Modeling the effect of hint timing on the idea generation process

Simona Doboli, Matthew Jacques, Ali Minai, Paul Paulus, Runa Korde and Alex Doboli

Abstract— **In this paper we study the effect of external ideas on brainstorming by means of two computational models: a transient emergent attractors model (TEAM) and a probabilistic associative model (PAM). New behavioral experimental results show that hints or others' ideas can either hinder or enhance ideas generated during exposure period, while they consistently enhance the quantity of ideas produced after exposure. The TEAM model consists of a neural network of concept nodes connected by means of category membership and relatedness. Ideas emerge dynamically from the activity of the network by temporarily strengthening the connections between co-active nodes. Local inhibition inactivates current idea nodes and allows another idea to form. Active nodes prime connected inactive nodes depending on the recent activity of the node. The model shows that hindering of the number of ideas during hint presentation depends on the strength of hints and that the speed and duration of priming is essential for the long-term priming effect of hints observed in experiments. For comparison purposes, a PAM model originally proposed by Brown and Paulus (1998) is used to explain the same experimental data.**

I. INTRODUCTION

BRAINSTORMING consists of coming up with creative ideas/solutions on a topic or problems. It can be done individually or in a group in a variety of settings. Group brainstorming is commonly employed in different workplace settings as a way to enhance creativity. While it is widely believed that group brainstorming is beneficial, experiments have shown that group productivity (i.e. the number of ideas produced) is lower than that of individual brainstorming. Among the factors that hinder groups are social (i.e. motivation, social comparison, free riding) and cognitive (i.e. production blocking, cognitive interference) [1], [2]. Certain conditions such as electronic brainstorming, brainwriting, and rules for speaking and turn taking [3], [4], [5], [6] improve group brainstorming. When groups are able to exchange ideas by writing or computers, they are sometimes able to outperform nominal groups in the number of ideas generated. One basis for such enhancement in groups is the stimulating effect of shared ideas [2]. Cognitive benefits of shared ideation have been demonstrated in studies in which participants are provided with hints in the form of ideas that were generated previously by participants on this topic. The main advantage of hint experiments is the ability to eliminate the contaminating role of social factors and to explicitly control the types of ideas and the nature of their presentation. Experiments have controlled the number (low or high [7], type (i.e. common or uncommon [8], timing (i.e. sequential, simultaneous) [9], and form (i.e oral, tape, electronic) of hint presentation.

To better understand the cognitive factors that influence the idea generation process a number of models have been proposed by our group [10], [11], [12], [13], [14], [15] and others [1] and used to explain and predict experimental results. In the probabilistic associative model (PAM) by Brown and Paulus (1998) [10] the idea generation process is modeled as a Markov process of category sampling. The model was successful in explaining/predicting the effects of the type of hints (common or uncommon [8], relevant or irrelevant [16]). It studied the interaction of groups by varying the attention to other's ideas, the overlap in the knowledge base, or the convergence/divergence characteristics of group members. The model could not account for novel or repeated ideas or for ideas expressed as conceptual combinations spanning more than one category.

Recently, our group has proposed a number of neural cognitive models [11], [12], [17], [14], [15] inspired by the neurobiology of semantic cognition [18], [19], [20], [21], [22], the connectivity of semantic memory [23], [24], [25], [26], working memory [27] and cognitive control [28], [29]. The complete model by Iyer et al. [13] consists of a modular and hierarchical organization of semantic knowledge (i.e. categories, concepts, semantic context, critic). The system can search for good ideas in the active search space as well as change its search space in response to low quality ideas. The model replicated experimental results on priming with relevant and irrelevant hints [13], [30]. A simplified model [11], [12] was proposed in which ideas are expressed as transient emergent attractors formed by a small group of concept nodes whose connections are temporarily strengthened. The model was able to replicate experimental results on the effects of common versus uncommon hints and that of simultaneous versus sequential hints [11], [12].

In this paper the transient emergent attractor model (TEAM) [12] and the PAM models are used to study the effect of hint timing. By using both models we can look at the idea generation process at two levels of complexity. Two recent experimental results from our group varied the order and timing of hints or others' ideas. The main common result in both experiments is the increased ideation after hints or group exposure compared to individual brainstorming. Simulation results with the two models offer insight into the possible mechanisms of long-term enhancing effects after hint exposure as well as hindering or enhancing ideation during hint presentation.

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II. Summary Experimental Results

While there are many studies on the effect of hints or external ideas on brainstorming, the focus on this paper is on modeling experiments that study the effect of their *timing*. Our group has recently conducted two such experiments. The first is an electronic hint experiment where hints are presented either in the first, middle or last period of the session. The second experiment consists of alternating group and individual sessions over four intervals, with either group or individual periods as starting intervals. Details about each study are presented below.

