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TOWARDS ARTIFICIAL MINDS

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The ultimate goal of cognitive sciences is to understand how the mind works and the ultimate goal of neural modeling is to build the artificial mind. Short summary of the state of art in this field is given. The symbolic/neural points of view are complementary rather than exclusive. The Floating Gaussian Model (FGM) introduced in this paper facilitates both neural and symbolic interpretations: supervised and unsupervised learning and self-organization of knowledge on the neural side, direct modeling of conceptual space, learning from general laws and retrieval of facts via searching procedures on the symbolic side.

1. INTRODUCTION

There are many interesting problems facing science today. There is, however, one problem that is so daring that many scientists treat it as a kind of utopia, never to be realized. Creation of artificial mind could have consequences that are impossible to predict. Is it feasible at all? In this short article I have tried to determine some properties that the artificial minds should have and describe a model that has some of the required properties. Understanding of the cognitive behavior is attempted at two different levels: mind, symbolic or software level; and brain, neural or hardware level. On the symbolic level there are conscious experiences, philosophical reflections on the nature of mind and thinking, psychological facts and theories, logic and artificial intelligence. On the hardware level there are electrical and chemical processes, many neurobiological and biochemical data about the brain, its structures, organization and operation, and the artificial models of neural systems [1,2]. A good model should reconcile these two levels.

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In the monist view the mind is the function of the brain, i.e. the symbolic/neural description is seen as complementary. This is much more fruitful assumption than the dualist philosophy, although a few famous brain researchers, such as Sir John Eccels or Wilder Penfield, turned to dualism in their later years, treating the brain more as a receiver rather than creator of mental states. Artificial intelligence is the oldest approach to artificial minds, focusing on the symbolic level and trying to imitate the results without understanding the real mechanisms. After almost 40 years precise limitations of such an approach are not yet quite clear. Symbolic AI projects, like CYC [3] still promise to capture human reason in a set of 100 million expert system rules. Nevertheless, one may argue that the AI has failed in many important aspects to deliver the promised machine intelligence.

Some experts look for the origin of the higher cognitive states at the quantum level [4], other speculate about the role of cell microstructures, such as microtubules. New approach to the artificial minds should start from the experimental data. Enormous amount of knowledge about the brain cells and their organization was accumulated, but it is not clear how relevant are all these details to the emergence of the mind as a result of brain's activity. After all the wings of the airplanes are much simpler than the bird's wings, but not less effective. More important is perhaps the knowledge of the structure of the mind. Cognitive science is sometimes described as the science of thought. Many experimental facts obtained by cognitive scientists give us precise data related to the mind at work. The interest in connectionist modeling grew very much in the past decade. There is no doubt that certain cognitive phenomena, such as associative memory, are relatively easily explained via neural type of models. Explanation of many other phenomena, such as language structures, logical and goal-directed thinking, or consciousness, appears to be rather difficult.

A synthesis of different approaches, symbolic and connectionists, is needed. First, I will list the minimal requirement for a system worthy of the name "artificial mind". Than a few remarks on the state of the art in cognitive modeling is given. In the main part of this paper I will describe a general network-type adaptive model that gives framework for cognitive modeling fulfilling some of the minimal requirements for the artificial mind. This model, capable of arbitrary associations, is viewed from both neural and symbolic points of view. From neural point of view it is a network of nodes acting as feature detectors, with feedback and local memory; from the symbolic point of view it allows for direct modeling of the conceptual space, employing a new way of knowledge representation, storing complex and fuzzy facts [5] and allowing for drawing inferences.

2. Artificial minds - what is required

Human mind is very complex and we should not expect that an artificial mind would be equivalent to human. Understanding of the world is determined to a substantial degree by our senses and past experiences. Creation of artificial mind (**AM**) capable of "understanding" and "making sense" of complex data is already a very ambitious goal. Is it possible to achieve it without access to sensory data? Examples of such people as Helen Keller, blind and deaf, who were able to communicate only via skin touch and gain most of their understanding of the world reading texts written in Braille alphabet (when Helen Keller wrote a book many people did not believe she did it on her own) seem to indicate that formation of the inner representation of the world via analysis of texts is to a large degree possible.

