

Framework for Modeling the Cognitive Process

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Abstract: Information is key to command and control. Yet information alone is not enough; information is neither the problem nor the solution when it comes to issues of command and control. Use of information is essential. That which is commonly called “information” generically exists in many forms, with each form having temporal implications. Furthermore, with so much information readily available and increasingly so, we must develop better ways to combat information overload. Interestingly, the cognitive process itself sheds much light on problems facing the information age and can provide insight into what is going on with information at a fundamental level. In considering such a process, one should examine where information comes from, where it is going, what it’s nature is and how it is used. This paper describes a signal-based perspective of information and how signals in general fuel the cognitive process. More significantly, we introduce a novel framework for conceptualizing the cognitive process.

We describe cognition and related topics at a high level and in simple terms using ordinary language. Yet seemingly simple concepts, when combined and viewed a certain way, can take on significant meaning. We present the concept of abstraction as one of two dimensions in our framework. Here abstraction is viewed overall as a function of space or form, with signals ranging anywhere from concrete to abstract. At one end of this spectrum are physical signals, for instance ones which are tangible and may readily be perceived by the senses. At the other end of the spectrum are abstract signals, for instance ones which may be conceived or realized by the mind but lack physical form. The second dimension in our framework represents time. Here the concept of generalization is portrayed overall as being a function of time or frequency, with signals ranging anywhere from data (time-sensitive, high frequency and least organized) to information to knowledge (time-insensitive, infrequently changing and most organized). In this dimension, signals tend to flow from many pieces of specific data (i.e., details) to fewer items having more significance (i.e., general knowledge). We combine the concepts of abstraction and generalization within our approach to form a unique perspective of the cognitive process, with information at the core, suggesting that this perspective may facilitate the modeling of cognition.

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1. Introduction

The word “cognition” is a derivative of the Latin word *cognoscere*, which means, “to come to know.” From this definition we can see that cognition involves the creation and acquisition of knowledge. This can lead to associating cognition with learning, and with understanding, and meaning and thinking and intelligence, and so on. Trying to describe these terms, especially cognition and intelligence, leads to many difficulties, not the least of which are various definitions and perspectives. While we do see similarities and differences among the processes of cognition and intelligence, we will mainly use the term cognition here at the expense of (our) intelligence. We will describe cognition and related topics using simple concepts and ordinary language. But first we try to place cognition within our overall perspective of intelligence.

We view intelligence to be an all-encompassing process that involves mind and brain, cognition and behavior, to include all mental and physical aspects of brain activity. For the purposes of this discussion, we view cognition to be an underlying process of intelligence, and especially one which helps accomplish knowledge acquisition and learning. We will not discuss here the differences between cognition and intelligence, nor will we discuss much about learning. However, within our perspective we view cognition to be a sub-process of intelligence that involves the transformation of raw data signals into information signals and then into knowledge signals. Very closely related to cognition is generalization, a

process by which signals may vary from specific to general at any point in space and thereby constitutes the state of signals as a function of time. We consider generalization to be a fundamental dimension of cognition. Another fundamental dimension of cognition identified here is abstraction. In the abstraction dimension, signals may vary from concrete to abstract at any point in time and constitute the representation of signals as a function of space. Together abstraction and generalization “frame” our perspective of cognition in a two-dimensional sense and may be used as a framework for modeling the cognitive process.

Our framework consists of many seemingly simple concepts. Yet when combined a certain way, these concepts take on significant meaning within our perspective. We describe basic concepts using common, everyday language. We define important terms to help clarify our perspective and give examples to help illustrate our meaning. We even discuss meaning itself with respect to cognition and intelligence, and suggest how meaning contributes to understanding within our framework. With this description, we will have combined many simple concepts to form the shell of a model of a tremendously complex process – the cognitive process.

From an information processing point of view, we are interested in how information gets transformed into knowledge in support of intelligence. This transformation process is literally the basis of cognition. Furthermore, we view intelligence as being an overarching process of cognition, with both processes being orderly and signal-based. We propose our framework as a way of portraying

this order and viewing the signal-based transformations in space and in time. We aim to understand portions of intelligence and to describe them as clearly as possible at a high level. Once fundamental concepts are realized and described, they may better be implemented using modeling and simulation technology. We have a long way to go for this. Given the significance of abstraction and generalization in our framework, two major challenges here are to formalize abstract concepts and to be as specific as possible while describing general concepts. Such is the nature of the beast. Our framework directly reflects these challenges. We have benefited from the work of many others in various disciplines while forming our unique perspective. We acknowledge that this work represents a mere sampling of the wealth of knowledge available on this complex topic.

The task before us represents a formidable challenge, one that involves the integration of information, intelligence and computers. Each of these entities is the subject of entire disciplines. Information, loosely speaking, is the lifeblood of intelligence. Intelligence is the product of the mind. And automation, as used here, represents the relatively recent capabilities enabled by the electronic computer. Our aim is to examine these and other disciplines while focusing on one piece of the intelligence puzzle from a modeling point of view. The piece we focus on is a framework, with details omitted. We have developed our conceptual model with the perspective that intelligence is an orderly, signal-based process involving complex transformations in space and time. Since we are ultimately dealing with a model of intelligence, and since all models are approximations of reality, we are not interested in developing an exact copy of natural intelligence. We aim to provide an approximation, a conceptual model, a basic description of cognition as part of the intelligence process. Most of the concepts presented in this modeling framework are relatively simple, and they are not new. However, as combined they form a new perspective on a theory of mind that may seem unbelievably simple at first. Our description is a contribution, however small, to the formidable task of modeling intelligence.

