Split Q Learning:
Reinforcement Learning with Two-Stream Rewards

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Neuroscience Inspirations

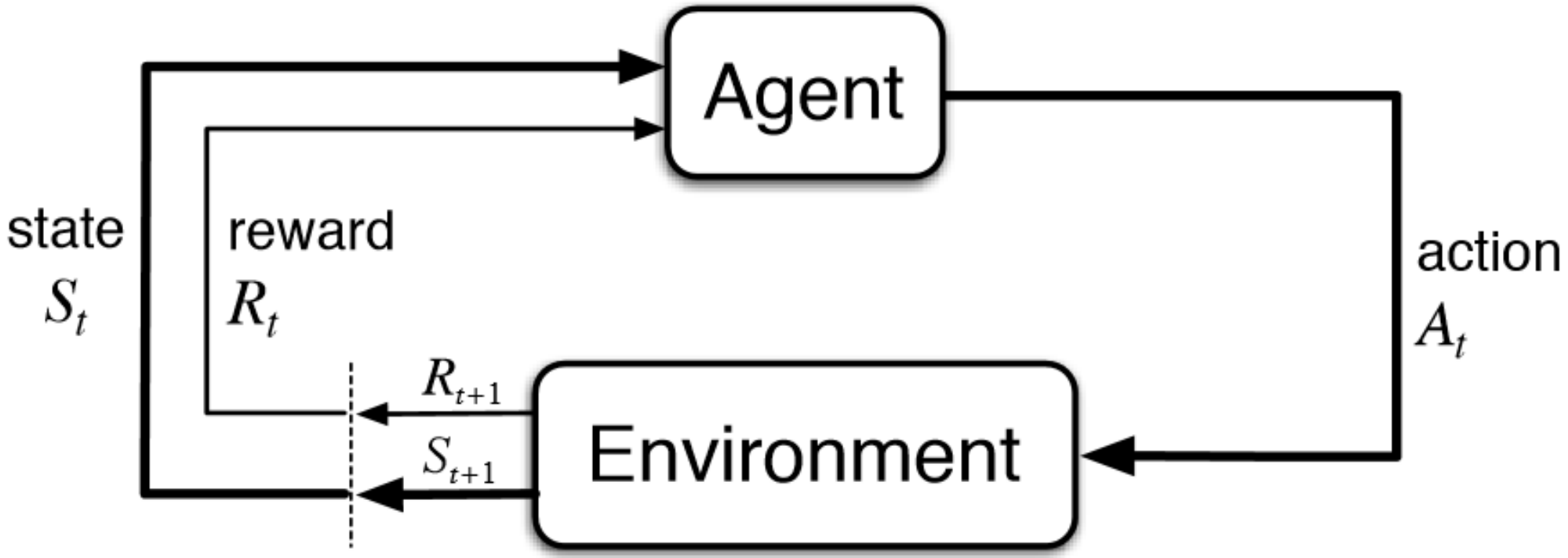
- Phasic dopamine signaling represents bidirectional (positive and negative) coding for prediction error signals.
- These mechanisms have downstream effects on motivation, approach behavior, and action selection.
- Many symptoms of neurological and psychiatric disease are related to biases in learning from positive and negative feedback.

