Sapient.inc 2025 Intro Booklet

Core Team

Guan Wang, CEO

- Founder of OpenChat, A 7B model Outperforming the 70B Llama2
- Lead Developer of OpenOrca, Leading Open-source LLM
- RL expert @ Shanghai AI Lab, Pony.AI, etc.

Austin Zheng, COO

- Serial Entrepreneur with experiences in computing, cloud gaming
- BA in Philosophy, Politics, and Economics

Meng Lu, Leading Research Scientist

- Assistant Professor @ Peking University, leading brain-inspired AI framework
- Senior Research Associate @ Cambridge University, pioneering neuroimaging AI
- Head of Biology @ Cambridge Infinitus Research Centre, developing ERnet AI system

Hengshuai Yao, Leading Research Scientist

- Former Senior Research Scientist @ Sony AI, developing sparse deep reinforcement learning
- Senior Staff Researcher @ Huawei Edmonton, leading AI & autonomous driving teams
- Adjunct Professor @ University of Alberta, pioneering Universal Option Models cited by DeepMind

1. Company Introduction

Sapient is a startup company based in Singapore and the San Francisco Bay Area (CA, United States), focusing on developing innovative self-evolving and scalable AI architecture that fundamentally elevates AI capabilities, especially in:

- Logical Reasoning
- Complex Task Planning
- Versatility and Adaptiveness
- Flexibility and Efficiency

1.1 Vision

Our research focuses on developing a **Brain-inspired Architecture** utilizing **Evolutionary Algorithm**-based training methodologies.

This approach has been partially implemented, and will continue to be incorporated, in our latest framework, **Sapient H**, which demonstrates exceptional capability in complex task management.

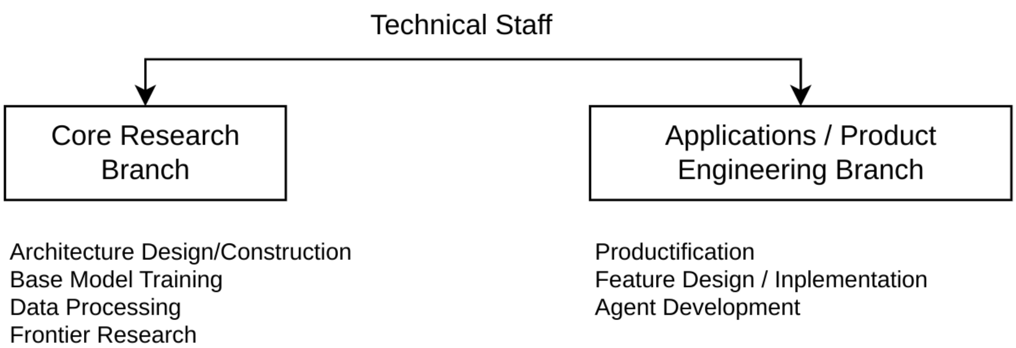
The framework represents a promising alternative to conventional transformer-based models, potentially offering a more efficient pathway toward **Artificial General Intelligence (AGI)** by circumventing traditional scaling-law limitations.

For Sapient H's technical specifications and related core technologies, please scroll to section 2.

1.2 Team

Sapient's technical workforce comprises 20 distinguished AI researchers and engineers, including alumni from leading technology companies such as **DeepMind, Google, Meta, and Microsoft**. Our team members have contributed to groundbreaking AI projects including **AlphaGo, Gemini, and Copilot**.