A. Hint Experiment

In this experiment, subjects entered ideas electronically for a duration of 30 minutes on the problem of "improving university life". In the control condition there were no hints (NoHints), while in the other three conditions 20 hints were presented at intervals of 30 seconds in either the first 10 minutes (First10), the middle 10 minutes (Middle10) or the last 10 minutes (Last10). Hints were chosen a-priori from a large database of ideas on the same problem collected in the past. All hints in this experiment came from common categories - categories with more than 30 known ideas. The plot in Figure 1 shows the mean number of unique ideas in 10 minute intervals in all conditions. The number of ideas is higher in the intervals after the hint exposure compared to the NoHint condition. Also, in all three hint conditions, the number of ideas during hint exposure is higher compared to the same interval of the NoHint condition.

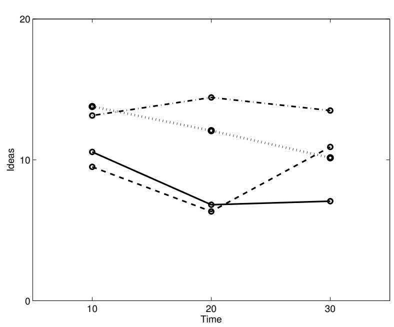

Fig. 1. Hint experiment: The mean number of ideas in 10 minutes intervals. Conditions are displayed as: NoHint - line, First10 - dotted line, Middle10 - dash-dotted line and Last10 - dashed line.

To analyze the effect of hints, the three ideas following a hint were evaluated if they were either elaborated, unrelated, or just a repetition of the hint. The percentage of hints elaborated, ignored and repeated over time is shown in Table I. Hints are elaborated the most in the First10 condition and the least in the Last10 condition.

TABLE I

Condition	Elaborated	Ignored	Repeated
First10	0.41	0.46	0.13
Middle10	0.39	0.56	0.05
Last10	0.34	0.57	0.09

B. Group Experiment

In this study subjects wrote ideas on the "thumbs problem" (e.g. ideas for using an extra thumb). Each experiment lasted 32 minutes and consisted of four periods of 8 minutes each. Each period was either an *alone* (A) or *group* (G) period. In the alone phases three subjects wrote each of their ideas on separate slips of paper and put them in the middle of the table. In the group phases, each subject passed each of their ideas to the next person. To avoid interference while expressing their ideas, an idea received from somebody else was read only after subjects finished writing their own. There were four conditions: AAAA - no exchange of ideas during all four periods, GGGG - interchange of ideas in all four periods, AGAG - alternating alone and group intervals, starting with an alone period, GAGA - same as AGAG, but starting with a group period. The mean number of ideas in all conditions is shown in Figure 2. The number of ideas in each G interval is lower than the corresponding interval in the AAAA condition. The number of ideas in each A interval following a G interval is higher than the same period in the AAAA condition.

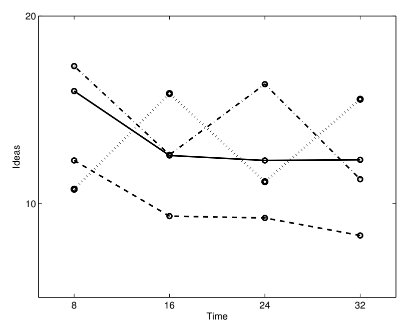

Fig. 2. Group experiment results: The mean and standard deviation of the number of ideas per person in 8 minutes intervals. Conditions are displayed as: AAAA - line, GAGA - dotted line, AGAG - dash-dotted line and GGGG - dashed line

The two studies - hint and group - are comparable since a hint exposure period corresponds to a G period. Also, in both studies there are both interactive and individual brainstorming periods in different orders. The two experiments differ in: idea and hint expression - electronic versus writing, setting - individual (hint) versus exposure to others' presence (group), type of hints - common (hint) versus any idea (group), type of problem - university problem (hint) with many ideas in each category versus thumb problem (group) a more divergent, open-ended problem.

C. Relationship with Previous Studies

There have been no previous studies of hint timing, only of the effects of hints. The study by Dugosh and Paulus [8] manipulated the familiarity of hints and found that more common hints had greater influence on the number of ideas generated than unique hints. There have been a number of studies that have examined the sequence of alone and group brainstorming. The literature on the effects of sequence has produced some mixed outcomes [31]. Some have found that the group to alone sequence leads to more ideas [32], while the reverse was found in [31]. Others have found no difference between the two sequences (e.g., [33]). It is likely that the effect of order depends on the specific procedures employed (e.g., length of the sessions, the degree of training, the complexity of the problem). No studies have examined multiple variations in alone and group brainstorming. It is possible that increasing the number of such variations will increase the positive impact of alternative group and individual brainstorming. Furthermore, the condition in which participants start alone has a number of advantages. It allows participants to generate ideas at a high rate initially since early in the session they will be able to tap the most easily accessible ideas. In contrast, those who begin as a group will start at a slower pace and may experience cognitive fixation based on the shared ideas. The fast pace of idea generation in an alone session may carry over into the group session.

