

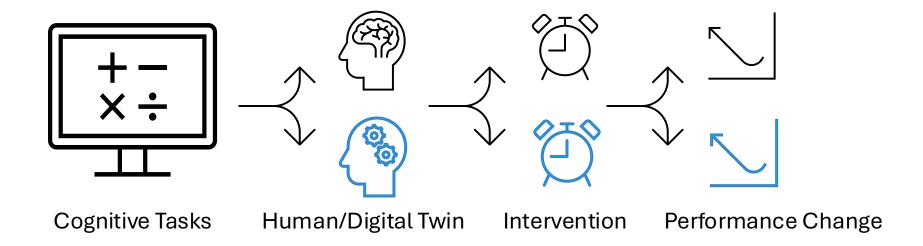


CogReact: A Reinforced Framework to Model Human Cognitive Reaction Modulated by Dynamic Intervention

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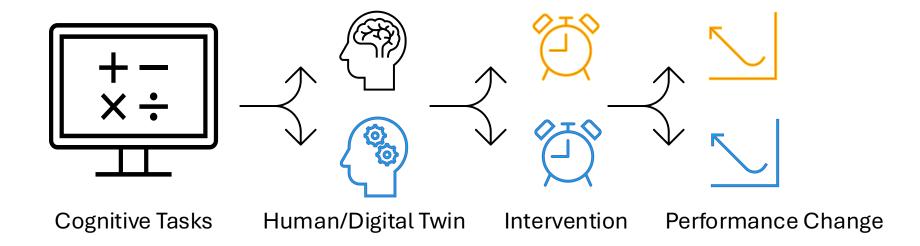
University of California San Diego

Motivation



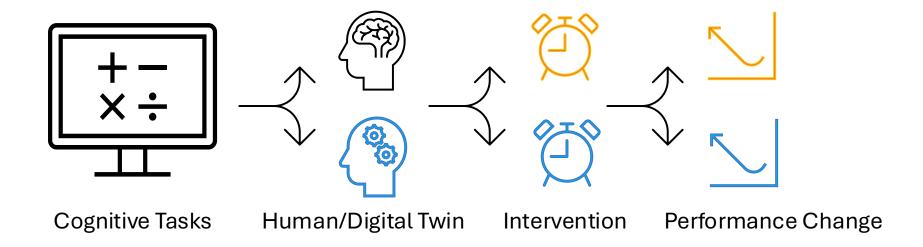
Modeling human cognition is a fundamental challenge in understanding human behaviors. A realistic simulation can enable a digital twin of human cognition.

Motivation



❖ Research Gap: Most existing work focus on cognitive simulation under ideal conditions, neglecting the influence of dynamic intervention from the environment.

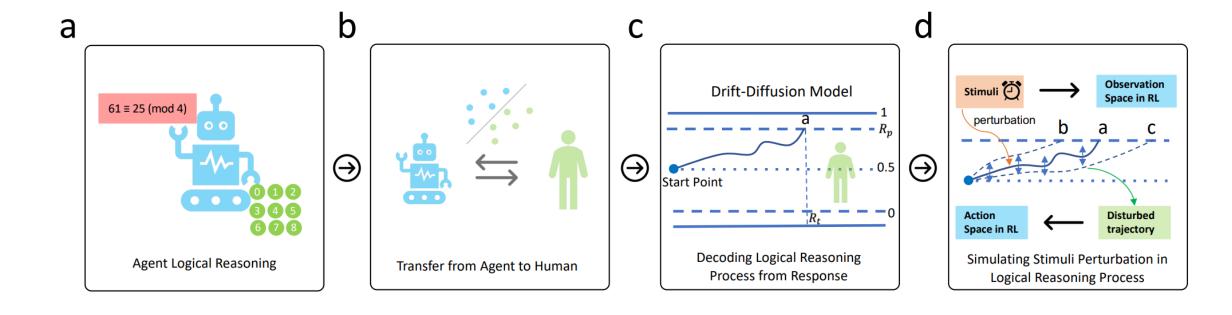
Motivation



❖ Our Core Research Question: How can we simulate the impact of dynamic environmental stimuli on the regulation of human cognitive behaviors with precision at a fine-grained level?

