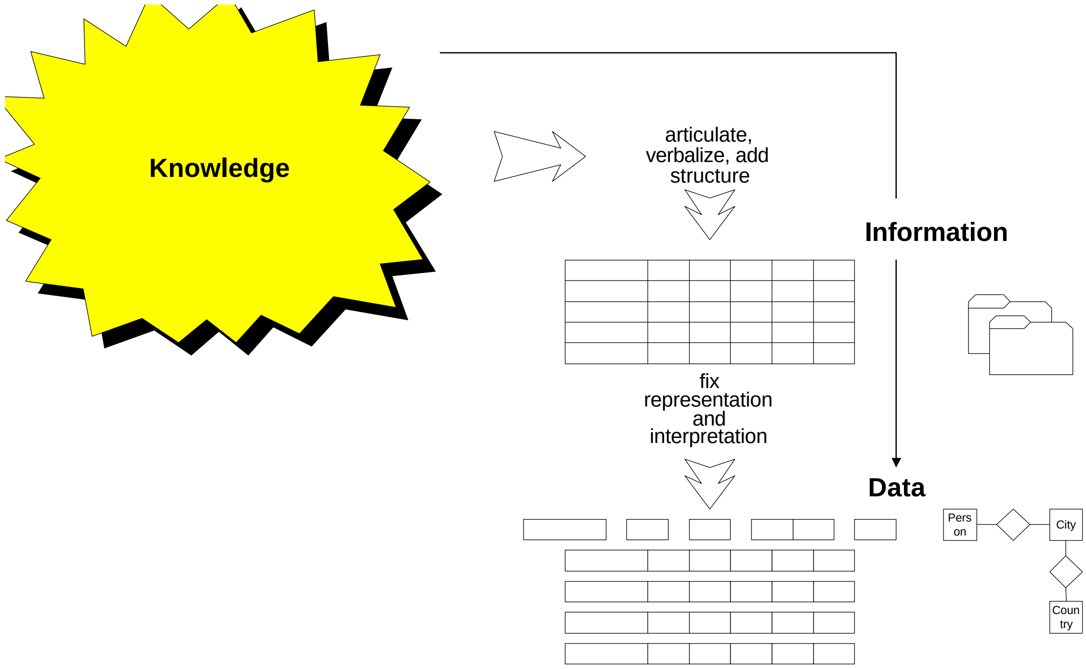

Figure 2. The reversed hierarchy.

Data, therefore, does not become information after meaning is added to it. On the contrary, data is created from information by putting information into a pre-defined data structure that completely defines its meaning. Instead of being raw material for information, data emerges as a result of adding value to information by putting it into a form that can be automatically processed.

This value adding depends on the fact that there are computers that can process information, and which need to store both programs and processed content in syntactically the same form. A similar relation between artifacts and corresponding “simple facts” that can be processed by them, however, underlies the empirical approach also more generally. For example, it is often thought that measurements made in a physical laboratory are the prototypical sources of empirical data. For instance, it is assumed that we can observe temperature using a thermometer, and based on the observed data points we can make sense of the data by giving it structure, and by creating a model that explains the data. This view, however, forgets that the meaning of the data is determined by the instrument itself. The creation of computer databases, shown above in Figure 2 is one specific example of this process. A more prototypical example from the domain of thermophysics is shown in Figure 3.