From evolutionary psychiatry to AI

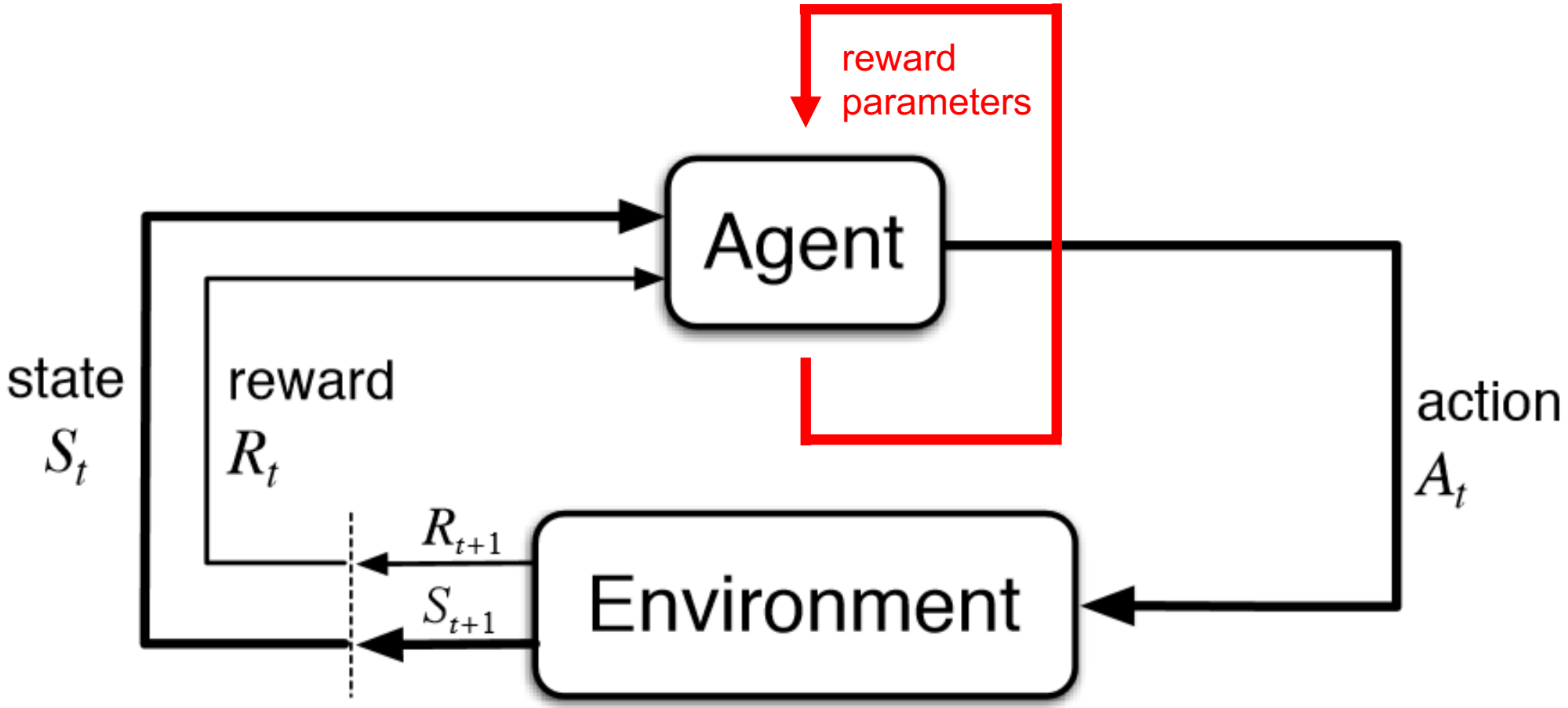
- Mental disorders → “extreme points” in a continuous spectrum of behaviors and traits developed for various purposes during evolution.
- Somewhat less extreme versions of those traits can be actually beneficial in specific environments.

