# Combining Minds and Machines: Investigating the Fusion of Cognitive Architectures and Generative Models for General Embodied Intelligence

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## Abstract

Cognitive architectures and generative models are two very different approaches for developing general embodied intelligence. This paper investigates their initial motivation, implementation ways, and the complementary strengths and weaknesses, and targets to fuse them into a general embodied intelligence so as to leverage strengths and complement weaknesses. Firstly, with analyzing their different application scenarios and the difficulties in further research and development, the potential synergy and possible integration strategies are explored between them. Then, by combining the strengths of cognitive architectures, which model human-like cognitive processes, and generative models, which excel in generating novel content based on learned patterns, it achieves the goal of creating embodied agents with enhanced overall capabilities. Finally, a comprehensive framework demonstrating the integration of cognitive architectures, generative models, and other AI methods to achieve general embodied intelligence is presented accompanied by an illustrative example.

## Introduction

The potential of artificial intelligence (AI) technology has been percolating in the background for years. But when ChatGPT, the AI chatbot, began grabbing headlines in laterly 2022, it put generative AI in the spotlight .

ChatGPT is a form of generative AI – a tool that lets users enter prompts to receive humanlike images, text or videos that are created by AI. Generative AI refers to sorts of unsupervised and semi-supervised machine learning algorithms that enable computers to use existing content like text, audio and video files, images, and even code to create new possible content. Its main idea is to generate completely original artifacts that would look like the real deal.

Generative AI can be applied extensively across many areas of the business. It make it easier to interpret and understand existing content and automatically create new content. Developers are exploring ways that generative AI can improve existing workflows, with an eye to adapting workflows entirely to take advantage of the technology.

From coding assistance to book summaries, people have been using the chatbot to help access and understand information where a simple Google query might fall short. The technology seems to have endless potential.

Such a range of capabilities in a single ChatGPT system is a strong sign of approaching general embodied intelligence. Innovations integrating such models will also expand along the maturation of such AI systems and exhibit unforeseeable applications that will have important impacts on several aspects of societies. In light of the remarkable progress in generative AI, as demonstrated by systems like ChatGPT, researchers in the field of CA have recently begun to inquire about its continued significance as another critical research direction in the field of AI.

CAs, which originate from the field of AI, implement models for problem-solving and decision-making. These architectures have a wide room for implementation in industrial applications ie. general embodied intelligence. CA provide a general framework for developing computational decision-making applications and are often, but not necessarily, based on theories of the human mind.

Autonomous decision-making ability is demanded in the context of the growing complexity of industrial applications. The CA have a potential to contribute to such applications. Unfortunately, till now, the few examples of industrial applications. Therefore, Kotseruba (2016, 2020) raise the question whether CAs are suitable to apply for software development besides of experiments. Wendt (2018) addressed this problem through proposing an approach to enhance the systematic application of CAs in the field of industrial systems. Liu (2021) argued that CA is most sutable way for general embodied intelligence.

In this paper, a comprehensive elucidation is presented of the principles and strengths underlying generative models and CAs. It thoroughly analyzes the limitations associated with each approach while identifying their potential complementarity. By conducting a comparative study, it proposes an integrated approach that harmoniously combines both methods. Through practical examples, it vividly demonstrates the successful implementation of general embodied intelligence using this integrated approach.

## CAs: Principles and Strengths

CA is the theory regarding the human mind, its structure, and how the various components work in sync to manage intelligent behavior in complex environments.

### CAs and Components

The motivation of CA is using cognitive psychology research to create a complete computer-based cognition model firstly. Afterwards, it aims to create artificial computational system processes that work like natural cognitive systems or humans. The technology works as a blueprint for intelligence agents, and its theory focuses on combining AI with cognitive sciences. With the rise in popularity and adoption for machine learning and AI technology, CA will only further garner research and become a more refined practice with a wide range of applications.

One notable feature of CAs is their ability to model general embodied intelligence in a rational manner, other than just algorithms, which are designed to solve a specific task. Cognitive model should be able to present solutions to a various field of problems.

In the context of developing general embodied intelligent agents, CAs offer the potential to provide agents with a rich cognitive framework that mimics human-like cognitive processes. These cognitive processes encompass a wide range of functions, including perception, learning, memory, decision-making, reasoning, and actions etc.

