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A conceptual neural model of idea generation

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***Abstract*— Understanding the neural mechanisms of the idea generation process has implications for research in brainstorming, creativity and innovation. In this paper we present a conceptual neural model for generating ideas. The model extends the associative memory model of Brown et al. (1998) by explicitly representing categories as networks of concepts and ideas as conceptual combinations. Simulation results are compared with experimental results on effects of priming on low, versus high accessibility categories.**

I. Introduction

THE purpose of this research is to study the cognitive and neural correlates on the idea generation process. Ideas are produced during brainstorming, or problem solving. Brainstorming, as first defined by Osborn (1957) [1], is a set of guidelines for groups generating novel ideas on a particular problem. Since then, behavioral experiments have shown that group brainstorming under these conditions does not increase the total number of ideas when compared to brainstorming alone with an equal number of individuals [2], [3]. However, it is still widely believed that group interaction provides cognitive and social stimulation that enhances, if not the total number of ideas, their quality and originality. So far, research has shown both facilitation and hindering factors in group brainstorming. Social factors, such as production blocking, free-riding, social comparison are the main inhibitors of group productivity [2], [3]. Others, such as increasing motivation and accountability on performance [2], [4], enhance both individuals and groups. It is believed that cognitive stimulation provided by groups helps individuals unveil remote associations that could have not been accessed alone. It was shown that ideas from others both inhibit or enhance an individual's own line of thought. Controlling the idea sharing protocol through explicit instructions or by means of electronic brainstorming to reduce cognitive load and production blocking has a positive effect [5], [6]. Priming with external hints during individual or group brainstorming has been shown to have beneficial effects [7], [8], [9], [10].

Cognitive models of idea generation process have been proposed before [11], [8], [12] and were used to explain and predict cognitive factors that enhance group or individual brainstorming productivity. The SIAM model by Nijstad and Stroebe (2006) [12] is a flow-chart diagram of the process of searching for ideas and is based on the free-recall model (SAM) by Raaijmakers and Shiffrin (1981) [13]. The model describes the logical interplay during idea generation between search cues, associative semantic memory, learning of retrieved ideas and storage in working memory and episodic memory. It is a high-level model that does not explain the details of how new ideas are generated. The associative model by Brown et al. (1998) represents semantic knowledge as a network of categories and the retrieval of ideas from it as a stochastic Markov type process. The model has been very successful in explaining brainstorming experiments [10], [8] and in predicting factors that would enhance brainstorming productivity. The model is able to emulate short-term memory effects and attention to others' ideas, and different styles of ideation (e.g. divergent and convergent thinking). The main shortcomings of both models are the abstract representation of individual ideas, and hence, their inability to study the quality of ideas generated. It has been shown that priming influences not only the number of ideas, but also their quality and that one needs to look at both. Original ideas, for example are those that are both novel and useful. New ideas are thought to be novel conceptual combinations [14], [15] of old concepts. The associative memory theory of creativity [14] predicts that the type and strength of associations between concepts (i.e. flat versus steep) is related to the ability to form new, distant associations, whereas the conceptual transformation theory [16] implies a reorganization of the conceptual space as a basis of novel ideas. The cognitive associative memory models [11], [12] cannot explicitly generate novel ideas, nor they can match the dynamics of the idea generation process.

A new, dynamic neural model of idea generation was recently proposed by our group [17], [18], [19] based on the concepts of adaptive modularity and dynamic selection mechanisms - all critical in any intelligent cognitive control system. We studied the process of searching for appropriate responses or ideas in familiar or novel contexts. Semantic memory is represented at different levels of abstraction: features, concepts, categories and previously generated ideas. The search process is guided by a search cue, or context, and is adaptively constrained by desirable response features. An internal evaluation process dynamically shapes the available conceptual space by expanding and contracting it depending on the feedback received. All modules can be mapped on known brain areas and neural mechanisms for semantic memory. These include parts of the left temporal lobe, prefrontal cortex, the anterior cingulate cortex, the orbitofrontal cortex and the locus coeruleus [20], [21], [22], [23], [24], [25], [26], as well as the basal ganglia [27], [28] and the dopaminergic system for indicating reward [29]. The model is able to generate good ideas in both familiar and unfamiliar contexts.

