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NEUROINFORMATICS: INDIAN PERSPECTIVE

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ABSTRACT

Current conception of information in terms of bits cannot accommodate the holistic nature of perceptual information. Category theory, which describes mathematical objects in terms of their relations to other objects, appears to be resourceful enough to capture the holistic nature of perception and memory. Recognizing the potential of category theory, National Brain Research Centre, India, has initiated a research program to bring category theory and higher dimensional algebra to bear on brain research. I will discuss a memory model called Form-Addressed Memory that we are developing. In this model, percepts and memories are modeled in terms of arrows $f{:}A \rightarrow B$, an indivisible whole in category theory.

I will also present the work of various Indian scientists: non-classical information theoretic analysis of sensory systems, applying stochastic resonance to neuroimaging and pattern recognition tools to neuroanatomical data, development of federated databases, and plans for databasing drug metabolism pathways and neuroactive drugs from Indian traditional medicine.

1. INTRODUCTION

The goal of neuroscience is to account for various brain functions such as perception in terms of neural information processing. Successful implementation of this neuroinformatics program critically depends upon the theoretical framework with which we think and reason about information and its processing. Information also figures prominently in our answer to the question: 'what brain does?' Brain stores and retrieves information. Information storage and retrieval are the two faces of the coin - memory. Currently we model information in terms of bits, which in turn readily lends itself to the feature list model of perceptual information and memory. Though powerful with numerous technological spin-offs, the feature list model is incompatible with the holistic, contextual, and constructive nature of percepts that has been brilliantly illuminated by Gestalt theory in recent times [1]. Our percepts are irreducible wholes or forms.

When we read a novel we remember the gist or summary of the story, though we may have trouble recollecting the exact sequence of sentences and words in the novel. Our memories are not photocopies and remembering is not reading off from the photocopy instead of the original [2, 3]. Our memory of the story is more like a form or structure of the story. When we retrieve or recollect the information that is in our memory, we are representing the form in words just as an artist builds a sculpture of an object she has seen earlier in the medium of her choice. The relation between the information that is on the pages and that in our memory is analogous to the relation between words and meaning. Even when we remember a list of words and reproduce them from memory, we are not reproducing the exact power spectra of the sound. In a sense, words in our memory are the meanings of sounds we heard. The notion of memory as form or the holistic and constructive nature of memory has recently been brought into sharp focus again [4, 5].

In neural networks information –both the perceptual information and information in memory– is represented as a feature list and eventually in terms of bits, strings of 0s and 1s. An example, dog = [1 0 1], where 1 denotes the presence of a feature such as 'tail' and 0 denotes the absence of a feature. According to this model, we recognize a stimulus as a dog by comparing features in the stimulus with the corresponding features in the memory one after another i.e., using a bit-wise computation. This model is inconsistent with the experimental investigations of visual object recognition and scene categorization, which clearly show that our visual system is capable of recognizing various objects such as animals and flowers without necessarily recognizing their features [6, 7, 8, 9, 10].

To do justice to all these experimental findings, we need a theoretical method to capture all the relevant information about a percept or a memory without breaking it into pieces (features) and to represent that information in a way that is amenable to computation. Mathematics gives us a hint. Mathematical objects such as number or group are like percepts in that they are structures or wholes that have no internal contents and all the information about these structures is in their relations to other structures. For example, all the information that there is to know about the number '2' is in its relations to other numbers. Category theory, which models this particular facet of mathematics, can provide the necessary tools to develop a theory of neural information processing that accords with experimental data.

Category theory describes mathematical objects not in terms of their constituent elements but in terms of their relations to other objects [11]. A set that contains a single element (singleton set), for example, can be described as a set to which there exists only one function from any other set. Here we are describing a singleton set not in terms of its internal constituents (elements) but in terms of its relations to other sets. Taking a cue from category theory, we developed a model of information storage and retrieval wherein information is not a list of features, but is a unitary whole formally represented as an arrow $f:A \rightarrow B$, with A and B thought of as endpoints integral to the line segment f. We call this memory model Form-Addressed Memory to be contrasted with the content-addressable memories of neural networks. To facilitate comparison, we take the Hopfield model and replace the element-wise computations underlying information storage and retrieval with operations defined in terms of arrows and their composition.

2. FORM-ADDRESSED MEMORIES

We begin with a brief recap of the basic operations of memorization and recognition in Hopfield neural networks [12]. An object (perceptual information) to be memorized is represented as a feature vector $Y = \begin{bmatrix} y_1 \\ y_2 \\ . \\ . \\ y_n \end{bmatrix}$, a matrix with n rows and 1 column, an $n \times 1$ matrix. Memory W of the vector Y is obtained by multiplying the vector Y with its transpose $Y^T = [y_1\ y_2 \ldots y_n]$, a $1 \times n$ matrix. Weight matrix $W = YY^T$, an $n \times n$ matrix. The elements of the weight matrix $w_{ij} = y_i y_j$ denote the Hebbs rule. If the neural network is stimulated with Y after it memorized Y, the network recognizes the stimulus as Y. $WY = YY^TY = Yb \simeq Y$, since $Y^TY = \Sigma y_i^2 = b$, the scalar product of Y with itself. Moreover, the weight matrix W satisfies $WW = W$. $WW = YY^TYY^T = YbY^T = bW \simeq W$.