### Modeling Cognitive Processes and Reasoning

Modeling human-like cognitive processes and reasoning is a fundamental aspect of CAs and a key strength in the development of general embodied intelligent agents. The architectures aim to capture the intricate workings of human cognition, including perception, attention, memory, and reasoning, to emulate human-like decision-making processes. By modeling these cognitive processes, CAs enable agents to analyze and interpret sensory information, extract meaningful patterns, and make informed decisions based on acquired knowledge and past experiences.

One of the primary goals of modeling human-like cognitive processes is to achieve a higher level of cognitive reasoning. CAs provide mechanisms for logical reasoning, problem-solving, and planning, allowing agents to engage in complex decision-making tasks. By employing symbolic representations, rule-based systems, and cognitive maps, the architectures facilitate the manipulation and manipulation of knowledge in a structured manner, leading to more sophisticated cognitive reasoning abilities. This modeling of human-like cognitive processes enables agents to exhibit flexible and adaptable behavior in response to changing environments and tasks.

### Notable Examples for CAs

Over 300 CAs have been proposed to date, with some of the most renowned ones being Learning Intelligent Distribution Agent (LIDA), Adaptive Control of Thought—Rational (ACT-R), and Soar etc. These highly acclaimed architectures serve as successful examples, offering diverse approaches to modeling the processes of cognitive activity.

### Applications and Successes of CAs

CAs have been successfully applied in AI, education, robotics, and decision support, enabling better modeling of human cognition and enhancing various domains. In addition, CAs also have bridged the gap between cognitive science and neuroscience, providing frameworks for studying brain function and cognitive processes. Overall, CAs have left a significant mark on numerous disciplines, enhancing our understanding of human cognition and fostering progress in various fields.

### Limitations and Challenges of CAs

One of CAs' significant limitation is the complexity of modeling human-like cognitive processes accurately. While CAs strive to emulate various aspects of human cognition, there are inherent gaps in our understanding of the intricacies of the human mind. Modeling complex cognitive phenomena, such as emotions, creativity, and social intelligence, poses challenges as these processes are not yet fully understood or replicated in computational frameworks. Another challenge faced by CAs is the difficulty in abstracting model knowledge from enormously complex scenarios.

## Generative Models: Principles and Strengths

A generative model is a type of AI model that is designed to generate new data that is similar to the data it was trained on. Generative models have numerous applications, including data augmentation, image and video synthesis, text generation, and more, making them a crucial component in the field of AI.

### Overview of Generative Models

Generative AI, also known as Generative AI model, is an AI approach that utilizes generative models to create new data and is aptly named after the fundamental technique it employs. This technology, it should be noted, is not brand-new. But it was not until 2014, with the introduction of generative adversarial networks, or GANs – a type of machine learning algorithm – that generative AI could create convincingly authentic images, videos and audio of real people.

On the one hand, this newfound capability has opened up opportunities that include better movie dubbing and rich educational content. It also unlocked concerns about deepfakes – digitally forged images or videos – and harmful cybersecurity attacks on businesses, including nefarious requests that realistically mimic an employee's boss.

### Generative AI Work Principles

Large language models (LLM) are actually a part of a different class of models called foundation models works with language. The term "foundation models" was coined since it seems a sign of new paradigm the field of AI converges to. Generative AI could include LLMs or foundation models when these are used for generative use cases, but not when used in other ways.

Where before, AI applications were being built by training, maybe a library of different AI models, where each AI model was trained on very task-specific data to perform very specific task. What predicted by using of LLM that it is going to start moving to a new paradigm, where it is a foundational capability, or a foundation model, that would drive all of these same use cases and applications. So the same exact applications envisioned with conventional AI before, and the same model could drive any number of additional applications. The point is that this model could be transferred to any number of tasks. What gives this model the super power to be able to transfer to multiple different tasks and perform multiple different functions is that it's been trained on a huge amount, in an unsupervised manner, on unstructured data. And what that means, in the language domain, It is basically when feeding a bunch of sentences – and it responses with terabytes of data there – to train this model. It's this generative capability of the model – predicting and generating the next word – based on previous words that it's seen beforehand, that is why that foundation models are actually a part of the field of AI called generative AI because it's generating something new in this circumstances, the next word in a sentence.

