Memory Functioning in Psychopathology II

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Abstract

In an earlier paper [17], we described the mental pathology known as neurosis in terms of its relation to memory function. We proposed, based on a neural network model, that neurotic behavior may be understood as an associative memory process in the brain, and that the symbolic associative process involved in psychoanalytic working-through can be mapped onto a corresponding process of reconfiguration of the network. As a first approximation, memory was modeled by a Boltzmann Machine represented by a complete graph. However, it is known that brain neuronal topology is selectively structured. In this paper, we further develop the memory model, by including some known microscopic mechanisms that control synaptic properties, showing that the network self organizes to a hierarchical, clustered structure. The model is illustrated through a computer simulation, where we show some mathematical properties of the resulting complex network.

1. Introduction

Psychoanalytic research regarding the *transference neuroses* has found that traumatic and repressed memories are knowledge which is present in the subject, but which is inaccessible to him. It is therefore considered *unconscious* knowledge [6]. Freud observed that neurotic patients systematically repeated symptoms in the form of ideas and impulses, and called this tendency a *compulsion to repeat* [7]. He related the compulsion to repeat to repressed or traumatic memory traces, caused by a conflict associated with libidinal fixation and frustration [6].

Neurotic analysands have been able to obtain relief and cure of painful symptoms through a mechanism called *working-through*. This procedure aims at developing knowledge regarding the causes of symptoms by accessing unconscious memories, and understanding and changing the way the analysand obtains satisfaction [7]. Lacan emphasizes the creative nature of transference [11].

Although inconclusive, psychodynamical theories seem to suggest correlations between creativity, psychopathology and unconsciousness [6, 7, 11, 14, 13]. We explored these commonalities and proposed, in a previous paper [17], a schematic functional model for some concepts associated with neurotic mental processes, as described by Sigmund Freud and further developed on by Jacques Lacan [6, 7, 11]. Our description is based on the current view that the brain is a cognitive system composed of neurons, interconnected by a network of synapses, that cooperate locally among themselves to process information in a distributed fashion. Mental states thus appear as the result of the global cooperation of the distributed neural cell activity in the brain [10, 15]. We also consider that the emergence of a global state of the neural network of the brain generates a bodily response which we call an *act*.

As a first approximation, in [17] memory was modeled by a Boltzmann Machine represented by a complete graph. It is known, however, that brain neuronal topology is selectively structured. Neurons interact mainly with spatially close neighbors, having fewer long-range synapses connecting them to other neurons farther away [8, 10]. In this paper, we further develop the memory model, by including some known microscopic mechanisms that control synaptic properties, and show that the network self organizes to a hierarchical, clustered structure. We thus represent brain mechanisms involved in neurosis, as a complex system, based on a neural network model and analyse it according to recent methods developed for the study of complex networks.

In the next section, we review our functional and computational model for neurosis. In Section 3, we describe a self-organizing model for generating hierarchically clustered memory modules, representing sensorial and declarative memories. We then show results from computer simulations with some mathematical properties of these complex networks. In the last section, we draw some conclusions and perspectives for future work.

2 Functional and Computational Model for the Neuroses

In this section, we review the model described in [17]. There we proposed that the neuroses manifest themselves as an associative memory process, a mechanism where the network returns a stored pattern when it is shown another input pattern sufficiently similar to the stored one [9]. We modeled the compulsion to repeat neurotic symptoms by supposing that such a symptom is acted when the subject is presented with a stimulus which resembles, at least partially, a repressed or traumatic memory trace. The stimulus causes a stabilization of the neural net onto a minimal energy state, corresponding to the memory trace that synthesizes the original repressed experience, which in turn generates a neurotic response (an act). The neurotic act is not a result of the stimulus as a new situation but a response to the repressed memory trace. Repression can be accounted for by a mechanism which inhibits formation of certain synaptic connections, in the cortical map formation process.

We mapped the linguistic, symbolic associative process involved in psychoanalytic working-through into a corresponding process of reinforcing synapses among memory traces in the brain. These connections should involve declarative memory, leading to at least partial transformation of repressed memory to consciousness. This has a relation to the importance of language in psychoanalytic sessions and the idea that unconscious memories are those that cannot be expressed symbolically. We propose that as the analysand symbolically elaborates manifestations of unconscious material through transference in psychoanalytic sessions, he is reconfiguring the topology of his neural net, by creating new connections and reinforcing or inhibiting older ones. The network topology which results from this reconfiguration process will stabilize onto new energy minima, associated with new acts. The process of slowly and repeatedly reconfiguring synaptic connections to elaborate knowledge accounts for the long durations of psychoanalytic processes, where repetition is specially important.