III. Model Description

In this section we present two models proposed by our group to study the dynamics of idea generation [11], [12], [15], [10]. The first model - a transient emergent attractor model (TEAM) [11], [12], [15] - is a connectionist model whose nodes represent semantic concepts and whose dynamics represents ideas as groups of concepts active together and embedded as transient attractors in the connections. The second model - a probabilistic associative model (PAM) [10] - represents ideas implicitly by sampling a category depending on a transition probability matrix, depletion of the category, and the capacity of working memory. The two models differ in their level of idea representation - explicitly as a combination of concepts (TEAM) and implicitly as category activation (PAM), local versus global parameters controlling the dynamics. The TEAM model is inspired by theories of conceptual combination [34], [10], [35], [1], [36], [37], [38], empirical data on the organization of semantic memory [23], [24], [25], [26] and neurally inspired mechanisms of inhibition and modulation [39], [40]. The PAM model is inspired by associative memory and memory search models [41], [42], [34], [35], [1], [38]. The two models are detailed below.

A. TEAM Model

TEAM model consists of N *concept nodes* connected randomly based on category membership as follows: nodes are grouped in C *categories* with no overlap. There are three category types: common, semi-common and uncommon, each with N_c nodes. Each node is assigned a type: typical, atypical or other. Common categories receive more connections from other category types and have more typical nodes than others. Typical nodes have more and more stronger connections than other nodes. Each pair of categories has a defined semantic proximity or *relatedness*. Common categories are more related among themselves than with semi-common and uncommon. Semi-common categories are more related to each other than to common and uncommon categories. Uncommon categories are relatively unrelated among themselves and to others. The probability of connection depends on whether connecting units are in the same category or in different categories and on the type of connecting units. Connections are symmetric, but their strengths are not. The probability of within category connections is currently set the same for all category types p_w. The probability of between category connections depends on the category relatedness or distance p_b. The connection strengths are stronger into typical nodes, while those between nodes in different categories are stronger if nodes belong to related categories.

The dynamics of the model is controlled by the following equations.The output x_i is determined by:

$$\dot{x}_i(t) = \begin{cases} (1/\tau_i^{up})(1-x_i(t))H_i(t) & : \quad H_i(t) \geq \theta_i^{act}(t) \\ (1/\tau_i^{down})(-x_i(t)) & : \quad H_i(t) < \theta_i^{act}(t) \end{cases} \tag{1}$$

where $H_i(t)$ is the i'th unit input from other units or from outside, global and local inhibition, priming and noise. The activity of a concept unit x_i increases up to 1 with a rate proportional to $H_i(t)$ with time constant τ_i^{up} when $H_i(t)$ is larger than a threshold value $\theta_i^{act}(t)$. Activity x_i goes down to 0 with a time constant $\tau_i^{down}(t)i$ if the value of $H_i(t)$ is below the threshold. $H_i(t)$ is updated by the following equation:

$$\begin{aligned} H_i(t) = g \sum_{j=1, j\neq i}^{N} w_{ij}x_j(t) + g^{self}w_{ii}x_i(t) + \quad (2) \\ +g^{ext}I_i^{ext}(t) + g_i^{prime}(t)P_i(t) \\ -g^{global}G_{inh}(t) - g^{local}L_i(t) + g^{noise}N_i(t) \end{aligned}$$

The parameters are: g is the gain of the input from other units, g^{self} the gain of self-feedback, g^{ext} the gain of external input $I_i^{ext}(t)$, $g^{prime}(t)$ the gain of the priming input $P_i(t)$, g^{global} the gain of global inhibition $G_{inh}(t)$, g^{local} the gain of local inhibition, and g^{noise}, the gain for the noise $N_i(t)$.

Global inhibition is computed as follows: $G_{inh}(t) = \sum_{x_i(t) > \theta^{inh}} x_i(t)$. The value of θ^{inh} determines the signal-to-noise ratio. This effect is similar to that of dopamine in the brain [43]: a higher threshold (i.e. low dopamine level) allows weakly activated units to build up their activity, whereas a lower threshold (i.e. high-levels of dopamine) allows only strongly activated units to stay active. There is evidence that insight during creative problem solving is affected by dopamine levels and takes place when weakly active units are allowed to become active (i.e. lower dopamine levels) [44].

