Generative AI and Agent-Based Intelligence for Construction

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Generative AI and Agent-Based Intelligence for Construction

Guest speaker: A/Prof. Wei Peng

School of Engineering
RMIT University

Overview

- My Background
- Introduction to GenAI
- Related GenAI Research: LLM (Explainable AI) and Agents (Workflow, Trajectory Learning)
- Construction major challenges
- GenAI application to construction

My Background

- 2025 – now: A/Professor, Principal Research Fellow in Industrial AI, School of Engineering, RMIT University
- 2019 – 2025: Research Director and AI Expert, BPIT, Huawei Technologies
- 2016 – 2019: Senior Lecturer, La Trobe University
- 2010 – 2016: Senior Data Scientist, AUSTRAC, Lenovo, Telstra
- 2008 – 2010: Research Fellow, RMIT University
- 2007 – 2008: Research Scientist, CSIRO ICT
- 2007: PhD from the University of Sydney in Agents in Design (CRC-CI)

Research Interests: *Large Language Models, Knowledge Representation, Cognitive Agents, and Embodied AI, along with their applications, 70+ papers, multiple patents*

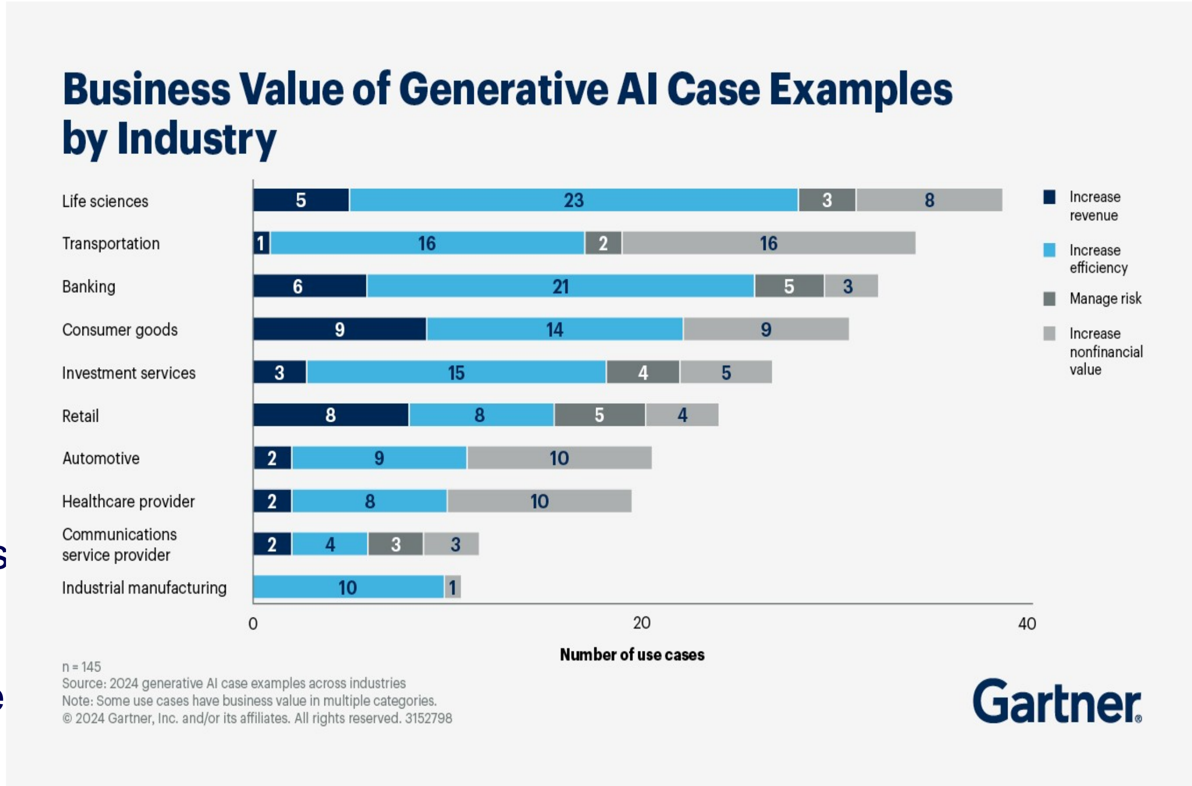
Career Highlights: *research, innovation, and commercialization across both industry and academia,* ***10 years professional experience in construction (Engineer, PM, Researcher)***

Generative AI basics

Artificial Intelligence	• Development of systems emulating human cognition in reasoning, learning, problem-solving and decision-making
Machine Learning	• Subset of AI that enables systems to learning from data and improve task performance without programming
Deep Learning	• Subset of ML that uses ANN with many layers (deep) to learn feature representations from large datasets to solve complex tasks.
Generative AI	• A class of AI techniques generating new/original contents based on learned representations from huge datasets, often leveraging advanced neuron architecture like LLMs, VAEs, GAN, Diffusion models, etc.