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In this paper we focus only on a partial version of the full model [17], [18], the conceptual-categorical semantic network. We look at how the functionality of the network is related to known results in behavioral experiments on priming during brainstorming. Each concept is encoded as a unit representing the activity of a population of neurons, while connectivity patterns reflect category structure (i.e. concepts related semantically) and category type: low, high or or medium accessible. A low accessible category is one that is less likely to become active due to its weak incoming connections from other categories, while high accessible categories are those that are most likely to be visited in a particular context. The model allows us to look at the novelty of an idea and at conceptual combinations. Simulation results are able to match the following aspects of experimental data: (a) The effects of external priming with hints from low versus high accessible categories, (b) The dynamics of the idea generation process during brainstorming with sequential priming and (c) Time evolution of novelty and conceptual combination measures.

II. Neural correlates of semantic knowledge and brainstorming

Theories of conceptual representation in the brain in general adhere to one of two principles: 1) The distributed perceptual or modal hypothesis [30], [31], by which concepts are organized based on sensory modality (i.e. visual for living things and functional/associative for non-living things) [31] or domain (i.e. animals, fruits/vegetables, tools) [23] and are processed in different brain regions, or 2) The unitary, amodal hypothesis [32], [33], [34], according to which concepts are represented as a collection of co-active features, or as a concept schema, with empty feature slots that are instantiated with different values depending on the instance. A more recent view is that conceptual knowledge is represented both distributed and unitarily [26] - called the distributed plus hub view, by which features converge on a single, amodal representation that encodes the semantic relationships between concepts [35]. This theory accounts for the ability to encode perceptually similar concepts as distinct ones, as well as perceptually different, but conceptually similar concepts. The brain area proposed as the hub is the anterior temporal lobe. The convergence zone theory by Damasio et al. (1996) [21] proposes distinct convergence zones where different aspects/properties become associated. These convergence zones act as a distributed, hierarchical gating system between the perceptual and conceptual systems. They help retrieve appropriate concepts depending on the context. Naming concepts requires, apart from the convergence zones, a different amodal lexical representation of words.

Starting with Warrington and Shallice (1984) [31], [36] experiments in patients with partial brain damage have shown selective semantic deficit in one or more categories, but not others. Many other category-specific semantic deficits have been reported since [24], [21], [37]. Damasio et al. (2004) [37] have shown that retrieval of category-specific words activates areas in higher-order cortices of the left temporal lobe, while retrieval of conceptual knowledge pertaining to the same entities activates, at least partially, other brain areas. Damage to word retrieval was not related to damage of conceptual retrieval (i.e. one may not recall the name of a concept, but could recall its properties). Abstract, amodal information about concepts, acquired from multiple experiences and used to generalize across different physical instantiations, activates neurons in the prefrontal cortex [38]. Amodal, category specific neurons were found in the inferior temporal and prefrontal cortex of monkeys [39]. Thus neurons acquired similar responses to visually different pictures of cats or dogs, while dog-like cats and cats-like dogs activated the correct category neurons.

The idea generation process requires not only a rich representation of domain related conceptual knowledge, but also a powerful adaptive control and selection mechanism. While there is not yet any direct evidence of neural activity during brainstorming or idea generation, neural correlates revealed by studies on spontaneous thought [40], problem solving with insight [41], action selection or decision making are all relevant. For example, spontaneous thought has been more correlated to activation of temporal lobe structures, suggesting that long-term memory plays a more dominant role [40] than that of prefrontal cortex, usually implicated in effortful or conscious thought processes. The interaction between the two areas and the two thought modes – effortful and spontaneous – might explain the formation of distant conceptual connections and might indicate a dynamic mechanism of switching between divergent and convergent thinking. Solving verbal problems with insight leads to activation of the right anterior temporal area as well as a sudden burst of gamma-band neural activity in the same area, just before insight, but not for non-insight solutions. This area is known to be involved in making connections across distantly related information during comprehension [41]. It has been suggested that the involvement of the right hemisphere may provide "short-cut" links between concepts, which are necessary for intuitive and creative thinking [42], [43].

