Memory Transmission in Small Groups and Large Networks: An Agent-Based Model

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About

- How does the collaborative-memory paradigm help us understand the social influences on the transmission of learning and memory?
- What are the practical constraints of past behavioral paradigms, and how does the agent-based modeling approach overcome them?
- What insights can we gain from the agent model about the mechanisms behind counterintuitive phenomena such as collaborative inhibition and the results?

Introduction

1. Memory transmission in various group sizes: The study focuses on understanding how memory or information is transmitted or shared among different sizes of groups, from small teams to vast networks.
2. Experimental Limitations : Scalability to Large Networks.
3. Computational approach using agent-based models: Instead of traditional experimental methods, a computational model is used. This model simulates individuals as agents, allowing for a more scalable and flexible approach to studying memory transmission.
4. Goal to link behavior and information spread: The overarching aim is to understand how individual behaviors relate to the broader spread of information within groups and networks.

Collaborative Memory in Small Groups

1. Paradigm measures info transmission: The collaborative memory paradigm is a method used to measure how information is shared within small groups.
2. Collaborative groups recall more but not to their full potential: When people work together to recall information, they remember more than they would individually. However, their combined recall is still less than the sum of what each person could recall separately.
3. Collaborative inhibition: This phenomenon, where the group's combined recall is less than its potential.
4. Group size Vs Collaborative inhibition
5. Post-Collaboration Vs Collaborative Recall

Computational Model: Agent based Modeling

1. Agents as simplified individuals: In the computational model, individuals are represented as agents. These agents have specific rules and behaviors that mimic human memory processes.
2. Transition from small groups to large networks: The model allows for studying memory transmission in settings ranging from small groups to vast networks.
3. Insights beyond experimental methods: Using this computational approach provides insights that would be challenging to obtain using traditional experimental methods due to scalability and flexibility.

Agent based Modeling…

1. Memory models and behaviors of agents: Each agent in the model has a memory structure that can store items and has behaviors like encoding (storing) and retrieving (recalling) information. Simulating human-like memory processes in a controlled environment.
2. Encoding and retrieval processes: Agents can take in new information and store it (encode) and can also recall or bring up stored information (retrieve).
3. Activation modifications: The likelihood of an agent recalling a piece of information can change based on various factors, like recent recall or exposure to that information.

Agent based Modeling…

$$\Delta \mathbf{A}_{\max} = -\boldsymbol{\beta} \mathbf{A}_{\max}$$

Activation Vector (A): Represents the probability of retrieving each item in the agent's memory.
A$_{max}$ - Activation of most active item
Interitem Associations (S): Represents pre-experimental knowledge, like semantic associations between words. Random values are assigned for this study.
S$_{max\,j}$ - strength of the association between the maximally active item and item j

α (learning rate for encoding),
β (learning rate for retrieval), and
γ (probability of retrieval)

$$\Delta \mathbf{A}_j = -\boldsymbol{\beta} \mathbf{S}_{\max, j} \mathbf{A}_j$$

$$\Delta \mathbf{A}_i = \boldsymbol{\alpha}\left[1 - \mathbf{A}_i\right]$$

$$\Delta \mathbf{A}_j = \boldsymbol{\beta}\, \mathbf{S}_{i,j} \mathbf{A}_j$$

$$\Sigma_i \mathbf{A}_i = 1$$

$$\Delta \mathbf{A}_{\max} = -\beta \mathbf{A}_{\max}$$

This equation reduces the activation of the most active item in the agent's memory.

- When a new item is to be encoded and it's not the most active item, the activation of the most active item is reduced using this formula.
- By reducing the activation of the most active item, it ensures that no single item dominates the agent's memory, allowing for a more balanced recall.
- This formula ensures that the agent's memory remains dynamic and adaptable, preventing over-reliance on a single dominant memory item.

$$\Delta \mathbf{A}_j = -\beta \mathbf{S}_{\max,j} \mathbf{A}_j$$

- This equation modifies the activations of semantic associates of the maximally active item.
- After reducing the activation of the most active item (using Equation 1), the activations of its semantic associates are modified using this formula.
- By modifying the activations of related items, it ensures that items semantically related to a dominant memory item are also considered during recall.
- This captures the interconnectedness of memories, reflecting how recalling one item can trigger related memories.

$$\Delta \mathbf{A}_j = \beta \mathbf{S}_{i,j} \mathbf{A}_j$$

- This equation modifies the activation of item i based on its association with item j and the current activation of item j.
- When item j is retrieved or activated, the activation of item i is adjusted based on their association strength and the learning rate.
- By adjusting the activation of related items based on their association strength, it ensures that items related to a recently recalled item also get adjusted in their activation, making them more or less likely to be recalled next.

$$\Delta \mathbf{A}_i = \boldsymbol{\alpha}\left[1 - \mathbf{A}_i\right]$$

- This equation increases the activation of the item that is being encoded.
- When an agent encodes a new item, its activation is increased using this formula.
- By increasing the activation of newly encoded items, it ensures that recent memories are more readily accessible for recall.
- This formula reflects the phenomenon where recent memories are often more vivid and easier to recall.

$$\Sigma_i \mathbf{A}_i = 1$$

- After all encoding and retrieval operations, the activations are normalized using this formula.
- By normalizing activations, it ensures that each entry in the activation vector can be interpreted as a proper probability, maintaining the balance and proportionality of memories.
- This the consistency and integrity of the agent's memory model, making sure that the total activation remains constant.