Local inhibition increases with past activity of unit i as follows:

$$\dot{L}_i(t) = \begin{cases} (1/\beta^{down})(-L_i(t)) & : \quad \forall i \\ (1/\beta^{up})(1-L_i(t)) & : \quad x_i(t) > \theta^{on} \end{cases} \tag{3}$$

This is consistent with a habituation/decay of activity with repeated firing [45], [46], [47]. In the model, local inhibition eventually decreases the input into an active unit allowing other units to become active, and thus other ideas to form.

Another parameter whose value depends on the recent activity of the unit is $\theta_i^{act}(t)$. Its dynamics is similar to that of local inhibition in equation 3: its value increases with activity and decreases otherwise. The transient increase in $\theta_i^{act}(t)$ results in a larger input needed to reactivate a unit in a short period of time.

Active units can prime inactive units in the model. This is consistent with long-term semantic priming effects and long-term conceptual priming [48]. Priming is updated as follows:

$$\dot{P}_i(t) = \begin{cases} (1/\gamma_i^{down}(t))(-P_i(t)) & : \quad \forall i \\ (1/\gamma_i^{up}(t))(P_{max} - P_i(t))H_i^{prime}(t) & : \\ for H_i^{prime}(t) > \theta^{prime} & : \end{cases} \tag{4}$$

where $H_i^{prime}(t)$ is the weighted sum from active units only: $H_i^{prime}(t) = \sum_{j,x_j(t)>\theta^{on}} w_{ij} x_j(t) g_j^P(t)$. The priming effect is mediated by the priming gain ($g_j^P(t)$) whose value goes down with repeated activity of a unit: $\dot{g}_j^P(t) = \tau_{g^P}(g_{min}^P - g_j^P(t))$. Thus, a repeatedly active unit has a decreased priming effect onto its connected units. Time constant $\gamma_i^{down}(t)$ controls the duration of the biasing effect and $\gamma_i^{up}(t)$ determines the speed of priming. The value of $\gamma_i^{down}(t)$ goes down with activity to reflect a shorter priming effect for repeated priming and up with no activity, while $\gamma_i^{up}(t)$ goes up with activity to reflect a weaker priming effect onto repeatedly active units. This is consistent with a decrease in neural activity with repetitive priming [49], [50].

Ideas are measured from the activity of the system as active units for a period larger than a threshold θ^{on}. Ideas form as transient emergent attractors through a *synchronization / desynchronization* mechanism detailed in [12]. It consists of short-term changes in the connection strengths: pairs of concept units whose activities $x_{(.)}(t)$ are close together, higher than a threshold θ^S, and are going up, undergo a *synchronization* process: the non-zero connections among them are strengthened temporarily. Pairs of concept units whose activity is higher than a threshold θ^D, but much smaller than that of the synchronized units undergo a *desynchronization* process, that temporarily decreases the strength of the connections between these units and the synchronized units. This procedure synchronizes temporarily the activity of a small set of almost active concept units, and desynchronizes units with lower activity. The local inhibition eventually shuts down an emergent attractor and allows another attractor to emerge. All connection strengths recover to their initial values and the emergent attractors disappear slowly. The time constant by which synchronized weights recover τ_r is an important parameter as it determines the 'stickiness' of an idea in the attractor space of the model and its likelihood to be repeated later. The number of repeated ideas has been found to go up with time during brainstorming sessions [51].

Hints are implemented in the model as an external input onto a very small number of units within a category lasting over a time interval of duration t_h. The gain of the hint input (g_{ext}) controls the influence it has on the current dynamics of the model: A strong hint input will lead to an abrupt change in activity to the hint units, while a weak hint input will bias the hint units, but it may or may not disrupt the current activity - depending on the strength of the currently active attractor. If activity switches into the hint category, it may activate some hint units and/or nodes related to them, or to the recently active units in the network. Thus the activity that results is a combination of the current state of the network and the hint input.

B. PAM Model

PAM model was proposed by Brown and Paulus (1998) [10] to simulate the idea generation process and to offer insight into the cognitive processes that influence individual or group brainstorming. The reason we use it here is because it successfully explained many experimental results and it is useful to compare its insight at a higher cognitive level than the TEAM model and to understand the limitations of both models.

The PAM model consists of a probability transition matrix $T = \{p_{ij}(t)\}$ of $C \times (C+1)$ elements, where C is the number of categories and $p_{ij}(t) = P(I(t) \in C_j | I(t-1) \in C_i)$ is the probability of the next idea $I(t)$ to come from category C_j when the past idea ($I(t-1)$) came from category C_i. The extra column corresponds to the probability of producing no ideas at time t, and diagonal values p_{ii} are the probabilities of staying in the same category. The sum of each row in T is normalized to 1. The sum over all rows is the accessibility of a category j: $p_j(t) = \sum_{i=1}^{N} p_{ij}$. Each row or category has a working memory coefficient: $w_i(t)$ that is increased to 1 whenever an idea is generated in that category, and then decreased each time step by α_w: $w_i(t) = \alpha_w w_i(t-1)$. A normalized value of $w_i(t)$ is multiplied by each row value to update the probability of generating an idea at time (t) from category i: $p_j(t) = \sum_{i=1}^{N} w_i(t) p_{ij}(t) / \sum_{i=1}^{N} w_i(t)$. The value of α_w is between 0 and 1 and it represents the capacity of the working memory (WM). A high value of α_w or high capacity WM means that the influence of past ideas onto the current idea is longer. It is known that there is a positive relationship between working memory capacity and creativity [52].