It appears that dynamic control of the interaction and communication between different modules encoding conceptual knowledge, episodic memory and working memory is critical for the idea generation process: It shapes the search space and reconfigures it dynamically. It is believed that inhibitory networks and oscillations are part of the control mechanism and that they are modulated by neuromodulators such as dopamine (i.e. reward) and acetylcholine (i.e. attention) from subcortical areas [44]. These mechanisms might help dynamically form cell assemblies [44], [45], [46] as needed by a particular context or mental state.

III. Conceptual Neural Model Description

The cognitive model by Brown et al. [11] accounts for many experimental results on individual and group brainstorming. It explains effects due to cognitive factors (e.g. divergent/convergent thinkers, low accessible categories, working memory, attention) and social factors (e.g. group composition and attention to others). Semantic knowledge is modeled at the category level, and individual ideas are not encoded explicitly. This limits the explanatory power of the model since it measures only the number of ideas generated and the dynamics of category transitions. A more detailed cognitive model is needed to better understand the dynamics of idea generation process and especially the factors that enhance/inhibit production of new ideas as novel combinations of old concepts [14]. The neural model we propose is inspired by the semantic network theory [14], modular organization of cortical columns with long range excitatory connections and local inhibition [47], [48], [49] and has the following features:

- It represents ideas explicitly as combinations of individual concepts.
- It generates ideas by means of a dynamic, adaptive neural system using biologically inspired mechanisms.
- It produces useful, novel conceptual combinations (i.e. new ideas) from one or more categories.
- The dynamics of idea generation is determined by: (a) connectivity pattern and strength of existing semantic relations between concepts, (b) sequence of previously generated ideas, and (c) modulation of activity controlling the semantic distance between co-active concepts.

The conceptual neural model consists of a single layer of N_r concept units, inter-connected among each other. Concepts in the same category are more likely to be connected among each other than with concepts in different categories. Each concept unit is composed of a coupled pair of units, one excitatory and one inhibitory, representing populations of excitatory and inhibitory neurons. The kth excitatory unit follows the equation:

$$\begin{aligned}\frac{1}{\tau_e}\frac{dE_k(t)}{dt} &= -E_k(t) + f(a_k E_k(t) \qquad (1)\\ &+ g_e \sum_{j=1, j\neq k}^{N_r} w_{kj}(t) E_j(t)\\ &- b_k I_k(t) - g_i I_{global}(t) + S_k(t) + \rho_k(t))\end{aligned}$$

where e stands for excitatory and i for inhibitory, E_k is the proportion of population activity in the kth excitatory unit, w_{kj} is the strength of the connection from excitatory unit j to excitatory unit k, b_k is the strength of local inhibition from the kth inhibitory unit, a_k is the strength of the self-recurrent excitation, $S_k(t)$ is an external, excitatory input, ρ_k is Gaussian noise, I_{global} is a global inhibitory input, representing lateral inhibition and defined as: $I_{global} = \sum_{j=1}^{N_r} E_j(t)$, and g_e, g_i are, respectively, the strengths of intra-excitatory units connections and of global inhibition. Similarly, the equation for the kth inhibitory unit is:

$$\frac{1}{\tau_i} dI_k(t)/dt = -I_k(t) + f(c_k E_k(t)) \qquad (2)$$

where I_k is the proportion of population activity in the kth inhibitory unit and c_k is the local coupling from the kth excitatory unit. The f function is the sigmoid $f(x) = 1/(1+exp(-\alpha_{(.)}(x-\theta_{(.)})))$, with $\alpha_{(.)}$ and $\theta_{(.)}$, controlling the shape of the sigmoidal activation function and having different values for the excitatory and inhibitory units. This model is similar to Wilson and Cowan's model of interacting excitatory and inhibitory neural populations [50]. The values chosen here are such that a concept unit exhibits limit cycle oscillations for a range of non-zero external input values and stable fixed point behavior for smaller or larger values. All parameters are the same for all concept units, except a_k, b_k and c_k for which a small random deviation around the fixed value is added to each.

