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SIMULATION OF DISSOCIATIVE EFFECTS ON EXPLICIT/IMPLICIT MEMORY TASKS FROM A CONNECTIONIST MODEL

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Two sets of simulations were carried out in order to bring forward evidence on the two basic theoretical approaches about the well-known implicit/explicit memory dissociations: different memory systems (see e.g. Schacter et al., 1993; Squire et al, 1993) versus one memory store or «processing view» (see e.g. Graf and Ryan, 1990; Roediger, 1990). In a multi-layer back-propagation models we simulated: 1) the anterograde amnesia effect (see Warrington and Weiskrantz, 1970, or why patients with anterograde amnesia show similar results as normal patiens in implicit tasks, whereas they show poorer performance in recall/recognition tasks); and 2) the type of processing made over the stimuli (semantic vs perceptual; see Graf and Mandler, 1984) that seems to affect only to explicit tasks, not to the implicit ones. Results support the processing view in the sense that these experimental dissociations can be explained as result of two different ways of processing the contextual information. Morever this latter theoretical approach seems to be more parsimonious than the different memory systems approach.

Simulación de efectos disociativos en tareas de memoria explícita/implícita desde un modelo conexionista. Se presentan dos series de simulaciones con el objetivo de determinar cual de los dos principales enfoques teóricos acerca de la dicotomía entre memoria explícita e implícita explica mejor las disociaciones experimentales halladas: el enfoque de diferentes sistemas de memoria (ver p.e. Schacter et al., 1993; Squire et al, 1993) vs el enfoque de un único sistema de memoria o «enfoque del procesamiento» (ver p.e. Graf and Ryan, 1990; Roediger, 1990). En modelos conexionistas multicapa de propagación hacia atrás simulamos: 1) el efecto de amnesia anterógrada (o por qué los pacientes con tal tipo de amnesia muestran resultados similiares a los obtenidos por sujetos sanos en tareas implícitas, mientras que rinden peor que éstos en tareas de recuerdo o reconocimiento; ver Warrington and Weiskrantz, 1970); y 2) el efecto del tipo de procesamiento hecho sobre los estímulos (semántico vs perceptual; ver Graf and Mandler, 1984) que parece afectar sólo al rendimiento observado en tareas explícitas, no así sobre tareas implícitas. Nuestros resultados parecen apoyar los postulados defendidos por el «enfoque del procesamiento» en el sentido de que tales disociaciones experimentales representan dos modos de procesar la información contextual asociada a los estímulos. Además este enfoque es más parsimonioso que el de los diferentes almacenes de memoria.

Explicit memory measures, mainly shown in recall or recognition tasks, reflect the conscious retrieval of past experiences, while implicit memory refers

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to memory that does not require a conscious retrieving of episodic or contextual traces (as occurs in priming tasks, categorization, habits and skills learning, classical conditioning, etc.; see Richardson-Klavhen and Bjork, 1988; Schacter, 1987, 1992; Schacter, Chiu and Ochner, 1993, for reviews).

A large number of studies have shown experimental dissociations between explicit and implicit memory tasks, and so giving consistency to that differentiation. Thus, a very conclusive result comes from the fact that the subjects who suffer from anterograde amnesia obtain very poor results in recall or recognition tasks but they get the same results as normal subjects in implicit tasks (Warrington and Weiskrantz, 1970; for a review, see Shimamura, 1986). Similar results are found in the case of schizophrenic patients (Schwartz, Rosse and Deutsch, 1993) or anaesthetized patients (Roorda-Hrdlickovà, Wolters, Bonke and Phaf, 1989). In the same way, Graf and Mandler (1984) have discovered that the kind of processing carried out on the stimulus (perceptual vs semantic) affects the observed execution in explicit memory tasks, but it does not affect the performance observed in implicit memory tasks (see also, e.g., Bowers and Schacter, 1990; Graf and Ryan, 1990).

There are two general theories which try to explain these dichotomies. The first one, based mainly on a neurophysiological tradition, states that different systems or stores would explain such dissociations. Thus, Squire, Knowlton and Musen (1993) defend the idea that declarative memory is based on limbic/encephalic structures, more recent in a philogenetic sense than non-declarative memory, while other types of memory not related to limbic/encephalic structures (more ancient, philogenetically speaking) would confirm the execution in implicit memory tasks, tasks that reflect the way in which living beings unconsciously respond to the environment. We will call this approach the «multiple systems theory» (see also Schacter et al, 1993).