Each time an idea is generated from category i, the probability of staying in that category goes down simulating depletion of ideas: $p_{ii}(t) = \alpha_d p_{ii}(t)$ with $\alpha_d \in [0, 1]$. At the same time, the accessibility of other categories is increased by multiplying all other values outside the column of the current idea category i by $(1 + (1 - \alpha_d) p_{k,i}(t)) p_{k,j}$, $\forall k \neq i$. At the end of each step, the whole associative transition matrix is normalized. This process increases the no idea values as well.

The model simulates the idea generation process as follows: It starts by generating the first idea according to the initial probability values $p_j(t)$ values obtained by summing all rows. Then at each time step: it updates $w_i(t)$, lowers accessibility of current category, normalizes T, recomputes the probability values $p_j(t)$ weighted by WM, and probabilistically chooses the idea of the next category. This process is repeated for all steps.

Hints or other's ideas in the PAM model are simulated as a switch into the hint's category when the hint is attended. Hints are attended probabilistically (p_h). A high hint attention corresponds to a strong hint in the TEAM model that switches the flow of ideas to the hint category most of the time, while a low hint attention allows the internal thought flow to proceed more often. A low hint attention is not directly comparable to a weak hint in the TEAM model, as in the latter model a weak hint can still influence activity but in a more subtle way, whereas a low hint attention means that most hints are ignored. To account for the long-term priming effect of hints seen in experiments, when a hint is attended to, the probability of staying in that category is actually increased by a parameter α_h, $\alpha \geq 1$, instead of being decreased as in a regular step of internal idea generation. The reason is that a hint can provide stimulation for more ideas in a category than one would have had on its own. This parameter was not included in the original model [10].

IV. SIMULATION RESULTS

A. TEAM Results

The TEAM model has $N = 500$ concept units, $C = 12$ categories, $N_c = 50$ nodes in each category, 4 categories of each type: common, semi-common and uncommon. Probability of typical/atypical/other nodes depends on category type: $p^{typical} = 0.5/0.4/0.3$ and $p^{atypical} = 0.2/0.3/0.4$ for common/semi-common/uncommon category types.

For the model to show a reduced rate of idea over time - similar to any brainstorming experimental results - the number of repeated ideas has to increase and the speed and magnitude of long-term priming have to decrease over time. Parameter values were chosen such that to maximize the number of repeated ideas over time and to decrease long-term priming effect from and onto previously active units. Critical parameters for the TEAM model are $\beta^{down} = 10$ which controls the rate by which units recover from local inhibition and thus the number of repeated ideas; $\gamma_i^{up}(t) \in [1, 2.5]$ which control the speed of long-term priming and the rate of ideas - higher for $\gamma^{up} = 1$ the initial value, and lower for 2.5; $\gamma_i^{down}(t) \in [5, 75]$ which controls the duration of priming, with 75 the initial value; and $\tau_r = 100$ the speed by which the strengthen connections revert back to their initial values and thus the duration an emergent attractor remains in memory. The model's step size is 0.01 of a time unit. To simulate 32 minutes we used 320 time units, with 100 time steps per unit.

To simulate the group study we presented 16 hints in each 8 simulated minutes of group periods, at equal intervals of 0.5 unit times or 30 seconds. A hint was implemented as an external input to two randomly chosen units - either typical or other type - from the hint category for a duration of $t_h = 1.5$ time units. The value of the hint gain (g_h) for a strong hint is 2 and that for a weak hint is 1.

Figure 3 shows the dynamics of a one simulation of the model with no hints (plot (a)) and one with strong hints from all categories in the GAGA condition (plot (b)). It can be seen that activity switches from one category to another during hint intervals in plot (b). After a hint period, the activity is more convergent and settles in common or semi-common categories. In plot (a) the activity is more convergent in the first 3 periods, but starts switching more often in the last period due to the change in priming parameters.