Generative AI Applications in Enterprise

- **Automotive:** Toyota uses GenAI to produce initial vehicle sketches, reduce time-to-design, minimize unexpected late design changes
- **Healthcare:** Mayo Clinic leverages Medical Chatbots to conduct dynamic interviews with patients and provide personalized care recomm.
- **Banking:** Ally’s contact center assistant to automate note-taking and summarizing customer calls, reduce manual call services, focus associates On customer interactions
- **Benefits:** Increase revenue, efficiency and othe nonfinancial value, manage risk



https://www.gartner.com/en/articles/generative-ai-use-cases

Hype Cycle for GenAI in 2024 (to watch out)

- 80% enterprises will deploy GenAI in production in 2026 (Gartner, 2024)

Strengths: automation, reasoning, creativity

Challenges: hallucination, factuality, explainability

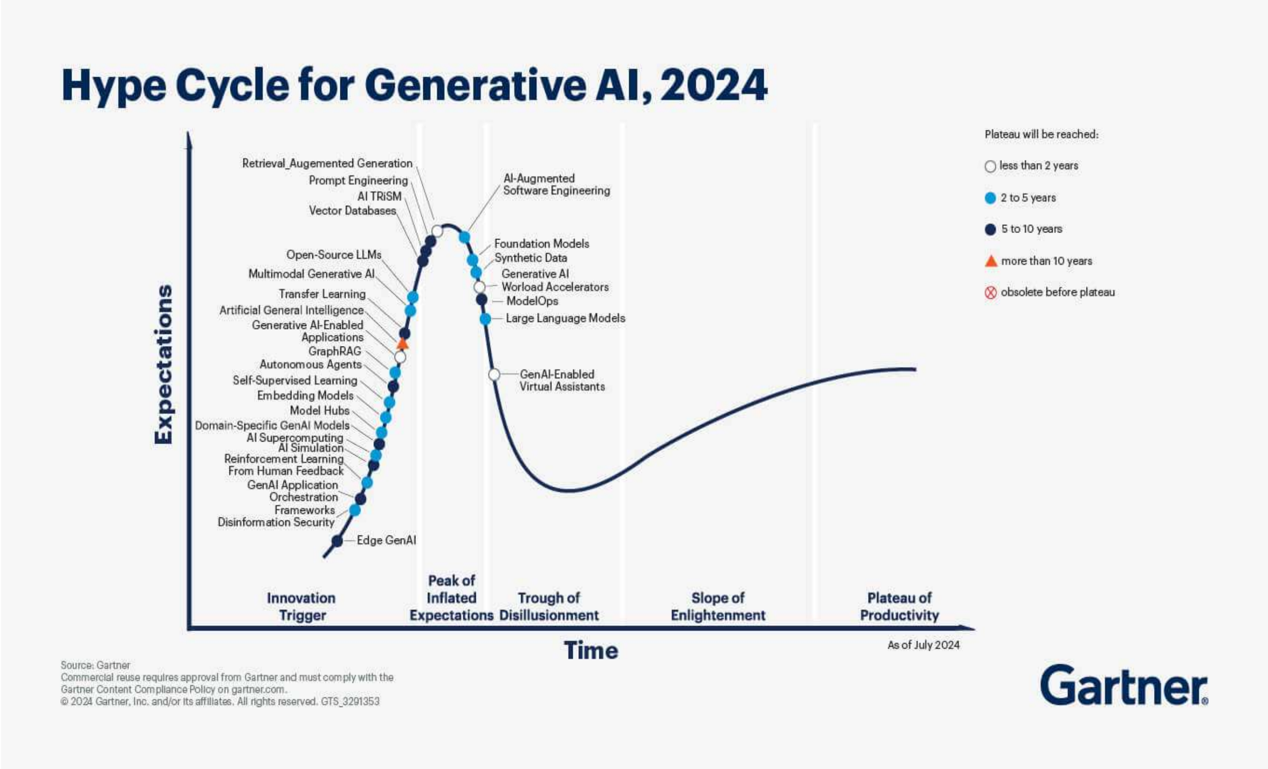
Four Main Core Technologies:

1. GenAI models: Bigger models, Embedding, Domain-specific, Edge GenAI, AGI

2. GenAI engineering: AI Trism, Disinformation, Orchestration, GraphRAG

3. GenAI application and use cases: Virtual assistant, GenAI software engineering, Autonomous agent, Synthetic data

4. GenAI enablement: Workload accelerators, AI simulation, Supercomputing, Self-supervised, Transfer learning



https://www.gartner.com/en/articles/hype-cycle-for-genai

My Research Stream I: XAI, Low-cost Intervention

- **Detecting Hallucination:**

Assessing Factual Reliability of Large Language Model Knowledge, in *Proceedings of NAACL 2024, Oral Presentation*, Association for Computational Linguistics (citation 23)

A survey on hallucination in large vision-language models, 2024, arXiv preprint arXiv:2402.00253 (citation 175)

- **Inconsistency (Semantics, Preferential Ranks):**

Enhancing Semantic Consistency of Large Language Models through Model Editing: An Interpretability-Oriented Approach, In *Findings of the Association for Computational Linguistics: ACL 2024,* Association for Computational Linguistics (citation 8)

