Artificial Neural Networks
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INTERPRETING IMPRECISE EXPRESSIONS: EXPERIMENTS WITH KOHONEN'S SELF-ORGANIZING MAPS AND ASSOCIATIVE MEMORY

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A vast majority of the present computer models of natural language processing are based on symbol manipulation, and especially work concerning semantics relies heavily on formal symbolic logic. Resulting models consist of a set of entities and relations connecting those entities. Words in natural languages, however, seldom are entities with such precise meanings and, therefore, cannot be accurately modelled with symbolic logic. The meaning of a word, say 'big', is not an entity with fixed boundaries precisely and constantly separating what is big from everything that is not big. Much more commonly, a meaning is fuzzy and changing, biased at any moment by the particular context. As such, words and their meanings bear an underlying similarity to self-organizing neural network computer models. We argue that such connectionist models have substantial advantages for dealing with knowledge acquisition and for handling context-dependency, exceptions, and the relations between words and meanings. In the present paper we present simulations in which Kohonen's self-organizing feature maps and associative memory are used to model the interpretation of some imprecise expressions. We also show some results on how to model the subjectivity of meanings.

1. SOME REMARKS ON INTERPRETATION OF IMPRECISE EXPRESSIONS

There are tasks in which reality or "pictures of reality" are mapped into linguistic expressions. Finding "entities" from a picture is not a trivial task, as revealed by attempts to give computers such pattern recognition abilities. Attempts based upon trying to specify the features of an entity usually succeeded only with highly constrained unnatural stimuli. A more promising approach has been found with self-organizing systems in which computers, like humans, learn to perceive.

A similar problem exists in the expression of natural languages. Through a gradual process of learning, people develop exquisite skills for dealing with words despite their imprecision and contextual dependency. People are fairly good at mapping continuous parameters (e.g. size) into apparently discrete expressions ("tiny", "big", etc.). A person understands that there may be subjective differences ("big" may mean something different to a child than to a adult), strong contextual influences ("big" in "big city" has different connotations than in "big fly"), and imprecision (in a given context, a person may reliably call one stimulus "moderate" and another "big", but in between is a gray range of stimuli not clearly one or the other). A person also reacts to the "surplus meanings" and associations to a word. E.g. "large" is a more sophisticated, less childish word than "big" and thus more likely to be used in scientific writing (a large difference between groups) or advertising aimed at adults (a large automobile). All of these ambiguities are dealt with accurately and indeed employed usefully by most adults in their language usage and understanding.

2. METHODS FOR SIMULATING NATURAL LANGUAGE UNDERSTANDING

Most computer models in semantics bear little resemblance to the way humans deal with words. The models based on symbolic deductive logic use propositions, truth-values, quantifiers, and connectives as the main building blocks for their theories of natural language. Reality is seen as consisting of discrete entities and relations connecting those entities. The relation between natural language and the world is seen as a one-to-one mapping.

The use of symbolic logic for modelling natural language semantics has been strongly criticized in several studies (cf. [1], [2] and [3]). There have been two more or less traditional ways used to try to solve the problems encountered with symbolic, deductive logic: the use of induction and the use of fuzzy logic. They both adopt the symbol-based paradigm. An important alternative is the use of the connectionist models and the artificial neural nets. Ritter and Kohonen [4] have presented in their novel work a self-organizing system which creates representations of lexical relationships. McClelland and Kawamoto [5] have developed a system which assigns roles to the constituents of sentences.

Our experiments here are based on Kohonen's self-organizing feature maps and associative memory. In the following, the methods are shortly introduced (sections 2.1 and 2.2) and the results of the experiments on the interpretation of imprecise expressions are presented (section 3).

2.1. Self-organizing feature maps

The *self-organizing maps* are based on the idea that neurons organize themselves to tune to various and specific patterns ([6], [7]). Kohonen has made a strong use of competitive learning in his Self Organizing Feature Maps [7]. Kohonen's algorithm creates a learning vector quantizer (LVQ) by adjusting weights from common input nodes to output nodes arranged in a two-dimensional grid. The output nodes are extensively interconnected with many local connections. The weights specify clusters that sample the input space such that the point density function at the centers of clusters tend to approximate the probability density function of input patterns. Denote the weights of processing neural units by m_r and the class where m_r belongs by C_r. The weights are updated as

$$m_c(t+1) = m_c(t) + a(t)(X(t)-m_c(t)), \qquad \text{if } m_c \in C_c \text{ and } X \in C_c$$
$$m_c(t+1) = m_c(t) - a(t)(X(t)-m_c(t)), \qquad \text{if } m_c \in C_c \text{ and } X \notin C_c$$
$$m_i(t+1) = m_i(t), \qquad \text{if } i \neq c$$

where X denotes the training vectors and a(t), $0<a(t)<1$, is a real monotonic decreasing function.