### Abilities for Generate Novel Content

The ability to generate novel content is a fundamental aspect of generative models in the field of AI. Generative models are designed to learn from existing data and then produce new data that resembles the patterns and distribution of the training data. This capacity to generate novel content is particularly prevalent in various types of generative models.

Through combining various AI algorithms to represent and process content, the generative power of these models has led to remarkable breakthroughs in fields like natural language processing, computer vision, and creative arts. They can produce realistic images, lifelike human speech, compelling music, and coherent text passages, among other outputs. This capability has wide-ranging applications, including data augmentation for training machine learning models, content creation for entertainment and artistic purposes, and even assisting in medical imaging and drug discovery. For example, ChatGPT, built on the principles of the Transformer architecture, has been trained on vast amounts of internet text, enabling it to capture the intricate structures and semantic relationships within language.

### Applications and Successes of Generative Models

The accomplishments of chatGPT exemplify the potential of generative models in enabling intelligent agents to communicate effectively, adapt to user needs, and generate human-like language, all of which are integral to advancing the development of general embodied intelligent agents.

Recent progress in transformers such as Google's BERT (Bidirectional Encoder Representations from Transformers), OpenAI's GPT and Google AlphaFold have also resulted in neural networks that can not only encode language, images and proteins but also generate new content. Diffusion models are a new class of state-of-the-art generative models that generate diverse high-resolution images. They have already attracted a lot of attention after OpenAI, Nvidia and Google managed to train large-scale models.

Nowadays, pioneers in generative AI are developing better user experiences that let you describe a request in plain language. After an initial response, user can also customize the results with feedback about the style, tone and other elements you want the generated content to reflect.

### Limitations and Challenges of Generative Models

One of the primary challenges is the issue of generating coherent and contextually appropriate responses consistently. While chatGPT excels at generating language, it can sometimes produce outputs that are nonsensical or lack relevance to the input query. This challenge stems from the difficulty of capturing the full complexity of language and context within the training data.

Additionally, generative models like chatGPT heavily rely on the data trained on, which means they may inadvertently perpetuate biases or generate inappropriate content if the training data contains such biases or inappropriate examples.

Another limitation of generative AI is the lack of rational controls over the generated outputs.

## Complementary Strengths and Integration Potential of CAs and Generative Models

AI's core is about creating machines that can think and act like humans, or even surpass human general embodied intelligence. Tremendous approaches have been tried and tested to achieve them, such as the symbolic, the connectionist, the hybrid, and whole-organism architecture etc. Though there are many approaches to creating AI, Hinton argued that there are two distinct paths to intelligence, and the two paths share knowledge between agents in very different ways. Though it can not be imagined out what does the Hinton's mortal and immortal computation look like upon a sudden, these two types of computation can be roughly felt they are similar to machine paradigm computation and human paradigm computation. These coincide with the algorithm-based and brain-inspired AI literally, which covers the gererative AI and CAs-based AI depicted above.

### Advantages and Drawbacks of Two Approaches

It is apparently that each AI method has his own strengths, drawbacks and complementary one each. The best way to achieve general embodied intelligence is to fully benefit the advantages of them and make complementary disadvantages for each others. For this purpose, Table 1 depicts a brief comparation of the strengths and the weaknesses of CAs and generative models.

It's needs to be pointed out that the strengths and weaknesses mentioned in above table are generalizations, and specific models within CAs and generative AI can have different characteristics and variations.