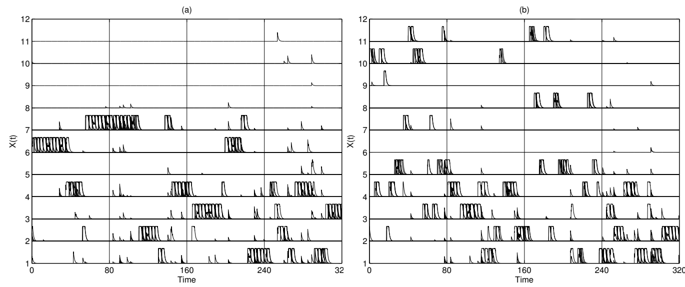

Fig. 3. Sample activity of all units: Plot (a) no hints; Plot (b) strong hints chosen from all categories in the GAGA condition. Units are grouped in 12 categories shown on the x axis, grouped by type: bottom four - common, middle four - semi-common and upper four are uncommon categories.

Figure 4 shows the simulation (plot (a)) and experimental results (plot (b)) of the group experiment. All simulation results shown are averaged over 5 different models. Each model starts with the same random seed in each condition. All hints are strong hints and are chosen from all category types equally likely. Simulation results match very well experimental ones. In the model, the decrease in number of ideas during hint periods is due to frequent switching as well as repeated hints - between 5 to 8 of the 16 given hints are repeated as ideas.

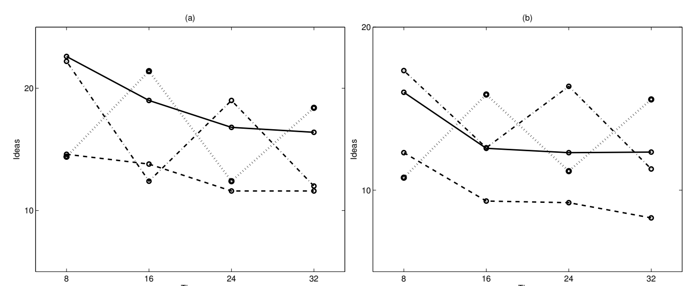

Fig. 4. Results of the group study: Plot (a) TEAM simulation results: the mean number of ideas over five random models in 8 minutes intervals; Plot (b) Experimental results. The conditions displayed are: AAAA - line, GAGA - dotted line, AGAG - dash-dot line, GGGG - dash line.

To account for the results of the hint study when the number of ideas went up during the hint period, we tested the dynamics of the network in the following cases: (I) weak versus strong hints, (II) type of hints: hints from all categories, hints from common categories - similar with the hint study - or hints from uncommon categories. Figure 5 shows the mean number of ideas in the GAGA condition with strong hints (plot (a)) and weak hints (plot (b)). The weak hints result in fewer hints repeated as ideas and thus a smaller decrease in the number of ideas compared to the strong hints simulations. The amount of priming in the period following the hints seems to stay the same as in the case of strong hints. The hint type is not relevant in this condition. Figure 6 shows the GGGG condition with strong (plot (a)) and weak hints (plot (b)). Weak hint from all categories produce the smallest decrease in number of ideas compared to the AAAA condition.

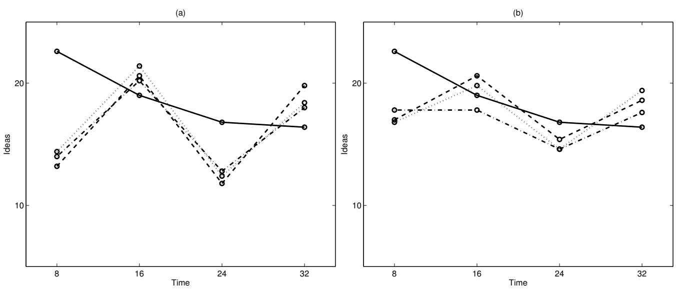

Fig. 5. TEAM simulations results: Mean number of ideas over 5 models in 8 minutes intervals: Plot (a) strong hints , Plot (b) weak hints. AAAA - line, GAGA all categories - dotted line, GAGA common categories - dash-dot line, GAGA uncommon categories - dash line.

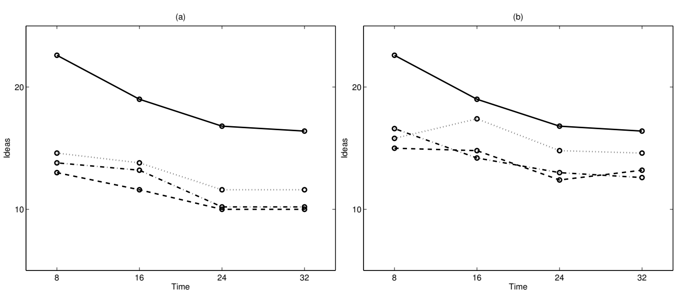

Fig. 6. TEAM simulations results: Mean number of ideas over 5 models in 8 minutes intervals: Plot (a) strong hints , Plot (b) weak hints. AAAA - line, GGGG all categories - dotted line, GGGG common categories - dash-dot line, GGGG uncommon categories - dash line.