2.2. Associative memory

The temporal associative memories [7] can define a mechanism by which timed sequences of states can be memorised and reconstructed. An associative memory holds copies of distinct "taught" input signals and is able to produce the particular input signal from a part of it. Denote the input signals by $\mathbf{x}=\{\xi_1, ..., \xi_n\}^T$, the output signals by $\mathbf{y}=\{\psi_1, ..., \psi_m\}^T$ and the weight matrix $\mathbf{M}= \{\{\mu_{00},...,\mu_{0m}\}^T,...,\{\mu_{n0},...,\mu_{nm}\}^T\}$. The system of equations

$$\psi_i = \xi_i + \sum_{j=1}^{m} \mu_{ij}\psi_j, \qquad d\mu_{ij}/dt = \alpha\psi_i\psi_j,$$

describes a simple adaptation of weights. Equation can be transformed into form $\mathbf{y} = (\mathbf{I}-\mathbf{M})^{-1}\mathbf{x} = \Omega\mathbf{x}$. According to [7] this leads to the matrix Bernoulli equation of fourth degree. Denote the matrixes formed of vectors $\mathbf{y}(t_i)$ and $\mathbf{x}(t_i)$ at t_i, $i=t_0,...,t_k$, as $\mathbf{Y}$ and $\mathbf{X}$. The best solution in the least-squares sense is obtained with the pseudoinverse [7] as $\Omega = \mathbf{YX}^+$. An approximate solution for the equation is $\Omega(t) = \mathbf{I} + \alpha\int^{t}\mathbf{x}^T(\tau)\mathbf{x}(\tau)d\tau$. The product $\mathbf{x}^T(\tau)\mathbf{x}(t_0)$, $t_0>\tau$, measures the similarity between $\mathbf{x}^T(\tau)$ and $\mathbf{x}(t_0)$. The components of $\mathbf{x}^T(\tau)$ dominate which match with the key pattern $\mathbf{x}(t_0)$. Thus the system forms a memory, and is called as Autocorrelation Matrix Memory (ACMM).

3. EXPERIMENTS AND RESULTS

A set of persons were asked to describe the size of rectangles they were shown. Triples with the width, the height and the adjective, was used as an example set for Kohonen's self-organizing map.

tiny	tiny	small	small	small	high	high	high	high
tiny	tiny	small	small	small	high	high	wide	wide
tiny	tiny	tiny	small	narrow	narrow	narrow	narrow	mass.
moder.	moder.	low	low	narrow	narrow	narrow	large	large
moder.	flat	low	low	moder.	big	big	large	large
flat	low	low	low	big	big	big	big	large
flat	low	low	low	big	big	big	big	large
flat	low	low	wide	wide	big	mass.	huge	huge
flat	flat	wide	wide	wide	mass.	mass.	mass.	huge

Figure 1. The cells labeled by the adjective eliciting strongest response.

After several hundreds of iterations, the map of 9*9 output neurons had organized itself so that the relation between the adjectives was reasonable (Fig.1): "small" and "big" adjectives were in their own distinct, widely separated sectors and "high" and "low" in their own, respectively.

As a result it was also noticed that the map showed how general or specific each adjective is: e.g. words 'big' and 'small' occupied relatively larger territory. A similar result was presented by Ritter and Kohonen [4] concerning the relations between general and specific terms.

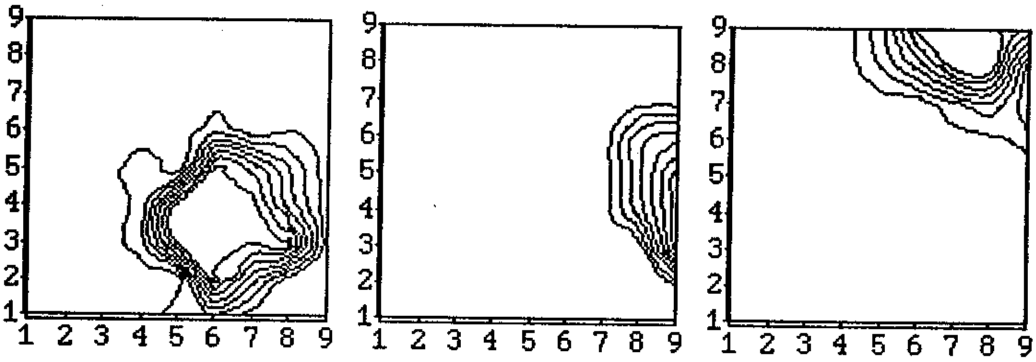

Figure 2. Contour maps for the adjectives a) big b) large and c) high. The area of the general term 'big' is larger than that of the other terms. (The coordinates refer to the neuronal grid.)

The associative memory model (see chapter 2.2) was used to simulate a context-dependent interpretation of the words 'some' and 'many'. The results were encouraging: with a rather small input material the noun to be qualified caused a different interpretation. For example "some friends" tends to become interpreted as a smaller amount of persons than "some people".