We now illustrate the methods of developing form-addressed memories by replacing the bit-wise computations (scalar product) with computations based on arrows and their composition. First, we provide a mathematical description of the information (percept), the vector Y, without referring to its internal contents, the elements y_i. Such a description may be treated as a holistic description. A $u \times v$ matrix Z can be represented as an arrow $Z:u \rightarrow v$. Matrix multiplication is given by composition of arrows subject to the condition that two arrows can be composed if and only if the target of one arrow is same as the source of the second. This intuitively corresponds to the idea that two journeys can be composed if the destination of the first journey is same as the starting point of the second. The vector Y is represented as an arrow $Y:n \rightarrow 1$ and its transpose Y^T as an arrow in the opposite direction $Y^T:1 \rightarrow n$. Memorizing Y corresponds to composing Y with its opposite Y^T. Memory, $W = YoY^T:n \rightarrow 1 \rightarrow n = n \rightarrow n$, where 'o' denotes composition of arrows. Figure 1 represents the process of memorizing percepts diagrammatically.

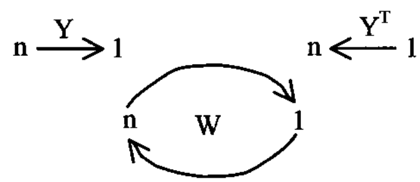

Figure 1. Percept Y and memory W of the percept.

In our model, memory W is an idempotent endomap, i.e., $WoW = W$ and $Y^ToY = I:1 \rightarrow 1$, an identity arrow [13]. Given these properties, we can readily show that if we present the information that was memorized i.e., Y as stimulus, the memory model will recognize the stimulus as Y, i.e., $WoY = Y$. $WoY = n \rightarrow n \rightarrow 1 = n \rightarrow 1 \rightarrow n \rightarrow 1 = n \rightarrow 1 = Y$. Recognition of the stimulus $Y:n \rightarrow 1$ by the memory $W:n \rightarrow n$ as $Y:n \rightarrow 1$ is depicted in the following commutative diagram (Fig. 2). Commutative diagrams assert the equality of two paths (Y and YoY^ToY) between two points (n and 1).

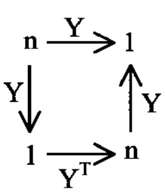

Figure 2. Recognition without bit-wise computations.

If we interpret the arrows as functions with sets as source and target of the arrows, memorizing information corresponds to adding structure i.e., an idempotent endomap to a discrete set (Fig. 3).

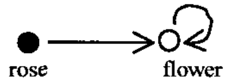

Figure 3. Idempotent endomap.

Let the stimulus information be a discrete set {rose, flower} where there is no way to relate one object 'rose' to the other object 'flower'. When the stimulus information is transferred to memory, then the objects in the memory are related to one another. The arrows in Figure 3 can be interpreted as 'is' [14]. Thus when the stimuli are memorized, we have 'rose is flower'. The fixed points of the idempotent endomap (e.g. flower) correspond to the minimum energy configurations in neural networks.

From a neurobiological perspective, synaptic strength w_{ij} is simply a concise notation for describing pre- and post-synaptic neurons x_i and x_j. In other words, when we say synaptic strength increased, we are simply saying that the number of receptors on the post-synaptic neuron or the amount of transmitter released by pre-synaptic neuron has increased. Along the same lines, we can think of a means to describe weight matrix W i.e., all the synaptic weights w_{ij}, w_{pq}, etc., as a single object. Our description of weight matrix W as an idempotent endomap $W:n \rightarrow n$ does just that.

The form-addressed memories that we have built are a generalization of the current neural network paradigm. In form-addressed memories, unlike the case of neural networks, the information to be stored and retrieved need not be a vector. Given the generalized nature of arrows in category theory, form-addressed memories can be used to compute with higher dimensional information. There is abundant data from experimental investigations of neural information processing underlying perception which suggests that higher dimensional objects such as 'squares' provide a more accurate depiction of neural information compared to the current conception in terms of bits. We discuss in detail these issues in our forthcoming paper [15]. The main motivation for developing form-addressed memories is to enable computations –classification and categorization– with these higher dimensional structures encountered in neuroscience.

3. DISCUSSION

There is a substantial body of category theoretic study of cognition by Ehresmann and colleagues, which among other things captures the key cognitive studies notion of 'whole is greater than the sum of its parts' in terms of colimit [16]. The present note, in a sense, is an invitation to category theory addressed to neural network community. This line of research can be extended further in many directions. We have modeled recognition as a one-shot process; we can also model the gradual iterative descent to stable states in neural networks using categorical shape theory [17]. Given that we represent information as arrows, comparison of arrows would require 2-dimensional arrows, which would eventually lead to n-categories [18].