- Modeling these disorder-related decision-making bias → better AI

Reinforcement Learning Problem

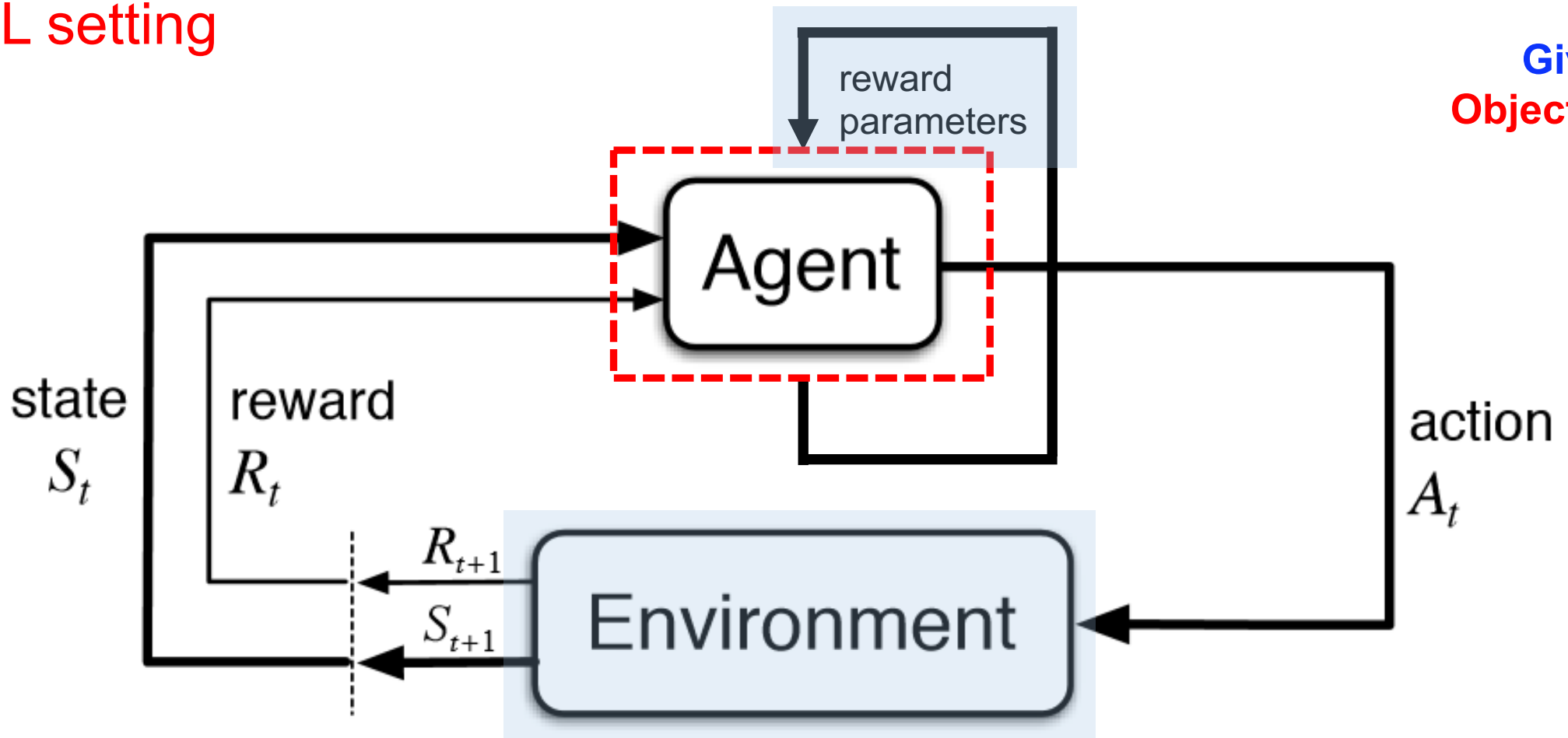


