## Title
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# An Interactive Activation Model for Priming of Geographical Information

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**ABSTRACT**

Clustering effects in observed performance on spatial recognition tasks give evidence that the judgment of spatial relationships is not based solely on Euclidean proximity, but can depend on other similarity relationships to an equal, or even to a greater, extent. Thus, the representation of spatial information must be coded as one of many features of an object, and these features are expected to interact with one another. A recurrent network using the interactive activation architecture of McClelland & Rumelhart (1981) is presented to illustrate the interaction of these featural representations, including a coarse coding representation of a Euclidean metric. The experiments of McNamara (1986) and McNamara, Ratcliff, and McKoon (1984) are simulated; the model results are in qualitative agreement with the data.

### Introduction

The location of an object is certainly one of its most salient features. This is especially true for objects which are geographically fixed, since features which are invariant tend to have greater salience. Using a model of positional information, we can consider the representation to be topographic, in that objects that are sufficiently proximal should have similar (overlapping) representations.

However, recording geographical positioning is not enough, as several recent studies have demonstrated that the memory for locations of landmarks is biased by hierarchical, and other non-spatial, information (Hirtle & Jonides, 1985; McNamara, Hardy, & Hirtle, 1989; Stevens & Coupe, 1978). For example, Stevens and Coupe (1978) showed that subjects judged Reno, Nevada to be north*east* of San Diego, California, even though it is north*west*, presumably because Nevada lies to east of California. That is, the superordinate relationship altered the memory of the subordinate locations. Further research has shown similar effects for areas without explicit boundaries, where clusters arise from differences in terrain (Allen, 1981; Allen & Kirasic, 1985), perceptions of neighborhoods (Hirtle & Jonides, 1985; Merrill & Baird, 1987), or semantic features on artificial maps (Hirtle & Mascolo, 1986).

### Spatial Priming within Regions

In order to model in a connectionist framework the contributions of both spatial location and cluster membership, we chose a more basic paradigm than that of distance and orientation judgments. In recent work, McNamara and his colleagues have shown that a priming paradigm can be used to infer spatial knowledge, in that items that prime each other are judged closer (McNamara, 1986; McNamara, Hardy, & Hirtle, 1989; McNamara, Ratcliff, & McKoon, 1984).

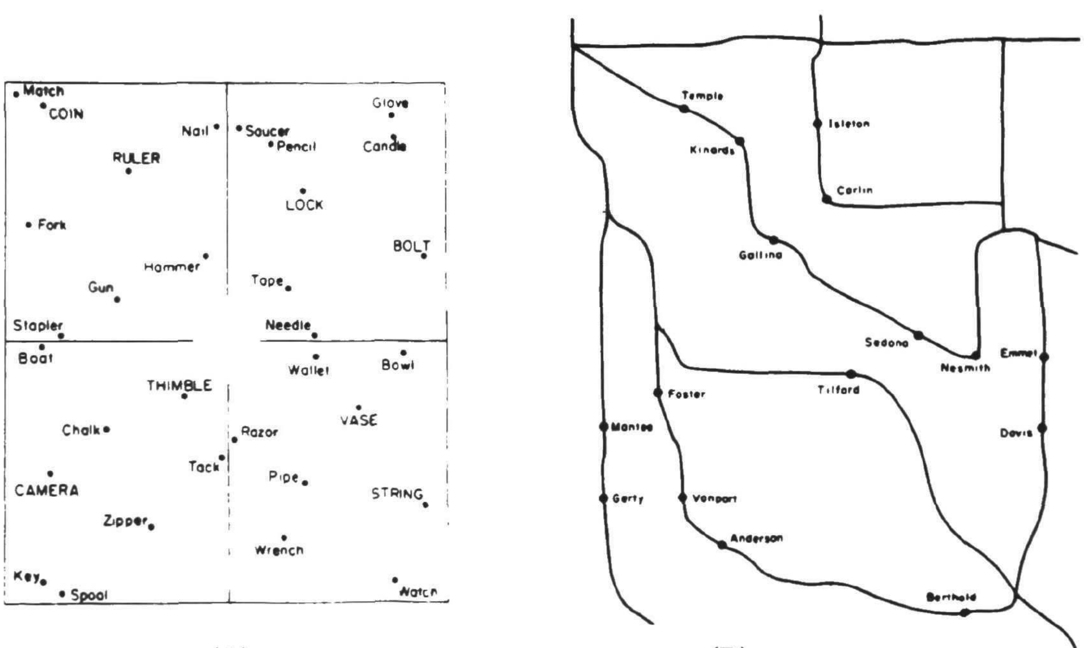
As one example, McNamara (1986) showed the effects of clusters on spatial memory. Subjects in this experiment learned either the locations of objects in a layout or the location of object names on map, where the spaces were divided into a two by two grid creating four regions, as seen in Figure 1a.