On the other hand, and from a more cognitive tradition, various authors support the idea that dissociations between both types of memory reflect the fact that different processes of codification and/or retrieval are involved in the access to the same memory trace (see, e.g., Graf and Mandler, 1984; Graf and Ryan, 1990; Roediger, 1990; Roediger, Srinivas and Weldon, 1989). That is why data-driven tasks are more affected by perceptual manipulation than conceptually-driven tasks, while the latter ones are more sensitive to semantic or conceptual elaborations. We will call this approach the «processing view theory» (see Roediger, 1990).

In order to bring forward evidence on such two basic theoretical approaches we conducted several simulations about two well-established experimental dissociations.

SIMULATION 1. Simulation of the effects of anterograde amnesia in implicit and explicit memory tasks.

We shall refer to the fact that amnesic subjects obtain very poor results in recall or recognition tasks, but they perform at the same level as normal subjects in implicit tasks (Warrington and Weiskrantz, 1970).

Method

In order to simulate such effect we shall begin by creating four different neural networks, whose basic structure appears in figure 1. All of these four networks share a series of characteristics: they consist of 3 layers back-propagation models (called, from bottom to top, input layer, hidden layer and output layer), interconnected through one-way bottom-up connections with random initial values in the range ±0.10, which work with a sigmoidal activation function and a back-propagation learning rule. The back-propagation algorithm uses a learning rate of 0.30 (in connections that linked input units to hidden units) and 0.15 (in connections that linked hidden units to output units). The value of the momemtum term was 0.40 (see Ruiz, Pitarque, Dasí,. and Algarabel, 1994, for more details about the back propagation networks).

The *input layer* was formed by 30 units grouped in 3 modules of 10 units each: the first one, or «contextual module», collects the contextual information asociated with the learning or the retrieval of a certain item. On the second, the «graphemic module» represents the graphemic information corresponding to each item. And the third represents the semantic information corresponding to each word, it is the «semantic module» (see figure 1). This idea of subdividing the input level in different modules, already appears in other works (see, e.g., Murre, 1992; Ratcliff, 1990; Schreiber, Rosset and Tiberghien, 1991). As it is known, codification and retrieval of an stimulus in recall and recognition tasks, are not only determined by the physical or semantic feautures of the item, but also the context in which it was acquired plays a key role (see, e.g., Feustel, Shiffrin and Salasoo, 1983; Jacoby, 1983; Schreiber et al, 1991). This phenomenon, initially revealed in the «encoding specific principle» (Tulving and Thompson, 1973), implies the need to include a module of input units in our model that allows us to represent contextual information associated to each item in a different way from other type of information (for example, physical or semantic features associated with the stimulus). On the contrary, in data-driven tasks (such as priming tasks, completion or identification tasks) perceptual or graphemic information seems to be more relevant in the retrieval of memory items than contextual information. This is the reason why our model will also include a module of input units that represents this graphemic information.

The *hidden layer* was always formed by 10 units, forming only one module only in the one-store or processing view proposal, or grouped in 2 modules of 5 units in the two-store proposal (see figure 1).

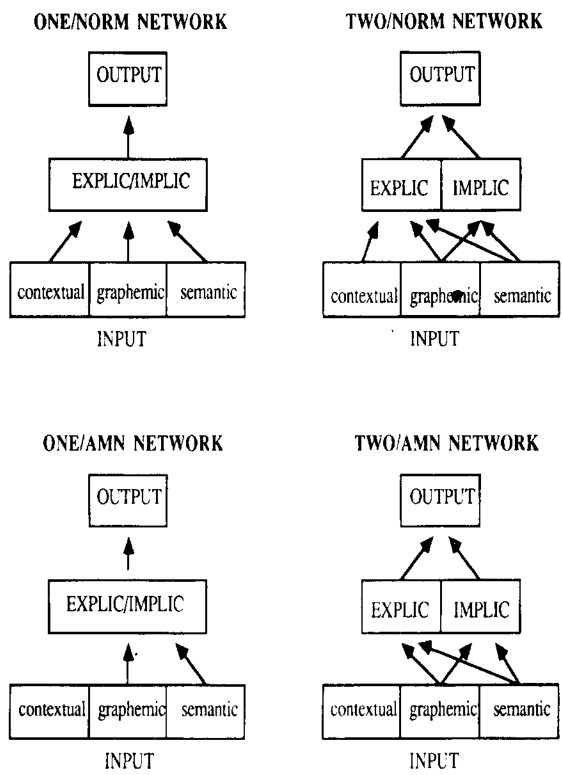
The *output layer* was formed by four units connected to all the units in the hidden layer, regardless of whether they are divided into one or two modules.