Minimal requirements that the artificial minds should fulfill to deserve that name are:

Universality: although human mind is not a logical reasoning devices but is subjective, full of prejudices, basing its judgment on previous experiences, it is commonly agreed that artificial mind should have the power of a universal computer (Turing machine).

Features of representation of the world, accepted by the AM should be represented by variables of logical, integer, continuous or fuzzy type associated with symbolic names. These variables may be divided into input, output and internal. Features correspond to symbols as well as subsymbolic representations that are hard to analyze verbally.

Inner world is made from combination of features of representation. Explicit representation of the inner world requires a feature space, with each independent feature taken as a separate dimension. Inner space contains **concepts**, corresponding to the symbolic level (mostly fuzzy concepts). The number of concepts should be very large, perhaps 100.000 is the lower limit for a rather simple mind. Some concepts are dynamic, like **actions** and unconditional responses to some inputs or learned sequences of responses.

Inner state is simply a state of all system variables. Some of the state variables appear to be conscious and these seem to appear one at a time. The number of possible inner states should be very large. Inner states partially mirror the input (world) states.

Understanding of the input patterns refers to the ability to predict and follow the change of these structures in the inner world. It involves **recognition** and **reasoning**.

Dynamics of the system changes the inner state in a usually coherent way and to a large degree is controlled by the input. The changes are determined by the learned patterns of state changes. Even in the absence of new inputs the **internal noise** causes random changes of states among neighboring states.

Learning of static and dynamic patterns: certain concepts or events are identified and memorized in a way that facilitates retrieval of such patterns. Learning requires **motivation** - in the simplest case the system may learn everything or may be set to learn selectively patterns connected with a certain set of ideas. Learning requires also **active exploration** by interacting with the world, asking questions and evaluating how interesting are the new structures that appear as answers.

Self-organization of the data and the ability to create new concepts (unsupervised learning). During the learning process AM should try to recognize the input data structures (make sense of them) and place them in relation to the other concepts it already has learned. If it is impossible new concepts are formed.

Generalization may be considered as rule learning when new output is required or as searching for the close-matching concepts when input is analyzed.

Attention or the ability to select from the large amount of input interesting data, disregarding the rest.

Language-like abilities are a unique feature of human mind. Ability to understand complex sentences is essential for such tasks as learning from texts and machine translation. The structure of the language reflects the structure of the world, therefore understanding of the natural language may require a mental picture of the situation.

Consciousness has access to some state variables, one at a time. The inner state is a model of the input data, using concepts that are accessible in the inner world. Among all features of mind consciousness is the most elusive, encompassing inner world, previous experiences, an idea of the self and the feeling that someone inside is watching the scene.

Reasoning has been for many years the favorite subject in AI. Goal-directed reasoning requires understanding and dynamics.

How far are we at present with realization of these minimal requirements?

3. Artificial minds - state of the art

Understanding of the mind is the main goal of the **cognitive sciences**. First, **cognitive psychology** has gained identity as a separate branch of psychology, soon joined by such branches of science as **psycholinguistics**, computational linguistics and computational vision. Knowledge representation issues became central to the artificial intelligence pursuit. **Cognitive philosophy** discussions influenced many cognitive scientists [1,2,6,7]. In the 1980s **neural models** started to gain slowly acceptance in the world of cognitive science but the discussion on the relevance of such models to understanding of cognition is still vigorous [2]. Most of the books on AI, written in the past few years, contain already chapters on neural models. Finally, in the 1990s serious theoretical attempts to understand consciousness appeared [8], together with neural computer hardware complex enough to exhibit interesting cognitive behavior [9].

A serious question concerns the relation between the brain and the mind. What is the level of **brain details** that the artificial mind models should take into account? Cognitive sciences tried to mimic the effects without looking at the **neurobiology**. Many cognitive scientists think that no reference to the brain is necessary, as no reference to the real computers is made in theoretical computer science. Other scientists try to make very complicated and precise models of single neuron. Recent results on the universality classes of neural nets built from different processing elements show that the time-dependent description of spiking neurons and the information transfer by frequency modulation does not give new computational powers to the system [10]. Logical two-state neurons are as good in this respect as any other, although the speed of learning and the efficiency of information coding obviously depends on the type of neurons. Results obtained for feedforward networks show that they may act as universal approximators with a wide range of the output functions of processing elements, including step functions, sigmoidal or localized Gaussian functions [11]. Therefore physiological plausibility does not seem to be a necessary ingredient of cognitive models, although detailed brain models are certainly very useful for understanding of brain functions [1].