B. PAM Results

The parameters of the PAM model are: T, α_w, α_d, α_h, p_h. The T matrix has the same number and type of categories as in the hint study: 26 categories (6/7/13 common/semi/uncommon). The initial values of the no idea column ($p_{i,C+1}(0)$) are set to 0.3 for common, 0.5 for semi-common and 0.7 for uncommon categories. The probabilities of staying in the same categories (diagonal values) are 0.5 for common, 0.3 for semi-common and 0.1 for uncommon. The difference to 1 on each category row was divided equally among all other categories. All simulation results were averaged over 100 different runs. A simulation lasts 180 steps or or a correspondence of 1 step to 10 seconds. The α_d value controls the depletion rate of ideas over time. The value of 0.7 was chosen in all simulation results shown here. A lower value decreases the number of ideas too fast and it did not match the experimental results. The hint attention (p_h) value is 0.5 close to the value observed experimentally in Table I.

The effect of long-term priming (α_h) is shown in Figure 7. Plot (a) shows the results of the original model [10] with $\alpha_h = \alpha_d$ and plot (b) $\alpha_h = 1.7$. In plot (a), all conditions but Last10 converge to the same values, whereas in plot (b) they are separated in the same way as in seen in the hints study (Figure(1). This long-term priming effect of hints requires $\alpha_h \geq 1$ in the PAM model.

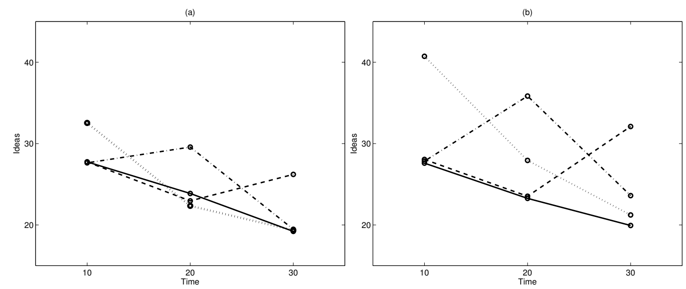

Fig. 7. Mean number of ideas over 100 repeated simulations in intervals of 10 simulated minutes (60 simulation steps). Plot (a) $\alpha_h = \alpha_d = 0.7$ and plot (b) $\alpha_h = 1.7$, $\alpha_d = 0.7$. Conditions displayed are: NoHint - line, First10 - dotted line, Middle10 - dash-dot line, Last10 - dash line.

The capacity of the working memory (α_w) determines the effect of past ideas/categories on current category choice. A high capacity working memory (large α_w) keeps the effect of past ideas longer. When the model attends to an external hint the probability of generating ideas in the hint category goes up with the value of α_h. A high value of α_h combined with a high-capacity working memory, leads to a larger number of ideas in the period immediately following the hint exposure. Figure 8 shows simulation results of the hint experiment with $\alpha_w = 0.3$ in Plot (a) and $\alpha_w = 0.9$ in plot (b). Both plots use $\alpha_h = 1.7$. It can be seen that in the high capacity plot (plot (b)), the number of ideas after a hint period is larger than in the low capacity memory (plot (b)).

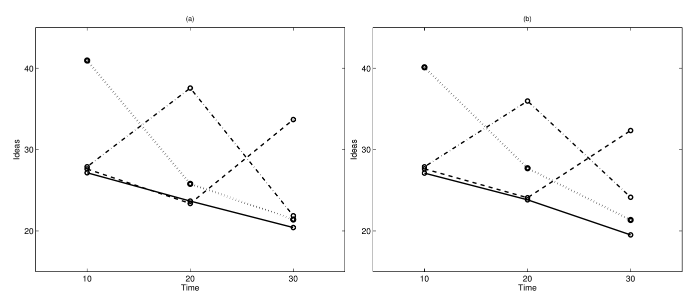

Fig. 8. Mean number of ideas over 100 repeated simulations in intervals of 10 simulated minutes (60 simulation steps). Plot (a) $\alpha_w = 0.3$ and plot (b) $\alpha_w = 0.9$. Conditions displayed are: NoHint - line, First10 - dotted line, Middle10 - dash-dot line, Last10 - dash line.

The simulation results for the hint study that best match the experimental results shown in Figure 1 were obtained for $\alpha_w = 0.9$, $p_h 0.5$, $\alpha_d = 0.7$ and $\alpha_h = 1.7$ (Figure 9 (plot (a)). They are shown side by side with experimental results in Figure 10 (plot (b)).