2. Definitions

We begin with a set of definitions. Admittedly, the terms we use can be defined in many different ways, and typically are. We merely provide these definitions as a basis of discussion. Intelligence is defined as the ability to transform a variety of signals into knowledge and to effectively apply that knowledge in a changing environment. Cognition is defined as the ability to acquire knowledge, or the ability to know and understand. As such, cognition is viewed as a sub-process of

intelligence. Understanding is the set of realizations of signal relationships that occur as part of cognition. These realizations involve the coupling of underlying physical structure (i.e., brain) with overlaying mental function (i.e., mind). Meaning is the result of the process by which signals are assigned values. Signals obtain value or meaning within the mind-model by associating activated formal structures with activated abstract functions using dynamic links. Learning is defined as the acquisition of knowledge. This implies first the ability to cognize signal relationships, then to make associations among them and, perhaps most importantly, to recognize them later. Learning causes change, and that change is recorded in a lasting structure that dynamically supports the functions of intelligence. Finally, information is a generic term used to describe signals that interact in many ways and are transformed during the intelligence process. The term information is often used elsewhere as being synonymous with data, knowledge and other forms of signals. We place the term information at the center of our conceptual framework and will distinguish our use of terms within the context of this framework.

3. A Conceptual Framework for Modeling the Cognitive Process

We will describe our conceptual framework using graphical examples to help illustrate main points. We form the two dimensions of our framework using the concepts of abstraction and generalization, as shown in Figure 1. In the abstraction dimension, signals are considered to be a function of space. This means that in this dimension signals must conceptually take on physical shape or *form*, varying anywhere from concrete to abstract at any point in time. The overall flow of signals in this dimension tends toward increasing abstraction. *Representation* of signals as a function of space becomes a major modeling issue. We will discuss abstraction more later in this section. Generalization is used as the other dimension in this conceptual framework, with signals being a function of time, or more literally, frequency. In this dimension, signal types can vary anywhere from specific to general at any point in space and their frequency designates their relative state of *processing*. This means that as signals become transformed during the cognitive process, the frequency of resulting *signal-states* can vary anywhere from quickly changing (data) to those which change less frequently (information) to states which are very slow to change (knowledge), if they change at all. This relative state of *processing* is another major modeling issue. The overall flow of signals in this dimension is toward increasing generalization. This aspect of cognition will also be described more later in this section.

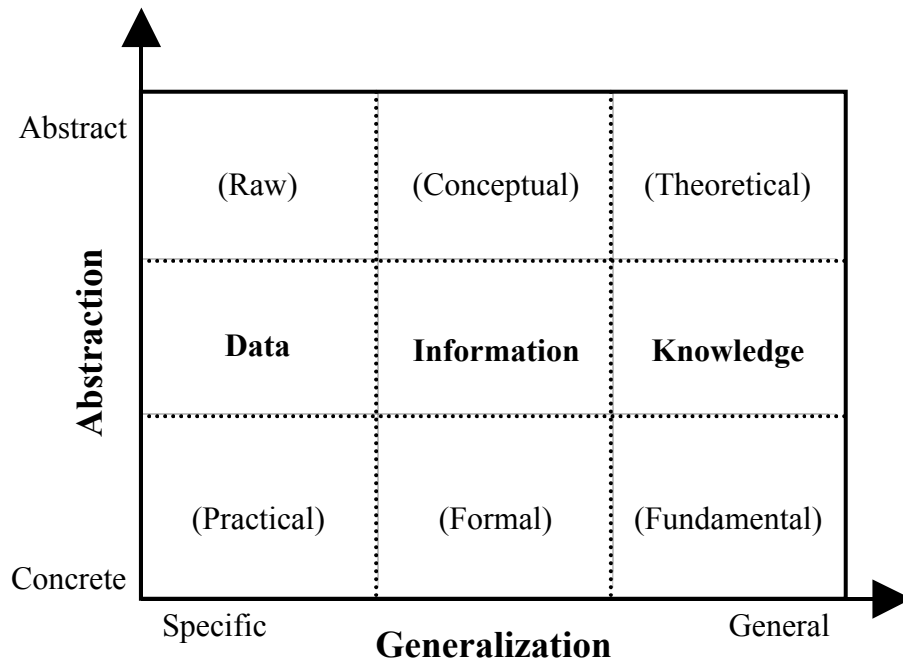


Figure 1. A conceptual framework for modeling the cognitive process.

3.1. Signal-Based Approach

When we use the term *signals* in our description of cognition, we imply mental signal activity, or signal activity modeled after that which must occur in the brain. Yet in reality, mental signals have physical characteristics as well, consisting of frequency, phase and amplitude components. In this overview we provide no details on the physical or mathematical nature of signals. And while much is known in various disciplines concerning neural signals and their related processes, too little is known about the actual nature of mental signals and especially the implications of these signals with respect to underlying cognitive processes. Nonetheless, we consider mental signals and their components as raw materials for cognition. Within our signal-based approach to automating intelligence, we acknowledge that order and organization must be present in mental signals and serve as a natural and fundamental part of cognition. We realize that to model cognition means to exploit its underlying order and organization. Naturally, our signal-based approach draws from many disciplines. In general, we consider *signals*, a more generic term for what the concept *information* represents, to be the lifeblood of intelligence.