Reinforcement Learning Reward Processing



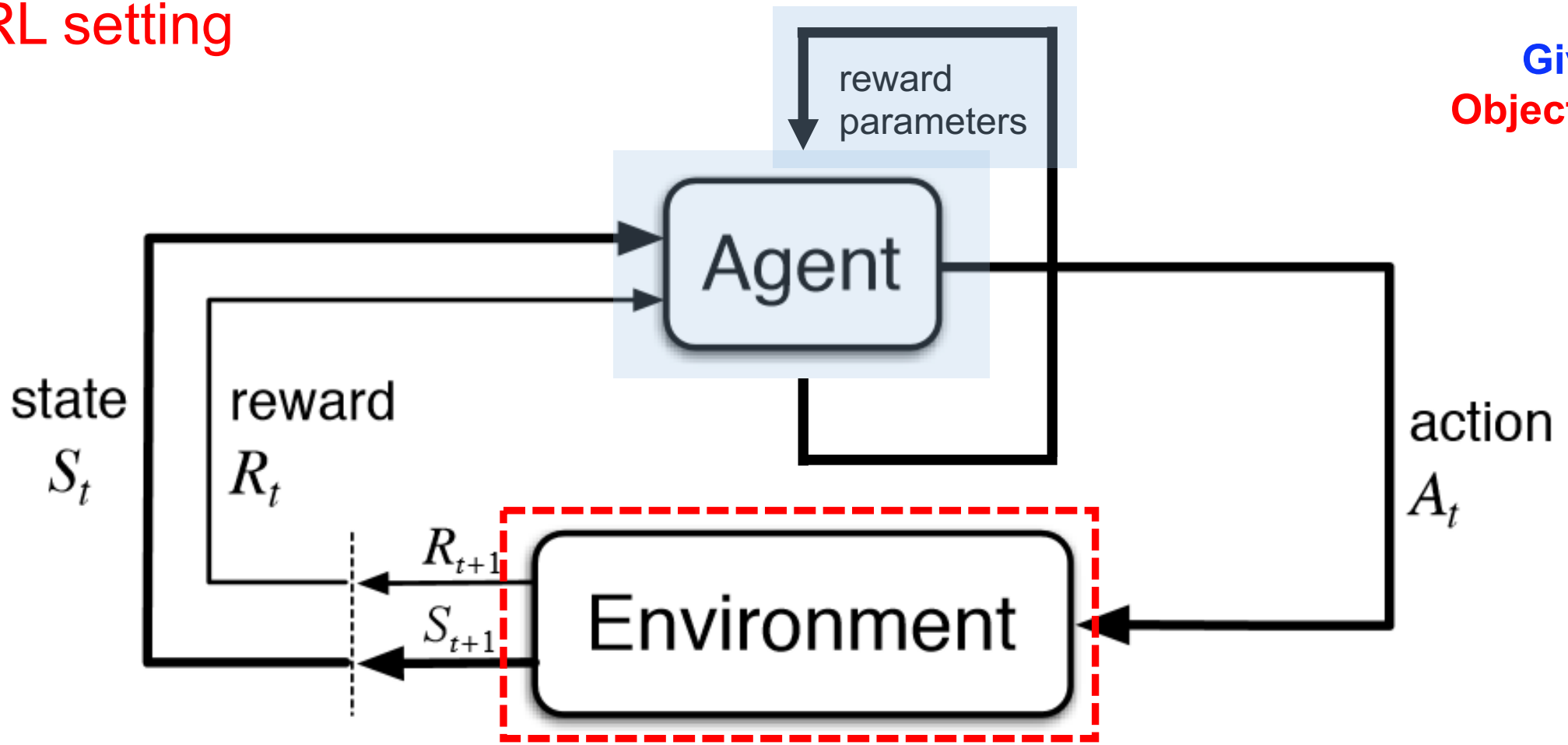
Reinforcement Learning Reward Processing