McNamara (1986) showed not only differences in standard spatial tasks due to region membership, but also differences in recognition times. Specifically, he showed that items are recognized faster if preceded with a item that was close in distance, and that items are recognized faster if preceded with an item from the same region. In the experiment, there were twelve pairs of locations in six experimental conditions (two pairs per condition) and eight filler locations, for a total of 32 locations, or eight locations per region. The three main independent variables were: distance between the two locations in a pair (either close or far), whether both locations are in the same region, and for locations in different regions, whether the locations were aligned or misaligned with respect to the region (cf., Stevens & Coupe, 1978). The results showed a strong effect of both distance and cluster membership. However, the effect of alignment was not consistent, in that alignment resulted in faster recognition times for far points, but slower recognition times for close points.

### Network Structure and Function

The model follows the interactive activation scheme introduced by McClelland and Rumelhart (1981) in their model of letter perception. This implementation consists of three sets of units (see Figure 2):

The **place** units each specify a particular site. In our simulations, these are labeled points on a map. More generally, they correspond to salient geographical locations.




(A) (B)

*Figure 1.* (A) Space of locations used by McNamara (1986). (Copyright 1986 by the Academic Press. Reprinted by permission.) (B) Space of locations used by McNamara, et al (1984). (Copyright 1984 by the American Psychological Association. Reprinted by permission.)

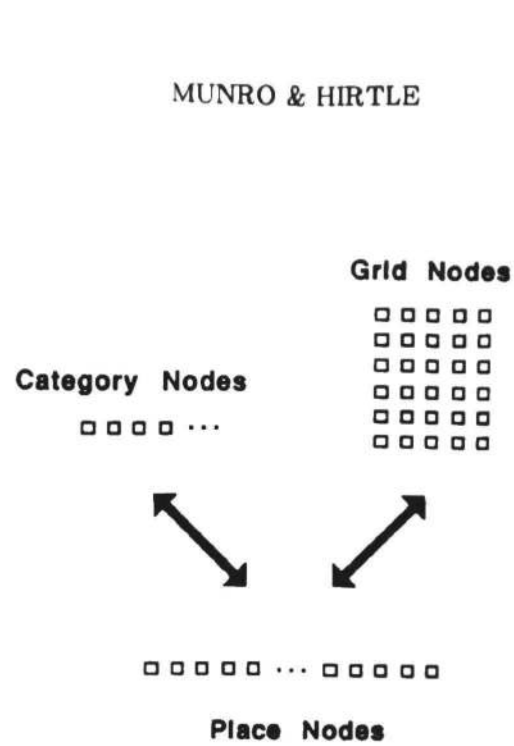



*Figure 2.* Network architecture for geographical priming.

The **category** units specify a particular category. Category membership is a binary function and is coded by positive and negative connections between category and place units.

The **grid** units represent a uniform rectangular grid across the map. The connections from a particular place unit to the grid units is determined by a Gaussian peak about the coordinates corresponding to the place unit.