Form-addressed memories bring out a key principle of neural information processing. In general terms, neural information processing is 'unification of opposites'. In the case of our memory model, neural information processing underlying memorization of a percept consists of composing the percept (an arrow, $A \rightarrow B$) with its opposite ($B \rightarrow A$). In neural networks, when we memorize a feature vector, we are composing (multiplying) the vector with its opposite (transpose). Thus the 'dog' in our memory is not an average of the 'dogs' we perceived, but is a composite of the percept 'dog' with its opposite. We will illustrate with an analogy. Consider a face of a coin, say, head. If we compare percept to head, then memory of the percept is the coin formed by composing or putting together head (percept) with tail (opposite percept). Memory, thus, is a completion of perceptual experience. This principle also applies to the neural information processing underlying perception, and clarifies what exactly we mean when we say 'visual perception is a creative process' [19]. Beginning with Hartline's discovery of contrast sensitive neurons to the relatively recent work of Hubel and Wiesel, we know that neurons detect change or contrast or boundaries [1, 20]. If edges or borders is the only sensory information available to the brain, then how do we see surfaces? Our perceptual world is not that of outlines. What is the nature of neural information processing that the brain applies to sensation to generate percepts. Here again brain takes sensation (change or contours) and composes with its opposite (constant or surface) to give rise to the percept of visual objects with their smooth surfaces and well-defined boundaries (e.g. computer in front of you). The notion that brain constructs percepts by composing sensation with its opposite is consistent with the current conceptualization of visual processing in terms of boundary and surface systems [21, 22, 23]. A key difference being instead of thinking of brain as filling-in point-by-point inside the outlines to obtain the percept, which cannot accommodate the recent work on afterimages [24], we suggest that brain, given sensation, constructs the opposite of sensation and composes it with sensation to generate the percept. To sum up, the neural information processing that transforms sensation into percept and percept into memory consists of creation and unification of opposites (Fig. 4).

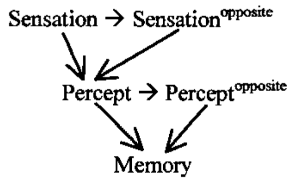

Figure 4. Creation and unification of opposites.

In addition to the memories of perceptual information that we have modeled, we have memories of sensation, concepts, and emotions [3, 25, 26, 27]. From an empirical standpoint, sensation, percepts, concepts, and emotions are clearly different from one another, but it has not been possible to formally distinguish them. Percepts and concepts are all represented as feature lists [28]. In our manuscript alluded to earlier [15], we argue that sensory, perceptual, conceptual, and emotional information constitute a hierarchy corresponding to that of points, lines, surfaces and solids, respectively. To calculate with these formal cognitive objects, the algebra of points (set theory) is not good enough. We need higher dimensional algebra - algebra of lines (or category theory), algebra of squares, cubes and so on [29]. Now that we have a formal description of the process of memorization independent of the nature of information that is being memorized, we can explicitly model memorization of sensation, percepts, concepts, and emotions while preserving their distinctions in the model.

It has long been recognized that the unit of learning and memory is a pattern [30]. Nevertheless the current neural network computations of pattern recognition, in view of the fact that they are based on computing scalar product or hamming distance between strings of 0s and 1s, are not really recognizing patterns. They are bit-recognition algorithms. In other words, pattern as a unit distinct from bits does never enter into the present-day neural network computations. Our representation of pattern as an arrow and pattern recognition via composition of arrows is a true pattern recognition algorithm. Our model readily lends itself to the development of gist-recognition systems and memory devices that can read a story and present a summary of the story, though much work remains to be done.

A defining characteristic of neural information processing is its contextual nature [1]. This contextual mode of brain function is particularly problematic to capture in terms of the current set-theoretic reductionist conception of the world. According to set theory, any object is completely determined by its elements, its contents. Whereas contextuality means 'what an object is' is determined by 'where it is' and not by 'what it contains'. For example, consider the meaning of the word 'banks' in the following two sentences: 'all banks are closed today' vs. 'we walked along the banks of Charles river.' The meaning of the word 'banks' is not determined by its contents but by its relations to other words. Within the framework of set theory we cannot provide a scientific account of contextuality since context is that which is left unaccounted for when we model any given object as a collection of elements or set. Fortunately, category theory, which recognized that a mathematical object's relations to other objects exhaustively spell out all the information about the given object, has developed methods to give a rigorous scientific account of contextuality or relational description of objects in the domain of mathematics. The similarity, from the perspective of context, between mathematical objects and cognitive objects such as percept, memory, and concept led us to put forth mathematics (as viewed from category theory) as a metaphor for brain to replace the currently popular computer metaphor.

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