- RL setting



Reinforcement Learning Reward Processing

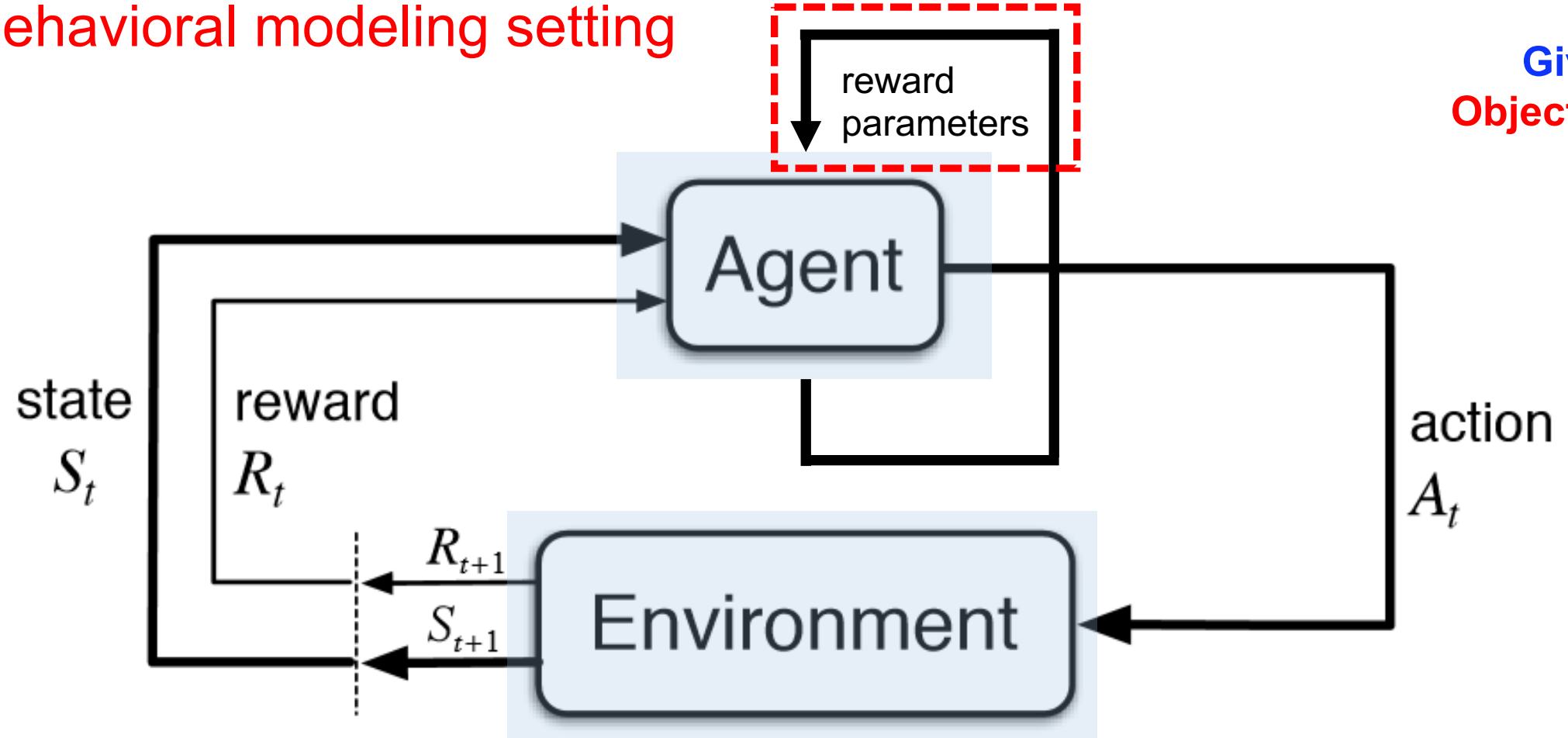
- IRL setting



Given Objective

Reinforcement Learning Reward Processing

- Behavioral modeling setting



Human Q Learning / Split Q Learning

Algorithm 1 Human Q-Learning (HQL)

For each episode t **do**
  Initialize s
  Repeat
    $Q(s,a) := \phi_2 Q^+(s,a) + \phi_4 Q^-(s,a)$
    action $i_t = \arg\max_i Q_i(t)$, observe $s' \in S$, r^+ and $r^- \in R(s)$
    $Q^+(s,a) := \phi_1 \hat{Q}^+(s,a) + \alpha_t(r^+ + \gamma \quad max_{a'} \hat{Q}^+(s',a') - \hat{Q}^+(s,a))$
    $Q^-(s,a) := \phi_3 \hat{Q}^-(s,a) + \alpha_t(r^- + \gamma \quad max_{a'} \hat{Q}^-(s',a') - \hat{Q}^-(s,a))$
  until s is terminal

parameters for reward bias on policy

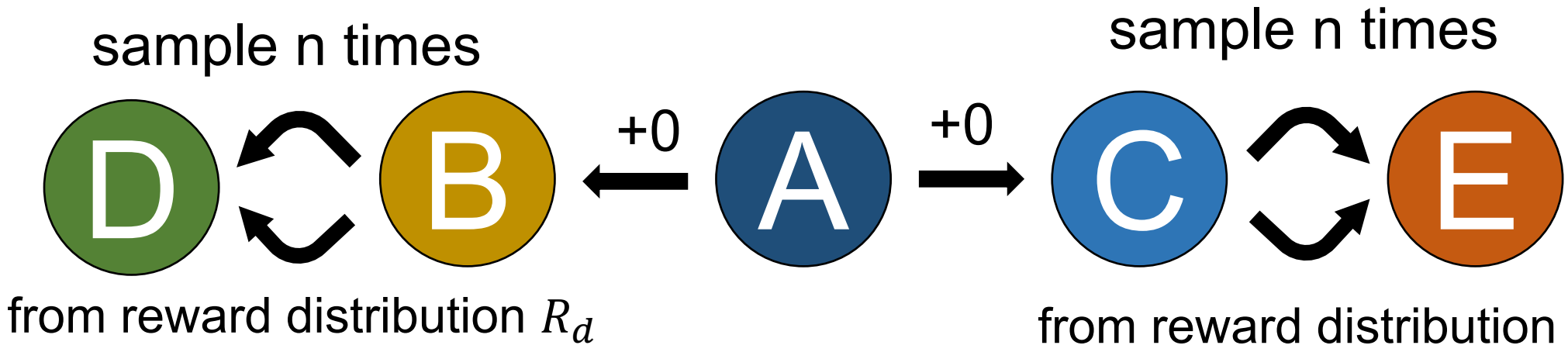
parameters for reward bias on historical information