### Complementary Aspects between Two Approaches

CAs provide a principled and structured framework for modeling human cognition, enabling agents to reason, simulate complex tasks, and exhibit explainable behavior. Generative models excel in generating coherent and contextually relevant content, allowing agents to engage in natural language interactions and produce creative outputs.

| | Cognitive architecture | Generative models |
|---|---|---|
| Disciplinary foundation | Cognitive psychology, brain science, neurobiology, logic, information science, etc. | Manchine learning, deep learning, reinforcement learning, and xNN. |
| Knowledge representation | Explicit. | Implicit. |
| Symbolic reasoning | Logical, rule-based. | Limited, emergent. |
| Cognitive plausibility | Emulates human cognition. | Lacks direct cognitive plausibility. |
| Interpretability | More interpretable. | Less interpretable. |
| Data generation | Not focused on data generation. | Proficient in data generation. |
| Unsupervised learning | Limited emphasis on unsupervised learning. | Leveraged for unsupervised learning. |
| Creative applications | Limited focus on creative applications. | Promising for creative applications. |
| Data augmentation | Limited utility for data augmentation. | Valuable for data augmentation. |
| Scalability | May face scalability challenges. | Can scale well. |
| Flexibility | Relatively rigid and less flexible. | More flexible and adaptable. |
| Learning from data | Limited learning from data. | Emphasize learning from data. |
| Knowledge acquisition | Require manual knowledge acquisition. | Learn knowledge from data automatically. |
| Model collapse | Not applicable to model collapse. | Model collapse can occur. |
| Evaluation challenges | Evaluation challenges vary. | Evaluation challenges exist. |
| Computational complexity | Computational complexity varies. | Can be computationally intensive. |
| Controllability | Higher controllability. | Lower controllability. |
| Possibility of loss of control | Lower possibility of loss of control. | Higher possibility of loss of control. |
| Wrong or misleading output | Outputs tend to be more reliable and accurate. | Outputs can be more prone to errors and inaccuracies. |
| Future prospects | Potential for improved cognitive understanding. | Promising for creative applications and data generation. |
| Future prospects for AI | Advancing explainability and human-like intelligence. | Expanding creative applications and data-driven capabilities. |
| Future prospects for general embodied intelligence | Potential with comprehensive reasoning. | Potential with diverse data generation. |
| Aspects for advanced robotics applications | Emphasis on advanced cognitive reasoning and decision-making in robotics. | Focus on enhancing robotic capabilities through data-driven learning and adaptation, with potential for advanced applications. |
| Roles for developing general embodied intelligent agents | Provide a framework for developing general embodied intelligent agents with a focus on cognitive reasoning and understanding. | Contribute to developing general embodied intelligent agents by leveraging data-driven learning and generation capabilities, enhancing perception and behavior. |

Table 1: The strengths and weaknesses comparison of CAs and generative AI models.

## Integration Enhance Overall Agent Capabilities

By integrating CAs and generative models, both strengths of the two approaches can be harnessed. The interpretability, explainability, and reasoning abilities of CAs can enrich the generative models' outputs, ensuring more controlled, contextually appropriate, and explainable responses. Similarly, the generative capabilities of models can enhance the CAs' ability to generate novel and creative content, enabling more adaptive and engaging interactions with the environment and users. These complementary aspects between CAs and generative models offers promising directions for exploring the fusion of these approaches and unlocking the potential for developing more advanced and intelligent embodied agents.

## Potential Benefits and Advantages of Integration

The integration of these two approaches and others it will hold several potential benefits and advantages in the pursuit of general embodied intelligence.

By integrating these approaches, it will leverage the interpretability and reasoning abilities of CAs to enhance the generative models' outputs. This integration offers the potential for more controlled, contextually appropriate, and explainable responses from the agents.

Furthermore, the generative capabilities of models can augment the CAs' ability to generate novel and creative content, expanding the agents' adaptability and versatility. The integration can also lead to more robust and adaptable systems that can learn from and adapt to new environments, improving their overall performance and intelligence.

Ultimately, the potential benefits and advantages of integration lie in the ability to create agents that possess a holistic set of cognitive and generative skills, enabling them to tackle complex tasks, engage in natural and meaningful interactions, and exhibit creative and contextually appropriate