Measuring the Inconsistency of Large Language Models in Preferential Ranking, In *Proceedings of the 1st Workshop on Towards Knowledgeable Language Models (KnowLLM 2024),* Association for Computational Linguistics (citation 5)

- **Activation Steering:**

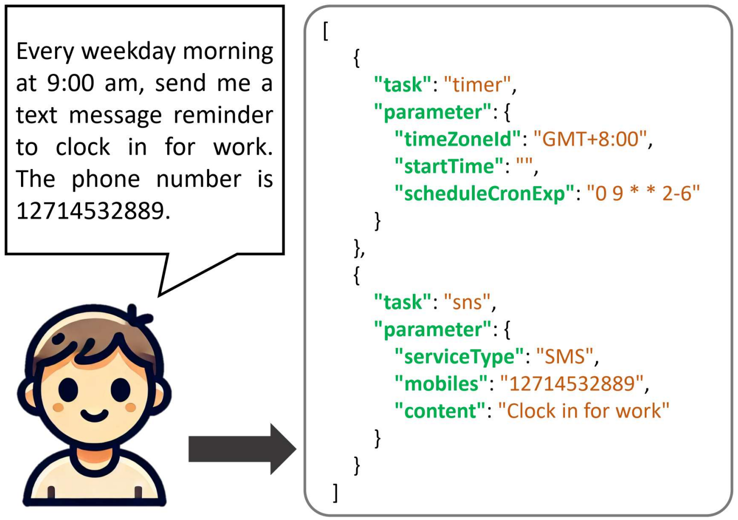
Semantics-Adaptive Activation Intervention for LLMs via Dynamic Steering Vectors, In Proceedings of ICLR 2025, https://arxiv.org/abs/2410.12299

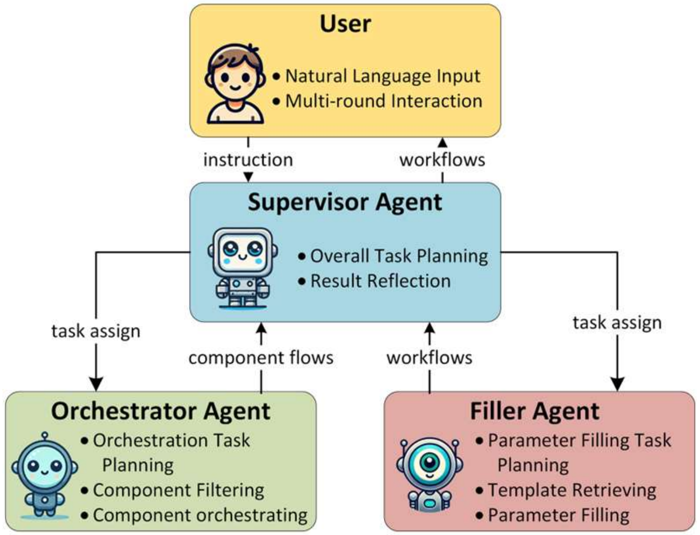
LF-Steering: Latent Feature Activation Steering for Enhancing Semantic Consistency in Large Language Models, 2025, arXiv preprint arXiv:2501.11036

My Research Stream II: Orchestrating Agents

- **Workflow Agents (NL2Workflow):**

WorkTeam: Constructing Workflows from Natural Language with Multi-Agents, In *Proceedings of NAACL 2025, Industry Track,* to appear, https://arxiv.org/pdf/2503.22473





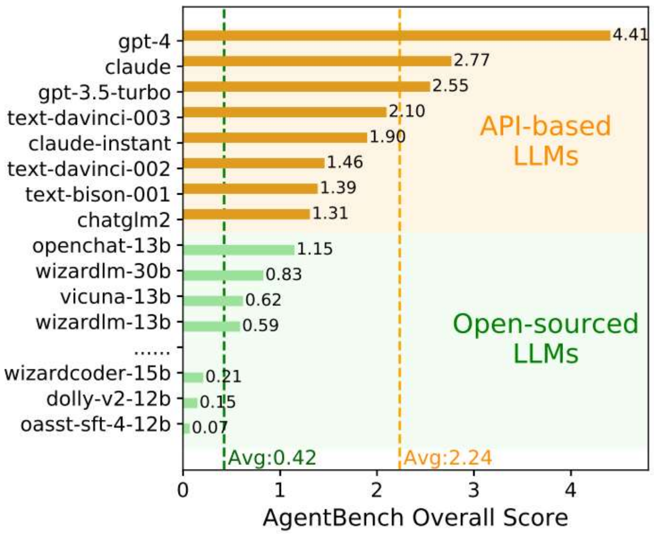
Methods	EMR (%)	AA (%)	PA (%)
GPT-4o	18.1	71.4	56.3
Qwen2.5-72B-Instruct	12.7	66.9	51.5
Qwen2.5-7B-Instruct	3.5	25.4	19.9
LLaMA3-8B-Instruct	1.6	19.4	16.6
RAG (Ayala and Bechard, 2024)	24.1	77.8	60.3
WorkTeam (ours)	**52.7**	**88.9**	**73.2**