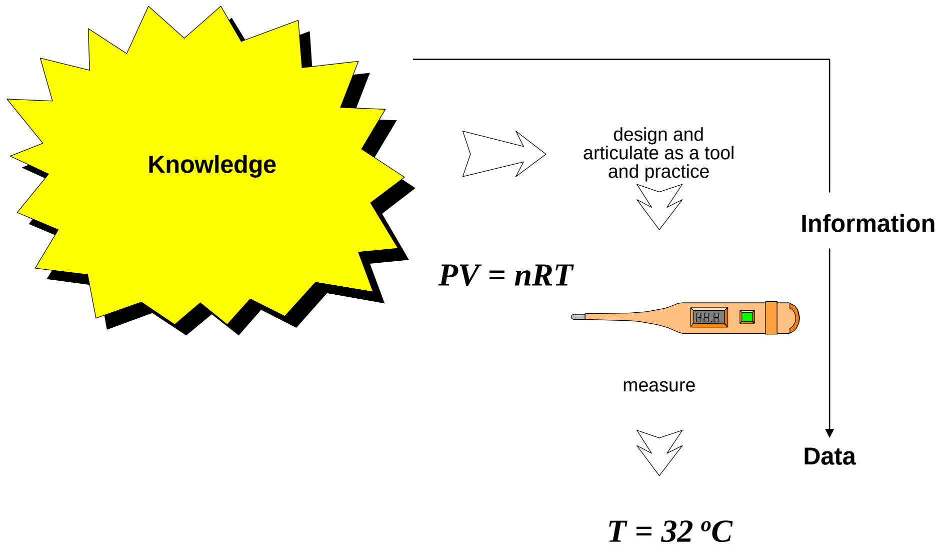

Figure 3. Contextual requirements for measurement of empirical data.

In the context of Figure 3 we can say that when the tool of measurement exists, we can no more freely re-interpret what its readings mean. In the process of creating a measurement tool important aspects of knowledge are sedimented into the structure of the measuring device. Another way of saying this is that the tool we use to collect data on temperature fixes those meaning relations that define what temperature is. Data, therefore, exists only after such a pre-judgment is made. A thermometer is created simultaneously with the possibility to observe temperature as data.

One of the reasons for emphasizing empirical observations is that they provide means to create interpersonal knowledge. When an artifact is created, it fixes part of the meaning of the world in its structure, and this artifact can be used by several people to coordinate the meaning in their respective worlds. Often, however, this requires more than just giving a tool such as a computer program or a thermometer to another person. Packaged with the tool there is a practice of using it, and most of the knowledge about this practice needs to be learned before the tool can be used appropriately. For example, to understand what a specific number means in an accounting database, one may have to learn accounting practices for several years, as well as to know what schemata were used to store knowledge in the database.

This, indeed, was exactly what Fleck [7] argued some sixty years ago. According to Fleck, the development of knowledge is a social phenomenon, and knowing, thinking, and knowledge creation are not something that an individual does, or can do. Instead, knowing and knowledge creation are processes that occur in social units that Fleck called “thought collectives.” Based on his historical analysis of the emergence of syphilis as a specific well-defined “disease,” Fleck illustrated that scientific facts make sense only within a given style of thought that is learned through socialization into the worldview of a specific thought community.

According to Fleck, a thought community is created when a relatively stable structure of meaning is established. Such a community reproduces itself through continuous regeneration of meaning. Within a thought collective, some facts make sense, and others don’t. It is only against this system of reproduced meanings that a scientific fact emerges.

As a result of cultural and social development, social activity may lead to creation of artifacts that articulate collective knowledge. Diagnostic practices and related tools described by Fleck, and organizational information systems, are examples of such accumulated knowledge. More generally, organizational knowledge emerges as plans, experiences, language, habits, models, practices, tools, and institutions that guide action within the organization [1; 5; 9; 12; 22].

Information as explicit knowledge

When we design information systems it is important to note that explicit and articulated knowledge is only a tip of an iceberg. For example, to make sense of a document stored in a computer system, a lot of contextual knowledge is needed, and usually this knowledge is not stored within the computer system. Instead, system designers implicitly rely on culturally shared and accumulated stocks of knowledge.

When shared stocks of knowledge can not be taken for granted, a natural response is to strive to add more contextual information, or to try to more fully represent that tacit organizational knowledge that was previously left unarticulated. This, however, is not a robust solution to the problem. Indeed, in practice it amounts to throwing more technology to solve a problem that was created by using this same technology. Instead of doing more of the same, we have to do something different.

For example, we have to reconsider the relationship between tacit and explicitly articulated knowledge. Michael Polanyi [15; 16] argued that "we can know more than we can tell." In Polanyi's terminology, knowing emerges in dynamic interaction between focal and subsidiary components of meaning. According to Polanyi, subsidiary knowledge consists of subliminal and contextual cues, which we cannot be aware as such. Instead, these subliminal and marginal cues provide the context against which focal knowledge gets its shape. For example, eye-muscle movements have to remain subliminal for perceptional stability to be possible. Similarly, there exist marginal cues "at the corner of the eye," which we see, but without being able to "know" them directly unless they become focal, and which we know only through their influence in the focal perception. According to Polanyi, marginal cues include both peripheral cues seen "at the corner of the eye," but also cues that result from our previous experiences and our expectations. This background component Polanyi called tacit knowledge, arguing that it acts as the necessarily unarticulated background against which all focal meaning is distinguished [17].