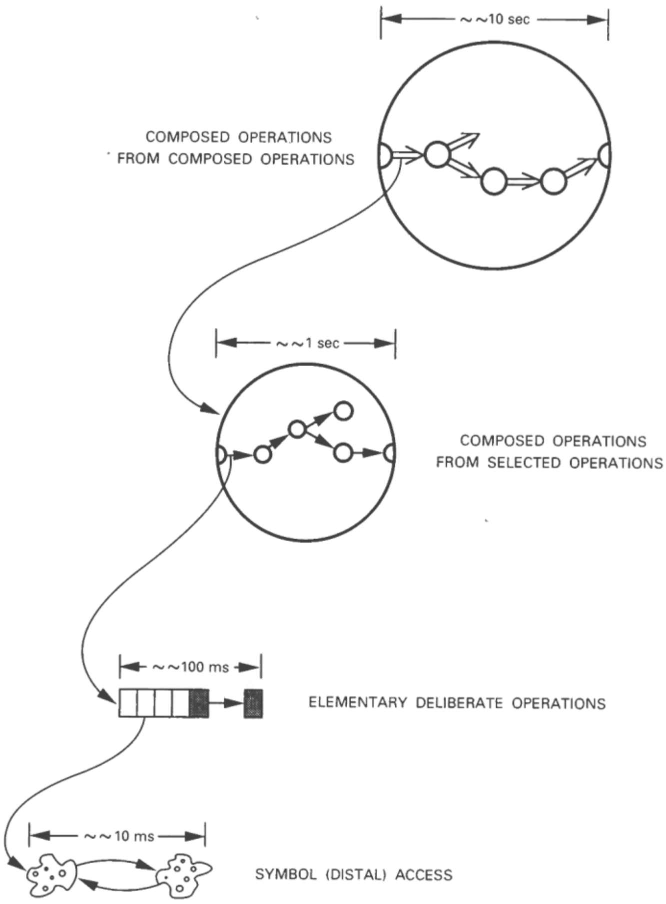
Sapient's technical staff is structured into two key divisions: a **core research** branch and a rapidly expanding **applications / product engineering** branch.



2. Core Research & Technical Advancements

2.1 Sapient H

Built upon neuroscience findings and the theories of cognition, **Sapient H is a Turing-complete hierarchical framework like the brain's cognitive function, composing operations to solve complex problems**.

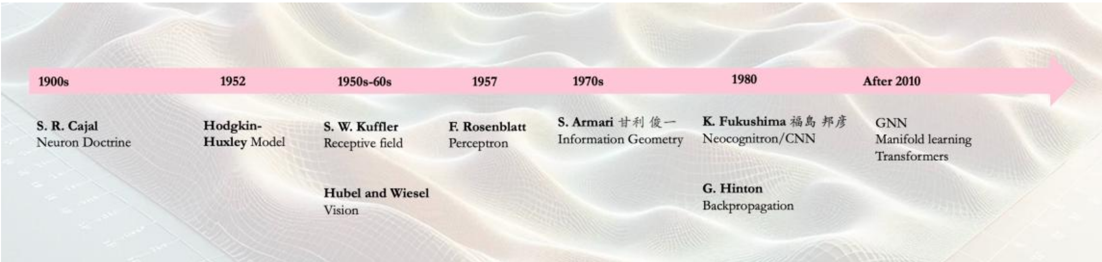


With an approximated backprop method, the training and inference of Sapient H are **parallelizable** and as **scalable** as modern deep learning models like transformers, but with similar efficiency.

Sapient H is also universal to neural network architectures and task types, including language models, robotics control policy, etc.

2.2 Brain-inspired Architecture (further incorporated in Sapient Frameworks)

Sapient believes that by integrating **modularity and hierarchy,** two foundational principles of biological and cognitive systems, into the design of AI models, we can achieve more **robust, specialized, and broadly capable architectures** than those produced by simple parameter expansion, which will lead to the next paradigm in scaling law, the **science-based scaling law.**



2.2.1 Framework Key Traits:

By incorporating this brain-inspired concept into our AI frameworks, our frameworks are tremendously elevated in terms of the following characteristics:

1. **Modularity & Integration**
2. **Hierarchy & Parallelism**
3. **Robustness & Plasticity**
4. **Exploration & Exploitation**
5. **Self-Organization & External Structuring**

2.2.2 The advantages of modular framework (compared to classic mainstream monolithic models):

1. **Specialized Processing**

- Monolithic Architecture: Processes diverse inputs through uniform layer sequences, resulting in potential parameter interference and computational inefficiencies
- Modular Architecture: Implements specialized expert modules for distinct subtasks, enabling optimized domain-specific processing

