电子科技大学
University of Electronic Science and Technology of China

Ph.D. Application Presentation

Embodied Agent

Zhiying Qiu

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Personal Introduction

🎓 Education Background

- **Bachelor of Engineering in Software Engineering,** *University of Electronic Science and Technology of China 2022 – Present*
- Average score: 90.71
- Ranking**:** 6 / 109 (Top 5%)
- Selected Coursework: Calculus I (94), Calculus II (96), Discrete Mathematics (98), Computer Architecture (98), Programming and Algorithms I (96), ARM Architecture Fundamentals (95)

🏆 Honor & Award

- National Endeavor Scholarship
- First-Class Excellent Student Scholarship
- Academic Excellence Scholarship

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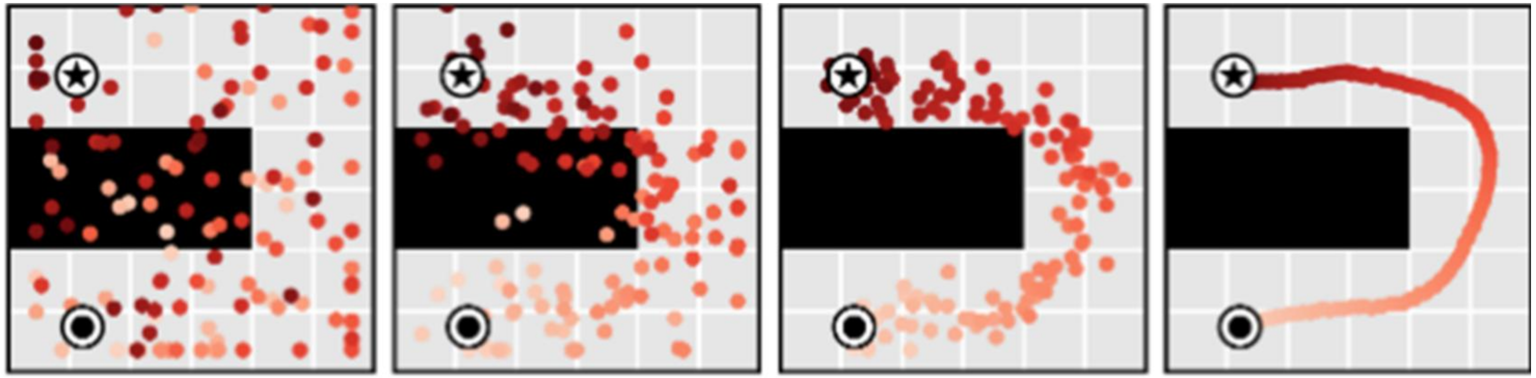
Introduction