WorkTeam deployed with a real-world benchmark of 93% accuracy

My Research Stream III: Agent Trajectory Learning

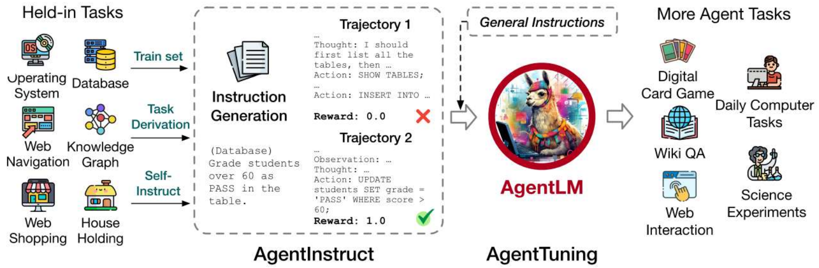
➢ **Agent Learning from Interaction:**

AgentBank: Towards Generalized LLM Agents via Fine-Tuning on 50000+ Interaction Trajectories, *In Findings of the Association for Computational Linguistics: EMNLP 2024*, pages 2124–2141, Association for Computational Linguistics (citation 9)



LLMs suffer even for SOTA commercial tools

Expert Trajectories



AgentTuning: only keep successful trajectories for training

Agents solve only simple tasks, hard to generalize

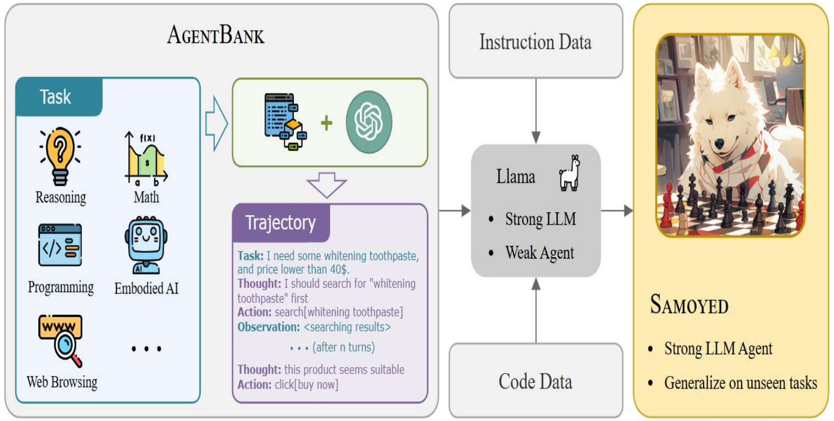
Skill Dim.	Task	Action Space	Tool	#Inst.	Avg. Turns	Action Annotation
Reasoning	HotpotQA (Yang et al., 2018)	Continuous	Search	4273	3.1	Explore
	StrategyQA (Geva et al., 2021)	Continuous	Search	1267	3.6	Explore
	TriviaQA (Joshi et al., 2017)	Continuous	Search	4134	2.5	Explore
Math	GSM8K (Cobbe et al., 2021)	Continuous	Calculator	7471	4.5	Reformat
	MathQA (Amini et al., 2019)	Continuous	Python	4000	2.0	Explore
	MATH (Hendrycks et al., 2021)	Continuous	Python, Wiki	2312	2.5	Explore
Programming	IC-SQL (Yang et al., 2023)	Continuous	MySQL	4540	4.8	Explore+Answer Force
	APPS (Hendrycks et al., 2021)	Continuous	Python	4408	1.0	Reformat
	HumanEval (Chen et al., 2021)	Continuous	Python	134	2.7	Explore+Answer Force
	MBPP (Austin et al., 2021)	Continuous	Python	608	2.2	Explore+Answer Force
Web	Mind2Web (Deng et al., 2023)	Discrete	-	7770	1.0	Reformat
	WebArena (Zhou et al., 2023)	Discrete	-	657	1.0	Reformat
	WebShop (Yao et al., 2022a)	Discrete	-	5315	3.4	Explore & Reformat
Embodied	ALFWorld (Shridhar et al., 2020b)	Discrete	-	3554	10.1	Reformat
	RoomR (Weihs et al., 2021)	Discrete	-	300	30.2	Search+Reformat
	IQA (Gordon et al., 2018)	Discrete	-	1627	28.4	Search+Reformat
	Total (AGENTBANK)	-	-	51287	3.9	-

We propose AgentBank to host 50000+ interaction trajectories

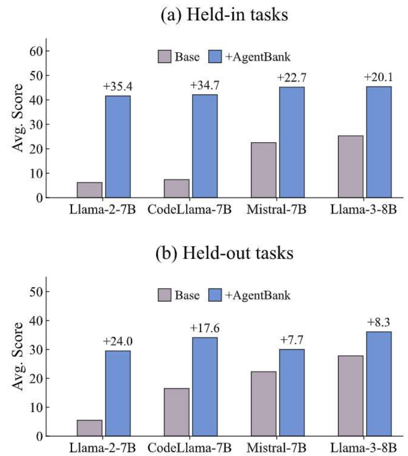
My Research Stream III: Trajectory Learning (cont.)