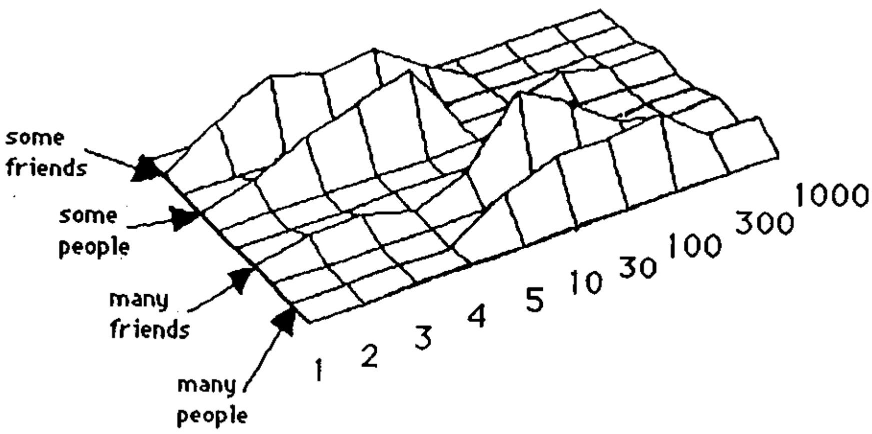

Figure 3. A simulation of a context-dependent phenomenon: the meaning of the words 'some' and 'many' is dependent on the noun they qualify.

The experiment using associative memory was enhanced to model personal differences in interpreting adjectives. Two sets of input vectors were used: the first one presented person A's descriptions of m*n sized rectangles and the other person B's. In figure 4 results are shown so that input vector contained knowledge of the person and the size of the rectangle. Only squares from size 1x1 to 9x9 were used which suppressed adjectives like 'low' and 'flat'. The results show some differences in the use of expressions. As an example person A would use words 'big' and 'small' more frequently while B uses richer vocabulary.

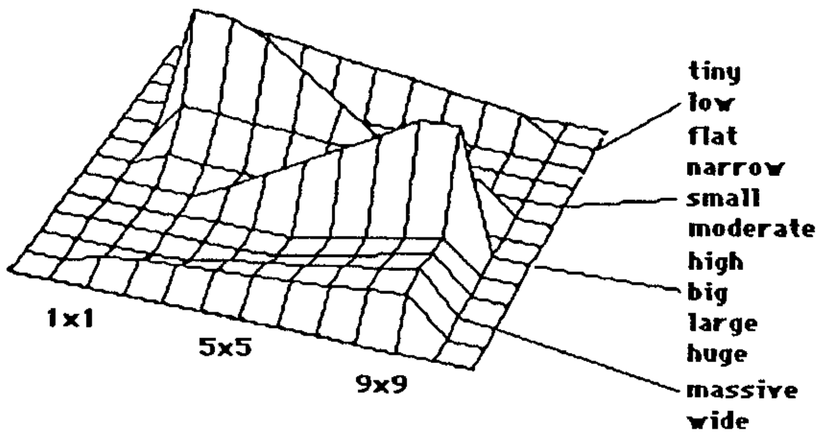

Figure 4. a) Associative mapping from squares of different sizes into various adjectives. Mapping is a result of examples given by person A.

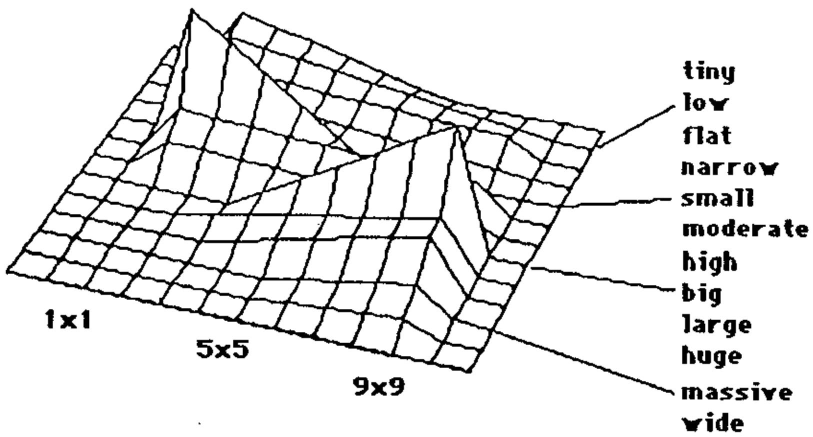

Figure 4. b) Associations as a result of person B's examples. Differences concerning e.g. words 'wide', 'massive' and 'large' are notable.

The associations reflect differences in the input. One possible way of use could be such that the system tries to "guess" what is the word each person would use in a certain situation.

4. CONCLUSIONS

In the connectionist model, the computer acquired knowledge via examples and the output neurons, through self-organization within the network, became organized in a manner resembling the likely semantic mapping of humans, with imprecise boundaries between concepts, contextual dependency and individual differences. We argue that connectionist techniques are an important method in the research concerning the semantics of natural language. Possible application areas are information retrieval (see e.g. [9]) and machine translation.

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