Existing models of cognitive behavior are in most respects rather poor. Expert systems have very poor internal representation of the world. Neural models created so far are specialized, recognizing a small number of patterns. The number of concepts stored in linguistic networks is of the order of hundreds only [12]. An elegant theoretical approach to cognitive systems was given by Smolensky [13], integrating symbolic and subsymbolic domains of knowledge representation, unfortunately it was never developed into a useful computational framework. Without a clear model of the inner world other requirements for the artificial mind, such as attention or understanding are also hard to realize. Learning, generalization and language abilities were demonstrated by neural models in restricted domains. Self-organization of knowledge was achieved using Kohonen mappings [14] for small cases of less than one hundred concepts.

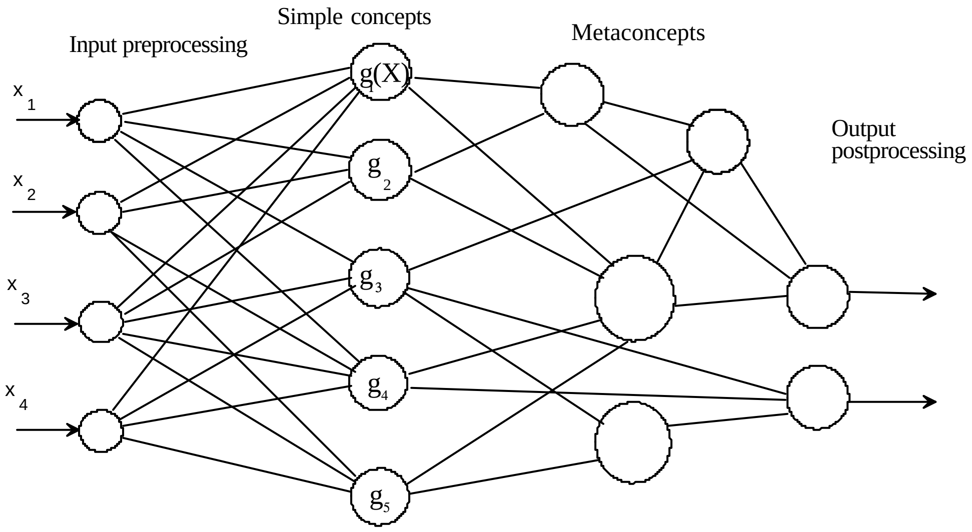
Consciousness is the most challenging of all aspects of the mind. A recent book by Douglas Dennett has a very provocative title "Consciousness Explained" [8]. Similar ideas are put forward in other recent books [1]. The mind is performing many things in parallel, the state of the mind is quite complex [6,7] but conscious cognition is serial. Dennett imagines a kind of virtual automata processing data. It is tempting to imagine that there is someone in our head, a homunculus, watching the "pictures in our head", a kind of "Cartesian Theater", as Dennett calls it. The problem is that it is impossible to find, via introspection, the one who looks (in fact Zen monks, masters of introspection, warn us that it is an illusion); any such attempt leads to infinite regress, looking at the one who looks at the one who looks...

In a recent book Aleksander and Morton [2] discuss in details the influence that the neural models may have on the cognitive science arguing that the question "neurons or symbols" is badly posed. In fact the whole book is a summary of the fierce debate of the neural and symbolic approach to cognitive science. The authors present a general framework for developing models of cognition based on a network of simple finite state model machines that they call **NSMM** (neural state machine model). Unlike typical neural networks connections of NSMM elements are not weighted. Training backpropagation networks is an NP-complete problem [15] and hence is slow and unreliable. The finite state automata was selected because the authors find it easy to link implementation of the system to its behavior. Such model is able to follow a prescribed program or it can learn simple facts and generalize.