Memory functioning is modeled by a Boltzmann machine, where node states take binary values [9]. Pattern retrieval on the net is achieved by a standard simulated annealing process, in which the network temperature parameter is gradually lowered by a factor α. We considered that the network initially had random connection weights, and was divided into two weakly linked subsets, representing conscious and unconscious parts of memory. These parts should correspond to a map formation described in [2], representing neurotic memory states.

To simulate the working-through process, we stimulate the net by means of a change in a randomly chosen node n_i belonging to the "unconscious" section of a neurotic memory pattern. This stimulus is then presented to the network and, if the Boltzmann machine retrieves a pattern with conscious configuration different than that of the neurotic pattern, we interpret this as a new conscious association, and enhance all weights from n_i to the changed nodes in the conscious cluster. The increment values are proportional to the products of the states of the neurons connected by the synapse and the learning parameter β. New knowledge is learned only when the stimulus from the analyst is not similar to the neurotic memory trace. This procedure must be repeated for various reinforcement iterations in an adaptive learning process, and also each set of reinforcement iterations must be repeated for various initial annealing temperature values.

3 Hierarchical Memory Model

In a further refinement of our model, we now consider that neurons belong to two different subsets corresponding *sensorial* and *declarative memory*. Memory traces stored in sensorial memory represent mental images of stimuli received by sensory receptors (located, in eyes, ears, skin, and other parts of the body). Sensorial memory represents brain structures such as the hippocampus. Declarative memory stores representations of memory traces stored in sensorial memory, i. e. *symbols*, and represents brain structures such as Broca's and Wernicke's areas and areas of the frontal cortex. These latter areas are associated with language and because of them, we can associate a word such as "red" to the visual sensation of seeing a red object. We thus consider that when a stimulus S, that retrieves a pattern in sensorial memory, stimulates also retrieval of an associated pattern in declarative memory, it becomes conscious. Stimuli of sensorial memory which do not cause activation of declarative memory, remain unconscious. This mechanism is similar to ideas proposed by Edelman in [4], and strongly reflects

Freud's concepts of conscious and unconscious mental processes, and the role of language in psychoanalysis.

In order to model structure of the topology of each of the two memories, we consider the following microscopic biological mechanisms. Brain cells in many animals have a structure called *on-center/off-surround*, in which a neuron is in cooperation, through excitatory synapses, with other neurons in its immediate neighborhood, whereas it is in competition with neurons that lay outside these surroundings. Competition and cooperation are found statically hardwired, and also as part of many neuronal dynamical processes, where neurons compete for certain chemicals [10]. For example, in synaptogenesis, substances generically called neural growth factors are released by stimulated neurons and, spreading through diffusion, reach neighboring cells, promoting synaptic growth. Cells that receive neural growth factors make synapses and live, while cells that have no contact with these substances die [10]. A neuron that releases neural growth factor guides the process of synaptic formation in its tri-dimensional neighborhood, becoming a center of synaptic convergence. When neighboring neurons release different neural growth factors in different amounts, many synaptic convergence centers are generated and a competition is established between them through the synapses of their surroundings. A signaling network is thus established to control development and plasticity of neuronal circuits. Since this competition is started and controlled by environmental stimulation, it is possible to have an idea of the way environment represents itself in the brain.

Based on these microscopic mechanisms, we developed the following *clustering algorithm* to model the self organizing process which results in a structured topology of each of the two memories.

Step 1 Neurons are uniformly distributed in a bi-dimensional sheet.

Step 2 To avoid the unnecessary and time-consuming numerical solution of the diffusion equation of the neural growth factors, we assume a gaussian solution. Therefore, a synapse is allocated to connect a neuron n_i to a neuron n_j according to a gaussian probability given by eq. 1

$$P_{Gauss} = \exp(-(\vec{r_j} - \vec{r_i})^2/(2\sigma^2))/\sqrt{2\pi\sigma^2}\,, \quad (1)$$

where $\vec{r_j}$ and $\vec{r_i}$ are the positions of n_j and n_i in the bi-dimensional sheet and σ is the width of the distribution and a model parameter. If a synapse is allocated to connect n_i and n_j, its strength is proportional to P_{Gauss}.