2. **System Scalability**

- Monolithic Architecture: Expansion requires comprehensive layer or parameter additions, often yielding diminishing returns
- Modular Architecture: Facilitates independent module expansion and metamodule capacity enhancement without complete system retraining

3. **Memory Management**

- Monolithic Architecture: Relies on internal attention mechanisms and unstructured memory states, potentially compromising long-sequence performance
- Modular Architecture: Incorporates distinct short-term and long-term memory systems with structured replay mechanisms, supporting sustained learning capabilities

2.2.3 Advantages of the Sapient Brain-inspired Framework Design

1. **Focused Specialization**

Each expert is tailor-made for a domain or feature set, improving learning efficiency and potentially achieving **higher performance** on specialized tasks.

2. **Efficient Coordination**

The metamodule exerts top-down control, directing attention and resources only where needed, mitigating **unnecessary computation**.

3. **Continuous Adaptation**

Through the replay and self-update loop, the system can **learn from fresh data** long after initial training, enhancing **plasticity** and avoiding catastrophic forgetting.

4. **Robustness and Fault Tolerance**

If one expert malfunctions or receives noisy inputs, the metamodule can partially compensate or rely on other experts, preserving **overall stability**.

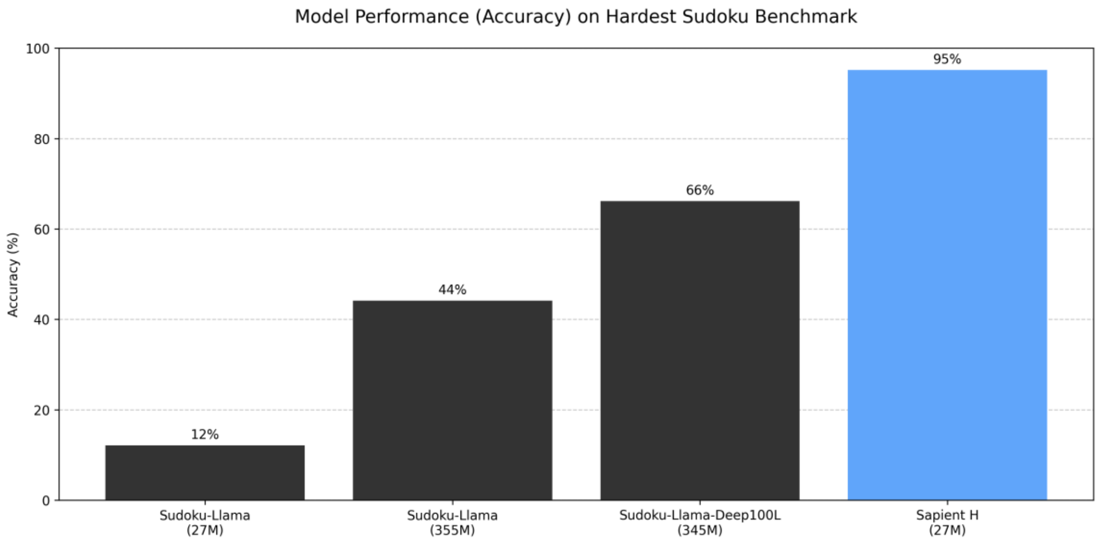
5. **Interpretable Structure**

Clearly defined modules and memory systems allow for **easier diagnostic** and debugging than a single huge end-to-end model.

2.3 Performance and Benchmarks

2.3.1 Solving Complex Constraint Satisfaction Problems (CSP)

We tested through solving the hardest Sudoku puzzles collected by the community in text. It is well-known that Sudoku could be solved with brute force search, but with millions of backtracks.

