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Memory Systems and Artificial Intelligence: Linking Human Cognition and Machine Learning

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DESCRIPTION

Memory systems are integral to human cognition, influencing how we learn, recall, and interact with our environment. In cognitive psychology, memory is often categorized into different types, such as sensory memory, short-term memory, and longterm memory, each serving distinct functions. As Artificial Intelligence (AI) technologies evolve, they increasingly draw upon principles of human memory systems to enhance learning algorithms, data storage, and retrieval mechanisms. This article explores the parallels between human memory systems and AI, examining how insights from cognitive psychology can inform AI development and its implications for both fields.

Understanding human memory systems

Human memory is a complex and dynamic system that can be divided into several components:

Sensory memory: Sensory memory is the brief retention of sensory information-visual, auditory, tactile, etc. It lasts only a fraction of a second and serves as a buffer for incoming stimuli. For instance, the ability to remember the last few notes of a song after it has stopped playing relies on sensory memory.

Short-Term Memory (STM): Short-term memory, or working memory, allows individuals to hold and manipulate information for brief periods, typically around 20 to 30 seconds. This system is important for tasks requiring immediate recall, such as remembering a phone number long enough to dial it. The capacity of short-term memory is often described by Miller's law, which suggests that the average number of objects an individual can hold is about seven, plus or minus two.

Long-Term Memory (LTM): Long-term memory is responsible for storing information over extended periods, from days to a lifetime. It is further divided into explicit (declarative) memoryconscious memories of facts and events-and implicit (nondeclarative) memory, which involves skills and conditioned

responses. The organization of long-term memory is often conceptualized through models like the semantic network theory, which posits that memories are interconnected.

Memory consolidation and retrieval: Memory consolidation is the process through which short-term memories are transformed into long-term ones, often occurring during sleep. Retrieval refers to the process of accessing stored memories, influenced by cues and contexts that can enhance or hinder recall.

Insights from human cognition

Artificial intelligence systems, particularly in the field of machine learning, share certain functional similarities with human memory systems. By understanding these parallels, researchers can enhance AI capabilities. AI systems require effective data storage and retrieval mechanisms akin to human long-term memory. Traditional databases serve as a form of memory storage, where information can be indexed and retrieved efficiently. However, as the volume of data grows, AI models like neural networks employ sophisticated methods to mimic the organization of human memory.

Neural networks: These models simulate the interconnected nature of neurons in the human brain, allowing for distributed storage of information. Just as long-term memory is organized in networks of associations, neural networks can learn complex patterns and relationships within large datasets.

Memory augmentation: Recent advancements have introduced Memory-Augmented Neural Networks (MANNs), which combine neural networks with external memory components. This approach enables AI systems to retain and recall information over extended periods, improving their performance in tasks requiring memory, such as language understanding and reasoning.

Learning mechanisms: AI employs various learning mechanisms inspired by human cognitive processes, particularly in the context of reinforcement learning and unsupervised learning.

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Reinforcement learning: This learning paradigm is similar to how humans learn through trial and error. Agents interact with their environment, receiving feedback (rewards or punishments) that guides future behavior. This process parallels how humans reinforce memories through positive or negative experiences.

Unsupervised learning: In unsupervised learning, algorithms identify patterns and structures in unlabeled data, reminiscent of how humans form associations and categorize information based on experience without explicit instruction.

Memory consolidation: Memory consolidation in AI can be likened to the process of fine-tuning models after initial training. Techniques such as transfer learning allow AI systems to adapt previously learned knowledge to new tasks, akin to how humans build upon existing memories to learn new information.

CONCLUSION

The interplay between memory systems and artificial intelligence represents an interesting frontier in cognitive science and technology. By drawing on insights from human memory, AI can develop more sophisticated learning mechanisms, improve user interactions, and address ethical considerations in data management. As we continue to explore this intersection, a collaborative approach will be important in shaping the future of AI in ways that enrich human experiences and expand our understanding of cognition. The drive toward creating AI systems that truly reflect the complexes of human memory has the potential to transform how we learn, interact, and coexist with technology.