Using this conceptual framework, we view signals from an “information processing point of view.” By this we mean that, while the signals themselves may generically be termed information or data or whatever, their relative state of representation and processing takes on special meaning with respect to cognition and the overall intelligence process. In the context of our framework, information is just one of several signal-states within the cognitive process. Furthermore, as part of the framework, information may exist at various levels of abstraction. Granted, many of the concepts presented here are themselves abstract and consequently difficult to explain, but this framework does provide a useful way of viewing cognition. In time, this framework will be improved upon in support of the many details needed to model cognition.

3.1.1. Symbol and Direction for the Framework

A basic symbol used here to represent this conceptual framework is shown in Figure 2. With only three states highlighted in one dimension (Data, Information and Knowledge), the overall framework is represented using a rectangular symbol with nine regions. For an even simpler symbol of the framework, the nine regions may be depicted with no states labeled.

DATA	INFORMATION	KNOWLEDGE

Figure 2. A symbol used to represent this conceptual framework.

The next illustration (Figure 3) shows cognition as a process that proceeds generally from left to right with respect to the overall conceptual framework. We choose this direction to reflect the significant role “knowledge” plays in the cognitive process. Later we discuss signal-flow in the abstraction dimension. While this description may seem overly simple, the proposed progression does

speaking. Note that our use here of the term *data* is quite different from more conventional uses such as in the terms “data processing” and “data analysis.” However, the main points here are that data signals are the least organized, have the highest frequency and comprise the majority of input signals. At the other end of the process, signals tend to be output as *knowledge*, the most organized of the three signal-states. Relatively speaking, knowledge signals have the lowest frequency, which implies that knowledge is slow to form and slow to change, if it changes at all. Furthermore, while cognition must involve iterative processes, knowledge does not always have to be output but may be stored within the mind-model for future activity, whether that activity be internal (as in thinking) or external (as in communication). Finally, *information* is the term used in the center of the framework (see Figure 1). As such, information will serve as the intermediate state between data and knowledge in the generalization dimension, and also as the intermediate form between abstract and

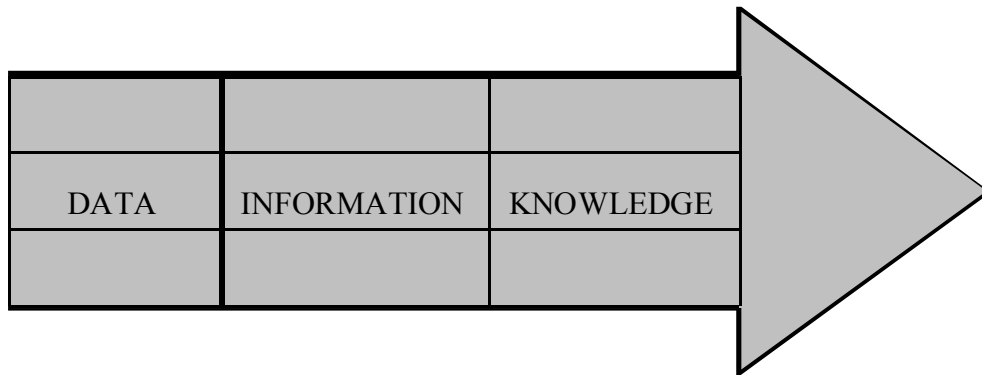


Figure 3. Overall direction of cognition within the framework.

help to constrain the cognitive process from a modeling standpoint by identifying an overall direction for the process. We do acknowledge that this work is merely a modeling effort, and that the human brain involves much more complex behavior, rich connectivity, feedback and all sorts of dynamic signal activity occurring in many dimensions.

3.1.2. Input and Output

Before we discuss what goes on inside the framework, we briefly discuss what goes on outside with respect to the cognitive process (i.e., inputs and outputs). Given the overall perspective as described above, signals enter from the left, with the majority of input signals defined as *data*, the least organized type of signals (Figure 4). Data signals have the highest frequency within our framework, which means that data signals vary quickly and its components are the most time-sensitive of all, relatively

concrete in the abstraction dimension. Whether the term information or data or knowledge is used to describe input to or output from a model is a relative issue. However, terminology does take on special significance with respect to modeling cognition due to implications concerning meaning.

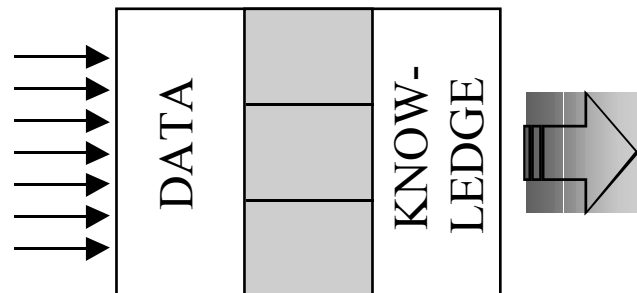


Figure 4. Data as Input and Knowledge as Output.

3.2 Abstraction

We turn now to signal activity within the conceptual framework. In a two-dimensional sense, the vertical dimension of our framework represents space. We are faced with the issue of describing the concept of space in terms of a single dimension, here called the abstraction dimension. That is, the three dimensions of “space” are treated as a single entity; this abstraction of “space” is a major modeling issue in it’s own right. In any case, we begin by describing abstraction as one of two dimensions within our conceptual framework.

Signal abstraction involves a hierarchy of signal forms in the vertical dimension. The signal forms are relative, varying anywhere from concrete to abstract (Figure 5). At the bottom of the hierarchy are *concrete* signal forms, but similar descriptive terms include: formal, certain, absolute, fundamental, simple, basic, primitive, practical, principle, factual, sensory and machine-like. These terms all have physical connotations and thereby represent physical aspects of modeling reality. At the other end of the spectrum are *abstract* signal forms, but similar terms include: conceptual, informal, apparent, complex, combined, notional, seeming, cognitive, ideal and intangible. These terms have more of a mental connotation to them, and thus represent mental aspects of modeling reality. Throughout the history of artificial intelligence (and other disciplines as well), the abstract nature of intelligence has proven to be most difficult to model. Yet from a modeling perspective, we cannot ignore the significance of abstraction within the intelligence process.