In figure 1, the differences between the four networks are shown. To make it more simple, not all the connections have been represented in that figure, but arrows show a total interconnection among all the units that form the related modules. The ONE/NORM network represents the one-store proposal (processing view) for a normal subject. It can be seen that all the input units are associated with all the hidden units, so that the stored information could be represented in just a trace, as proposed by authors like Roediger (1990) or Graf and Mandler (1984). On the other hand, the TWO/NOR network represents the multiple-system memory approach in normal subjects, in which the explicit module receives inputs from the three inferior modules, while the implicit module is not connected to the contextual input module, since implicit memory does not seem to be related with the context in which items are learned (see Squire et al, 1993).

As regards the simulation of amnesia in the context of a neural network, we have opted to identify the concept of

Figure 1

Representative scheme of the four types of neural networks used in simulation 1. The three levels of units that form each network are (from bottom to top): (a) input layer with 10 units representing contextual information associated with each item, 10 units representing the graphemic information and 10 units for semantic information; (b) hidden layer (explicit memory/implicit memory), with 10 units, subdivided, in the two-store proposal, into an explicit memory module (5 units) and an implicit memory module (5 units); and (c) output layer with 4 units. More details in the text.



amnesia with the removal or «freezing» of certain connections, in such a way that from the moment when the network is «damaged», those connections will stop modifying themselves as learning advances (see also, e.g., Murre, 1992; Wolters and Phaf, 1990). So, ONE/AMN and TWO/AMN networks represent the one-store and two-store proposals, respectively, for amnesic subjects. As shown by the ONE/AMN network, the connections that associate the units in the contextual module with units of the hidden layer have been deleted, while comparing the TWO/AMN network with the TWO/NORM network, the connections that associate the units of the contextual module with the units of the hidden layer of the explicit memory module have been also removed.

Given that the results obtained in a back-propagation model can differ from one simulation to other, and since the weights of connections are randomized at the beginning of each simulation, so being different (see Kolen and Goel, 1991; Ratcliff, 1990), we carried out 10 different simulations (with the same data) with each of the aforementioned networks. In this way, each of these replications would simulate the answers given by 10 different «artificial» subjects, being treated as such in the statistical analysis carried out afterwards (see Murre, 1992).

Once the four types of network were created, we then carried out the training process of the networks (or *training phase*). The task to simulate consisted of a category learning task in which each network had to learn to classify correctly 40 exemplars, each corresponding to one of four different semantic categories (belonging 10 exemplars per category). In order to do so, a file formed by 40 stimuli (exemplars) was created, each one formed by:

(a) a sequence of thirty 1 or 0 (*input pattern*), the first 10 representing the contextual information associated to each stimulus, the next 10 representing the graphemic information, and the rest representing the semantic information associated to each item. The modules that represented contextual and graphemic information were random sequences of 1 and 0, given that graphemic and contextual features can vary from one stimulus to other. Contrary to this, the semantic features that defined each examplar were common 90% of the time within the 10 exemplar that formed each semantic category, while there was no relationship among the four different categories.

(b) a sequence of four orthogonal vectors (formed by one 1 and three 0: 0001, 0010, 0100, 1000) that indicated the category each examplar belonged to (*target pattern*).

During the training phase the network readapted the weights of its connections during 5000 processing cycles (limit at which we observed that the learning of networks was satisfactory).

After the learning phase, we carried out the *test phase*, each model being measured in a recall as well as in an identification task. The recall task was operationalized presenting the contextual module of the input pattern previously learned to the network, and observing if it was able to classify the examplar into the correct category. On the other hand, in the identification task, the graphemic module of the input pattern previously learned was presented to the network, also observing if the network categorized each examplar correctly.