Although the NSMM system is an interesting device for theoretical study it is rather impractical and does not show the missing link between the symbols of the **inner space** and the **neural structure**. Moreover, concentrating on the finite state machines it is hard to grasp the fuzziness of symbols and concepts used by humans. I will introduce now another model that may be reduced to NSMM but is more practical and more direct. I will use the acronym **FGM** (Floating Gaussian Mapping) to refer to this model. The inner representation of concepts in FGM is fuzzy, although they may be as sharply defined as one requires. It is convenient to present FGM model in a form of a network, although it does not have to be a neural network using distributed representations. FGM is an adaptive system, creating its internal representation of the incoming data, and adapting itself to the new data, allowing for small corrections. In my view logical approach to AI fails because it is impossible to make "fine tuning" and self-organization of the knowledge captured in fixed symbols - something that is quite natural in FGM.

4. Neural/symbolic model of mind

One could avoid many problems facing neural networks - long training times, problems with false minima, realization of serial algorithms, lack of symbolic interpretation - by constructing the functions realized by the network in an explicit way. The simplest node functions with suitable properties are of the gaussian type. Other functions, like products of two sigmoid functions $\sigma(x)(1-\sigma(x))$, or the sigmoid functions $\sigma(-\|X-D\|^2)$, are very similar to the gaussian, but only the gaussian functions are factorizable:

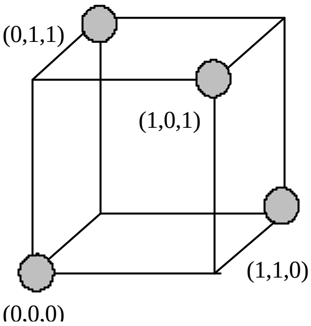


Example of the network realizing Floating Gaussian Mapping

$$G(X,D) = e^{-\sum (X_i - D_i)^2/\sigma_i} = \prod_{i=1}^{N} e^{-(X_i - D_i)^2/\sigma_i}$$

In the N-dimensional space this function has non-vanishing values around the point D. Each node in the network computes one or more of such functions. Factorization is crucial in reduction of multidimensional searches to a series of one-dimensional searches. Gaussian functions will be centered on the data vectors $D=(D_1, D_2, ... D_N)$ with dispersion proportional to the error or uncertainty of the variables D_i. A generalization to the asymmetric gaussian functions is straightforward, giving greater flexibility in modeling various density distributions [16].

Each variable defines a new dimension, the data vector is a point and together with the associated uncertainties the data vector defines an ellipsoid in N-dimensional space, given by a constant density of *G(X,D)* function. Gaussian functions are a fuzzy representation of these data points. Thus a direct connection of the neurons and the symbols is made. Indeed, there is functional equivalence of the two approaches. I will use the term "fact" for a collection *D* of input and output values that we want to store in the FGM adaptive system. Facts belong to the conceptual space which has many dimensions but is finite. In case of human knowledge the number of concepts, or **elements of reality** that we are able to distinguish, is of the order of 10^5 . Combinations of these elements create facts and mental models. Each network node corresponds to a concept; a distributed neural representation of node's function by a specialized neural net is possible. I have justified elsewhere [17] that if the amplitudes rather than frequencies carry the information in the network than processing elements (nodes) in neural network models should filter the data rather than act as simple threshold devices. Single neurons in the brain may selectively react to a very specific sensory data, giving plausibility to our assumption.



Solution to XOR problem in the C-space.

CONCEPTUAL SPACE. The FGM function for a collection of facts **D**={D^p} has the following general form:

$$FGM(X,\mathbf{D}) = \sum_p W_p G(X,D^p) = \sum_p W_p \prod_i e^{-(X_i-D}$$

and does not vanish only around the data vectors **D** stored in the FGM function. The weights **W** and the dispersions **s** are the adaptive parameters defining FGM mapping for a given set of **D** input values. If the data values are noisy also the gaussian centers **D** may be treated as adaptive parameters as it is done in the LVQ model [14], facilitating "fine tuning" and self-organization of knowledge.

The simplest nontrivial problem for neural networks is the XOR (exclusive OR) since it defines mapping that is not linearly separable:

$$(0,0) \to 0, (1,1) \to 0, (1,0) \to 1, (0,1) \to 1$$

In the FGM linear separability is never an issue since all data points are defined in the space of inputs and outputs. In this case FGM function has 4 additive factors with the non-zero values sharply concentrated in 4 corners of the cube defined in the conceptual space (C-space). One may think, in a natural way, about concepts and symbols in the C-space, and go back and forth between the symbolic and network descriptions.