Reward Processing with Different Biases

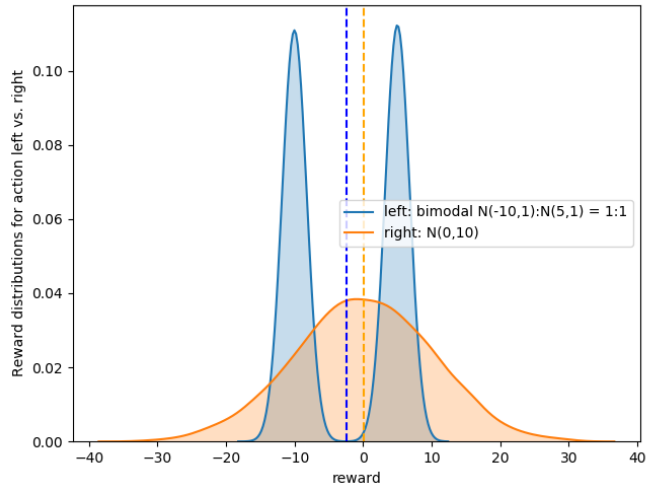
Table 1: Algorithms Parameters

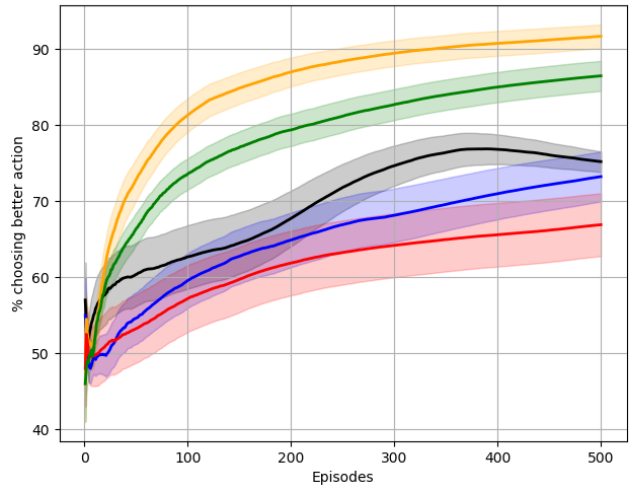
	ϕ_1	ϕ_2	ϕ_3	ϕ_4
"Addiction" (ADD)	1 ± 0.1	1 ± 0.1	0.5 ± 0.1	1 ± 0.1
"ADHD"	0.2 ± 0.1	1 ± 0.1	0.2 ± 0.1	1 ± 0.1
"Alzheimer's" (AD)	0.1 ± 0.1	1 ± 0.1	0.1 ± 0.1	1 ± 0.1
"Chronic pain" (CP)	0.5 ± 0.1	0.5 ± 0.1	1 ± 0.1	1 ± 0.1
"bvFTD"	0.5 ± 0.1	100 ± 10	0.5 ± 0.1	1 ± 0.1
"Parkinson's" (PD)	0.5 ± 0.1	1 ± 0.1	0.5 ± 0.1	100 ± 10
"moderate" (M)	0.5 ± 0.1	1 ± 0.1	0.5 ± 0.1	1 ± 0.1
Standard HQL (SQL)	1	1	1	1
Positive HQL (PQL)	1	1	0	0
Negative HQL (NQL)	0	0	1	1