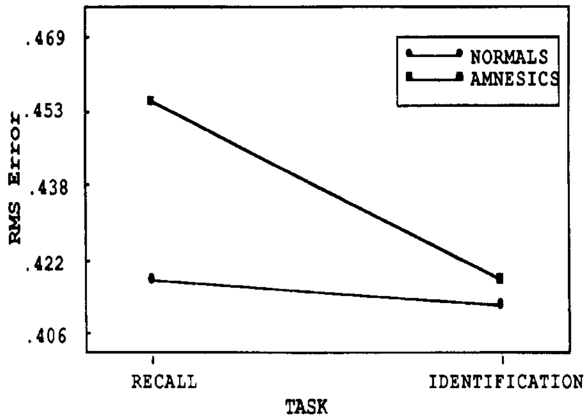
The execution of the network was measured (dependent variable) calculating the square root of the quadratic mean error (from now onwards, RMS error) made during the classification of the 40 examples. This value shows both the root of the quadratic mean difference between the activation value in each of the output units and the activation value that was expected in each case, taking the average of the 40 patterns. That is to say,

$$RMS_{error} = \sqrt{\frac{\sum_{p=1}^{q} \frac{\sum_{i=1}^{s} (t_{ip}-o_{ip})^2}{s}}{q}}$$

where o_{ip} represents the activation of the output unit *i* for the pattern *p* and t_{ip} represents the expected activation for that unit for the same pattern (target pattern), *s* is the number of output units (4 in our simulations) and *q* is the number of input units (40 in our simulations).

Figure 2

Simulation 1: means of the interaction subjects by tasks in one-store networks



In each network, and before the learning phase, the RMS error was also measured, in both recall and identification tasks. The aim of this was to measure the execution of networks before they learned anything, in order to obtain a baseline (or control line) from which the results could be compared. The average RMS error of all untrained networks was 0.50, with hardly any variability among them. In this way, every execution of a network which gives rise to a RMS error below 0.50 would be an indication that the network recalled or identified in some way the presented examplars.

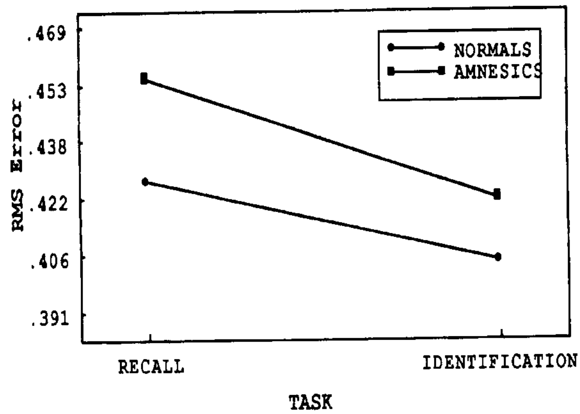
Results and discussion

We analyzed separately the data corresponding to the one-store proposal vs corresponding to the two-store proposal. We began by making an ANOVA 2*2 subjects (normal vs amnesic; between subjects variable) by task (recall vs identification; within subjects variable) for the one-store networks. This analysis showed as significant the main effects of the variables task ($F(1,18)=15.939$, $MSe=0.000125$, $p<0.0001$) and subjects ($F(1,18)= 76.480$, $MSe=0.000125$, $p<0.0001$), as well as the interaction of both variables ($F(1,18)=67.053$, $MSe=0.000125$, $p<0.0001$). The means of this interaction for one-store networks appear in figure 2.

A simple effects test for the analysis of this significant interaction was carried out, and the result was that the differences in the means between amnesic and normal subjects in the recall task reached statistical significance ($p<0.01$), while in the identification task that difference was not statistically significant. This result coincides completely with the data found by authors such as Warrington and Weiskrantz (1970) in experimentation with humans.

Regarding the analysis carried out on the data coming from the two-store networks, the 2*2 ANOVA (subjects: normal vs amnesic; task: recall vs identification) also showed significant the main effects of the variables task ($F(1,18)=463.560$, $MSe=0.0000056$, $p<0.0001$) and subjects ($F(1,18)=64.147$, $MSe=0.0000056$, $p<0.0001$), as well as the interaction between both variables ($F(1,18)=20.927$,

Figure 3
Simulation 1: means of the interaction subjects by tasks in two-store networks.