The model can explain the main trends observed in the hint study. The decrease in number of ideas after hint exposure

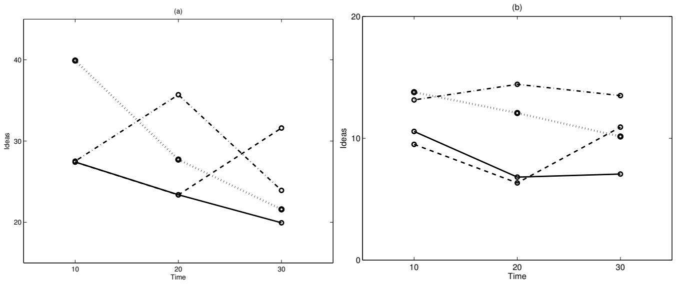

Fig. 9. Plot (a): Mean number of ideas over 100 repeated simulations in intervals of 10 simulated minutes (60 simulation steps) for $\alpha_d = 0.7$, $\alpha_w = 0.9$, $\alpha_h = 1.7$, $p_h = 0.5$. Plot (b) Experimental results. Conditions displayed are: NoHint - line, First10 - dotted line, Middle10 - dash-dot line, Last10 - dash line.

intervals is smaller in experiments than in the PAM model. Critical parameters for the long-term priming effects after hint exposure are the increase in the probability of staying in a hint category in case of an attended hint (α_h) and capacity of the working memory α_w. Parameters which affect the number of ideas during hint exposure interval are: initial no idea probabilities and hint attention (p_h). An effect not captured by the current PAM model is the plateau in the number of ideas generated after the first interval in the no hints condition. Instead, the model shows a continuous decrease in number of ideas over time.

The same model was used to simulate the group study results (Figure 2). In this experiment, the long-term priming effects of interactive brainstorming periods are much stronger than in the hint study, while during group interaction periods the effect is inverse - the number of ideas is reduced compared to no hints case. In the current PAM model, hints can never result in a decay in number of ideas compared to no hints case. At most, they have no effect at all if $\alpha_h = \alpha_d$ and the hint attention is 0. Analyzing the difference in experimental settings between the hint and the group studies, we observe that in the group study there is time lost in passing one's own idea to another person in the group and in picking up an idea from others and reading it. To account for this, we introduced a no idea step after each attended hint. We used the same T matrix, $\alpha_d = 0.7$, $\alpha_w = 0.9$, and $p_h = 0.5$. The only parameter changed was the amount of long-term priming: $\alpha_h = 1$ after a hint is attended. The higher value: $\alpha_h = 1.7$ used in the simulation of the hint study resulted in an increase in number of ideas in the GGGG condition versus AAAA and over time, both not observed experimentally. In the group study - GGGG condition - the number of ideas is smaller than the AAAA condition and i goes down over time. In other experiments where hints were presented sequentially throughout a brainstorming session the number of ideas generated stays the same [9]. Plot (a) of Figure 10 shows the simulation results of the mean number of ideas in all four conditions of the group study, while plot (b) the experimental results. PAM results show the same trends as experimental results in all conditions except GGGG, which is not lower than AAAA and it does not slope downwards over time as in the experiment.

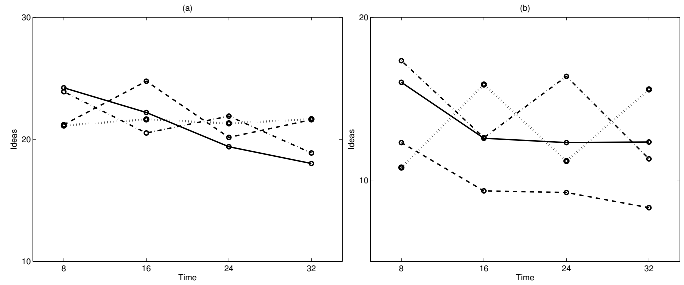

Fig. 10. Results of the group study: Plot (a) Simulation results with PAM model: mean number of ideas over 100 simulations every 8 simulated minutes of the 32 simulated minutes) , Plot (b) Experimental results of the group study. Conditions displayed are: AAAA - line, GAGA - dotted line, AGAG - dash-dot line, GGGG - dash line.

V. Conclusions

The goal of this paper is to understand through modeling the timing effect of hints and other's ideas during brainstorming. We used two models at different levels of complexity and abstraction: the TEAM model - a dynamic conceptual model in which ideas are expressed as transient emergent attractors, and the PAM model - a probabilistic model in which ideas are expressed implicitly through a Markov process of category sampling. The TEAM model was essential in understanding the cognitive interference of hints or other's ideas that force the activity to switch often, as well as the long-term enhancing effect after exposure to hints or others' ideas - through priming inactive units. Weak hints do not disrupt the activity of the network and show the same magnitude of long-term enhancing effect as strong hints, but they do not inhibit as much idea generation during hint exposure. A prediction of the model is that hints from all types of categories - common, semi-common and uncommon are better than hints from only one type of category. The PAM model can also explain the long-term enhancing effect after hint exposure - through unveiling potentially unknown ideas in the hint's category, but it currently does not model well the cognitive interference of hints during hint exposure.

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