Thus, connections exist in both directions between the place and category units (connection matrix **M**) and between the category and grid units (connection matrix **N**), with reciprocal connections having equal strength. The activity level of each unit is updated iteratively, by summing a decay term with an interactive term (Grossberg, 1978; McClelland and Rumelhart, 1981). The interactive term includes weighted sums of the activities of other units plus an occasional externally applied signal corresponding to an experimental stimulus. Thus, the activity $a(t)$ of a unit at time $t$ receiving net activation $x(t)$ from the other units is updated according to the following differential equation:

$$\frac{da(t)}{dt} = -\gamma a(t) + \begin{cases} x(t)(1-a(t)) & x(t)>0 \\ x(t)a(t) & x(t)\leq 0 \end{cases}$$

Each iteration consists of two strokes: [1] update of the place node activities, $P_i(t)$, integrating decay with input from the category units, grid units, and the external stimuli, $E_i(t)$ and [2] update of the category and grid node activities, $C_i(t)$ and $G_{ij}(t)$, integrating decay with input from the place units. The coupling of the activation equations is given in Table 1.

The connection matrices, **M** and **N** are determined as functions of the distance between places and grid sites, and membership of places in the various categories, respectively. Since two indices are used to denote position of grid nodes, the activities $G_{ij}$ have two indices indicating row and column in the grid, and elements of the matrix **M** have three

**Table 1**
**Activity Notation and Input Computation**

| Unit | Activity $a(t)$ | Net Input $x(t)$ |
|---|---|---|
| place unit $i$ | $P_i(t)$ | $\sum M_{ijk} G_{jk}(t) + \sum N_{ij} C_j(t) + E_i(t)$ |
| category unit $i$ | $C_i(t)$ | $\sum N_{ji} P_j(t)$ |
| grid unit $ij$ | $G_{ij}(t)$ | $\sum M_{kij} P_k(t)$ |

indices; $M_{ijk}$ denotes the connectivity of place node $i$ to the grid node in row $j$, column $k$. The elements of the other matrix, $N_{ij}$ are set to a positive constant, $\alpha_1$ if place $i$ is in category $j$, and to a negative constant, $-\alpha_2$, otherwise:

$$M_{ijk} = \beta \exp\left[ -\frac{D_{ijk}^2}{\sigma^2} \right]$$

$$N_{ij} = \begin{cases} -\alpha_2 & i \notin j \\ \alpha_1 & i \in j \end{cases}$$

where $D_{ijk}$ is the Euclidean distance between the points represented by $P_i$ and $G_{jk}$. The representation of a place by the grid units is a regularized form of coarse coding, as described by Hinton, McClelland and Rumelhart (1986). The network parameters $\alpha_1$, $\alpha_2$, and $\beta$ are scale factors on the connection matrices, and are generally small, to keep the system stable. The parameter $\sigma$ sets a distance scale on the Gaussian sampled by the grid matrix **M**. In our experiments, $\sigma$ was usually about 1/3 the size of a map edge.

It is important to realize that both the set of grid nodes and the set of category nodes represent positional information; these representations differ in a number of respects, but from an abstract point of view, they are equivalent.

### Simulation Results: Spatial Priming within Regions

Each simulation consisted of three stimulus intervals: stimulus of the prime, relaxation, and stimulus of the target. These stimulus intervals consisted of maintaining the external input to the appropriate place node at a constant level (usually 0.1) for a fixed number of iterations. No external stimulus was applied in the relaxation period; this allowed the activity levels to decay (due to $\gamma$). Reaction time data was simulated by measuring times for activities to reach a criterion level. Parameters were determined empirically by examining the time courses of node activities from selected simulations. A particular activity level (the response criterion) was estimated to correspond to the ability to name the place in the experimental paradigm.

The three phases were typically 200 iterations, 50 iterations, and 200 iterations. The time courses of several place nodes are plotted in Figure 3 for a simulation of the experiment by McNamara (1983). For this simulation, the grid was 6 by 5 and there were 4 category units representing the four categories.