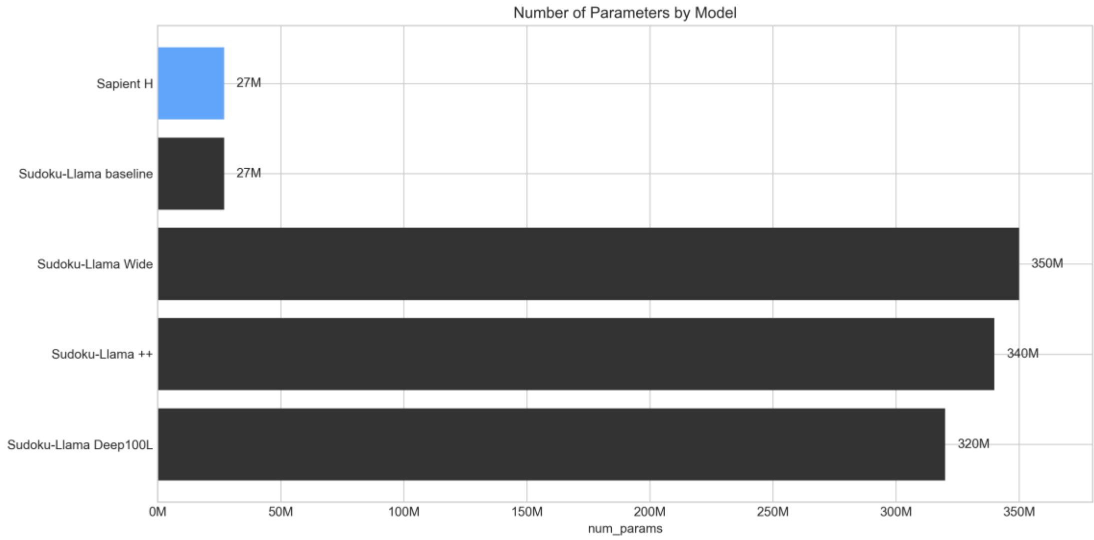


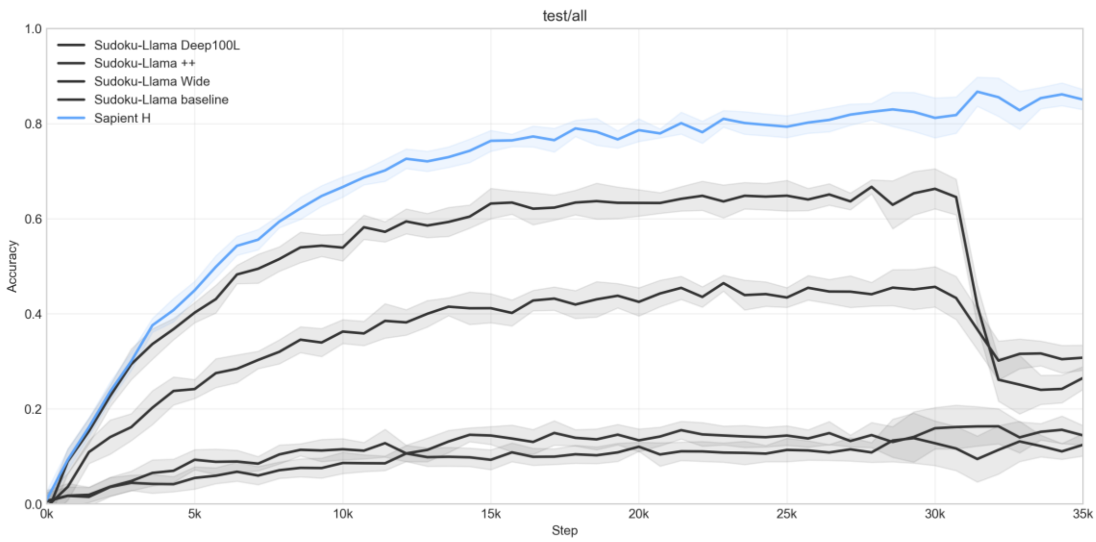
Through performance comparisons with mainstream large language models, Sapient H demonstrates significant advantages in this domain:

- **Exceptional Parameter Efficiency:** With only 27M parameters, Sapient H achieves 95% accuracy. This represents a 99.998% parameter reduction compared to models with 1200B parameters, and a 92.4% reduction compared to the 355M-parameter Llama model.
- **Substantial Performance Improvements:**

- Accuracy is 83 percentage points higher than Llama models of comparable parameter size.
- Accuracy exceeds that of the Llama (355M) model, which has 13 times more parameters, by 51 percentage points.
- Even compared to the optimized Llama DeepNet 100L model, Sapient H maintains a 29 percentage point accuracy advantage.