Following Polanyi, Nonaka and Takeuchi base their knowledge creation model on dynamic interaction between two types of knowledge. *Tacit* knowledge, according to Nonaka and Takeuchi, is personal, context-specific, and therefore hard to formalize and communicate. *Explicit* knowledge, in contrast, refers to knowledge that is transmittable in formal, systematic language [14]:59. The central idea in the Nonaka-Takeuchi model is that new knowledge is created in articulation of tacit mental models, in a kind of "mobilization process." In this process, tacit knowledge is converted into explicit form.

As Nonaka and Takeuchi start with the primary distinction between tacit and explicit knowledge, it is worth noting the different ways Polanyi and Nonaka and Takeuchi use this distinction. For Polanyi, tacit knowledge is a precondition for meaningful focal knowledge, and there is no explicit knowledge without subsidiary, marginal, and tacit meaning structure that underlies all focal knowledge. It is therefore impossible to separate two different “stocks” of knowledge, one tacit, another focal. Instead, the tacit stock of knowledge is the background from which the knower attends to the focal knowledge.

Using Polanyi’s concept of tacitness, therefore, knowledge is not converted into a separate set of explicit knowledge. Instead, the structure of meaning changes so that some parts of it become focal, in relation to “the rest” which provides the periphery and the background.

On the social level, essentially the same process happens when individual tacit knowledge becomes collectively shared tacit knowledge. In this “socialization” process the tacit background is provided by socially shared meaning structure, built through a social and cultural process that is internalized by the members of the society during their cognitive and social development.

Explicit knowledge could then be understood as decontextualized information. Such decontextualization is, of course, necessary if we store information in a computer. As Vygotsky [29] noted long time ago, written text is the prototypical cognitive tool that can be used for such decontextualization. Therefore we could also say that when computers are used for knowledge management, they are primarily used as media for decontextualized communication, and not as tools for automatic data processing. Decontextualization, however, has to be understood as a process where some aspects of knowledge are made explicit against a “non-focal” background meaning that remains tacit. In other words, decontextualization can only happen in a context.

The problem of interpersonal information

When organizations use information systems to support knowledge management and organizational memory, the problem is often viewed from the point of view of someone trying to understand data stored in computer systems. This view leads to the conventional data-information-knowledge hierarchy. Somewhere in the memory of a computer some information is stored in the form of data, and the problem is to find it and make sense of it.

This view, however, does not produce the complete picture. In practice, the problem of interpreting organizationally stored data resembles the one shown in Figure 4. Someone has articulated knowledge using languages and conceptual systems available, and—in the case of a computer database—represented the articulated knowledge using a predefined conceptual schema. Someone else then accesses this data and tries to recover its potential meaning.

As was discussed in the previous section, the success of this sensemaking attempt depends on the sensemaker's stock of tacit knowledge. Moreover, if the person who stored the data wishes that the sensemaker interprets the data in a predefined way, both the original articulator and the sensemaker need to have overlapping meaning structure. One could say that they have to share some world where the data can make sense. A primary requisite is, for example, that the sensemaker approaches the data as meaningful data that is intended to mean something. Underlying this is an attitude that is based on trust: the sensemaker has to expect that the data are not only random noise and bits, but that there is a message waiting to be interpreted [26]:74.