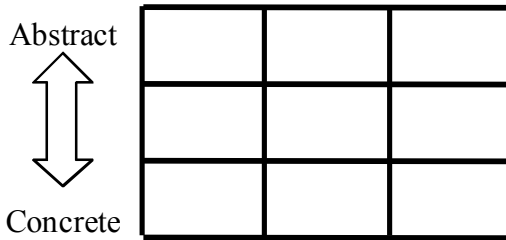


Figure 5. Abstraction – internal signal transformations in the vertical dimension.

A simple example of cognitive activity having three levels of abstraction includes thinking, speaking and writing. Naturally, all three of these activities involve thinking. Later we discuss how the various levels of abstraction may contribute to thinking, but using this example we can at least distinguish between three levels of abstraction within our framework. Ordinary or plain thinking (with

no output involved) happens to be the most abstract (or least formal) activity of the three mentioned. This places ordinary thinking in the upper level of the framework. However, when we express ourselves using speech, we must output what is “on our mind” in a way that is more formal and more concrete than ordinary thinking. This places speaking somewhere below the level containing ordinary thinking within our abstraction hierarchy. The third level of abstraction in this example, writing, resides in the lowest level of the framework. With writing we express what is “on our mind” in the most formal (or least abstract) fashion of all, by definition. This example illustrates the spatial hierarchy of abstraction within our framework and highlights the apparent differences between these three mental activities, but also implies that these activities are intimately related.

3.2.1. Flow Within the Abstraction Dimension

We have talked about how signals take on physical shape or *form* in the abstraction dimension. We have also stated that the overall flow of signals in this dimension tends toward increasing abstraction. We choose this direction from a high level perspective by considering what happens outside the mind-model as well as inside. The region outside the mind-model is called the environment or external world, which obviously has an effect on the model with respect to signal inputs and outputs. In the external world, signals are physical and time-sensitive by their very nature. Our mind-model must be able to accept these signals as they occur (i.e., in whatever form they exist). Thus, in the abstraction dimension, signals enter the mind-model mainly in a physical sense. These signals are then processed and transformed into levels of increasing abstraction. This results in an overall signal flow which proceeds from concrete (formal) to abstract in this dimension. Granted, this is a high level perspective, but it is consistent with our overall framework, and this perspective literally helps frame underlying representation issues.

As part of cognition, we realize that abstraction is an exceptional mental ability. The ability to abstract in humans is believed to exceed that of all other animals on the earth, by far. This is in sharp contrast to the exceptional sensory abilities of most animals, believed to exceed those of humans in many cases, by far. A significant part of the human cognitive process involves taking physical, sensory signals from the environment and transforming them into higher and higher levels of abstraction within our mind. With respect to this modeling task, we acknowledge that an abstraction hierarchy exists by making it part of our cognitive framework.

3.2.2 Function and Structure

The next conceptual leap we make within our framework involves associating “abstract” with “function” along the top and “concrete” with “structure” along the bottom, as shown in Figure 6. In this figure, the arrows imply equivalence. This association may appear trivial or contrived, but again it serves a useful modeling purpose. One of our main goals here is to characterize the cognitive process such that we may better model it using computer technology. A major difficulty in modeling cognition and intelligence involves resolving complex relationships between mental function (i.e., mind) and physical structure (i.e., brain). By associating *abstract* with *function* and *concrete* with *structure* within our framework, we touch upon this great paradox of intelligence, albeit at a very high level. Our motivation at this high level is simple: to realize and describe concepts, to stimulate new ideas and to foster the development of theories in support of modeling the cognitive process.

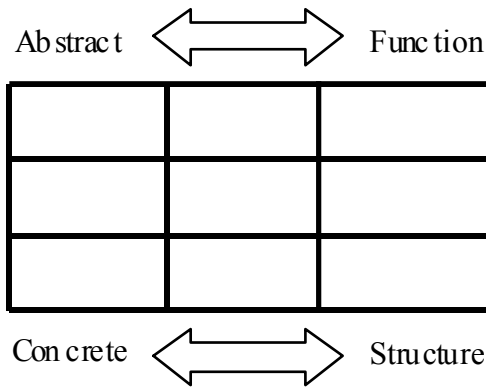


Figure 6. Associating levels of abstraction with function and structure.

Given that structure resides at the bottom of our framework as shown in Figure 6, we acknowledge this implied structure must come from somewhere and, according to our perspective, this structure comes from learning. That is, the learning process produces some kind of lasting structure (i.e., memory). Granted, as perceived in the brain, this so-called structure cannot be rigid or fixed but must be dynamic in nature; but structure exists nonetheless. To go one step further, function is enabled by *using* that which is

learned (i.e., by using existing structure). To be sure, learning not only produces structure but also enables function, and the distinction between function and structure gets very fuzzy with respect to learning and cognition. Suffice it to say that having something physical (i.e., structure) is not important if there is no ability to *use* that “something” effectively (i.e., function). In considering any model of the cognitive process, we must come to grips with the age-old paradox concerning function and structure, two very real aspects of intelligence. Unfortunately, humankind has not yet resolved this paradox. So-called hard sciences like physics, chemistry and biology have not yet fully embraced the abstract nature of mental function. Likewise, so-called soft sciences like psychology, philosophy and sociology have not yet fully embraced the physical and concrete nature of brain structure. Our framework merely provides a conceptual bridge between this metaphorical gap.