Step 3 We verified in [2] that cortical maps representing different stimuli are formed, such that each stimulus activates a group of neurons spatially close to each other, and that these groups are uniformly distributed along the sheet of neurons representing memory. We thus now randomly choose m neurons which will each be a center of the representation of a stimulus. The value of m should be chosen considering the storage capacity of the Boltzmann machine [9, 1].

Step 4 For each of the m centers chosen in Step 3, reinforce adjacent synapses according to the following criteria. If n_i is a center, $sum_{n_i} = \sum_j |w_{ij}|$, where w_{ij} is the weight of the synapse connecting n_j to n_i. For each n_j adjacent to n_i, increase $|w_{ij}|$ by Δw_{ij}, with probability $Prob_{n_j} = |w_{ij}|/sum_{n_i}$, where $\Delta w_{ij} = \eta Prob_{n_j}$ and $\eta \in \Re$ is a model parameter chosen in $[0,1]$. After incrementing $|w_{ij}|$, decrement Δw_{ij} from the weights of all the other neighbors of n_i, according to: $\forall k \neq j$, $|w_{ik}| = |w_{ik}| - \Delta w_{ik}$, where $\Delta w_{ik} = (1 - |w_{ik}| / \sum_{k \neq j} |w_{ik}|)\Delta w_{ij}$.

Step 5 Repeat step 4 until clustering criterion is met.

In the above clustering algorithm, steps 1, 2 and 3 are justified in the algorithm's description. Step 4 strengthens synapses within a cluster and reduces synapses between clusters (disconnects clusters). By cluster, we mean a group of neurons that are spatially close, with higher probablilty of being adjacent by stronger synapses. This step represents a kind of preferential attachment criterion with some conservation of energy (neurosubstances) among neurons. Neurons that have received stronger sensorial stimulation and are therefore more strongly connected, will stimulate there neighborhoods and promote still stronger connections. This is in agreement with the microscopic biological mechanisms we described above.

The growth of long-range synapses is energetically more costly than short-range synaptic growth, and therefore the former are less frequent in the brain than the latter. For allocating long-range synapses which connect clusters, we considered the basic learning mechanism proposed by Hebb [4, 10, 9], based on the fact that synaptic growth among two neurons is promoted by simultaneous stimulation of the pair. This also suggests a mechanism through which the external world, culture and language, reflects itself in the brain. Memory traces stored by configurations of certain neuronal states, which receive simultaneous stimuli, should enhance synaptic growth among these neurons, allowing association among traces. Since memory traces represent sensorial information and concepts (declarative memories), we are also representing association of ideas or symbols by long-range synapses. This suggests a way in which basic language structure (and maybe Chomsky's concept of Universal Grammar [3]) is mapped onto brain topology.

We are studying these processes and, since we are still not aware of synaptic distributions that result in such topologies, as a first approximation, we allocate synapses randomly among clusters. Within a cluster C, a neuron n_i is chosen to receive the connection with probability $P_i = \sum_j |w_{ij}| / \sum_{n_j \in C} \sum_k |w_{jk}|$. If the synapse connects clusters in different memory sheets (sensorial with declarative memories), its randomly chosen weight is multiplied by a real number in interval $[0, 1]$.

Mechanisms of memory storage and retrieval by the Boltzmann Machine and simulation of the working-through psychoanalytical process are then carried on as reviewed in Section 2 and described in [17].

4 Simulations and Network Properties

We illustrate the model with a preliminary simulation experiment for a network with $N = 32$ nodes, such that $N_{sens} = 16$ of them belong to the sensorial memory subset. Synapses connecting different memories are multiplied by $\kappa = 0.5$, and the other parameters for the annealing process in the Boltzmann Machine are attributed the same values we have presented in [17].

In Fig. 1 we show one of the topologies generated after executing only the clustering algorithm and in Fig. 2 the corresponding topology after long-range synaptic generation. Although the number of neurons is still quite small, we can have an idea that the algorithm self-organizes the network in a clustered and hierarchical manner. Fig. 3 gives a more quantitative view.