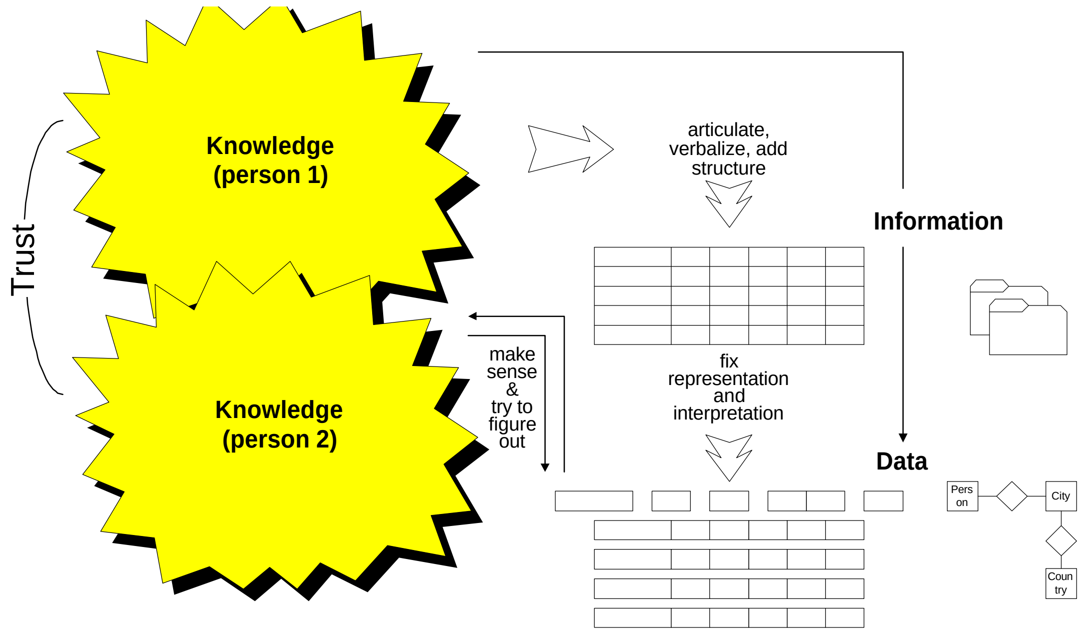

Figure 4. Information in the interpersonal process.

In Figure 4, the second person actively tries to reconstruct meaning to the data created by the person who first articulated and stored it. In this process, she or he uses all available meaning structure, most of it tacit and not represented in the computer system. One could view the small downward arrow in Figure 4 as a process that tries to imitate the original articulation process. If it is obvious what the articulated data means, for example, what are the procedures for recording a specific item in a database, not much effort is needed to figure out what the articulator thought when storing the data. Then the process represented in the small upward arrow simply consists of making sense of the data itself. However, more generally this sensemaking requires that the second person has to understand also the way the original articulator decided to fix the meaning structure and represent it in a computer system. Thus, the data-information-knowledge hierarchy emerges only after the knowledge-information-data articulation has created data. The fact that the two downward arrows in Figure 4 are often missed is because most early information systems have been developed for routine operations. There the articulation process is, indeed, defined in detail, and often formalized as standard operating procedures. A similar situation exists more generally when social institutions effectively off-load the task of interpretation from the system user. For example, an accountant does not need to understand what went through a data entry worker's mind when he or she keyed in the numbers. In this case, social institutions and pre-defined division of labor are key aspects of the system operation.

In knowledge intensive, non-routine, non-automated, and creative organizational processes, the forms of articulation and the processes of sensemaking cannot be taken for granted. The model shown in Figure 4 has therefore implications on the design of knowledge management and organizational memory systems. I discuss these in the next section.

Implications for knowledge management and OM design

At the beginning it was argued that the conventional hierarchy easily leads to waste of organizational resources. As organizational memory and knowledge management systems are often used in essentially open settings, the tacit and socially shared components cannot, in general, be taken for granted. If the design principles and methodology cannot address the tacit component, it cannot tell us where and how much we should invest in the explication of knowledge. In general, it can be argued that there has been too little emphasis on the sensemaking aspects of information systems. This is becoming an increasingly important issue as information systems are increasingly used for collective meaning processing.

On a very practical level, the conventional hierarchy is also reflected in the assumption that information access is a key to knowledge management problems. For example, it is often believed that we can do knowledge management by "putting information on the web," without considering what it takes to make sense of such decontextualized information. As a result, there are now millions of documents on the web, waiting for someone to read them. When the interpretation of information and data is seen as an unproblematic issue, it is easy to believe that information availability is a goal in itself. When we, in turn, react to the resulting information overload by developing new schemes for representing metadata and new algorithms for data mining and filtering, we probably could benefit by considering more carefully the socio-cognitive aspects of collective meaning processing.

When traditional computer databases are used to store knowledge, the conceptual design of the database fixes the semantics and makes it difficult or impossible to re-interpret stored data [24]. This is a problem, for example, if the computer system is used to support strategy processes, business intelligence, or creation of new product designs [25]. In all these cases, information is ambiguous and equivocal—not because we would lack information, but because the world is not ready, but under construction.