Connections between different excitatory units - the only inter-concept unit connections for now - are chosen to reflect the structure of categories in the network and are asymmetric. A category contains semantically similar concepts, while a connection from concept j to concept k is a measure of the number of times the two concepts are active together in the same idea compared with the number of times j is active alone. In this paper, the connectivity structure between concepts in different categories is modeled such as to reflect the different probabilities of switching into a particular category, and hence representing low, medium and high accessible categories (see below).

The dynamics of the model, given a transient initial activation within one category, depends on the balance between inter-concept excitation and inhibition (g_e and g_i) and is as follows: With no global inhibition ($g_i = 0$) and with g_e larger than a threshold, all concept units become active and stay active; lowering the inter-concept excitation, the model exhibits synchronized oscillations; lowering g_e further causes the activity dies out. With non-zero and higher than a threshold global inhibition, the dynamics is more interesting; the activity remains confined to a small number of concepts, and switches from one set of active concepts to another (i.e. from one idea to another). The small, non-zero mean Gaussian noise added to each excitatory unit ensures that the activity does not die out.

The model has short-term dynamic connection strengths between different excitatory units: connections between concepts active at small positive time differences are going slowly down to 0 with a time constant τ_d while all weights lower than the fixed, initial value - the steady state value - are going back up with a time constant τ_r. This added depletion plus recovery dynamics has an inhibitory short-term effect that lowers the likelihood of the same idea being generated again in the near future. It corresponds to slowly lowering the probability of staying in the same category while generating ideas from it. This is also a feature of the associative model of Brown et al. (1998) [11]. Switching to a new image to generate ideas in the SIAM model [12] is actually modeled as an increase in the likelihood of repeating ideas (i.e. associations between images and previously generated ideas are strenghten). The ratio between τ_r and τ_d controls the speed with which connections between concepts in previously active ideas go down and up.

Ideas are extracted from the activity of excitatory units - all units with an activity over a threshold θ_{on} form an idea. The novelty of an idea depends on the connectivity structure and strength between co-active concept units. Also, more novel ideas are likely to be spread over concepts in more than one category (i.e. conceptual combination [14]). The definition of the novelty of idea m spread over N_m concepts is:

$$Z_m = (1 - < W_m >)(1 - \frac{[W_m]}{T_m}) \qquad (3)$$

where W_m is the set of non-zero weights among co-active concepts in the m-th idea, $< W_m >$ is the mean and $[W_m]$ the size of W_m, $T_m = N_m(N_m - 1)/2$ is the maximum number of connections between N_m nodes. Each product term varies between 0 and 1. The right-side product term is a measure of the number of zero connections between co-active concepts in one idea, compared to the maximum number of connections. The smaller this fraction (i.e. the fewer the number of existing connections), the higher the novelty is. The left-side product term is higher if the mean value of existing connections is lower, meaning that a high novelty can be obtained either by a concept set that is very sparsely connected or by one that is very weakly connected. A measure of the degree of conceptual combination of idea m is: $D_m = \frac{C_m}{N_m}$, with C_m the number of categories active in idea m.

The purpose of this study is to model the effect of priming with hints from low-accessible categories (i.e. a category that is more difficult to activate, starting from other categories) versus high-accessible categories on idea generation, as well as priming with a low number versus a high number of hints sequentially during a brainstorming session. There is previous evidence from both experiments and modeling that priming low-accessible categories is more beneficial than priming high-accessible ones in individual brainstorming [8], [51]. Here, the N_r concept units are divided equally into N_c categories, with no overlap. Also, the N_c categories are divided equally in three sets: low, medium and high accessible categories. We interpret the accessibility of a category as directly related to the number of incoming connections from other categories. To differentiate the effect of connectivity versus overlap between concepts, the overlap between concepts in different categories is set to zero in the current version of the model. All connections are chosen randomly, with probability of connecting two concepts in one category the same, independent of category type, while concepts in different categories have distinct probabilities: lower if the destination concept is from a low-accessible category, and higher if it is from a medium or high accessible category. Also, all connection strengths come from one of two Gaussian distributions, both with the same variance, but one with a larger mean (i.e. strong connections) and another with lower mean (i.e. weak connections). The choice of random connections between concepts was chosen to serve as a baseline case. The current model is purely abstract, with its structure reflecting the hypothesized structure of semantic representations in the brain. The goal is to study the dynamics of this network, and its implications for idea generation. In the future, we plan to simulate the model with more realistic connectivity patterns similar to those observed in semantic networks [52].