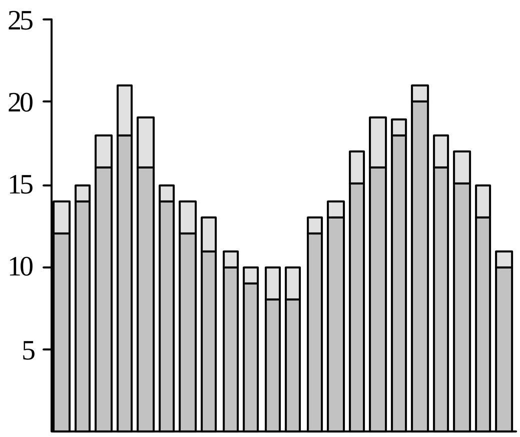
Although the model allows for many choices I will investigate in this paper only the simplest one: W_p parameters will be taken as 0 or 1, and the true facts are equivalent to FGM values around 1. There is no problem with storing negative knowledge, i.e. the facts that must not be true - one of the axis may be labeled as true/false and the position of the gaussian on this axis will correspond to the true/false facts.

REASONING. Perhaps the most **distinct feature of FGM** model is the way associations are retrieved or inferences from partial input data are made. If there are many factors influencing the answer and some elements are fixed humans frequently reason by making a series of one-dimensional searches, i.e. assuming for a moment that only one additional factor is important, fixing the value of this important factor and moving to the next factor. An expensive alternative is searching in many dimensions, trying to fix all missing factors describing one fact (like in simulated annealing). The searching strategy in FGM [17] is more similar to what humans do, as will be clear from the examples presented below. The searching algorithm will find all facts consistent with the fixed values of the known factors, not only the best one; the depth of the search is equal to the number of unknown factors, which is usually not large. The number of facts checked is at most equal to the number of relevant facts, since not all nodes are connected to all inputs: some facts may be totally irrelevant since their input space may be completely orthogonal to the input space of the question at hand. Searches are **one-dimensional**, therefore at a given stage the value of only a single gaussian factor is computed.

Multilevel approach to learning in FGM systems is possible: focusing on relevant data by making all facts very diffused at the beginning of the search procedure and than reducing the gaussian ellipsoids to smaller regions in conceptual space. For large dispersions at most points of the parameter space the values will be non-zero and gradients will allow to find the closest matching facts. This is analogous to transition from the general intuitive ideas to precise, logical reasoning in a restricted area. An easy way to estimate the importance of various factors at arriving at the fact is to look at dispersions: those factors with small dispersion are probably decisive.

I will give now a few **examples** of what the FGM networks can do. Problems involving learning associations, generalization, inference and logical relations are easily solvable via FGM. Even simple problems involving counting and manipulation of numbers require recursive approaches - although solvable by FGM they are more difficult and shall not be presented here. In principle FGM network should do all that NSMM is capable of [2].

ASSOCIATIONS. Many examples of associations and retrieval of information from partial inputs, as given in the PDP books [13], are solved in a trivial way by the FGM model. Several neural network models are tested on the **schemata for rooms** (cf. [8], Vol. II, p. 22). 40 descriptors are given for five different kinds of rooms: living room, kitchen, office, bathroom, bedroom. One can create FGM mapping giving examples of room furniture plus other descriptors for these schematic rooms and retrieve a prototype room description from partial description. Most of these descriptors, like oven, computer, toilet, are of the binary type (present - not present), some have few values (room size may be very-large, large, medium, small, very-small). Treating all descriptors as binary 40-dimensional hypercube is obtained with 2^{40} possible states (corners). The 5 schemata for rooms correspond to more than 5 corners of this hypercube since many descriptors are not unique to one schemata. However, in this 40-dimensional space there are only 5 areas, overlapping in some dimensions but well resolved in others, defining the schemata for rooms. Rumelhart *et.al.* [8] estimated the probability that each of these descriptors are present in the schemata for a given kind of room. One may use these probabilities to set dispersions for different descriptors of the 5 network nodes that correspond to the 5 schemata. One additional dimension is added, for the name of the room, kept with other descriptors as a concept (fact) in the C-space. The network has 41 external lines (treated as inputs/outputs) and 5 hidden nodes.