MSe=0.0000056, p=0.0002). The means of this interaction for two-store networks appear in figure 3.

A simple effects test for the analysis of this interaction showed that the differences in the means between amnesic and normal subjects in the recall task and in the identification task reached the statistical significance ($p<0.01$). The latter result, indicating that the performance of amnesic and normal subjects differs significantly in the identification task, contrasts, however, with the data found Warrington and Weiskrantz (1970).

Taking these results into account, the one-store proposal seems to be more suitable than the two-store proposal simulating the dissociative effects showed by normal vs amnesic patients in explicit and implicit memory tasks. The crucial point of this simulation is that it demonstrates that the damage in an specific structure of the network affects only to a certain kind of memory (the explicit one), allowing a normal execution in the other. Overall, the results found support the predictive capacity of a distributed connectionist model, in agreement with the results found by other connectionist models of human memory (see, e.g., Masson, 1991; McClelland and Rumelhart, 1985; Murre, 1992).

SIMULATION 2. Simulation of the effects of the type of processing of stimuli on implicit and explicit memory tasks.

Graf and Mandler (1984) subjected two samples of subjects to two types of tasks either a semantic processing of words (in particular, each subject was asked to rate them on a 5 points scale depending on the level of concretion/abstraction, number of meanings, and pleasure or displeasure that they connoted), or a graphemic or perceptual processing (where subjects had to decide whether two particular words had letters in common, count the number of letters in each word that orthographically formed a closed space, for example as in Q, P, or D, or were formed by intersecting lines, as occurs with T, L, H, etc.). On confronting the performance of both samples in a word completion task (HOUS_ type) vs a recognition task, they saw that the semantic processing of information only affected the execution observed in the explicit task (improving the percentage of correct recognitions), but it did not affect the performance observed in the implicit task. These results are consistent, and have also been achieved in other types of tasks (see, e.g., Bowers and Schacter, 1990; Graf and Ryan, 1990; Pitarque, Algarabel and Meseguer, 1992).

Method

The procedure of simulation took on three steps. First, we subjected eight ONE/NORM networks and eight TWO/NORM networks, similar to those used in the previous simulation, to the learning of the 40 previous examples corresponding to 10 different semantic categories, during 3000 cycles, so that these trained networks showed the knowledge that subjects have when they undertake experiments such as the one carried out by Graf and Mandler (1984). Secondly, half of the networks (each network representing an artificial subject) were made to process information semantically, while the other half processed information perceptually. Finally, their performance in a completion task (implicit) and in a recognition task (explicit) was measured.

With no doubt, the most complex part of this simulation was to operationalize what a semantic or perceptual processing of an stimulus means in the context of a neural network. We decided to operationalize the perceptual processing by presenting the graphemic module of each stimulus, not allowing the connections that associate the input units with hidden units to be modified, while the connections that associate hidden units with output units were able to benefit from that graphemic processing. This is because the perceptual processing of an stimulus seems to be an automatic bottom-up process not related with the creation of new associations between the context and the item (see e.g. Graf and Mandler, 1984). By other hand, to operationalize the semantic processing we decided that networks processed the input patterns of the graphemic and semantic learned modules, giving a noise of 50% to the contextual module (because context can vary every time that a stimulus is processed), letting the connections modify by this semantic processing. Each stimulus was processed, perceptually or semantically, eight times (that is to say, the group of 40 examples was processed for 320 cycles).

The completion task was operationalized by presenting to the networks the first seven units of the graphemic module previously learned (see figure 1), in a similar way to a typical completion task. In these tasks, the first letters of a stimulus are presented (e.g., HOUS_), and the subjects are required to complete the chain with the first letter they can think of. The recognition task was operationalized by presenting to the networks the input pattern learned corresponding to the three input modules (contextual, graphemic and semantic; figure 1).