3.2.3 Learning and Recall

While we acknowledge that learning plays a key role in the cognitive process, we must also acknowledge the importance of signal recall as part of the process. What we learn is literally of no use unless we can recall it appropriately. Within a modeling system, learning begins with the presentation of input signals, as discussed earlier, resulting in system change and the formation of lasting structure (memory). Cognition is a complex byproduct of learning which occurs in an “intelligent system” only after much learning has taken place. Note that while cognition as used here occurs (arguably) near the *end* of the intelligence process, we acknowledge the process as being iterative in nature. *Recall* can only occur *after* presentation and *after* cognition, and as the prefix *re-*implies, *recall* literally involves signal *re*-presentation and *re*-cognition (Figure 7). Our signal-based perspective acknowledges the significant iterative relationship between learning and recall.

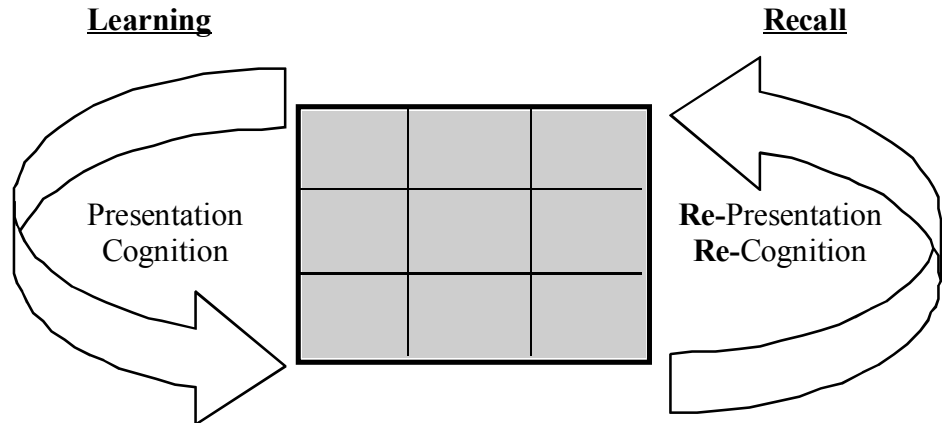


Figure 7. Learning and recall as part of the iterative cognitive process.

3.2.4 Meaning and Understanding

The next two concepts we discuss are meaning and understanding, obviously important with respect to intelligence. The word understanding implies that some kind of foundation or structure is needed. Furthermore, the activity implied by understanding is one that involves “making sense” out of signals present. This means several things from our perspective. First, to understand something, we must recognize the inherent order and organization present in signals (i.e., we must recognize signal structure). We must also recognize the potential use of such signals (i.e., we must recognize signal function). Then we must link function to structure. Once we realize or “make real” the links between structure and function within our mind-model, the result represents signal meaning. Meaning occurs by associating formal physical constructs with abstract mental counterparts. In a more global sense, the total set of activated physical constructs in the brain coupled with the set of activated mental functions which “makes use” of those constructs represents *understanding*. When we perceive something and it “makes sense” to us, part of what must occur is for activated abstract concepts to resonate with activated physical constructs within our mind-model. Understanding and meaning are the result of realizing and activating resonant links within the neural network. The level of understanding depends upon the nature of signals “realized” and the nature of resulting signal resonance.

After providing such a brief description of meaning and understanding, we realize that we have come up short in very many respects. However, it is important to reiterate that, for modeling purposes, we are after a high-level description here. Over time this description must be improved upon and details added. But we emphasize that before any description can occur, the *realization* of ideas and concepts must occur. That is, *we must first realize concepts in our mind before we can model them external to our mind*. The risk we take here in simplifying this complex subject is offset by the potentially far-reaching benefits that come from modeling cognition.

3.3 Generalization

We now describe generalization, or internal signal transformations in the horizontal dimension of our framework (Figure 8). From an information processing point of view, all signals involve oscillations or pulses. Thus the signals naturally contain frequency, phase and amplitude components and, as already mentioned, the composite signals may transition from data to information to knowledge, respectively, as a function of decreasing frequency. Signals with the highest relative frequency, termed data here, happen to be the least organized. In a modeling sense, signals ought to be processed according

to a purpose or direction, and within our perspective an underlying purpose of cognition is to produce fewer signals containing a higher order or greater significance (i.e., to produce “knowledge”). This highlights an important aspect of the generalization process. As large amounts of data are input and processed in an intelligent system, the signals become more ordered and more organized (i.e., the signals literally come to be “in formation”). However, the process does not stop there. Remaining signals may further be reduced, filtered, ordered and organized into knowledge. This perspective offers a convenient way of viewing the cognitive process.

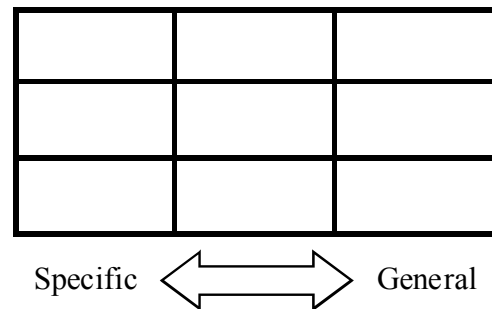


Figure 8. Generalization – internal signal transformations in the horizontal dimension.