- **Surpassing Ultra-Large Scale Models:** Even certain ultra-large models with 1200B parameters failed to achieve effective results on this task. At equivalent parameter scales, Sapient H demonstrates nearly 8-fold performance improvement.





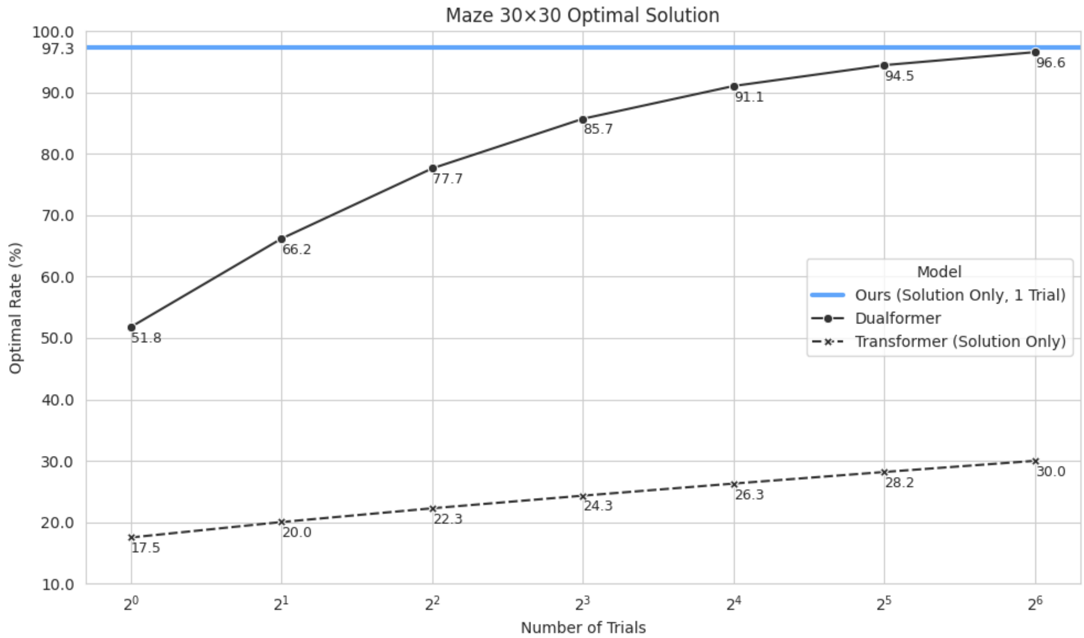
Results of Different Models

2.3.2 Solving High-Dimensional Discrete Variable Optimization Problems

Solving Navigation Puzzles, with a "**one-chance mechanism**" (for robot navigation and control).