We generated 1000 topologies from the same initial parameter values and measured the average node degree (k) distribution for these complex network structures. In Fig. 3, the cross symbols represent the values found in our simulations and, the curve in logarithmic scale a fit of a Poisson distribution. It is known that random graphs follow the Poisson distribution of node degrees [12]. Our graphs are not random, but the spatially homogeneous allocation of synapses of the clustering algorithm may explain the close fit of the distribution for smaller values of k. The deviation from Poisson distribution for higher values of k may be attributed to the competitive biological mechanisms we described in the previous section, which introduce some structure to the topology.

The average clustering coefficient as defined in [16, 12] for the topologies we generated is 0.38. This is higher than the value of 0.28 which was measured for the neural network of the worm *C. Elegans* [12].

For the initial topology shown in Fig. 2, the network stored 13 memory patterns before working-through. After working through, 38.4% of the original patterns were still stored , which shows that the network does adapt with the simulation of working-through, freeing itself from some of the “neurotic” states. For smaller values of κ the network has learning difficulties, which suggests a difficulty in associating unconscious memory traces among themselves and with declarative memory. We have not yet explored this parameter dependency thoroughly, which we should continue to do in future work.

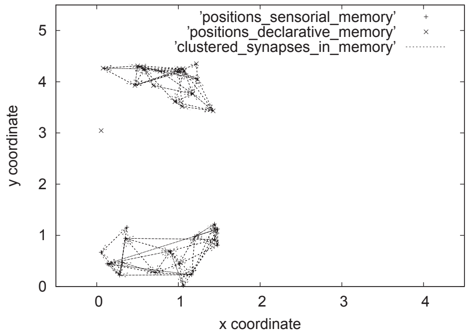

Figure 1. Network topology after clustering.

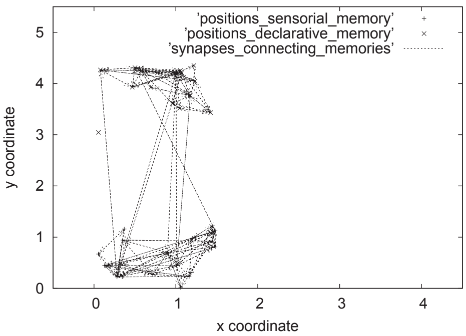

Figure 2. Network topology with long range synapses.

5 Conclusions

We have further developed the memory model presented in [17] to include microscopic biological neuronal mechanisms, and verified that the memory complex network self organizes into a hierarchical clustered structure. This memory structure and functioning along with an adaptive learning process is used to explain a possible mechanism for neurotic behavior and psychoanalytical working-through. We are proceeding in further model refinement and analysis. It is still necessary to test dependence of model behavior on various parameters such as temperature and κ. We are very interested in trying to map language structure and processing into network topology and dynamics, although we are not sure if this is possible. Although biologically plausible,

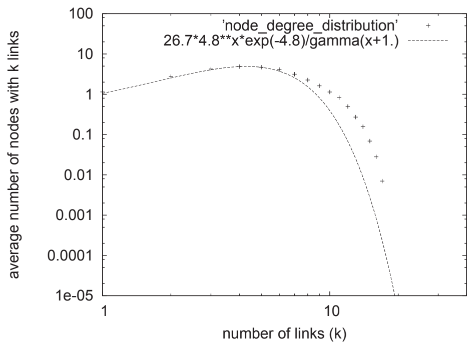

Figure 3. Node degree distribution in logarithmic scale. Cross symbols represent values found in our simulations and the curve a fit of a Poisson distribution

in accordance with many aspects described by psychodynamic and psychoanalytic clinical experience, and experimentally based on simulations, the model is very schematic and far from explaining the complexities of mental processes. It nevertheless seems to be a good metaphorical view of facets of mental phenomena, for which we seek a neuronal substratum, and suggests directions of search.

We finish with a quote from the Introduction of [5], an early work of Freud from late 1890's, first published in 1950: "The intention is to furnish a psychology that shall be a natural science: that is, to represent psychical processes as quantitatively determinate states of specifiable material particles, thus making those processes perspicuous and free from contradiction." Although Freud stopped work on this model for lack of instruments at the time, these ideas pervaded all of his work, and it impresses one to see how his ideas regarding the unconscious give strong insight into contemporary models of consciousness [4].

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