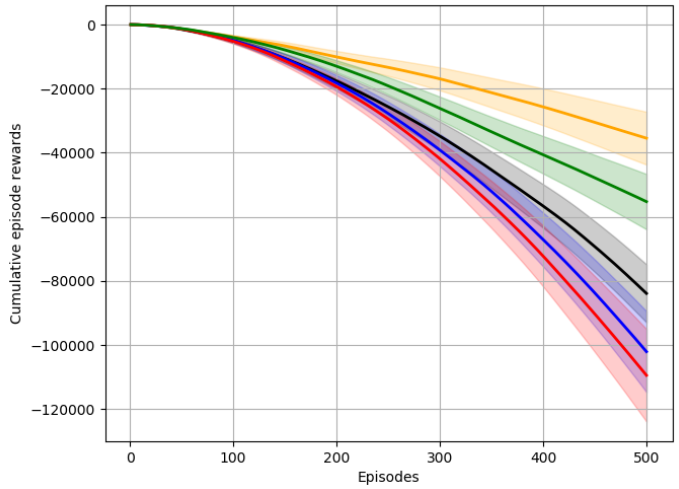
MDP Problem with not-Gaussian rewards

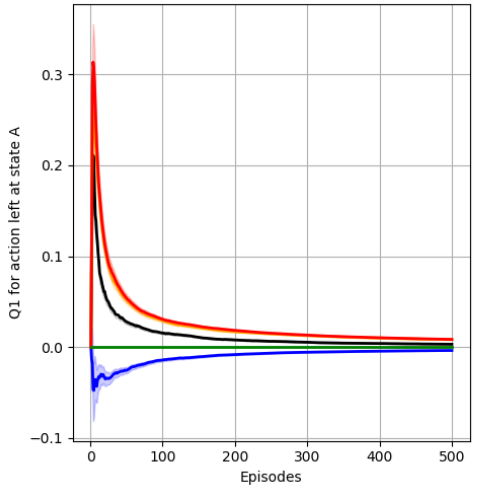


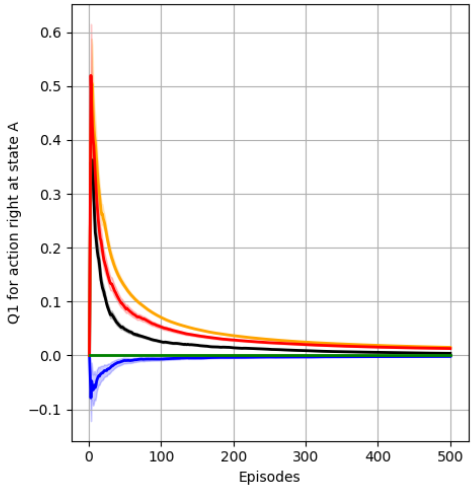
MDP Problem with not-Gaussian rewards

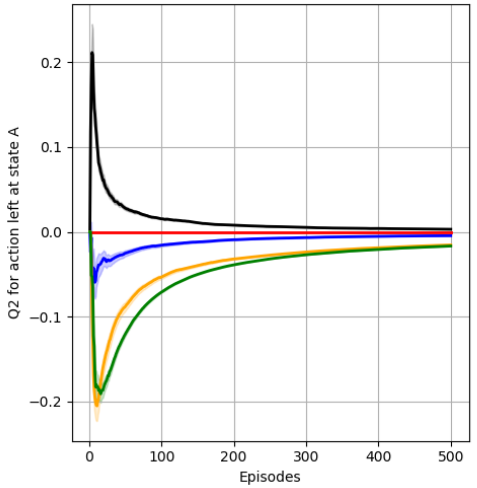


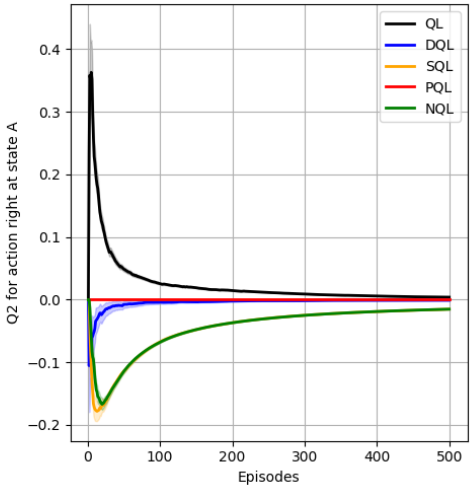












MDP Problem with not-Gaussian rewards

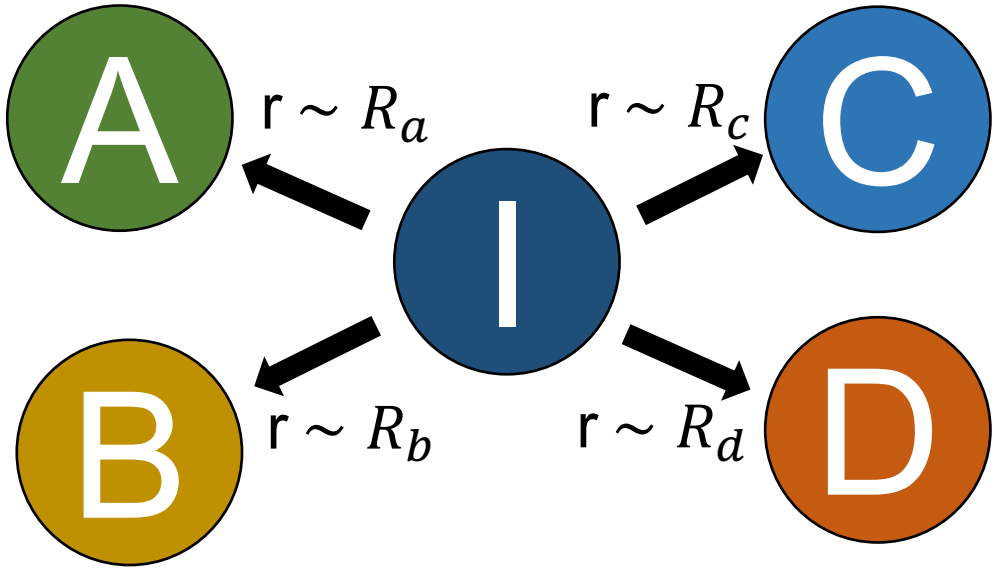
	QL	DQL	SQL	PQL	NQL
QL	-	46 : **54**	34:**66**	72 : 28	44 : **56**
DQL	54:46	-	34:**66**	59:41	50:50