➢ **Agent Learning from Interaction:**

AgentBank: Towards Generalized LLM Agents via Fine-Tuning on 50000+ Interaction Trajectories, *In Findings of the Association for Computational Linguistics: EMNLP 2024*, pages 2124–2141, Association for Computational Linguistics (citation 9)



Model	Held-in Tasks						Held-out Tasks					
	Reason	Math	Program	Web	Embodied	Avg.	Reason	Math	Program	Web	Embodied	Avg.
Closed-Source Model												
GPT-4	61.6	73.0	54.9	40.6	77.8	59.8	41.6	51.0	69.4	69.4	36.4	53.6
GPT-3.5-Turbo	41.0	41.5	51.2	42.0	10.5	40.2	32.0	32.0	54.8	66.7	21.2	41.3
7B Open-Source Model												
Llama-2-7B-Chat	4.0	7.5	2.5	13.9	0.0	6.2	4.0	8.0	7.0	0.4	7.8	5.5
Vicuna-7B	29.0	2.0	19.0	24.2	6.0	17.1	8.8	14.0	19.0	18.2	12.8	14.6
CodeLlama-7B	3.5	3.5	1.5	24.8	0.0	7.4	1.0	13.0	21.8	**41.3**	5.5	16.5
AgentLM-7B	29.5	10.0	12.0	**37.2**	63.4	26.7	19.2	13.0	50.5	13.5	13.3	21.9
Agent-FLAN-7B	31.0	10.5	13.1	35.4	**65.3**	27.3	22.2	11.0	53.1	17.9	14.1	23.7
Samoyed-7B	**48.0**	**30.5**	**41.6**	36.4	61.2	**41.6**	**32.0**	**18.0**	**59.2**	24.2	**14.2**	**29.5**
13B Open-Source Model												
Llama-2-13B-Chat	12.5	10.5	8.2	11.2	0.0	9.4	9.6	11.0	33.0	17.6	7.3	15.7
Vicuna-13B	25.5	6.5	30.4	34.2	2.2	21.7	24.8	17.0	37.0	34.2	14.8	25.6
CodeLlama-13B	13.5	18.5	5.1	15.3	0.0	11.7	6.4	16.0	11.1	**46.5**	5.5	17.1
AgentLM-13B	38.0	13.5	22.8	38.1	52.2	30.8	20.8	13.0	46.6	21.6	14.6	23.3
Samoyed-13B	**54.5**	**38.5**	**55.4**	**40.9**	**72.4**	**50.1**	**35.0**	**23.0**	**62.4**	38.9	**18.4**	**35.5**

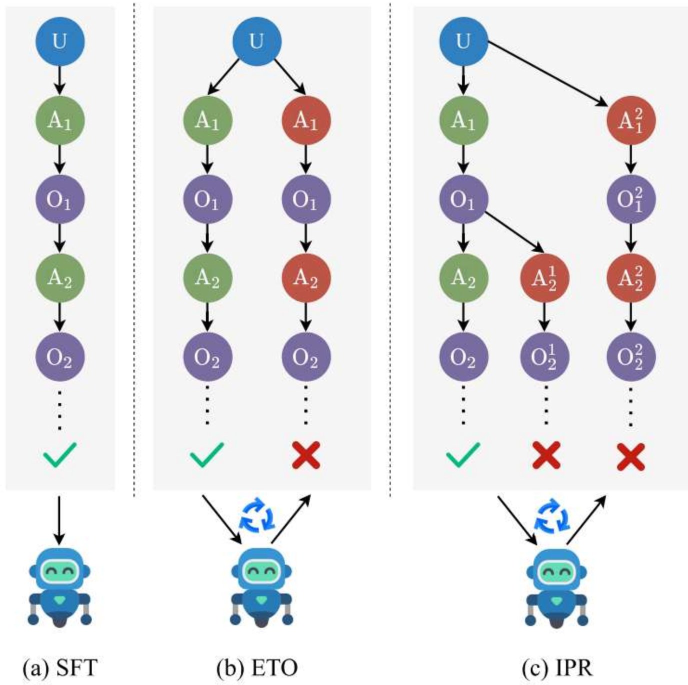


Organize trajectories into multi-turn dialogues, mix general domain instructions and codes, utilize failure trajectories and propose the exploration-based trajectory optimization (ETO) method to learn the task-solving process, leading to significant performance gains.

My Research Stream III: Trajectory Learning (cont.)