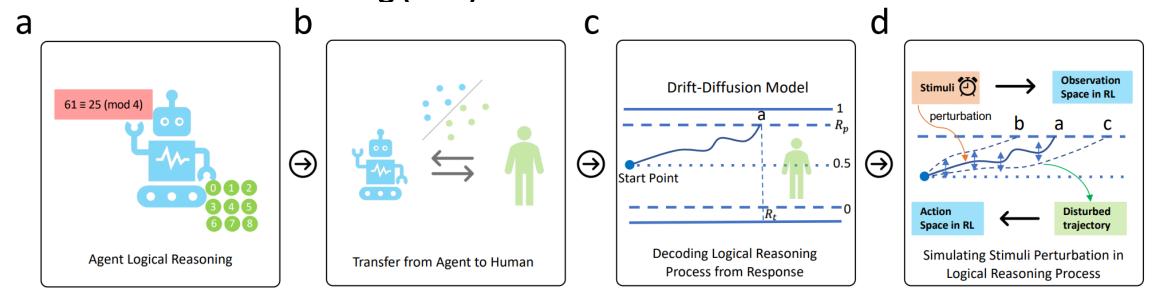
Framework

- ❖ Integrate sequential models from cognitive science with data-driven deep reinforcement learning (DRL).
- Data-Driven Model: Hard to represent the internal mechanisms of the cognitive process.
- Drift-Diffusion Model: Represent cognitive process in a sequential manner.



Framework

Integrate sequential models from cognitive science with data-driven deep reinforcement learning (DRL).

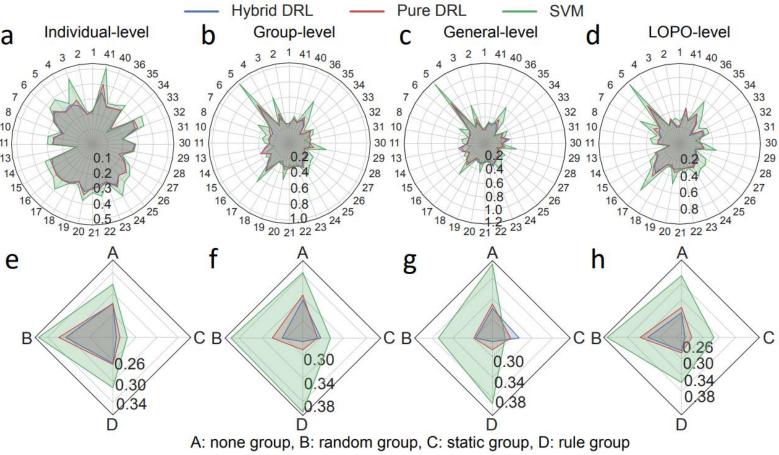


- Step 1: A machine agent to solve cognitive tasks.
- Step 2: Transfer task info from agent to human.
- Step 3: Decoding human cognitive process in task solving with drift-diffusion model (DDM).
- > Step 4: Simulating stimuli perturbation on cognitive process with DDM-integrated DRL agent.

Evaluation: Response Time Simulation

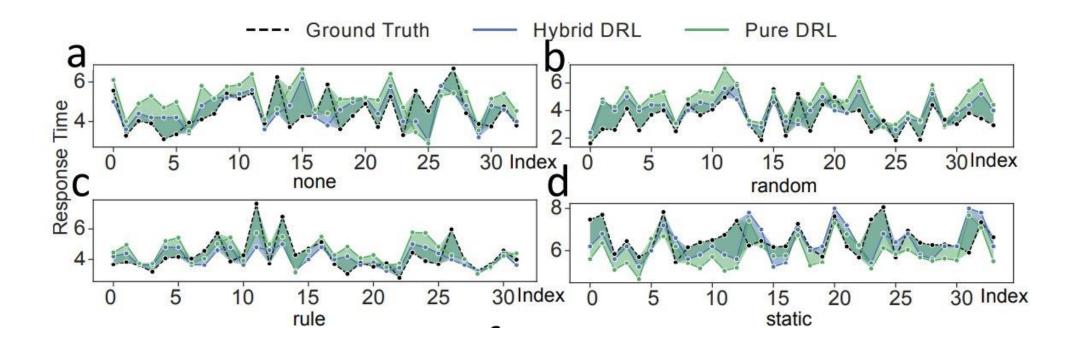
			MAPE		
	Model Input Type	Model Type Name	Mean	STD	
	I.	hGRU		0.2486	
	Task: Video, Feedback: Video	LSTM + AlexNet		0.2602	
		LSTM + VGG-16		0.2708	
		LSTM + ViT-B-16		0.2573	
		MLP + 3D ResNet	0.3330	0.2507	
	II.	LSTM-V1 + 3D ResNet	0.3334		2
	Task: Encoded String, Feedback: Video	LSTM-V2 + 3D ResNet		0.2169	
		MLP + 3D ResNet	0.3331	0.2550	
		Transformer + 3D ResNet	0.3306	0.2496	
		CogReact	0.2999	0.2318	
	TTT	LSTM-V1 + 3D ResNet	0.3341	0.2617	10
	III. Task: Numeric, Feedback: Video	LSTM-V2 + 3D ResNet	0.3286	0.2538	11
		MLP + 3D ResNet	0.3333	0.2579	13
		Transformer + 3D ResNet	0.3315	0.2526	1
	TX /	Decision Tree	0.3617	0.3640	
	IV. Task: Numeric, Feedback: Numeric	Linear Regression	0.3595	0.3608	
		LSTM	0.3059	0.2434	
		MLP	0.3293	0.2441	
		Random Forest	0.3650	0.3684	
		SVM	0.3299	0.3108	
		Transformer	0.3052	0.2446	
		CogReact	0.2703	0.2224	
-	X7	Decision Tree	0.3639	0.3639	
	V. Task: Encoded String, Feedback: Numeric	Linear Regression	0.3512	0.3469	
		LSTM	0.3278	0.2478	
		MLP		0.2577	
		Random Forest		0.3630	
		SVM	0.3245		
		Transformer	0.3299		
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More realistic simulation across both individuals and stimuli.