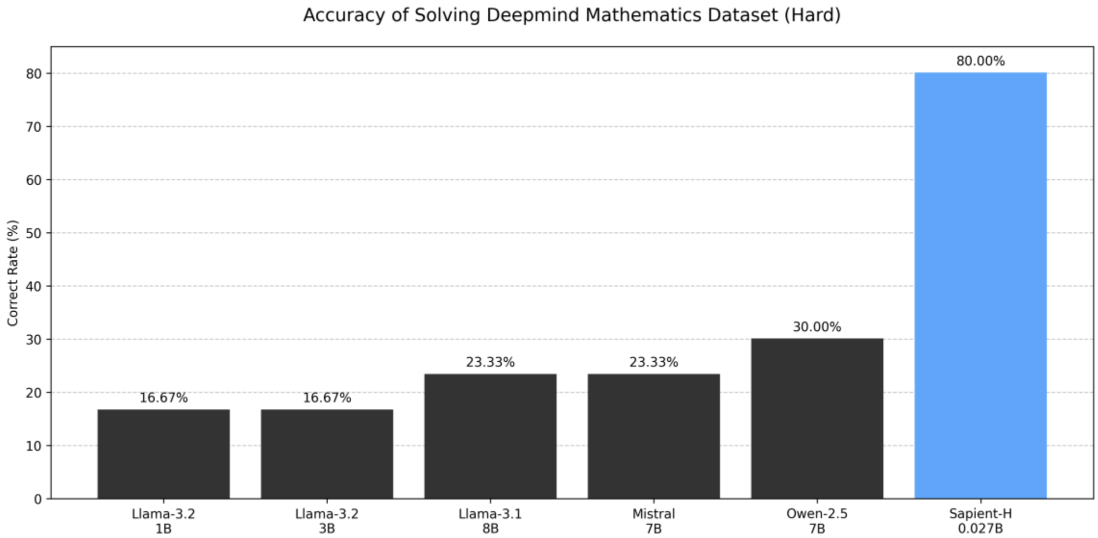
Notably, existing models like Dualformer require distillation from the A* algorithm when handling such tasks, relying on mimicking known human algorithms. Additionally, Dualformer's reliability currently depends on multiple trials and errors - its reported 96% performance is based on the best result after 64 attempts. This is impractical for real-world complex problems; for instance, a robot performing a water-pouring task cannot have 64 attempts, but only **one chance** to succeed.

In contrast, our model learns using only the solutions (Solution Only) and can independently learn and generalize deep reasoning algorithms without relying on external algorithmic guidance or numerous attempts. This distinction demonstrates Sapient-H's efficiency and reliability in solving complex discrete optimization problems, better aligning with real-world application requirements.



Sapient-H vs Dualformer vs Baseline Models' performance on descrete variable optimization problems

2.3.3 Solving advanced math problems



Mathematical Task Results: With minimal parameters, Sapient-H significantly outperforms other models in mathematical reasoning tasks

In short, the Sapient-H Framework demonstrates superior logical reasoning and complex task planning capabilities with great efficiency and model flexibility.

3. Potential Applications and Products

3.1 OpenChat (a Flexible Open-source General-purpose Model)

OpenChat is an innovative open-source language model that has achieved remarkable performance comparable to ChatGPT, despite using only a 7B parameter model that can **run on consumer-grade GPUs like the RTX 3090**. OpenChat learns effectively from mixed-quality data without requiring preference labels, and has scored an average of 64.5 across major benchmarks and notably outperforming larger models like Grok-0 (33B) and Grok-1 (314B) on several metrics.

OpenChat 3.6 was released in May 2024, **surpassing the official Llama 3 8B Instruct model.**

	OpenChat OpenChat 3.6 - 8B Measured	Meta Llama 3 - 8B RLHF – Reported	Meta Llama 3 - 8B RLHF – Measured	Google Gemma 7B - It SFT – Reported	Mistral 7B Instruct DPO+SFT – Reported	Nous Hermes 2 Theta Merged Llama3 Instruct Measured
MMLU 5-Shot	66.3 CoT	**68.4**	49.6* CoT	53.3	58.4	67.6 CoT
GPQA 0-shot	**35.4**	34.2	28.8	21.4	26.3	33.8
HumanEval 0-shot	**73.2**	62.2	61.6	30.5	36.6	58.5
GSM-8K 8-shot,CoT	**81.5**	79.6	74.5	30.6	39.9	77.0
Math 4-shot,CoT	**30.5**	30.0	12.6*	12.2	11.0	28.9
Average	**57.4**	54.9	45.4	29.6	34.4	53.2

Related Links:

https://github.com/imoneoi/openchat

https://huggingface.co/openchat/openchat

3.2 Weather Forecast

Sapient combines HyperNetwork architecture with Vision Transformers for multi-scale feature processing and GANs for probabilistic predictions. The system processes multi-channel weather data and generates forecasts through path integration. Initial tests on WeatherBench data achieved RMSE of 1.87 for month-ahead temperature predictions, showing promise for handling complex **Subseasonal-to-Seasonal (S2S) forecasting** challenges.