Figure 3 contains three "snapshots" of the place node activities in their corresponding locations (cf. Figure 1a). In the simulation, place unit 21 was stimulated for 200 iterations, stimulation ceased for the next 50 iterations, and place unit 25 was stimulated for

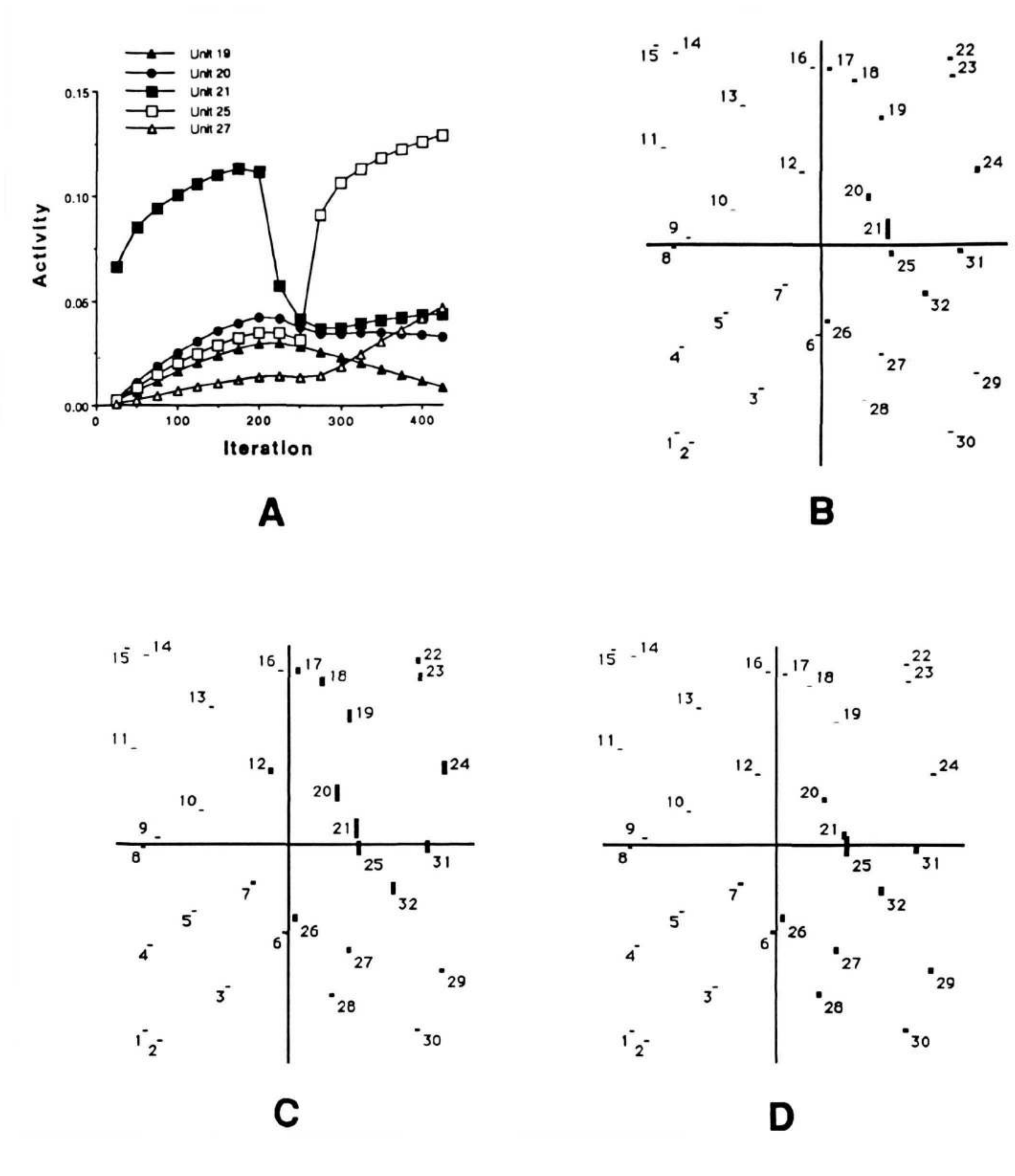



*Figure 3.* Time course of place node activity when stimulating node 21 for 200 iterations, followed by 50 iterations of relaxation, followed by stimulating node 25 for 200 iterations. (A) Plot of place node activity for 5 of the 32 nodes, and snapshots of activation levels of all place nodes after (B) iteration 200, (C) iteration 250, and (D) iteration 450.

the final 200 iterations. For this simulation, parameter values were $\alpha_1 = 0.4$, $\alpha_2 = 0.0$, $\beta = 0.3$, $\gamma = 1.2$, $\sigma = 4$, and the time step in our approximation to the differential equation was $\Delta t = 0.05$. In comparing our model with McNamara's data, we set the response level 0.11. The simulation results are compared with the experimental data in Table 2.