➢ Agent Learning from Interaction:

Watch Every Step! LLM Agent Learning via Iterative Step-Level Process Refinement, In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing (EMNLP 2024),* pages 1556-1572, Association for Computational Linguistics (citation 17)



➢ Agents start to learn from Interactions and explorations: from SFT on trajectories to ETO (SAMOYED)

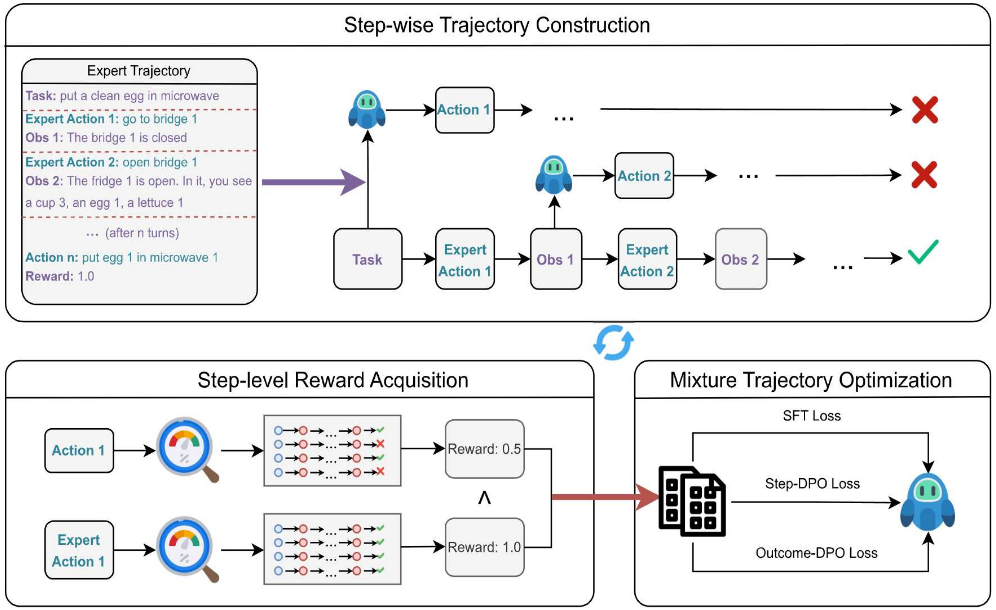
Treat an entire trajectory as single entity during training and prioritize the final reward of a trajectory over the process, thus overlooking exploitable information throughout interaction process.

We need to consider step level optimization

My Research Stream III: Trajectory Learning (cont.)

➢ Agent Learning from Interaction:

Watch Every Step! LLM Agent Learning via Iterative Step-Level Process Refinement, In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing (EMNLP 2024),* pages 1556-1572, Association for Computational Linguistics (citation 17)



Design Step-level Process Refinement: Step-level Reward Acquisition and Iterative Agent Optimization.

Monte Carlo method to estimate rewards via sampling N trajectories to construct step award.

$$\{e^{(i)}|i=1,...,N\} = MC^{\pi_s}(e_{t-1};N),$$

$$r_s(s_t,a_t) = \begin{cases} \frac{1}{N}\sum_{i=1}^{N} r_o(u,e^{(i)}), & \text{for } t<n \\ r_o(u,e_n), & \text{for } t=n \end{cases}$$

$$\mathcal{L} = \mathcal{L}_{\text{o-DPO}} + \mathcal{L}_{\text{s-DPO}} + \mathcal{L}_{\text{SFT}}$$

- Outcome-DPO Loss

$$\mathcal{L}_{\text{o-DPO}} = -\mathbb{E}_{(u,e_n^w,e_m^l)\sim\mathcal{D}_t}\Big[\log\sigma(\beta\log\frac{\pi_\theta(e_n^w|u)}{\pi_{ref}(e_n^w|u)} - \beta\log\frac{\pi_\theta(e_m^l|u)}{\pi_{ref}(e_m^l|u)})\Big],$$

- Step-DPO Loss

$$\mathcal{L}_{\text{s-DPO}} = -\mathbb{E}_{(e_{t-1},e_{t:n}^w,e_{t:m}^l)\sim\mathcal{D}_s}\Big[\log\sigma(\beta\log\frac{\pi_\theta(e_{t:n}^w|e_{t-1})}{\pi_{ref}(e_{t:n}^w|e_{t-1})} - \beta\log\frac{\pi_\theta(e_{t:m}^l|e_{t-1})}{\pi_{ref}(e_{t:m}^l|e_{t-1})})\Big],$$

- Supervised Loss

$$\mathcal{L}_{\text{SFT}} = -\mathbb{E}_{(u,e_n^w,e_m^l)\sim\mathcal{D}_t}\Big[\log\pi_\theta(e_n^w|u)\Big],$$

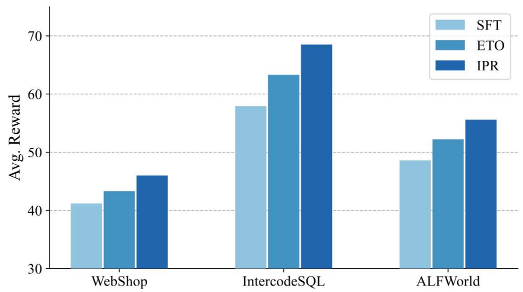
My Research Stream III: Trajectory Learning (cont.)