Technical Advantages – S2S & Longer Meteorological Model

High Accuracy, Stability, Scalability, and Consistency

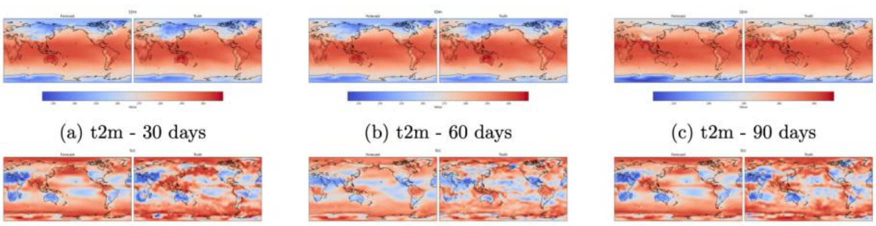
The model's preliminary results at a 5.625° resolution for different forecast lead times (1 month, 2 months, and 3 months) have been analyzed.

- 2-meter air temperature (t2m) measured by Root Mean Square Error (RMSE) and accuracy (ACC), Weekly total cloud cover (tcc) also assessed using RMSE and ACC.

	1-month lead		2-months lead		3-months lead	
Variable	RMSE	ACC	RMSE	ACC	RMSE	ACC
Weekly t2m	1.87K	97.0%	2.17K	92.8%	2.23K	95.9%
Weekly tcc	13.5%	42.7%	13.5%	62.2%	13.6%	71.1%

Preliminary Results at 5.625° Resolution for Different Lead Times (Ongoing Work)