The results from the simulation correspond with the experimental data to a degree, but not in close detail. They match well for the close and far conditions within a region, and for the comparison of same-region to different-regions. However, whereas the data indicated a mild interaction of alignment with distance, the simulations show a mild interaction in the other direction. The weights in our model assumed an isotropic metric (Euclidean); generation of weights using a city block metric, may lead to an interaction consistent with the data.

### Spatial Priming Along Routes

As a second example domain for the network, we turned to a related study. In an earlier experiment, McNamara, Ratcliff, and McKoon (1984) showed similar effects for a map where hypothetical cities were located along one of six different routes, as shown in Figure 1b.

The three main conditions were close in both Euclidean and route distance (CE-CR), close in Euclidean, but far in route distance (CE-FR), and far in both Euclidean and route distance (FE-FR). (The fourth logical condition of far in Euclidean distance, but close in route distance is geometrically impossible.) In addition, McNamara, et al (1984) used two distinct learning protocols (Experiment 1 versus 2). The data suggest that route distance is the critical determinant of psychological distance in the cognitive map of the subject, and that these results are not dependent on the learning protocol.

### Simulation Results: Priming along Routes

Simulations of the McNamara, et al. (1984) study were performed by modeling recognition of the same pairs of items. The parameter values used for this simulation were close to the values for the previous simulation, but not identical. The grid units were arranged in a 6 by 5 array as in the previous simulation. Here, six category units were used, each

**Table 2**
**Simulation Results for Priming within Regions**

| Condition | Mean Iterations | RT (*msec*) |
|---|---|---|
| Same Region | | |
| Close | 45.0 | 705 |
| Far | 52.0 | 768 |
| Different Regions | | |
| Close/Aligned | 61.0 | 773 |
| Close/Misaligned | 87.5 | 753 |
| Close/Overall | 74.3 | 763 |
| Far/Aligned | 155.0 | 782 |
| Far/Misaligned | 104.0 | 797 |
| Far/Overall | 129.5 | 790 |

| Table 3<br>Simulation Results for Priming along Routes | | |
|---|---|---|
| Condition | Mean Iterations | RT (*msec*) |
| CE-CR | 13.3 | 624 |
| CE-FR | 26.0 | 670 |
| FE-FR | 47.4 | 673 |

corresponding to one of the routes. We used $\alpha_1 = 0.4$, $\alpha_2 = -0.08$, $\beta = 0.3$, $\gamma = 1.2$, $\sigma = 4$, and set the response criterion 0.08. The simulated results show a similar ordering as the data (Table 3). However, there is again a small discrepancy in that the simulations show a greater effect due to distance than appears in the experimental data.

## Discussion

The network was able to represent both the locational information given by the geographic coordinates and the semantic information encoded by category membership, whether the categories are regions or routes. The model presented is in contrast to a spreading activation model that McNamara (1986) presents to account for his data. It has an advantage over the implementation proposed by McNamara in that the time component is made explicit.

These results point to a framework for representing positional information over a set of maps, rather than a single one. These representations may be orthogonal or overlap to various degrees. For example, the routes in the second simulation could be represented such that intersecting routes have common features. This could be implemented by having each category unit correspond to an intersection. We did not choose this representation because it has a problem of non-uniqueness (see Figure 1b).

The model presented complements previous connectionist models on related topics, such as examining the role context on spatial references in language (see, Cosic & Munro, 1988; Douglas, Novick, & Tomlin, 1987), and models examining spatial search (e.g., Barto & Sutton, 1981, Zipser, 1986).

Further research is planned to extend the model to more complex semantic structures. For example, McNamara, Hardy, & Hirtle (1989) have demonstrated that the ordered tree paradigm (see Hirtle & Jonides, 1985) can be used to determine the semantic structure imposed by subjects on an otherwise nonstructured array of landmarks. Thus, a small modification to the strategy above would be required as the resulting structure is hierarchical rather than a single set of regions or routes. However, the general approach should prove beneficial in the modeling of spatial knowledge.

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