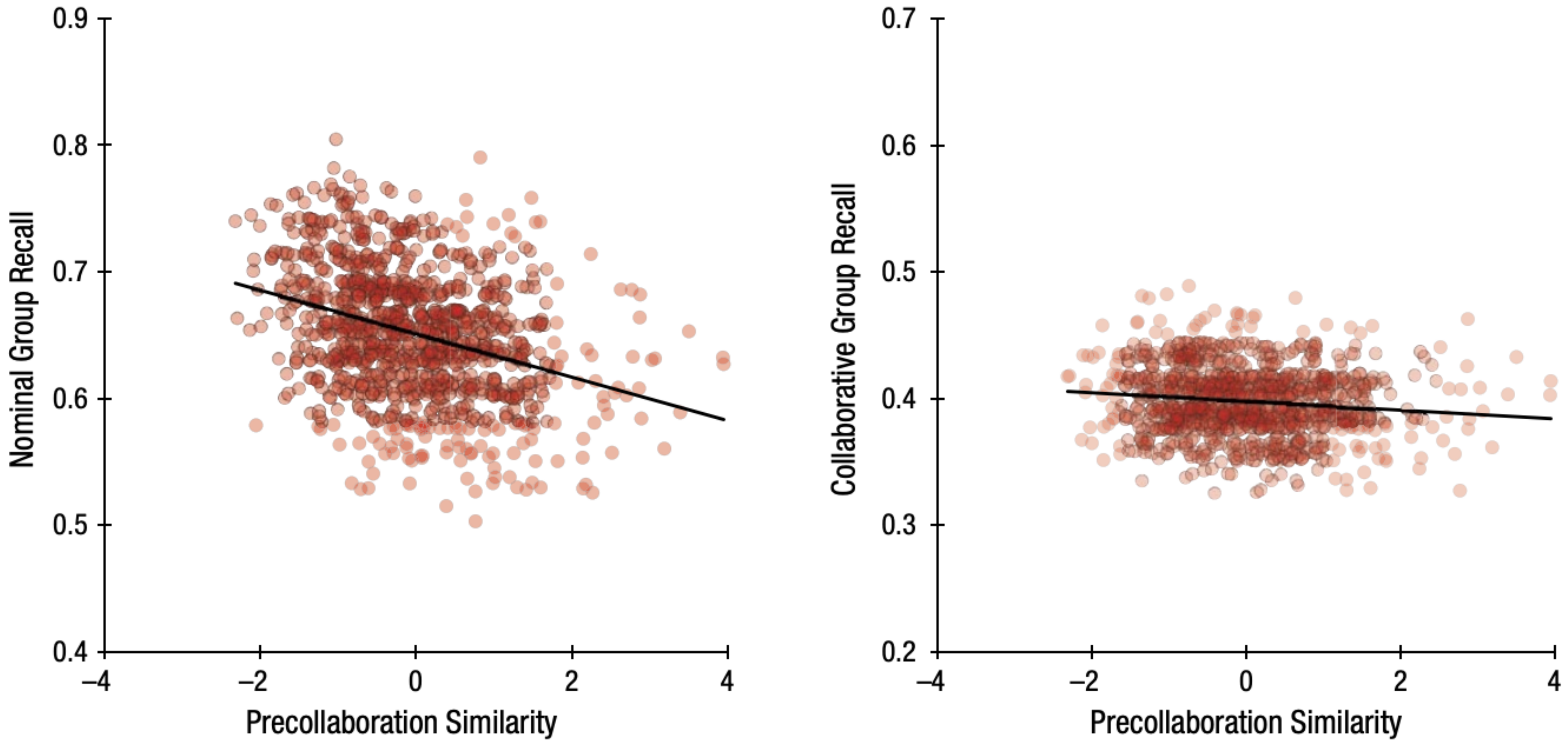
Study 1: Validating the Agent Model

- **Task design and agent interactions:** The study designed tasks that closely mimic real-world memory tasks. Agents interacted in these tasks, simulating real-world group interactions.
- **Collaborative inhibition observed:** The study found that agents, when working together, exhibited collaborative inhibition, just like humans do.
- **Impact of precollaboration similarity on recall:** The more similar agents were in their memory structures before collaborating, the less effective their combined recall was.

Results

1. Collaborative recall among agents leads to a phenomenon called collaborative inhibition, where group recall is less than individual recall.
2. The more similar agents are before collaboration, the fewer unique items they recall, leading to reduced group performance.
3. Collaboration tends to make agents' memories more similar, which can be both beneficial (for memory convergence) and detrimental (for diverse recall).

Results


0.9
0.8
0.7
0.6
0.5
0.4
Nominal Group Recall
–4
–2
0
2
4
Precollaboration Similarity
0.7
0.6
0.5
0.4
0.3
0.2
Collaborative Group Recall
–4
–2
0
2
4
Precollaboration Similarity