3.3.1 Signal Frequency and Period

An example of relative frequency components of signals within our framework (using frequency of rotation) is given in Figure 9. Using the analogy of interconnected gears, data is shown to be the smallest gear and as such must rotate much faster than information to remain engaged in the cognitive process. Likewise, information must rotate more quickly than knowledge to remain engaged. This example not only highlights the relationship of frequency components but also their relative significance within the cognitive process. While the slowest frequency is associated with knowledge, the largest size as shown implies that knowledge carries with it the greatest significance.

Given the importance of frequency components in our signal-based approach, and given the inverse relationship between frequency and time, the following points can be made concerning signals in the generalization dimension. Since data signals are assigned the highest frequency within our framework, these signals consequently have the shortest period or timeframe. Information signals have an intermediate timeframe associated with them, and knowledge has the longest timeframe. This implies that knowledge signals tend to change value least often, if they change at all. Therefore, knowledge holds its value longer than data and information, and it follows that

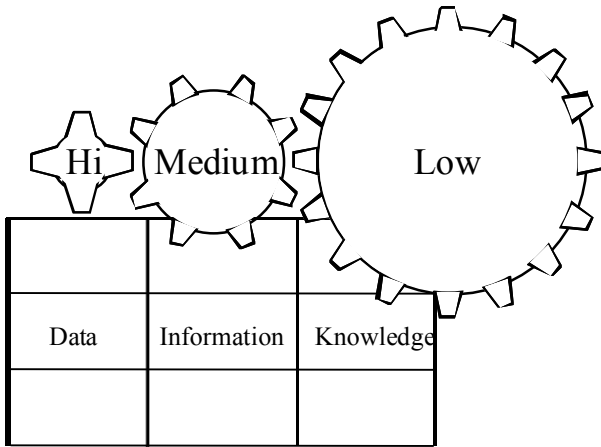


Figure 9. Analogy of gears and the cognitive process highlights signal frequency relationships.

knowledge is more significant than data or information. Consistent with our view of the cognitive process, we see generalization as a process that uses many data signals to produce fewer information signals and even fewer yet more significant knowledge signals. Note that this many-to-few progression within brain activity represents a natural tendency across many levels of brain function, from single neurons to neural clusters and even up to consciousness.

3.3.2 Signal Sequencing

Another consequence of generalization in our signal-based approach has to do with signal sequencing. By sequencing we mean the orderly combination of signals over time. An example of this is found in language. Letters of the alphabet are used to produce words, and the letters may be arranged in many possible ways. But for any given word, a specific sequence of letters must be followed. Furthermore, words may possibly be arranged in many different ways, but for any given phrase or sentence, the exact sequence of words matters, thereby fixing their meaning (i.e., their meaning depends on the use of formal structures). This example serves as a simple reminder of the important role sequencing plays in the cognitive process. Out of the very many sequences of signals that may possibly occur within a mind-model, for any given sequence, specific forms become activated, identified and associated with existing signal-states, thereby giving meaning.

Even at more abstract levels, the signal-sequencing concept may be used to reinforce the point that cognition tends to proceed

toward the creation of knowledge, going from many specific constructs to fewer general ones. For example, sequences of many specific sights and sounds combine to trigger abstract thoughts and ideas, and thoughts and ideas combine to form main points in the reasoning process. Again, we aim to exploit this in a modeling sense by recognizing the inherent hierarchy of abstraction within cognition and also by acknowledging the direction of signal flow as proceeding from specific to general in support of knowledge creation.

3.3.3 Signal Hierarchy

The inherent order and direction of the cognitive process naturally bring forth many interesting characteristics. One such characteristic with respect to generalization is shown in Figure 10. Within the basic hierarchy given, many pieces of data combine to form fewer pieces of information, and information pieces combine to form knowledge. Figure 10 shows only one piece of knowledge, and that piece is shown larger than the others, which implies that knowledge is more significant. In the brain, neuronal processes are not so simple or clear-cut, but this concept is important nonetheless. From a signal processing standpoint, data signals have the lowest amplitude and the highest frequency compared with information and knowledge, as already mentioned. As signals are processed, filtered and combined, the end product is knowledge, which consists of signals having the lowest frequency and largest amplitude or significance, relatively speaking.

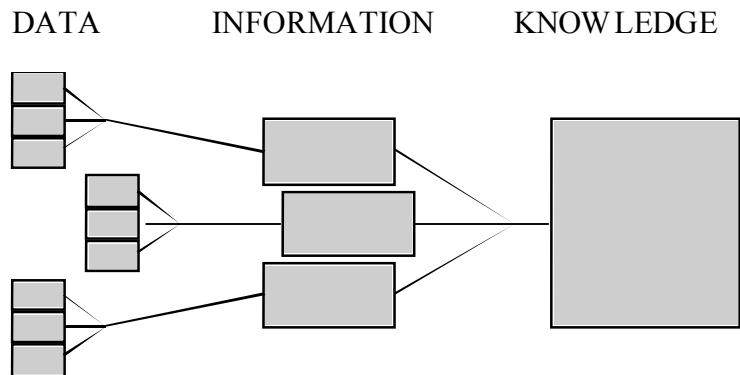


Figure 10. An illustration of signal hierarchy in the generalization dimension.