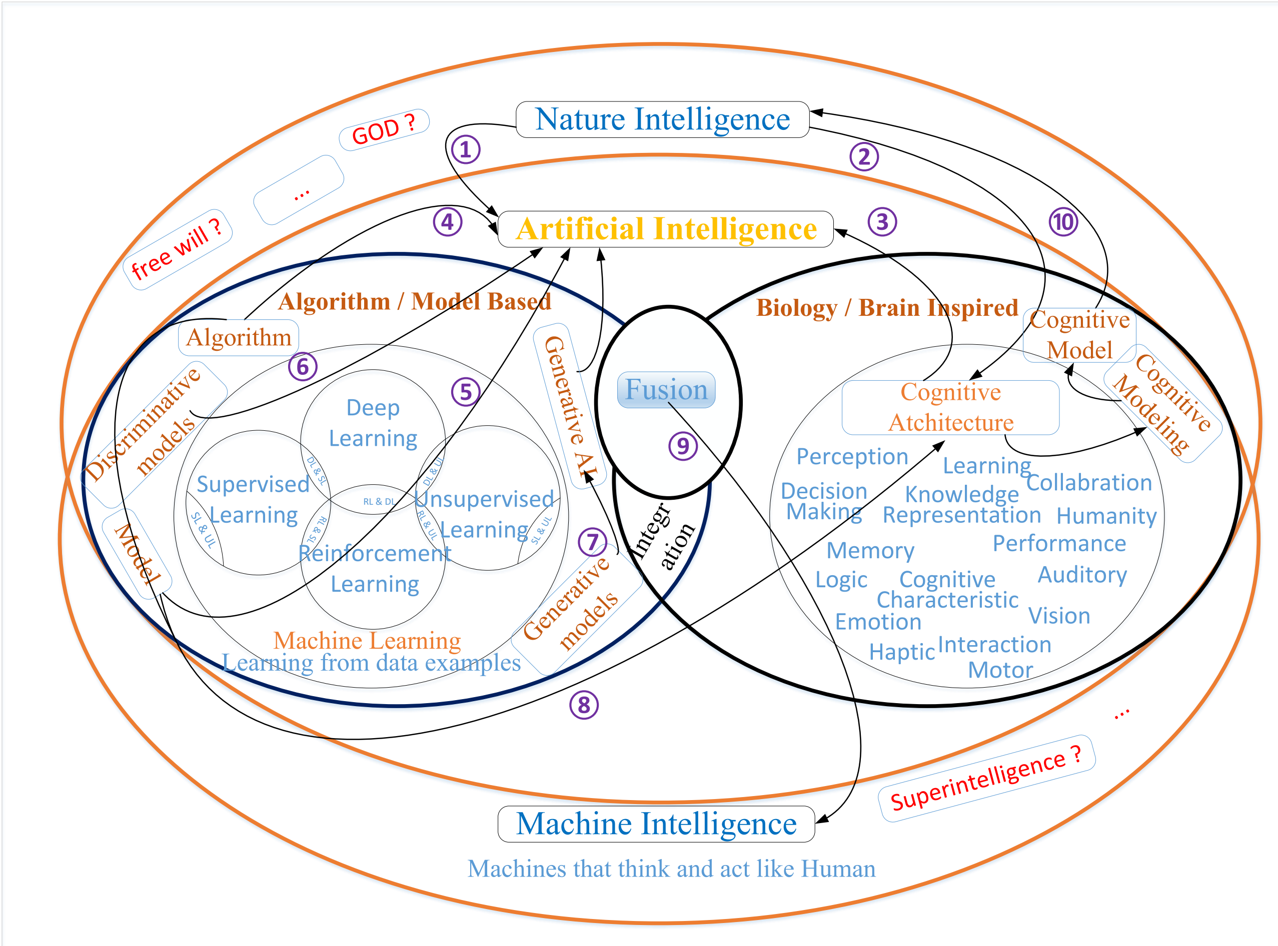


Figure 1: Two AI approaches (CAs and generative model) and their fusion to implement human-like intelligence.

behavior in a wide range of real-world scenarios.

## Approaches for Integration

By bringing together the principled framework of CAs, which capture human-like cognitive processes, with the power of generative models, the intelligent agents created with can possess both reasoning and generative capacities. Through a comprehensive exploration of the approaches for integration, it will pave the way for a deeper understanding of how combining minds and machines can lead to the development of general embodied intelligent agents with enhanced cognitive and generative abilities.