Experience

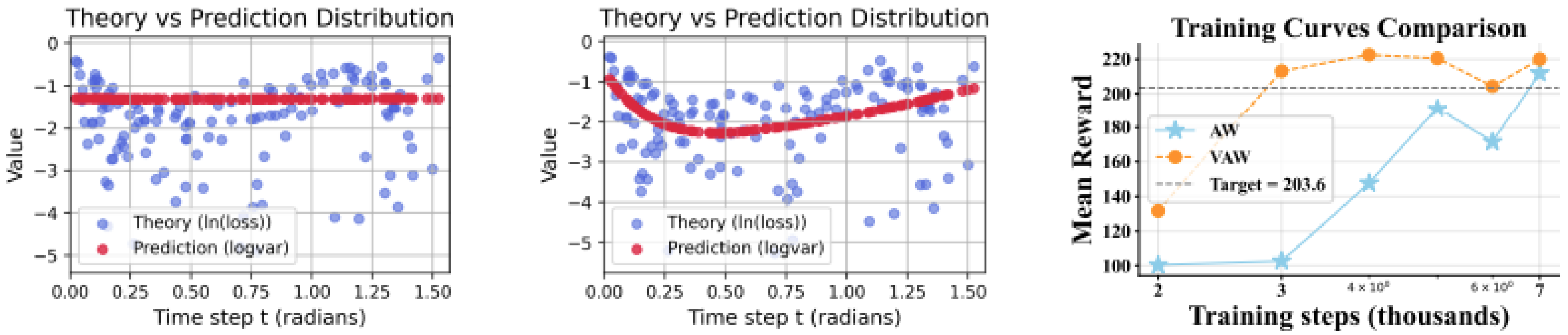
Plan

Research Experience



- **Title**: Fast and Stable Diffusion Planning through Variational Adaptive Weighting
- **Time**: Dec 2024 – May 2025
- **Advisor**: Prof. Tao Lin, Westlake University
- **Task**: Maze2D involves guiding a ball through a maze to a target location, where the reward function is defined as follows:
  - ✓ r = 0: The ball has not reached the target position.
  - ✓ r = 1 : The ball has reached the target, defined as being within a Euclidean distance of less than 0.5 meters from the goal.

Research Experience



(a) (b) (c)

Motivation

- ➢ We identify a research gap: No systematic study on training efficiency in diffusion planning.
- ➢ Our work aims to address this gap by proposing an uncertainty-aware weighting function ω(t) under the flow-based generative modeling framework. As shown in Figure 1:
  - ✓ MLP-based weighting fails to capture the true importance of samples at early training stages.
  - ✓ In contrast, our variational weighting function better approximates the target u*(σ), leading to significantly faster convergence.

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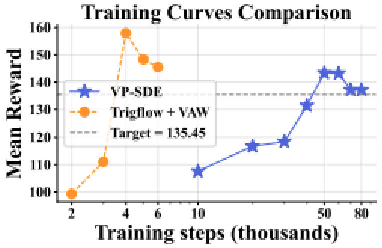
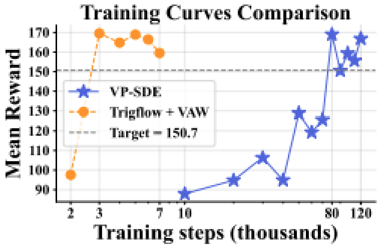
Table 1: Performance of various offline-RL methods. Our method achieves the best performance across all benchmark tasks. Our results are averaged over 150 episode seeds. We omit the variance over seeds for simplicity. The best average performance on each task set is marked in bold fonts.

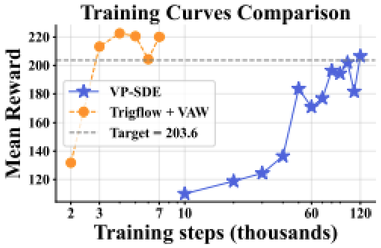
Dataset	Env	BC	CQL	IQL	SfBC	DQL	IDQL	Diffuser	AD	DD	HD	DV*	FV (Ours)
Kitchen	Mixed	47.5	51.0	51.0	45.4	62.6	66.5	52.5	51.8	75.0	71.7	72.0	72.5
	Partial	33.8	49.8	46.3	47.9	60.5	66.7	55.7	55.5	56.5	73.3	80.1	82.1
	avg.	40.7	50.4	48.7	46.7	61.6	66.6	54.1	53.7	65.8	72.5	76.1	**77.3**
Maze2D	Large	0.0	57.5	43.6	74.4	–	90.1	123.0	167.9	–	128.4	203.0	222.6
	Medium	0.0	15.4	70.6	73.8	–	89.5	121.5	129.9	–	135.6	150.7	164.8
	Umaze	0.0	36.4	57.1	73.9	–	57.9	113.9	135.1	–	155.8	134.5	157.9
	avg.	5.0	12.5	58.6	74.0	–	79.2	119.5	144.3	–	139.9	163.6	**181.8**



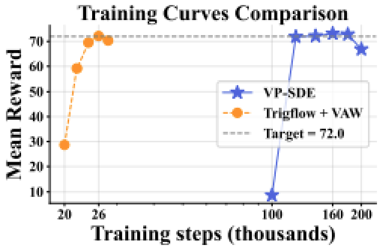
(a)



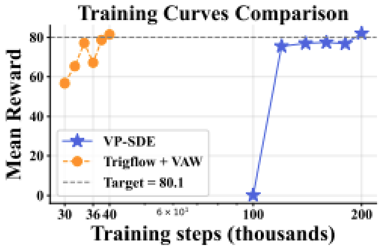
(b)



(c)



(d)



(e)

Performance and Results

- Outperforms VP-SDE across diverse tasks
- Achieves 5×–40× speedup in training convergence
- Consistently reaches SOTA performance with significantly fewer steps

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2. Natural Language Understanding (Roberta-base + GLUE)

All LoRA methods are intergrated on all linear layers of the transformer except embedding layer and the lm head. We set rank as 8.