RMSE	1 month	2 month	3 month
t2m	1.87 K	2.17 K	2.23 K
tcc	13.5%	13.5%	13.6%

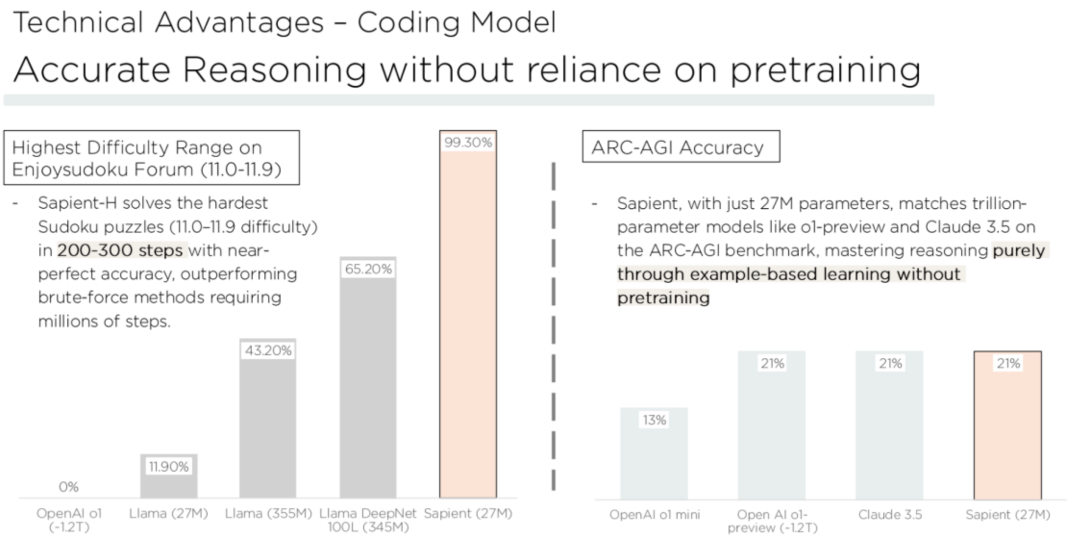


(a) t2m - 30 days (b) t2m - 60 days (c) t2m - 90 days

(d) tcc - 30 days (e) tcc - 60 days (f) tcc - 90 days

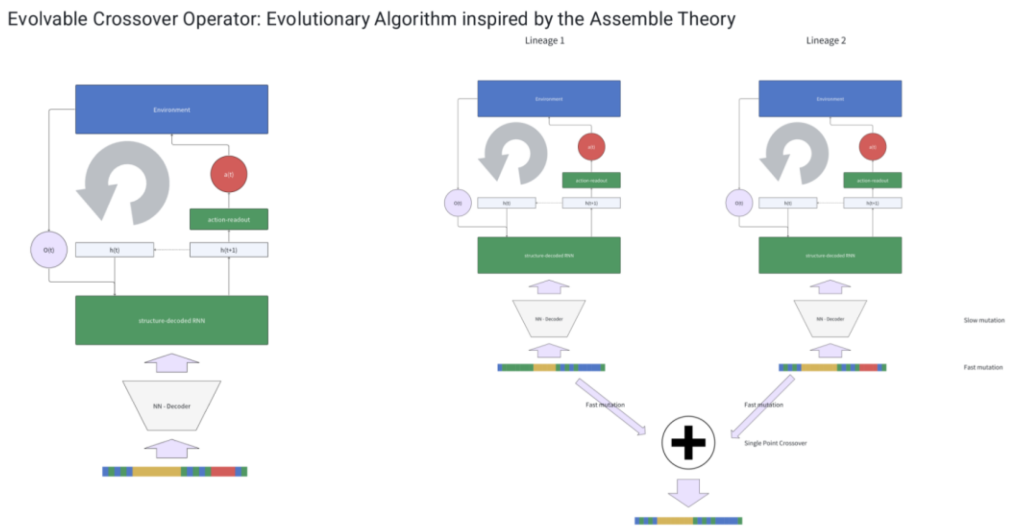
3.3 AI Coding

Our framework's outstanding logical reasoning capabilities make it great for handling coding-related tasks such as end-to-end code-generation and feasibility verification.



3.4 Robot (Remote/Autonomous) Control and Manipulation

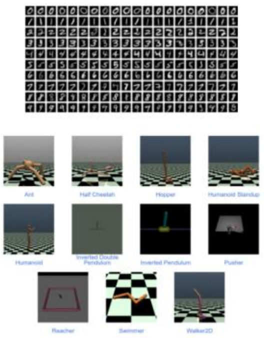
The Sapient framework shows exceptional advantages in robot control and manipulation due to our evolutionary algorithm-based learning method.



Training Phase 1：ANN Gene Sequence Simultaneously Evolves with the RNN Encoder

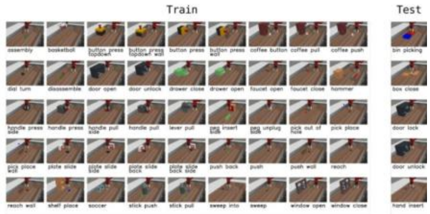
Training Phase 2：Through Evolutionary Algorithm, Make the RNN Encoder Adapts to the【crossover】Manipulation

Training Task Transfer: By progressively transitioning from simple environments to robotic simulations, ECO will become the foundation for next-generation complex robotic controllers.



Capability Stage 1: Traditional Machine Learning Tasks
For example: MNIST, GYM(RL)

Capability Stage 2: Open-ended Meta Reinforcement Learning
For example: XLand-MiniGrid



Capability Stage 3: Robot Meta Reinforcement Learning Tasks
For example: MetaWorld

Sapient H's modular architecture and proven performance in optimization problems would integrate effectively with ECO's evolutionary approach to robotic control. ECO's progressive training methodology, which evolves from basic machine learning tasks to complex robotic simulations through its RNN encoder and gene sequence evolution, aligns well with Sapient H's hierarchical framework. This combination would enable efficient adaptation to various manipulation tasks while maintaining Sapient H's demonstrated parameter efficiency and robust performance.

3.5 **Other Fields That We Are Seeing Promising Results:**

1. Disease and Longterm Health Prediction
2. Anti-money-laundering
3. End-to-end Quantitative Trading