### Researches and Approaches for Integrating CAs and Generative Models

The overarching objective of AI is to develop machines that can exhibit human-like behavior and perform tasks typically executed by humans. Significant efforts have been dedicated since its inception, and result in remarkable progress. Through conducting a comprehensive literature review and method analysis, this study elucidates the interrelationships among different AI efforts, as illustrated in Figure 1.

Drawing intelligence research inspired by nature intelligence, AI researches are classified into 10 comprehensive categories labeled with circled number. In Figure 1, ① indicates the way creating AI directly from nature intelligence, this research like Merel's work (2019). The work creating CA from nature intelligence is labeled with ②, such as Anderson's (2004, 2005) and Baxter's work (2008). The work from CA create AI labeled with ③, such as Lieto (2018) and Liu (2021). Creating AI with Algorithm is labeled with ④, work such as Malekmohamadi (2020), Team (2021), and Wittkuhn (2021). Label ⑤ indicates the method creating AI from model, such as Richards's work (2022). The method from discriminative model create AI is labeled with ⑥, for example Graves (2016). Creating Generative AI from generative model is labeled with ⑦, such as Taniguchi and Yüksel. Building CAs from algorithm/model is marked with ⑧, and work such as Bertolero (2015), Taniguchi (2021), and Petersen (2015). Fusion/Integration to achieve AI is with ⑨, and work for example Banino (2018), Flesch (2018), Gupta (2023), Langley (1989), Miyazawa (2019), and Wayne (2018). Another research on AI is to study nature intelligence through CA which is shown with ⑩, and the example like Laird's work (2017).

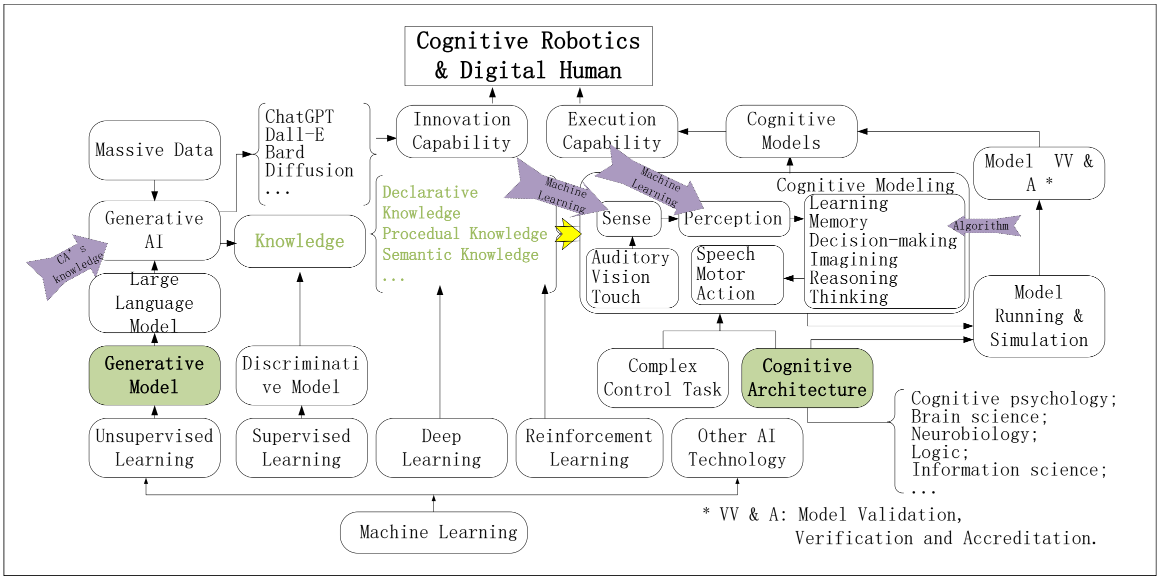


Figure 2: Fusion framework of generative model and CA for cognitive robot & digital human.

The existing research and approaches strongly indicate a clear trend towards the integration of CAs and generative models. This fusion of them is crucial in providing valuable insights into achieving general embodied intelligence.

## Incorporating Generative Components into CAs

CAs incorporate mechanisms for learning and adaptation, essential components of human cognition. These architectures employ techniques such as reinforcement learning, unsupervised learning, and incremental learning to enable agents to acquire new knowledge, refine their existing knowledge, and adapt their behavior based on feedback and experience. This capacity for learning and adaptation allows agents to continually improve their cognitive processes and reasoning abilities, leading to enhanced performance and decision-making capabilities over time.