3.3.4. Signal Filtering

Another interesting characteristic is that much signal filtering must occur in support of underlying cognitive processes. One way of illustrating signal filtering at a high level is shown in Figure 11. Here many data signals having relatively low amplitude and high frequency are filtered into fewer information signals and then again into knowledge. The amplitude or significance of the signal components is shown to increase along the way. Thus knowledge consists of signals having the largest amplitude and lowest frequency, relatively speaking. This kind of filtering may be used to model processes at the neuronal level, but conceptually this filtering may also be used across many layers and dimensions as well. As believed evident in the human brain, this filtering process could support a sophisticated modeling hierarchy having rich connectivity. Of course, vast amounts of detail must be worked out with respect to signal filtering and then integrated into a cohesive model, which is no small task.

corresponding transformation processes. Admittedly, details of the differences between fusion for abstraction and fusion for generalization must be worked out, but the fusion concept applies to both sub-processes nonetheless.

3.4. The Essence of Generalization

As part of cognition, many data signals are processed into fewer information signals and then further into fewer knowledge signals. Consequently, resulting knowledge is considered the most significant of all the signal-states in this progression. Implicitly this means that as a result of all the underlying transformations, knowledge must contain the basic elements of data and information, as well as something more. The cognitive process is such that it cleverly extracts the essence of data as it produces information, and then extracts the essence of information as it produces knowledge. And a curious thing happens along the way. As signals proceed from data to information to knowledge, nonessential elements in time

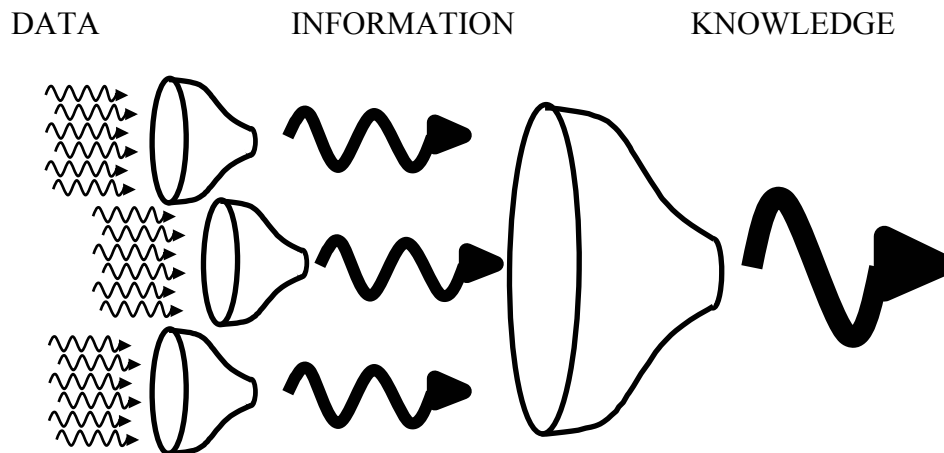


Figure 11. An illustration of signal filtering.

3.3.5 Signal Fusion

Another characteristic function of biological neurons we would like to model is signal fusion. By fusion we simply mean a process that takes many input signals and fuses them together to produce a single output (Figure 12). We consider signal fusion an important modeling function because, as already implied, biological neurons must perform a function similar to this. The fusion concept is also consistent with the overall flow of signals occurring in both dimensions of this conceptual framework. Abstraction and generalization are both envisioned as involving signal fusion, with many input signals being combined to produce fewer output signals as part of the

are abstracted out while essential elements in space are maintained. This implies that the essence of generalization is to produce knowledge^{*}; that is, to produce timeless, spatially concise versions of many specific signals. This aspect of cognition is often taken for granted in everyday life. Our generalizations tend to be overshadowed by the immediate nature of specific, sensory signals, and also by the near-term role consciousness plays in mental activity. Nonetheless, the mind performs generalizations on a regular basis.

^{*}For the purpose of this paper

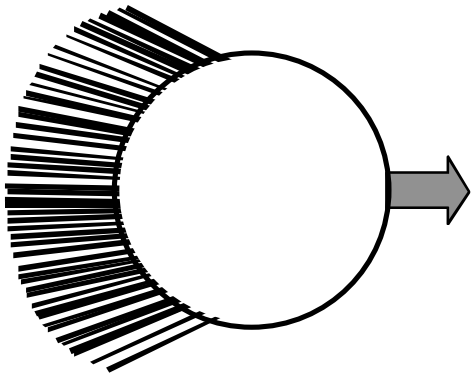


Figure 12. An illustration of signal fusion.

3.5. The Essence of Abstraction

In a similar fashion, based on our previous discussion in the abstraction dimension, the elements of space or *form* become abstracted out as signals proceed in the direction of concrete to abstract. This implies that the essence of abstraction is to produce concepts; that is, to produce formless, temporally concise versions of many concrete signals. The abstraction process tends to take many physical, formal signals and produce fewer yet more abstract versions of them. This is a form of generalization as well, implying that the abstraction and generalization processes are inextricably entwined. And similar to generalization, the abstraction concept is often overshadowed in everyday life with respect to cognition, making abstraction somewhat mysterious and counterintuitive, not to mention hard to describe. Considering the nature of our senses and the concrete role consciousness plays in assigning meaning to signals, our mind tends to weigh physically sensed signals more heavily than abstract ones. Yet overall, the mind does perform abstractions on a regular basis, making this another aspect of cognition often taken for granted. From this we can infer that two of the most important aspects of cognition are the ability to abstract and to generalize.

3.6. Corner Regions of the Framework

Finally, we complete this overview by describing the corner regions of our framework. But first, a couple of observations about the framework overall. One observation is that physical entities tend to reside in the lower levels of the framework while mental entities reside in the upper levels. This corresponds to the spatial hierarchy within the framework and also has implications concerning signal-flow in the abstraction dimension. Second, entities which change most often tend to be on the left-hand side of the framework while entities which change less often are on the right. This corresponds to the temporal hierarchy within the framework and has signal-

flow implications as well in the generalization dimension. Thus the overall framework consists of these overlapping hierarchies which, when combined, form the various regions of this two-dimensional framework (see Figure 1).