IV. Simulation Results

The model simulated here has $N_c = 12$ categories, each with $N_r = 25$ unique concepts. The first four are designated low-accessible, middle four medium accessible and last four high-accessible categories. They differ by the probability of an incoming connection from another category: for low, this value is 0.005, for medium ones, 0.015 and for high ones, 0.03. The intra-category probability of connection is the same for all categories and it is 0.3. For non-zero connections between concepts in the same category, the strong ones (i.e. Gaussian mean 0.6 and variance 0.04) are selected with probability 0.6, while the rest have mean 0.3 and variance 0.04. Non-zero connections between concepts in different categories have a probability of 0.4 to be strong (mean = 0.6, variance = 0.04 , while the rest are weak (mean = 0.1, variance 0.04).

The mean values of the coupling parameters for a concept unit are: $a_k = 1$, $b_k = 1$, $c_k = 2$, with a standard deviation of 0.01. The time constants are: $\tau_e = 0.4$, $\tau_i = 2$. The parameters of the sigmoidal activation function are: $\alpha_e = 12, \theta_e = 0.3$ for excitatory units and $\alpha_i = 18, \theta_e = 0.65$ for inhibitory units. Other parameters are: $g_e = 0.14$, $g_i = 0.05$, noise $N(0.1, 0.1)$. The model equations were simulated with Runge-Kutta numerical integration, constant integration step of 0.01.

Experimental results [51], [7], [10] on priming with hints during individual brainstorming, varied the number of hints per session, the number of times hints are offered (either sequentially or simultaneously) [10] and the type of hints: either from low-accessible, or unique categories [51] or from high-accessible categories, or unique or common hints [7]. The results of manipulating the number of hints are more conclusive than those for the type of hints. In general more hints produce more non-repetitive ideas than less hints. But, simultaneously presented hints are less effective than hints presented sequentially at equal intervals [10]. Also, it was shown that relevant hints stimulate more than irrelevant, or distracting cues. Leggett (1997) [51] did experiments where hints were presented at equal intervals. All hints per presentation were from the same category, either a high or a low-accessible category. The categories were chosen from data gathered in other experiments: High-accessible categories are defined as categories with a large number of ideas, while low-accessible categories as categories with a low-number of ideas. The number of hints per presentation varied from 3 (low number of prime) to 6 (high number of primes). The total number of hints in the first case is 15 and in the second case is 30. Hints are presented on a tape and participants are instructed to pay attention to hints. Results show, indeed that a high number of hints results in more non-repetitive ideas compared to the control case when no hints are presented. Also, hints from low accessible categories increase the number of unique ideas generated compared to the no hints situation. But there is apparently no statistically significant effect in the number of ideas produced in high-accessible hints versus no hint condition [51] . The semantic network model predicts that directing attention to low-accessible categories should result in generating ideas that otherwise would not have been generated.

In the model, low-accessible categories are indeed harder to reach, unless primed. Figure 1 shows the activity of excitatory units in all 12 categories when the initial state is already in a high-accessible category (top third of the graph). It can be seen that bumps of activity are spread mostly over the high-accessible categories, due to their higher-number of incoming connections. Rarely the activity spreads in middle and low thirds of the graph corresponding to medium and low-accessible categories, respectively. Thus, the model reproduces the same behavior as seen in experiments for high- and low-accessible categories: high-accessible categories are sampled more frequently than low-accessible ones.

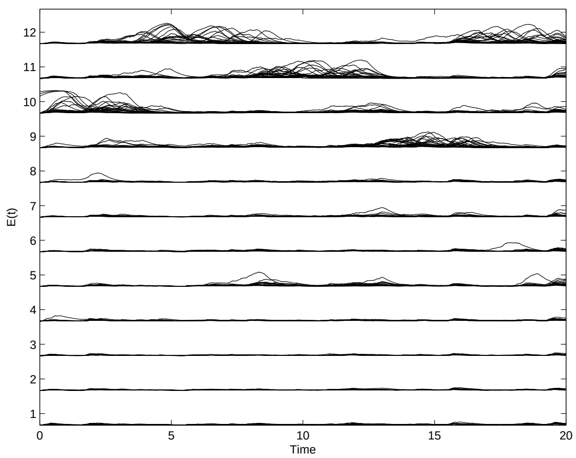

Fig. 1. Activity of excitatory units over time in each category. Plots numbered 1-4 represent low-accessible categories, 5-8 medium-accessible categories and 9-12 high-accessible categories.

