# Continual Learning and Adaptations in GenAI

# GROUP : GEN-AI SENTINELS


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# TOPICS TO BE COVERED

- Introduction
- What is Continual Learning
  - Approaches to Continual Learning
  - Continual Learning Methods
  - Applications and Challenges
- What is Gen AI
  - Adaptation in Gen AI
- Continual Learning in Generative AI
  - Continual Pre Training
  - Continual Instruction Tuning
  - Continual Alignment
- Conclusion

# INTRODUCTION

- Abstract: In the context of generative artificial intelligence (Gen AI), this presentation explores the idea of ongoing learning and adaptation.
- What is Continual Learning? Continual learning is the process by which artificial intelligence (AI) systems, like human adaptability, continuously gather, update, and utilise knowledge over the course of their lives.
- What is Gen AI? Gen AI is the next stage of AI systems' development, where they are able to create new ideas, content, and solutions on their own.
- In the framework of generative artificial intelligence (AI), continuous learning is essential for improving the system's capacity to produce original and excellent material by adjusting to changing tasks and data distributions.
- The Reasons for Surveying Continuous Learning in Gen AI is Our goal  to comprehend how continuous learning enables Gen AI to produce new content and adapt on its own, promoting its progress across a range of applications and areas.

# WHAT IS CONTINUAL LEARNING

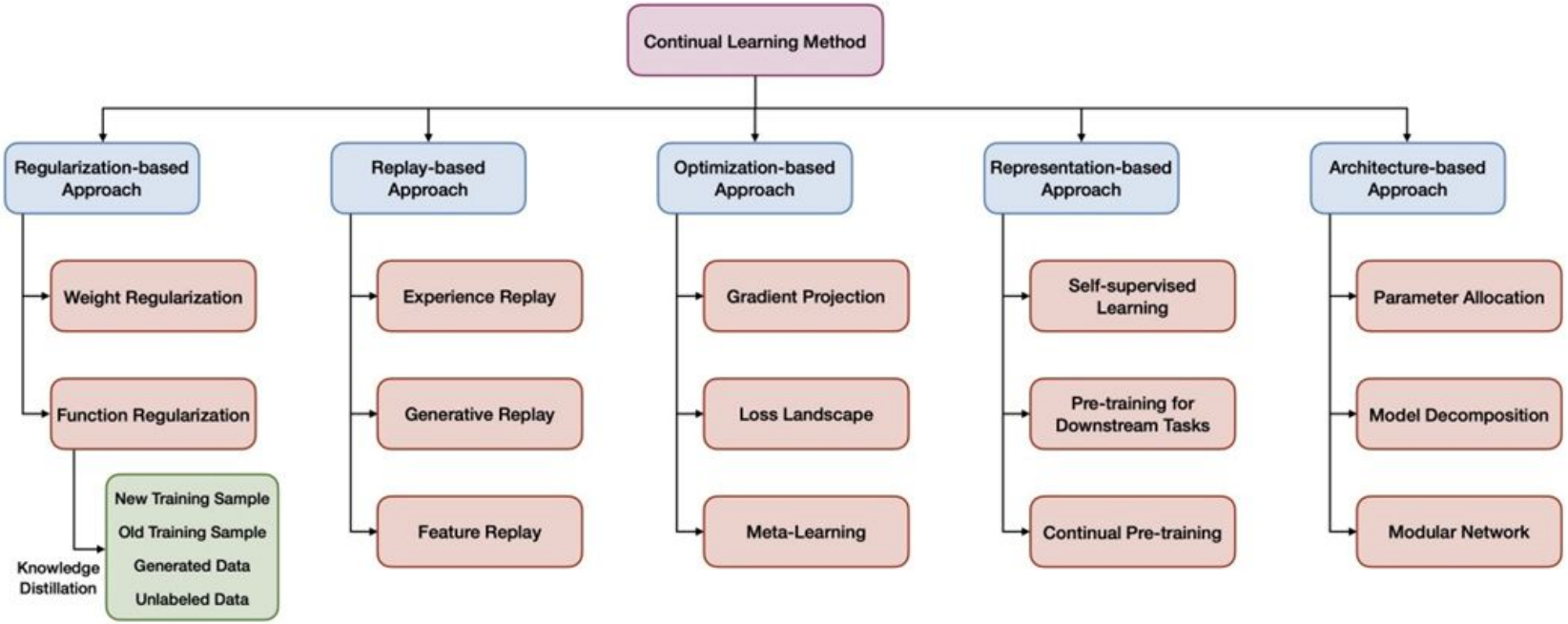
- The capacity of an intelligent system to gradually gather, update, amass, and utilise knowledge over the course of its existence is known as continuous learning.
- It makes it possible for AI systems to grow and adjust to the dynamics of the real world.
- Catastrophic forgetting, on the other hand, limits continuous learning by causing the performance of previously learned activities to deteriorate when a new task is learned.