## Incorporating Cognitive Cells into Generative AI

Incorporating cognitive components into generative models open up new possibilities for enhancing the contextual understanding and reasoning abilities of these models, thereby advancing their potential for general embodied intelligence.

One approach is to integrate cognitive components inspired by frameworks into the architecture of generative models. By incorporating cognitive reasoning mechanisms, such as working memory and attentional processes, into the generative model, it becomes capable of generating more contextually informed and coherent responses. This integration allows the generative model to exhibit reasoning abilities and produce outputs align with human-like cognition.

Another strategy involves leveraging CAs to guide the training and fine-tuning of generative models. By incorporating cognitive principles and constraints during the training process, the generative model can learn to generate content that adheres to cognitive rules, exhibits plausible reasoning, and aligns with human-like behavior.

Hybrid architectures that combine elements of both generative models and CAs have been proposed to strike a balance among various efforts for machine intelligence.

## Exploration of Hybrid Models and Challenges

Hybrid models aim to leverage the strengths of both approaches, creating a symbiotic relationship that allows for seamless integration. However, the implementation of hybrid models comes with its own set of challenges. One challenge lies in finding an optimal balance between cognitive reasoning and generative creativity. Another challenge involves managing the trade-off between control and novelty. Hybrid models must strike a balance between generating novel and contextually relevant content while avoiding overreliance on pre-learned patterns or biases.

# Case Studies and Examples

By fortunate circumstances, a nuclear power plant (NPP) was presented with an opportunity to implement these comprehensive integration for its intelligence applications. Figure 2 illustrates the overarching framework of this process.

## Case Studies and Their Outcomes

The overall requirements for AI technology in NPP can be summarized into two application entities: cognitive robots and digital humans. Cognitive robots perceive the on-site environment and collaborate with the team to control onsite operations and gather dynamic information. Digital humans, on the other hand, are intelligent agents that can be customized according to specific needs within the enterprise intranet. They have the ability to utilize data resources and work together with humans and robots to accomplish collaborative tasks and decision-making processes. Digital Humans can also leverage generative AI to address inquiries related to cognitive entities, propose design and planning solutions, and handle procedures for issues or incidents. Both cognitive robots and digital humans can effectively use internal data and collaborate with internal cognitive entities to achieve seamless and cooperative operations.

### Improved Performance and Capabilities for Both

To address possible errors or biases that may arise from using generative models and lead to decision-making mistakes, the decision-making knowledge from cognitive models are integrated into the decision phase for controlling behavior of robots or digital humans. For decreasing the intensive manual labor of knowledge's extraction during cognitive modeling, model firstly learns from the vast enterprise data using generative models, and following that, critical decision-making knowledge is either manually intervened or subject to evaluation for permission, so as to ensure alignment with the cognitive model's requirements.

This integration augments decision process' controllability and helps avoid generating negative outcomes. Moreover, utilizing generative AI for pre-generating knowledge during cognitive modeling significantly improves modeling efficiency and enhances the overall application level.

### Strengthened Task Behavior for Applications

By combining two approaches and more, robots or digital humans experience significant enhancement in perception, learning, and decision-making capabilities. The acquisition of cognitive model knowledge and the ability to innovate are achieved are achieved through generative AI. Communication and collaboration between humans and robotics are effectively facilitated by speech recognition, speech-to-text, and text-to-speech technologies. AI-powered image and speech recognition enable audiovisual sense and perception. Leveraging generative AI for learning and further refining cognitive model knowledge ensures more reliable and efficient decision-making behavior.

Furthermore, the implementation of sense, perception, and cognitive functionalities during cognitive modeling all incorporate generative models and AI algorithms.

## Conclusion

By leveraging the complementary strengths of these two approaches, we have witnessed the potential for creating intelligent agents with heightened capabilities. Through a thorough analysis of their principles and strengths, we have highlighted the power of CAs in modeling human-like cognitive processes and reasoning. Similarly, generative models have demonstrated their prowess in generating novel content based on learned patterns.

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