There were four hint presentations spread equally during simulation time. A hint was encoded as the activation of either 3 or 6 excitatory units chosen randomly from either a low or a high accessible category. Thus, all four categories of each type represented in the model - either low or high accessible - received hints during one simulation. Ideas were extracted from the activity of the excitatory units ($E_k(t)$) as follows: The active concept units were determined at each time step as those with $E_k(t)$ greater than a threshold (0.7). If the set of active concepts were different than the previous set, it was recorded as an idea. Figure 2 shows the number of unique or non-repetitive ideas in all five conditions: low/high number of hints, low/high accessible categories and the control condition, when no hints where presented. In this last case, the activity starts from a small background noise. Results show that more hints increase the number of non-repetitive ideas, independent of the type, and that hints from low-accessible categories are more stimulating than those from high-accessible categories. These results were also predicted by the Brown et al. (1998) model [8] and are consistent with experimental results [51].

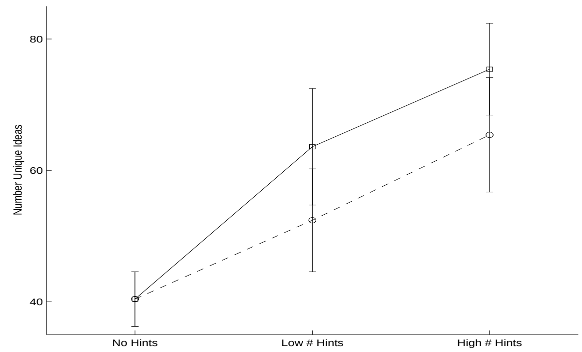

Fig. 2. Mean and standard deviation over five different models of the number of unique ideas for no hints, a low number of hints or a high number of hints presented four times during the simulation at equal intervals in either low-accessible categories (squares) or high-accessible categories (circles).

Figure 3 shows the number of ideas generated over time and grouped in bins of 500 steps. The three conditions shown are: high number of primes in low and high accessible categories and no hints. It can be seen that the number of ideas in the simulations with hints does not decrease over time, and peaks during hint presentations. In the no hint simulation, the number of non-repetitive ideas goes down over time. A similar result was observed by Coskun et al. (2000) [10] where sequential priming keeps the flow of idea generation from going down. The main difference between low and high category priming is seen at the beginning and at the end of the simulation: Initially, there are more ideas generated in the high condition, probably because more accessible ideas are generated faster, especially when primed), but towards the end there are more ideas generated in the low condition.

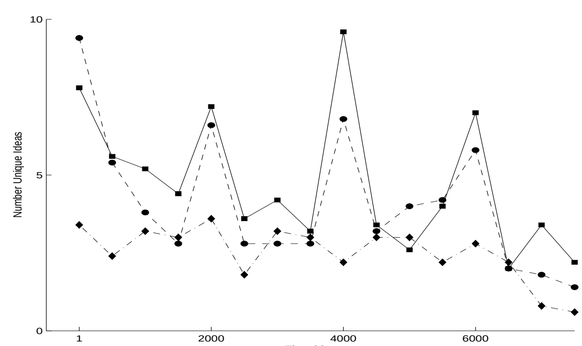

Fig. 3. Mean number of unique ideas grouped in 500 bins and averaged over five simulation models: squares - high number of primes from low-accessible categories, circles - high-number of primes from high-accessible categories and diamonds - no primes. Hints are presented at intervals of 2000 steps.

Figure 4 shows the number of categories spanned by ideas generated in each 500 steps time bins, in the high prime low and high accessible categories and no primes. It can be seen that there are more categories visited in each of the primed conditions compared with the no hints simulation, as well as more categories in the low compared to high accessible condition.