➢ Agent Learning from Interaction:

Watch Every Step! LLM Agent Learning via Iterative Step-Level Process Refinement, In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing (EMNLP 2024),* pages 1556-1572, Association for Computational Linguistics (citation 17)

Paradigm	Models	WebShop	InterCodeSQL	ALFWorld		Average
				Seen	Unseen	
Prompt-based	GPT-4 (Achiam et al., 2023)	63.2	38.5	42.9	38.1	45.7
	GPT-3.5-Turbo (Ouyang et al., 2022)	62.4	37.8	7.9	10.5	29.7
	Llama-2-7B (Touvron et al., 2023)	17.9	4.0	0.0	0.0	5.5
Outcome Refinement	Llama-2-7B + SFT (Chen et al., 2023)	60.2	54.9	60.0	67.2	60.6
	Llama-2-7B + PPO (Schulman et al., 2017)	64.2	52.4	22.1	29.1	42.0
	Llama-2-7B + RFT (Yuan et al., 2023)	63.6	56.3	62.9	66.4	62.3
	Llama-2-7B + ETO (Song et al., 2024)	67.4	57.2	68.6	72.4	66.4
Process Refinement	Llama-2-7B + Step-PPO	64.0	60.2	65.7	69.4	64.8
	Llama-2-7B + IPR (ours)	**71.3**	**61.3**	**70.3**	**74.7**	**69.4**

Training Scheme	WebShop	InterCodeSQL	ALFWorld
w/o o-DPO	70.2	59.3	72.4
w/o s-DPO	66.4	58.0	70.2
w/o SFT	61.8	31.7	64.9
Iteration=1	63.6	56.6	68.7
Iteration=2	63.7	58.2	70.2
Iteration=3	68.2	59.2	**74.7**
Iteration=4	**71.3**	**61.3**	73.5
Iteration=5	68.1	57.9	71.4



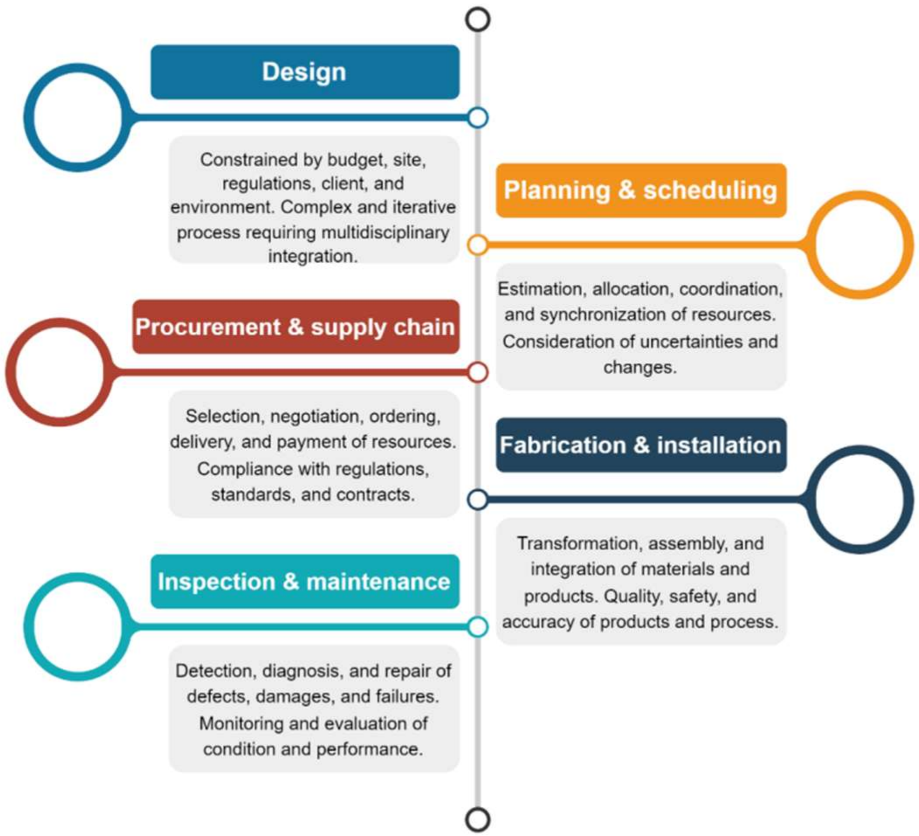
Conclusion：

- ➢ Agent learns from interaction via trajectory with step awards
- ➢ Learning from failure actions
- ➢ Automated process reward acquisition
- ➢ Step level process supervision via mixture trajectory optimization
- ➢ Enhanced performance on three benchmarks
- ➢ Generalizable on unseen hold out