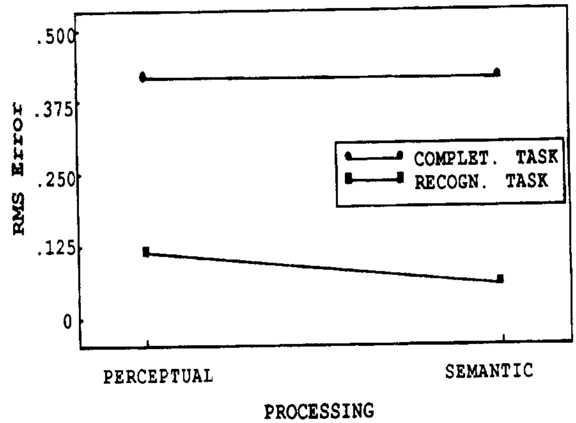
As in the previous simulation, the RMS error was the dependent variable, reflecting the level of accuracy in the categorization of the previously learned examplars. The rest of the characteristics and parameters of this simulation remained similar to the simulation 1.

Results and discussion

As before, we analyzed separately the data corresponding to the one-store proposal vs corresponding to the two-store

Figure 4

Means of the interaction type of processing (perceptual vs semantic) by tasks (completion vs recognition) corresponding to simulation 2 (one-store networks).



proposal. With regard to the one-store networks, an ANOVA 2*2, type of processing of stimuli (semantic vs perceptual; between subjects variable) by type of task (recognition vs completion; within subjects variable) showed as significant both the main effects of the type of processing ($F(1,14)= 33.421$, $MSe= 1.795*10^{-4}$, $p<0.0001$) and type of task ($F(1,14)= 5327.125$, $MSe= 1.676*10^{-4}$, $p<0.0001$), as well as their interaction ($F(1,14)= 34.236$, $MSe=1.676*10^{-4}$, $p<0.0001$). The means of this interaction are represented in figure 4.

A simple effects test for the analysis of this significant interaction showed that the type of processing of stimuli did not influence significantly the results obtained in the completion task ($F(1,28)= 0.014$, $MSe= 0.0001$, $p = 0.91$), while it did on the explicit task ($F(1,28)= 67.609$, $MSe=0.0001$, $p < 0.001$), in accordance with the results obtained by Graf and Mandler (1984) and other laboratories.

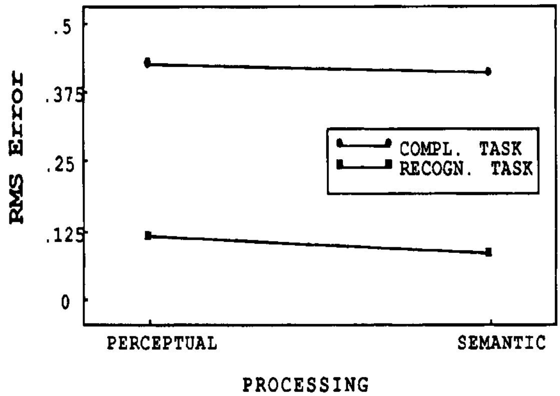
By other hand, with regard to the two-store networks, the ANOVA 2*2 showed as significant both the main effects of the type of processing ($F(1,14)= 19.249$, $MSe= 2.078*10^{-4}$, $p=0.0006$) and type of task ($F(1,14)= 3993.438$, $MSe= 2.031*10^{-4}$, $p<0.0001$), but not the interaction ($F(1,14)= 2.159$, $MSe=2.031*10^{-4}$, $p=0.1638$). The means of this interaction are represented in figure 5.

So our results, together with those found by other authors (see, e.g., Graf and Ryan, 1990; Schwartz et al, 1993), seem to confirm then the validity of the one-store processing theory to explain such kind of explicit/implicit dissociations.

General discussion

The results of the simulations carried out regarding the theoretical controversy between one-store models vs two-store models on explicit/implicit memory support the proposal that just one store can explain the results found. The models that simulated normal and amnesic subjects assuming the existence of only one memory store, have reproduced the data in a large number of experimental investigations (see, e.g., Challis and Sidhu, 1993; Graf and Ryan, 1990; Schwartz et al, 1993). In considering the one-store model simulating the execution of amne-

Figure 5
Means of the interaction type of processing (perceptual vs semantic) by tasks (completion vs recognition) corresponding to simulation 2 (two-store networks).



sic subjects, such performance in explicit tasks does not seem to depend so much on the damage in a certain structure, but on the damage in certain connections. To be more specific, those who would not permit the conveying of information concerning the context or episodic characteristics related to the stimulus, at the time of the study. This is what seems to be confirmed by the first group of simulations. Besides, from a theoretical point of view the results are coherent with the fact that a one-store proposal is always more parsimonious than a theory which treats different sub-systems as the reason for the different experimental effects found.