# APPROACHES TO CONTINUAL LEARNING

- The difficulties associated with continuous learning fall into five areas, which have been addressed by a variety of approaches:Regularization-based approach
  - Replay-based approach
  - Optimization-based approach
  - Representation-based approach
  - Architecture-based approach

By maintaining appropriate intra/inter-task generalizability and a sufficient stability-plasticity trade-off, these techniques seek to accomplish the goal of continuous learning.

# WHAT ARE CONTINUAL LEARNING METHODS



# REGULARIZATION METHOD

- Reducing catastrophic forgetting, strike a balance between stability and plasticity.
- Method: Using uncertainty-based regularisation to effectively manage neural network parameters.
- Features:
  - Calculating uncertainty at the node level eliminates extra parameters.
  - novel regularisation terms based on KL divergence are introduced.
- Findings: Excellent results are obtained in supervised and reinforcement learning, surpassing criteria for EWC, SI, and VCL.

# OPTIMIZATION METHOD

- Improving the model's capacity to pick up new skills while maintaining mastery of existing ones.
- Method: Concentrating on modifying model parameters ($\theta$) in order to achieve a task-to-task balance.
- Features:
  - gradient projection is used to guide updates while taking effect on all activities into account.
  - makes use of the loss landscape to keep performance high during tasks.
- Findings: Provides a nuanced equilibrium in learning techniques, assisting the model in sustaining performance throughout various tasks.

# REPLAY BASED METHOD

- Implementing memory systems, prevent catastrophic forgetting.
- Method: Resetting class representations using selective amnesia and generative replay.
- Features:
  - Using an altered version of the Variational Autoencoder (VAE) to produce data samples.
- Results: Shows effectiveness in managing dynamic class information and preventing memory loss.

# APPLICATIONS AND CHALLENGES OF CONTINUAL LEARNING

- Adapting continuous learning techniques to real-world settings like few-shot, semi-supervised, and unsupervised ones.
- Attention is also being paid to other domains in vision, such as object detection and semantic segmentation, and to fields like reinforcement learning and natural language processing.
- In these applications, continuous learning has unique difficulties that need to be understood in order to facilitate more research in the field.

# WHAT IS GEN AI

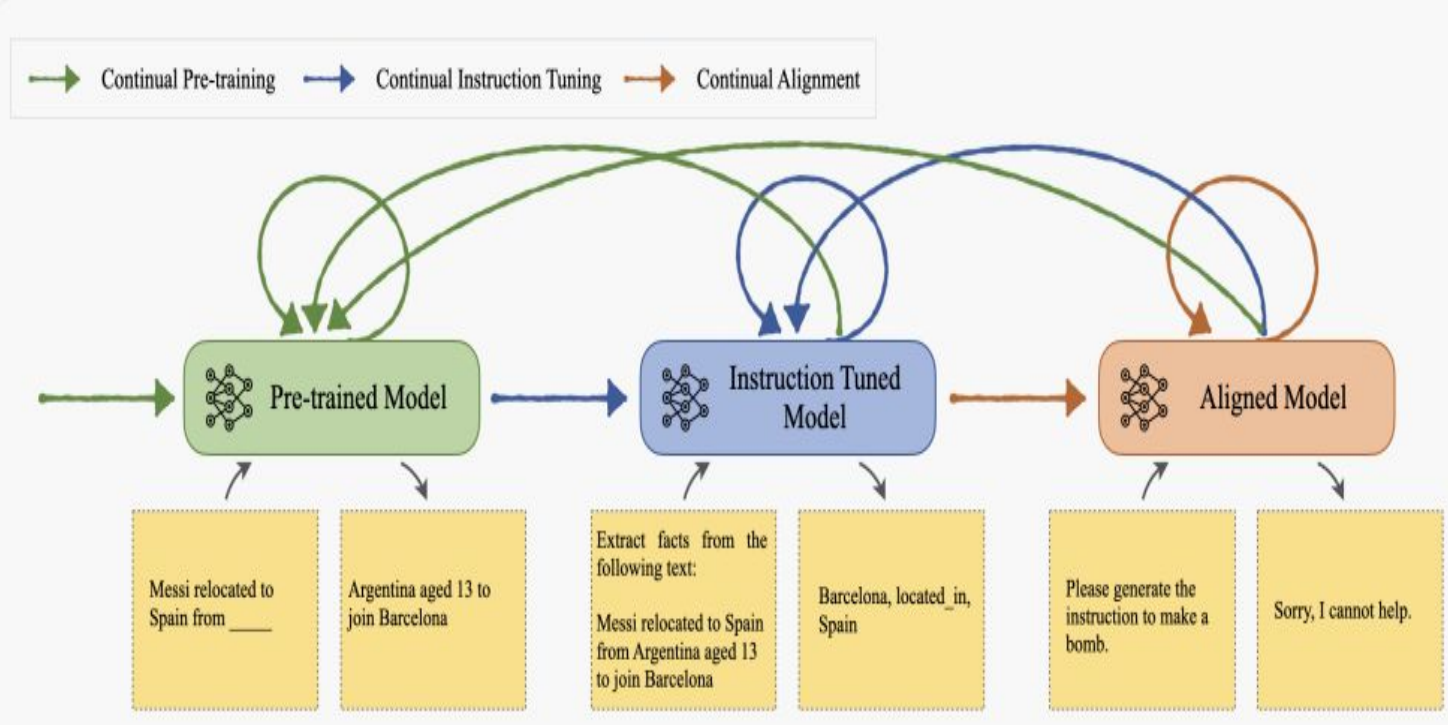
- Generative AI (Gen AI) refers to computational techniques capable of producing new, meaningful content such as text, images, or audio from training data.
- Generative AI systems are evolving to produce diverse and realistic content tailored to different needs and situations.
- Generative AI systems serve as intelligent question-answering tools, assisting in a wide range of tasks and applications.
- The technology not only enhances creativity but also poses challenges for responsible and sustainable technology steering, emphasizing the need for ethical and societal alignment.