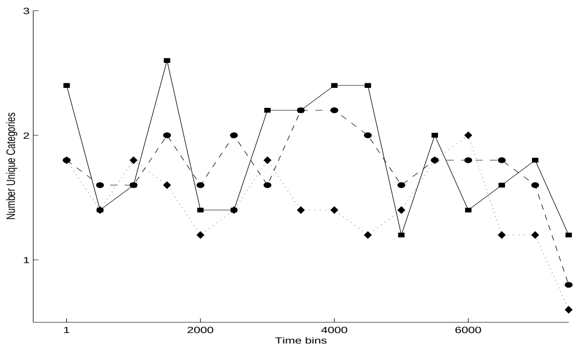

Fig. 4. Mean number of unique categories spanned by ideas generated in each bin of 500 steps, averaged over five different models. squares - high number of primes from low-accessible categories, circles - high-number of primes from high-accessible categories and diamonds - no primes. Hints are presented at intervals of 2000 steps.

The novelty measure shown in equation (3) (Z_m) was averaged over each condition, over time and over five models and is summarized in Table 1. Results show a small effect of the number of primes in the high-accessible condition, but a much bigger one for the low-accessible condition, in which a small number of hints seem to generate very few new ideas - as measured by the number and strength of connections between co-active concepts. An explanation for the large novelty of high-accessible priming is the larger number of incoming connections from other categories. This is also predicted by [14], who suggests that more spread out connections are the basis for generating novel combinations. The degree of conceptual combination shows an effect only for no hints versus hints condition. From the model point of view, the result can be explained by the effect of biasing concept nodes that switch the activity to a different category at regular intervals. It might be that the higher conceptual degree is due to the dynamics during hint presentation that makes concepts from different categories be associated in time. Currently there are no experimental results to mirror this results, since ideas rated by humans are assigned one category only.

TABLE I

NOVELTY (Z_m) AND DEGREE OF CONCEPTUAL COMBINATION (D_m) AVERAGED OVER CONDITION, FIVE MODELS AND OVER TIME.

	Low/ High-acc	Low/ Low-acc	High/ High-acc	High/ Low-acc	No Primes
Z_m	0.13	0.05	0.12	0.13	0.02
D_m	0.24	0.23	0.22	0.24	0.13

V. CONCLUSIONS AND DISCUSSION

We proposed a neural model of conceptual knowledge for generating ideas and simulated a number of priming experiments to test the validity of the model with respect to similar behavioral experimental results. The model predicts well the trends seen experimentally in the situation of priming with hints from low- versus high-accessible categories.

The model is a simplified representation of conceptual knowledege with assumptions that need further refining, such as: (a) the connectivity structure between concepts, (b) the overlap between concepts in different categories, (c) the unstructured representation of ideas. For example, Steyvers and Tenenbaum (2005) [52] studied the structure of associations in large-scale real conceptual networks and found that they share characteristics from both scale-free and small-world networks. In the current model, the connectivity is random. Also, the model has no overlap between categories. This is rather artificial, as concepts belong directly or indirectly to more than one category. The model generates ideas at the level of conceptual combinations, with no concern to structure or meaning. In brainstorming situation, a combination of concepts must be 'spoken'. This involves associations between concepts and words and also structure in formulating full sentences. Same words can have different meanings which can spark indirect associations between concepts. Also, the connectivity between concepts is influenced by the context or the features of the problem. Some associations might be masked or revealed by context alone. In the present model, we consider the context fixed. Concepts are associated through a range of semantic relations of different types. In the model there is only one type of association.

The simulation results replicate the trends seen experimentally. However, humans have access to many more categories and concepts than simulated here with a much richer structure. Also, ideas in Leggett (1997) [51] experiments were spoken on a tape at regular intervals, whereas in the model, a number of concepts was activated in batches for each category. Ideas chosen as hints were of similar frequency in their categories, whereas in the model they were chosen randomly. The model introduces two new measures, the novelty and the degree of conceptual combination. These are currently not matched by any similar experimental measures. Theoretically, one could use real semantic networks such as WordNet to decompose ideas into concepts and to find the number and strength of semantic distance between them.

In future work we plan to expand the model to account for richer and more realistic conceptual representations and to model more experimental conditions.

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