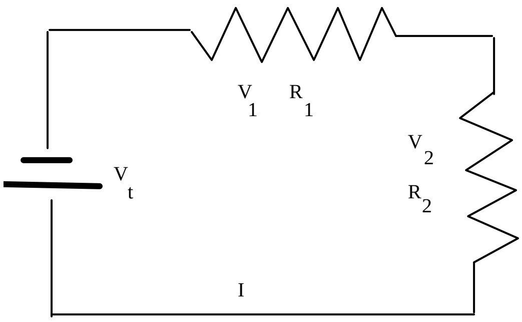
Histogram of a spectrum with error bars corresponding to a gaussian function in 22 dimensions.

This example illustrates how the FGM searches are made. **Fixing the room type** all descriptors forming a room schemata are easily recovered in 40 steps, each a binary check-up. **Fixing one descriptor** that is characteristic to some room schemata, like an oven, recreates the whole schemata for kitchen. Fixing descriptors that could apply to many rooms, like telephone, will activate several searching paths (at most 5). A question like "can the kitchen have a telephone" requires fixing the type of room variable at kitchen and checking the telephone variable, with the dispersion of the telephone variable and the value of FGM function estimating probability of positive answer to the question.

The FGM representation of the room schemata may be regarded as an example of a database, returning the results of the queries with probabilistic interpretation. In physics and chemistry many databases of such kind are needed. As an example of nontrivial associations that FGM is capable of let us consider a spectrum stored in a form of a histogram. Since the spectrum corresponding to a given chemical system may be distorted each value of the histogram is given with an error bar equal to the dispersion of the gaussian in a given direction. The gaussian represents therefore a range of spectrums (a fuzzy spectrum) connected with the same chemical system. A database of spectrums allows for identification of many different systems from distorted spectra or partial spectra. Thanks to the gaussian product form of the FGM function multidimensional searches do not lead to prohibitive retrieval times.

LEARNING FROM GENERAL LAWS. Frequently the knowledge is derived from a set of examples. In many cases there are general laws that may be applied to a given situation. These laws may be either deduced from examples or stored as *a priori* knowledge. Neural networks are usually trained on examples while expert systems are based on the rules: FGM model can do both.

When thinking we do represent the knowledge contained in equations in qualitative way. Ohm's law **V**=**I**∗**R**, for example, involves 3 parameters, voltage **V**, current **I** and resistance **R**. A set of training facts is derived and internalized as "intuition" from this law: when the current grows and the resistance is constant, what happens to the voltage? If we designate changes of **V**, **I** and **R** as + for increase, 0 for staying constant and – for decrease, than the number of all possible combinations of the 3 values for the 3 variables is $3^3 = 27$. Ohm's law says in effect that only 13 of them are true, for example if **V** is constant **I** and **R** may not decrease or increase simultaneously.

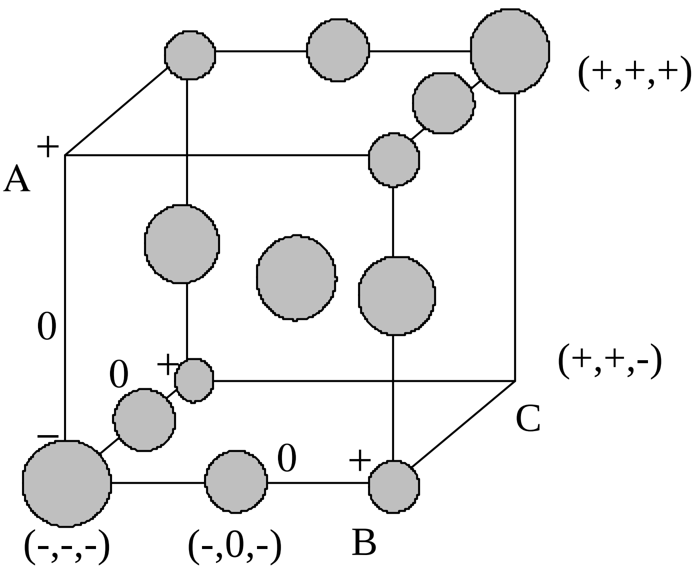


$$V_t = V_1 + V_2$$
$$R_t = R_1 + R_2$$
$$V_1 = I \cdot R_1 ; V_2 = I \cdot R_2 ; V_t = I \cdot R_t$$