# ADAPTATION IN GEN AI

Three main stages of Adaptation in Generative Artificial Intelligence

- The adaptation plan for Gen AI is structured into three main stages: initial learning, dynamic adaptation, and ethical alignment.
- Initial learning involves the initial training of AI systems, while dynamic adaptation focuses on incorporating new information and adjusting to changes.
- Ethical alignment ensures that AI decisions and actions remain ethically sound according to evolving human standards, emphasizing the importance of aligning with societal norms.

# CONTINUAL LEARNING IN GENERATIVE AI




https://arxiv.org/pdf/2402.01364.pdf

# CONTINUAL PRE TRAINING

- Pre-training must be ongoing in order for systems to gradually improve their knowledge in order for General AI to be developed.
- Approach: Application of ETA-DACP, ETS-DACP, and DACP techniques.
- Key findings:
  - In particular industries like as finance, domain-specific continual pre-training (DACP) greatly enhances the domain knowledge adaptation for large language models (LLMs).
  - Model performance is maximised while training costs are minimised with the Efficient Task-Similar DACP (ETS-DACP) and Efficient Task-Agnostic DACP (ETA-DACP) approaches.

# CONTINUAL INSTRUCTION TUNING

- Pre-trained Language Models (PLMs) are more adaptable for lifelong learning when they are trained continuously.
- Approach: DYNAINST method applied for ongoing instruction tweaking.
- Key Findings:
  - Both at the instance and task levels, PLM generalisation is enhanced by the Dynamic Instruction Replay (DYNAINST) technique.
  - DYNAINST surpasses current benchmarks, demonstrating resilience against forgetfulness and the capacity to maintain performance during assignments.

# CONTINUAL ALIGNMENT

- Continual alignment in Generative AI (Gen AI) is a constant endeavour to keep AI systems ethically aligned and relevant in an ever-changing world.
- Unlike traditional AI systems, which may become obsolete over time, continual alignment seeks to keep AI dynamically aligned with evolving human knowledge and social ideals.
- The analysed papers look into ways for implementing continuous alignment, emphasising the need for AI systems to learn and adapt to new knowledge and changing contexts.
- Continual alignment in Gen AI paves the way for AI systems that can meet the needs of both present and future generations by staying adaptable and aligned with human advancements.

# CONCLUSION

- Continuous learning and adaptability are critical components of Generative AI (Gen AI) systems, assuring their long-term development and relevance.
- AI systems can maintain their effectiveness and ethical alignment with changing human standards by learning and adapting on a continuous basis.
- Understanding the value of continuous learning and adaptability is crucial for the development of AI technology.
- Ongoing efforts are required to improve AI system capabilities and satisfy changing demands and preferences.