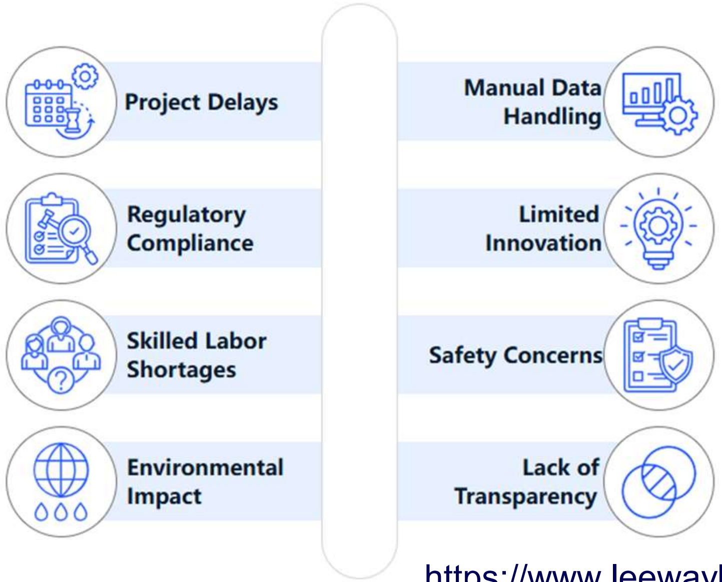
Limitation：

- ➢ Overfitting with limited data (need to leverage AgentBank data)
- ➢ MC method constrained by sample size
- ➢ Consider GPT 4 to label process supervision data

Construction Major Processes and Challenges



https://arxiv.org/abs/2402.09939



https://www.leewayhertz.com

Complex and Dynamic Processes:

- **Coordinate and integrate various resources, disciplines, stakeholders**
- **Manage multiple constraints, uncertainties, changes**
- **Significant difficulties and risks**
- **Low productivity, high cost, long delay, poor quality, high environment impact**

GenAI Applications in Construction

- **Design optimization and automation**

DALL-E and GPT generate structure layouts, rendering, automate compliance check (building code), reduce manual cost and speedup iterative design process

- **Safety and Risk**

Use of ChatGPT for improving hazard recognition on construction site, automated classification of contractual risk clauses

- **Construction schedule, planning**

Auto-alignment of long-term and short-term plan, Use of LLM to generate a construction schedule for a project, RoboGPT uses ChatGPT for automated sequence planning to handle construction assembly

- **BIM enhancement**

Integrates BIM with GPT with a NL-based interface for information search

- **Automate information processing**

Use OCR to automate invoice data entry, GPT to summarize documents, automate report generations

https://arxiv.org/pdf/2402.09939

Can Generative AI help?

Yes!

Potential Applications: https://arxiv.org/pdf/2310.04427

Phase	GenAI Use Cases	Beneficiary	Model Type
Feasibility	• GPT for report automation (feasibility, regulatory compliance, bid, etc.) • Visualize site conditions, traffics, zoning, terrain, climate for site selection • Predict milestones, success criteria for different phases • Create contracts and agreements, meeting transcripts	stakeholders owners	text-to-text text-to-image video-to-text
Design	• Conceptual design visualization/automation, design optimization (cost, material, energy efficiency), project concept animation • Complex design check (code, routing check, requirement, cost/time estimation) • Contractor selection based on project criteria, performance	architect, owner, stakeholder, engineer	text-to-task text-to-text text-to-video
Procurement	• Visualize material delivery schedule • Automate inventory management • Optimize supplier identification and supply chain management (cost fluctuation, supplier dependency) • Optimize subcontractor bidding and selection	PM, procurement, logistic, contractor	text-to-3D text-to-text
Construction	• Information extraction, report classification and generation, translation • Optimize cost estimation workflow, optimize schedule path • LLM/LVM for progress tracking/analysis, real-time safety inspection/prevention, quality control to identify defects, from code to task, site coordination agent • Task assignments and communications, meeting transcripts	contractor, estimator, PM, safety manager	text-to-text text-to-image/video text-to-task video-to-text
Operation Maintenance	• Automate routine maintenance tasks, facility usage instruction, • Maintenance schedule generation, predictive maintenance (senor data) • Energy efficiency analysis and optimization • On-boarding video	facility manager, technician	text-to-text text-to-image video-to-video

Challenges of GenAI in Construction

- **Hallucination and Accuracy**

GenAI produces hallucinations due to limitation of data, training, contextual influence. It is the nature of GenAI. Invest in XAI technologies to detect and rectify hallucination, enhance interpretability of innate mechanism. GenAI fits in training data will have to deal with generalization across unseen real-world problems.

- **High Computation Cost**

SFT on LLMs very costly in computational cost, need to seek more efficient ways in post-training, invest in model compression, distillation or inference time computing (in-context learning) or activation steering.

- **Domain Data and Knowledge Gap**

LLM pre-trained on human general knowledge. Gap in domain knowledge due to lack of data. Need to ensure data quality and availability, Leverage domain data generation and knowledge integration, like domain data enhancement, RAG/KAG

- **AiTRISM**

Tackling trust, risk, security of GenAI. Protect sensitive project and ensure the security of AI, ensure ethical and responsible AI by protecting data privacy

Thanks

Questions & discussion

welcome.