A convenient way of expressing intuitions about Ohm's law or any other law of the form A=B∗C or A=B+C, in general A=f(B,C), are facts expressed as:

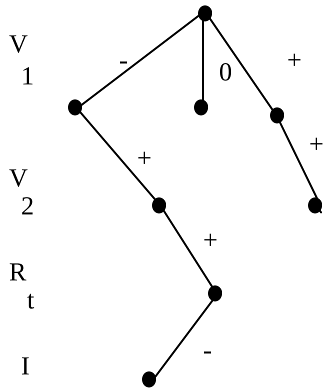
(A,B,C) = (+,+,+), (+,+,0), (+,0,+), (+,+,–), (+,–,+)
(0, 0, 0), (0,+,–), (0,–,+),
(–,–,–), (–,– –,0,–), (–,+,–), (–,–,+)

The relevant part of the C-space representing these facts is shown on the next page. I will present now a more complicated example of the FGM application for representation of qualitative knowledge necessary for understanding of electric circuits. Although the circuit



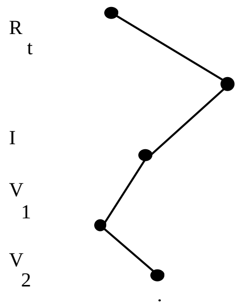
Representation of relation A=B∗C or A=B+C in FGM model.

shown here is very simple untrained people need some time to answer questions about current/voltage changes in the circuit. There are 5 relevant equations:



Each equation has 3 variables. Five 3-D subspaces (cubes), corresponding to these equations, are present in the 7-dimensional ($\mathbf{V_t}$,$\mathbf{V_1}$,$\mathbf{V_2}$,$\mathbf{R_t}$,$\mathbf{R_1}$,$\mathbf{R_2}$,$\mathbf{I}$) space. The question that one may ask now may be of the following type (Smolensky, 1984, in: [13]): if $\mathbf{R_2}$ increases and $\mathbf{V_t}$ and $\mathbf{R_1}$ are constant what happens with $\mathbf{I}$ and $\mathbf{V_1}$, $\mathbf{V_2}$? This example was originally given for the Boltzman machine and the harmony model type of neural network and is not so trivial to solve in these models: answering such a question is done via multidimensional searches using simulated annealing and require lengthy computations giving sometimes wrong results. In the FGM the answer requires searching for non-zero values at a few points of the function FGM($\mathbf{V_t}$=0,$\mathbf{V_1}$,$\mathbf{V_2}$,$\mathbf{R_t}$,$\mathbf{R_1}$ =0,$\mathbf{R_2}$ =+,$\mathbf{I}$) along the four ($\mathbf{V_1}$,$\mathbf{V_2}$,$\mathbf{R_t}$,$\mathbf{I}$) directions. Since all 5 equations have to be fulfilled simultaneously total FGM function is taken as a product of 5 node functions, each containing 13 terms (shown in the C-space above) corresponding to the internalized intuitions about equations.

The search goes first along $\mathbf{V_1}$ dimension. For $\mathbf{V_1}$=+ the FGM function does not vanish, therefore a search for the second variable is initiated. FGM does not vanish only for $\mathbf{V_2}$= + and only one unknown is left: FGM($\mathbf{V_t}$= 0, $\mathbf{V_1}$ =+,$\mathbf{V_2}$ =+, $\mathbf{R_t}$, $\mathbf{R_1}$ = 0, $\mathbf{R_2}$ = +, $\mathbf{I}$). The function vanishes for all values of $\mathbf{R_t}$ therefore a step back is made and $\mathbf{V_1}$ = 0 taken. The only values of ($\mathbf{V_2}$, $\mathbf{R_t}$, $\mathbf{I}$) for which FGM function does not vanish are (+,+,–). Only few nodes have been visited in the search procedure, the process has some similarity to the usual human



reasoning in such cases. More experienced people will first choose the ordering of variables: if **R_1** = 0, **R_2** = + than it is obvious that **R_t** =+ and since **V_t**= 0 therefore **I** has to decrease and **V_1** = –, **V_2** =+.