The intersection of the abstraction and generalization dimensions helps define the corner regions of our framework. This intersection places raw signal activity in the upper left corner, practical activity in the lower left, theoretical activity in the upper right and fundamental activity in the lower right-hand corner. By “raw” activity here we basically mean unorganized, quickly changing signals. These signals are considered specific and abstract within the context of our framework. By “practical” we mean specific, high-frequency signals that have more form and structure than do raw signals. This implies that these signals have more of a physical presence, indicating that they may more readily be “sensed.” By “theoretical” we mean the combination of abstract and general concepts. For instance, this framework may be considered theoretical. Finally, “fundamental” represents the combination of concrete concepts and general principles. Something theoretical may be considered fundamental once its principle structure becomes formally realized and generally accepted. Together these four corner regions, along with the regions previously mentioned, complete the shell of our conceptual framework.

4. Conclusion

We have provided a very general description of cognition as part of the intelligence process and have proposed using a unique conceptual framework from which to view the cognitive process. Abstraction and generalization form the basis of this framework in a two-dimensional sense, with space taken as one dimension and time serving as the other. We have used a graphical presentation of basic concepts to help illustrate main points of this framework.

We by no means want to trivialize the significance or complexity of cognition or intelligence by providing such a simple description. Our intent is to develop a new perspective on a theory of mind that, by combining seemingly simple concepts in a certain way, takes on fundamental significance.

The goal of this work is to develop computer technology that can perform information processing in a more intelligent fashion. We use this framework to help understand the order and organization present in natural intelligence in an effort to model its underlying order. The ultimate purpose of this modeling effort is to assist humans in the performance of functions heretofore unachievable. Computer technology will provide much of

the infrastructure needed for this. Yet before we can simulate desired functionality using computer technology, we must develop an adequate model for it, which ultimately involves having a sufficient description of relevant concepts. Computers perform very many information processing tasks for us each day. We hope to enable more functions by adding new forms of intelligence to existing automated models.

5. Bibliography

- [1] M. Arbib, Editor, *The Handbook of Brain Theory and Neural Networks*, MIT Press, Cambridge, MA, 1995.
- [2] P. Churchland and T. Sejnowski, *The Computational Brain*, MIT Press, Cambridge, MA, 1993.
- [3] D. Crevier, *AI: The Tumultuous History of the Search for Artificial Intelligence*, Basic Books, NY, 1993.
- [4] F. Crick, *The Astonishing Hypothesis: The Scientific Search for the Soul*, Simon and Schuster, NY, 1994.
- [5] D. Fogel, *Evolutionary Computation: Toward a New Philosophy of Machine Intelligence*, IEEE Press, Piscataway, NJ, 1995.
- [6] S. Hawking, *A Brief History of Time*, Bantam Books, NY, 1988.
- [7] M. Hearst and H. Hirsh, "AI's Greatest Trends and Controversies," *IEEE Intelligent Systems*, pp. 8-17, January/February 2000.
- [8] R. Kurzweil, *The Age of Intelligent Machines*, MIT Press, Cambridge, MA, 1990.
- [9] D. Marr, *Vision: A Computational Investigation into the Human Representation and Processing of Visual Information*, W. H. Freeman and Company, San Francisco, CA, 1982.
- [10] P. McCorduck, *Machines Who Think*, W. H. Freeman and Company, NY, 1979.
- [11] M. Minsky, *The Society of Mind*, Simon and Schuster, NY, 1986.
- [12] A. Newell, *Unified Theories of Cognition*, Harvard University Press, Cambridge, MA, 1990.
- [13] N. Nilsson, *Artificial Intelligence: A New Synthesis*, Morgan Kaufman Publishers, Inc., San Francisco, CA, 1998.
- [14] F. Peat, *Artificial Intelligence: How Machines Think*, Simon and Schuster, NY, 1985.
- [15] R. Penrose, *The Emperor's New Mind: Concerning Computers, Minds and the Laws of Physics*, Oxford University Press, NY, 1989.
- [16] R. Pfeifer and C. Scheier, *Understanding Intelligence*, MIT Press, Cambridge, MA, 1999.
- [17] G. Rawlins, *Slaves of the Machine: The Quickening of Computer Technology*, MIT Press, Cambridge, MA, 1997.
- [18] H. Rheingold, *Tools For Thought: The History and Future of Mind-Expanding Technology*, MIT Press, Cambridge, MA, 2000.
- [19] S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*, Prentice Hall, Englewood Cliffs, NJ, 1995.
- [20] A. Scott, *Stairway to the Mind: The Controversial New Science of Consciousness*, Springer-Verlag, NY, 1995.
- [21] H. Simon, *The Sciences of the Artificial*, 3rd Edition, MIT Press, Cambridge, MA, 1996.
- [22] T. Stonier, *Information and the Internal Structure of the Universe: An Exploration into Information Physics*, Springer-Verlag, London, 1990.
- [23] D. Stork, Editor, *HAL's Legacy: 2001's Computer as Dream and Reality*, MIT Press, Cambridge, MA, 1996.
- [24] P. Yaworsky, "Toward Automating Intelligent Information Processing," Air Force Rome Laboratory Report, RL-TR-97-46, 1997.
- [25] P. Yaworsky and J. Vaccaro, "Neural Networks, Reliability and Data Analysis," Air Force Rome Laboratory Report, RL-TR-93-5, 1993.