On the other hand, the results of the second group of simulations (one-store networks) that attempted to simulate the dissociative effects of the type of processing to what the stimuli was subjected to, coincide with those experimentally obtained by Graf and Mandler (1984) and Graf and Ryan (1990). The data given by simulations show how the performance in the explicit task is better compared to the implicit one when the stimuli have been previously subjected to semantic processing. In this sense, it is a confirmation of the fact that there has to differentiate between contextual information associated to a stimulus and the physical and semantic features that describe it, in accordance with the ideas pointed out by Jacoby (1983; also see Feustel et al, 1993) and already implemented in other simulation models (Murre, 1992; Ratcliff, 1990; Schreiber et al, 1991). In this way, while semantic and physical features associated to the processing of an stimulus are usually constant, to a certain extent, from a processing to another, contextual features vary. A connectionist model is able to integrate into one trace all the information (contextual, graphemic, and semantic) associated with the repeated processing of a stimulus, in such a way that assertions like that semantic knowledge comes from the massive processing of episodic traces (see e.g., Feustel et al, 1983) can be explained in a easy way from such kind of networks. This is what occurs in the second simulation shown above, where the change of context associated to the different processing of each item does not seem to affect its recognition afterwards.

The explanation of this would be, according to the theory of Graf and collaborators (Graf and Mandler, 1984; Graf and Ryan, 1990), that, while in an implicit task there is just automatic activation, strengthening and *integration* of pre-existent traces already consolidated through previous learning, without new connections being created, in a recall or recognition task there is an *elaboration* of new links that associate the context in which an item appears with the memory trace that represents it. The terms integration and elaboration have been identified with the synonym terms of familiarity, activation or perceptual fluency, and memory for new associations, respectively (see, e.g., Light et al, 1992). According to Graf and Ryan (1990), these two different types of processes would be responsible for the results found in both types of memory tasks. Our data totally confirm this idea.

To summarize, the simulations on the whole have revealed that a multilayer neural network based on the back-propagation learning algorithm (or generalized delta rule) is valid to simulate the experimental evidence concerning the dichotomy explicit memory/implicit memory. Morever, it has been shown that it is not necessary to postulate two different stores to explain the dissociations between explicit and implicit tasks. These results are in accordance with those presented in other areas of Psychology where similar connectionist models have been applied to fields as diverse as the conversion of written characters in voice (e.g., Seidenberg and McClelland 1989), category learning (Kruschke, 1992), implicit learning of events structure (Cleeremans and McClelland, 1991), language learning in children (Plunkett and Marchman, 1991), or identification of faces depending on the context (Schreiber et al, 1991), among others. Negative results with back-propagation networks, such as those found by Ratcliff (1990), seem to be due to formal defects in the training of these models rather than in its incapacity to simulate the overall functioning of human memory.

Future research should validate the model here proposed, using other experimental dissociations regarding the controversy of explicit memory vs implicit memory.

References

Bowers, J.S. and Schacter, D.L. (1990). Implicit memory and test awareness. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 16*, 404-416.

Challis, B.H. and Sidhu, R. (1993). Dissociative effect of massed repetition on implicit and explicit measures of memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 19*, 115-127.

Cleeremans, A. and McClelland, J.L. (1991). Learning the structure of event sequences. *Journal of Experimental Psychology: General, 120*, 235-253.

Feustel, T.C., Shiffrin, R.M., and Salasoo, A. (1983). Episodic and lexical contributions to the repetition effect in word identification. *Journal of Experimental Psychology: General, 112*, 309-346.

Graf, P. and Mandler, G. (1984). Activation makes words more accesible, but not necessarily more retrievable. *Journal of Verbal Learning and Verbal Beha ior, 23*, 55-3-568.

Graf, P. and Ryan, L. (1990). Transfer-Appropiate processing for implicit and explicit memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 16*, 978-992.

Jacoby, L.L. (1983). Perceptual enhancement: Persistent effects of an experience. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 9*, 21-38.

Kolen, J.F. and Goel, A.K. (1991). Learning in parallel distributed processing networks: Computational complexity and information content. *IEEE Transactions on Systems, Man and Cybernetics, 21*, 359-367.