	MRPC (Acc)	COLA (Mc)	RTE (Acc)	STSB(SPEAR)	SST2(Acc)	QQP(Acc)	QNLI(Acc)	MNLI(Acc)	**AVG**
FT (All layers)	89.95	62.01	**80.87**	90.07	**94.84**	91.98	92.97	87.66	86.29
FT (All layers except embedding layer and the lm head)									
LoRA variants									
AdaLoRA	89.71	63.86	81.59	91.00	94.61	90.03	92.82	88.06	86.46
DoRA	89.46	60.27	81.28	90.57	95.07	91.07	91.28	87.62	85.83
LoRA	89.46	63.36	81.28	90.45	94.61	91.43	92.51	86.92	86.25
Init Trick									
PiSSA	89.22	63.77	78.70	90.48	94.50	91.27	92.72	87.35	86.00
LoRA-GA	90.69	66.52	80.87	90.49	94.72	91.34	92.73	87.30	86.83
LR Trick									
LoRA+					94.5	90.6	92.49	87.72	
Merging Weight									
LoRA-RC-abla1	90.93	65.63	80.80	90.83	95.41	91.34	92.81	87.19	86.87

- **Title**: Systematic Evaluation of Fine-Tuning Strategies for Foundation Models
- **Time**: Aug 2024 – Nov 2024
- **Advisor**: Prof. Tao Lin, Westlake University
- **Contributions**:
  - ✓ Reproduced 8+ LoRA-based fine-tuning variants on RoBERTa-base
  - ✓ Benchmarks: GLUE, SQuAD v1/v2
  - ✓ Internal reports written to support lab-wide fine-tuning practices

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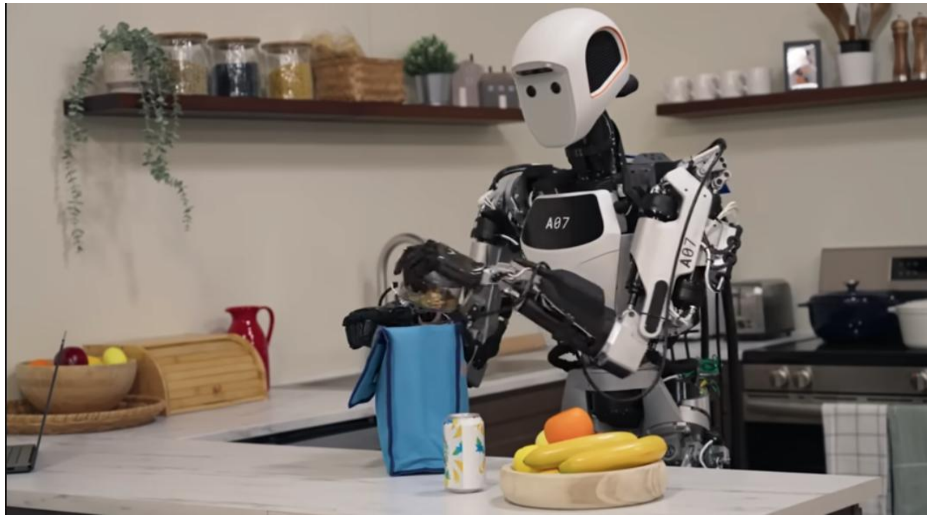
Research Plan

WOOP Framework: From Vision to Reality

- **Wish**: Bring *Baymax* to life — real-world general-purpose robot assistants
- **Outcome**: Build embodied world models for on-device, real-time decision-making
- **Obstacle**: Diffusion models are too slow — step-by-step sampling hampers real-time use
- **Plan**: Speed up inference for embodied world models to enable real-time robotics



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Thank You!

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June 2025