When tacit knowledge is articulated and data is created out of it, a lot of flexibility in interpretation is lost. This may lead to organizational rigidity. It may look attractive, for example, to create organization-wide information systems where the same repositories of data are used in all organizational processes [2]. Underlying this view is sometimes an exceedingly empiristic and objectivistic belief that when we get the semantics "right" the organization will be able to function as a perfect machine. In some cases, one could argue that, indeed, the organization has become a perfect machine that is fixed in its operations by the information systems that it has implemented. Therefore, a major challenge for the designers of organization memory and knowledge management systems is to understand, not only the relationships between tacit and explicit stocks of organizational knowledge, but also the costs of changing their relationships when the world changes. The human mind can change the relation between peripheral and focal knowledge in a fraction of a second. Individual and collective reconfiguration of meaning may happen is minutes, days, or months. But often the reconfiguration of semantics in large organizational information systems takes years, especially if everything depends on everything, and all meaning has to be reinterpreted when any of the articulated meaning relations are touched. Therefore, the organizational cost of neglecting the tacit stocks that underlie organizational knowledge processes may be very high. The traditional data-information-knowledge hierarchy easily leads to this neglect, and therefore we need to remind ourselves that it should not be taken for granted.

It may appear that the inflexibility that is created by "hard-wiring" organizational semantics can be overcome by storing knowledge in the smallest possible semantic atoms and by deploying multidimensional databases, data mining, and other data discovery tools. In a technical sense, this roughly equals to finding an algorithmic way to categorize Rorschach pictures, so that we reliably find all those where there is a bat. In practice, the design trade-offs depend on the stability of the mapping between the conceptual model that underlies the design and the cognitive models that we use to interpret the world. In some cases, the "conceptual atoms" may be relatively stable, for example, if they are core concepts in culturally central practices. For instance, as long as we stay within one continent, our definition of temperature does not often change. In general, however, we have to look for "knowledge atoms" that have the right life-cycle properties in relation to the world they are describing, and in relation to the uses they have within an organization.

In rapidly changing environments it may be difficult to find enough stability to widely use semantically fixed databases to store organizational knowledge [28]. A practical implication is that theoretically it can be said that the search for the "perfect atoms of knowledge" is a dead end.

On a more positive side, the reversed hierarchy also points to interesting areas for information systems research as well as to new motivation for some existing lines of research. For example, when we explicitly address those communication processes that facilitate the creation of shared meaning, we can develop knowledge management systems that support collective meaning processing. In practice we can, for example, implement systems that support peripheral knowing, social learning within thought communities, or develop design methodologies that explicitly address interactions and conflicts between several cooperating social activity systems [27].

As was discussed above, information systems for knowledge management and organizational memory should be seen as media that is used as an interpersonal cognitive artifact. A critical factor in designing such artifacts is to consider those knowledge stocks that are needed to make sense of the information stored in the system. As long as information systems are used for automatic processing of limited types of routine work, it may be relatively easy to expect that people who use the computer system share all that knowledge that is needed to make sense of the outputs generated by the system.

In practice, it is, however, important to view knowledge management and organizational memory systems as essentially social systems, where technology complements and supports the processing of knowledge and meaning. An important implication of this is that information system designers need to understand those social processes that underlie meaning processing. Knowledge management systems are not automatic data processing systems, and therefore knowledge management initiatives easily fail if they are conceived as technology problems. The difficult thing, of course, is that knowledge management then requires a broad understanding of social, technical, and cognitive aspects of human organizations. The relevant contributions of the related different traditions and disciplines are not well known at this point of time.

Conclusion

In this paper, the commonly used hierarchy of data-information-knowledge was analyzed, and it was shown that it is useful to turn the conventional hierarchy around. Information can be created only after there is knowledge, and data emerges as a by-product of cognitive artifacts that assume the existence of socially shared practice of using these artifacts.

When both meaning and its representation can be taken for granted, it becomes natural to assume that knowledge has a close connection to bits stored in computer memory. Indeed, the whole knowledge-based economy can then be reduced to "information economy," and information can be defined as "anything that can be digitized" [20]:3. Given the discussion above, we might expect, however, that such a definition misses some key characteristics of information systems that can enable knowledge based economy.

A practically important aspect of knowledge management and organizational memory support systems is the social process that makes it possible for the users of the system to make sense of each other's worlds. Organizational memory and knowledge management systems cannot be understood as stand-alone systems; instead, they combine technical artifacts with social processes. Much of the effort of designing successful systems goes into designing those social processes that make the use of these systems possible. Although in some cases the underlying social processes are so standardized that knowledge management can be reduced, for example, to effective document management, in most cases this is not the case.

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