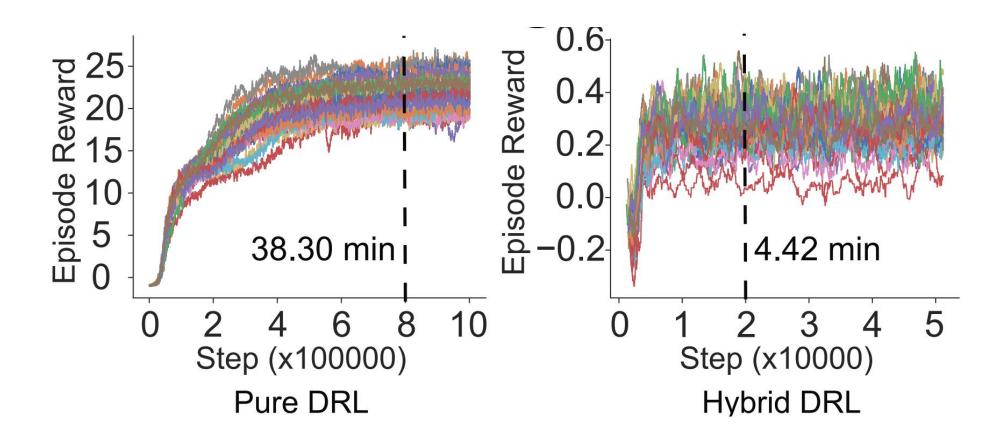
Evaluation: Response Time Simulation

More consistent response time trends as real humans.



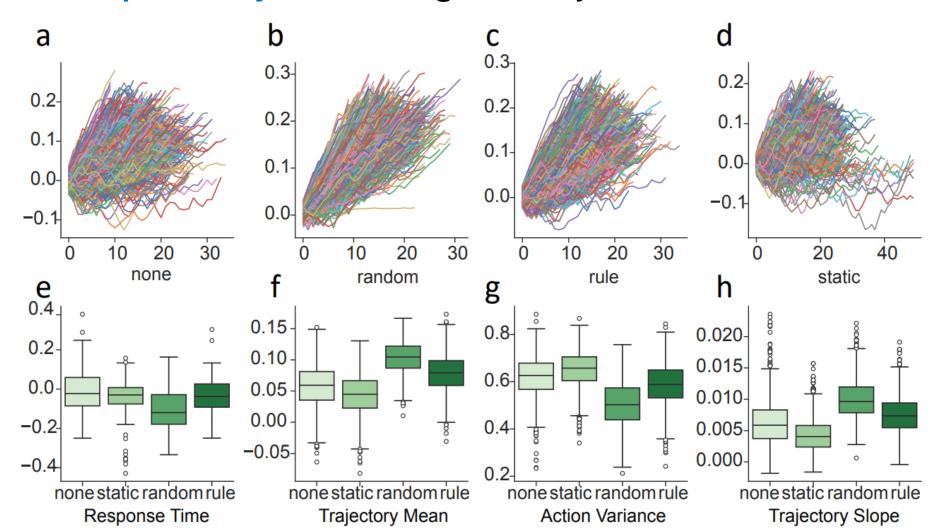
Evaluation: Better Training Efficiency

Better training efficiency for fast convergence.



Evaluation: Interpretability

Interpretability: Reflect cognitive trajectories as humans.



Evaluation: Generalization

❖ Diverse cognitive tasks, and different feedback modalities.

Table 2. Task/feedback information and dataset properties.

Task Information				Simulation Modality		Dataset Information			
Task Type	Response Type	User Action	Cognitive Response	Task	Feedback	Stage 1	Source	Size	User
Math Reasoning	Active	Binary	Response Time	String	Visual	Math Agent	Ours	21,157	50
Decision Making	Active	Binary	Response Time	Numeric	Numeric	Risk Agent	Public	30,489	240
Learning	Passive	Continuous	Curiosity	Textual	Textual	LLM Agent	Public	12,804	300

Evaluation: Generalization

Diverse cognitive tasks, and different feedback modalities.



Scan this barcode to find more details about our paper (https://arxiv.org/abs/2301.06216).