Kruschke, J.K. (1992). ALCOVE: An exemplar-based connectionist model of category learning. *Psychological Re iew*, 99, 22-44.

Light, L.L., La Voie, D, Valencia-Laver, D, Owens, S.A.A. and Mead, G. (1992). Direct and indirect measures of memory for modality in young and older adults. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 18*, 1284-1297.

Masson, M.E.J. (1991). A distributed memory model of context effects in word identification. En D. Besner and G.W. Humphreys (eds.), *Basic processes in reading: Visual word recognition*. LEA, N.J.

McClelland, J.L. & Rumelhart, D.E. (1985). Distributed memory and the representation of general and specific information. *Journal of Experimental Psychology: General, 114*, 159-188.

Murre, J.M.J. (1992). *Learning and categorization in modular neural networks*. Harvester Wheatsheaf. N.Y.

Pitarque, A., Algarabel, S., and Meseguer, E. (1992). Degree of elaborative processing in two implicit and two explicit memory tasks. *Bulletin of the Psychonomic Society, 30*, 217-220.

Plunkett, K. and Marchman, V. (1991). U-shaped and frecuency effects in a multi-layered perceptron. *Cognition, 38*, 43-102.

Ratcliff, R. (1990). Connectionist models of recognition memory: Constraints imposed by learning and forgetting functions. *Psychological Re iew, 97*, 285-308.

Richardson-Klavhen, A., and Bjork, R.A. (1988). Measures of memory. *Annual Re iew of Psychology, 39*, 475-543.

Roediger III, H.L. (1990). Implicit memory: Retention without remembering. *American Psychologist, 45*, 1043-1056.

Roediger, H.L., Srinivas, K. and Weldon, M.S. (1989). Dissociations between implicit measures of retention. En S. Lewandosky, J.C. Dunn and K.Kirsner (eds.), *Implicit memory: Theoretical issues*. Hillsdale, N.J.: Erlbaum.

Roorda-Hrdlicková, V., Wolters, G., Bonke, B. and Phaf, R.H. (1989). Unconscious perception during general anaesthesia demonstrated by an implicit memory task. En B. Bonke, W. Fitch and K. Millar (eds.), *Memory and awareness in Anaesthesia*. Amsterdam: Swets & Zeitlinger.

Ruiz, J.C., Pitarque, A., Dasí, C. and Algarabel, S. (1994): Simulaciones en una red conexionista de propagación hacia atrás. *Psicológica, 15*, 121-140.

Schacter, D.L. (1987). Implicit memory: History and current status. *Journal of Experimental Psychology: Learning, Memory and Cognition, 15*, 3-12.

Schacter, D.L. (1992). Understying implicit memory: A cognitive neuroscience account. *American Psychologist, 47*, 559-569.

Schacter, D.L., Chiu, C..P. and Ochner, K,N. (1993). Implicit memory: A selective review. *Annual Re iew of Neurosciences, 16*, 159-182.

Schreiber, A., Rosset, S. and Tiberghien, G. (1991). FACENET: A connectionist model of face identification in context. *European Journal of Cogniti e Psychology, 3*, 177-198.

Schwartz, B.L., Rosse, R.B. and Deutsch, S.I. (1993). Limits of the processing view in accounting for dissociations among memory measures in a clinical population. *Memory and Cognition, 21*, 63-72.

Seidenberg, M.S. and McClelland, J.L. (1989). A distributed, developmental model of word recognition and naming. *Psychological Re iew*, 96, 523-568.

Shimamura, A.P. (1986). Priming effects in amnesia: Evidence for a dissociable memory function. *Quarterly Journal of Experimental Psychology, 38a*, 619-644.

Squire, L.R., Knowlton, B., and Musen, G. (1993). The structure and organization of memory. *Annual Re iew of Psychology, 44*, 453-495.

Tulving, E. and Thompson, D.M. (1973). Encoding specificity and retrieval processes in episodic memory. *Psychological Re iew, 80*, 352-373.

Warrington, E.K. and Weiskrantz, L. (1970). Amnesic syndrome: Consolidation or retrieval?. *Nature, 228*, 628-630.

Wolters, G. and Phaf, R.H. (1990). Implicit and explicit memory: Implications for the symbol-manipulation versus connectionist controversy. *Psychological Research, 52*, 137-144.