If the variables in the FGM function are reordered the search may be shorter, starting from FGM(**R_1** = 0, **R_2** =+, **R_t** , **V_t**= 0, **I**, **V_1**, **V_2**). The "reasoning process" is more ordered now. The dependence of the reasoning, or drawing inferences, on the search strategy is similar to what the humans do: trying several possibilities and than changing the strategy if it doesn't work. How to select the best search strategy? This meta-knowledge about the solutions of problems is learned from examples when we solve a number of problems. It can also be coded in the FGM models. The search in a 4-dimensional space of unknown variables is replaced by a series of searches in the one-dimensional spaces. The knowledge stored in the FGM may be treated as **heuristics** used in the expert systems to reduce the blind search procedure. The last search procedure is illustrated in the drawing below.

Fuzzy character of facts stored in the FGM allows for representation of many data using a modest number of facts or network nodes. One of the models of associative memory, CMAC (Cerebellar Model Arithmetic Computer), derived from data on cerebellar function, consists of mapping from the input space to the "conceptual space" in which each point becomes a circle [19]. FGM model may be regarded as generalization of CMAC model to a fuzzy decision regions and the nodes of FGM network represent the non-zero regions of conceptual space.

To avoid excessive number of facts in our conceptual space and to preserve good generalization training data are represented by fuzzy facts. Learning for **large amount of data**, as in the case of handwritten character recognition, is done in the same was as in the Learning Vector Quantization method [14]. Instead of the codebook vectors **m_c** gaussian (or asymmetric gaussian) functions are used and the distance of the input data **X** to the nearest fact (center of a gaussian found along the gradient at point **X**) in the C-space is calculated. The FGM adaptive system tries to minimize an error function by adapting the positions of gaussians and their dispersions. In some applications, where facts are sharply defined, one may prefer less generalization in the inference procedure, keeping the conceptual space almost empty (small dispersions), while in other applications conceptual space should be divided in decision regions that cover the whole space (large dispersions). New facts are allowed if the knowledge stored in the old facts cannot be stretched to cover new data. For a large number of facts the system may work in a **self-organizing** mode, reflecting the density of the probability function of the input data p(**X**). Kohonen has described formation of topological maps of patterns in a self-organizing systems. To achieve this self-organization each new input data point **X** should influence not only the fact in the C-space that matches the data in the best way, but also facts in the larger neighborhood of conceptual space should be pulled in the direction of **X**. This algorithm finds in an unsupervised way interesting features in the data and allows for fine-tuning of learned knowledge.

RELATED APPROACHES. An approach similar to FGM is the theory of **abductive reasoning networks** [18]. Abduction is the reasoning process, or deductive process, under uncertainty. In this approach numeric functions and measures are used in the reasoning and for the description of relationship among the data items. A network of functional nodes performing numerical operation on data items is called an abductive network. In practice a hierarchical, feedforward layered network structure is used, with the approximations by linear, quadratic and cubic functions of the spline types. To avoid too many adjustable parameters in networks of this type data items are grouped together and the relationships in each group summarized in a node that passes the values to the next layer. This subdivision of the problem is an approximation that does not always work and is avoided in the FGM model. The Abductory Induction Mechanism (AIM) is the machine-learning procedure that attempts to determine automatically the best network structure, type of nodes, connectivity and coupling coefficients minimizing the combined error measure and network complexity, proportional to the ratio of the number of network parameters and the number of training data. Abductive networks are a particular type of **fuzzy expert systems**.

5. Conclusions

For the first time in the history detailed theories leading to construction of artificial minds are formulated [1,2,6-8]. Although at present there are no realizations of the artificial minds fulfilling our minimal requirements it is quite likely that some interesting systems will appear before the end of this decade. Hardware build for complexity, not for speed, developed for connectionist neurocomputers [9] should enable much richer inner representations of data than it is currently possible.

FGM model introduced here bridges the gap between symbolic and neural orientations, offering a model of certain cognitive features. FGM facilitates: symbolic interpretation, direct modeling of conceptual space, fuzzy facts, association, generalization, supervised and unsupervised learning, learning from general laws, fine tuning of knowledge, self-organization of knowledge, retrieval of facts via one-dimensional searches, multi-scale approach to concentration on relevant parts of conceptual space. This approach is based on networks of processing elements acting as feature detectors instead of typical threshold elements of neural network models. Although FGM may not yet be a suitable model for an artificial mind I do not know what are the limitations of this model.

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