SQL	66:34	66:34	-	77:23	62:38
PQL	28:**72**	41:**59**	23:**77**	-	45:**55**
NQL	56:44	50:50	38:**62**	55:45	-
avg wins (%)	0.49	0.49	**0.68**	0.34	0.50

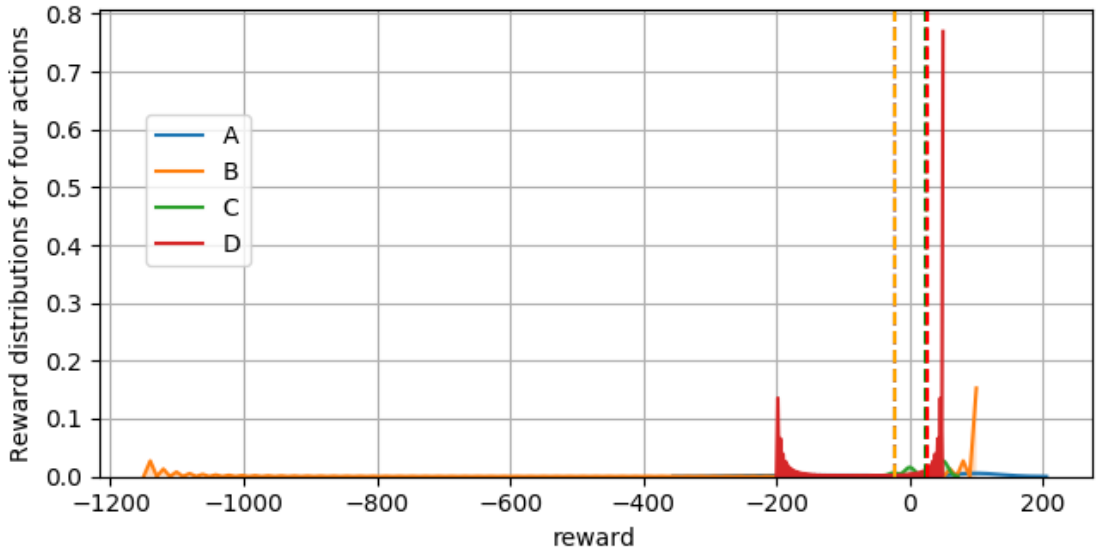
SQL		ADD	ADHD	AD	CP	bvFTD	PD	M	avg wins (%)
29:**71**	QL	60:40	65:35	73:27	43:**57**	75:25	38:**62**	49:**51**	0.58
22:**78**	DQL	54:46	80:20	81:19	61:39	77:23	52:48	53:47	0.65
-	SQL	78:22	94:6	95:5	67:33	89:11	66:34	81:19	**0.81**
-	avg wins (%)	0.36	0.20	0.17	0.40	0.16	0.48	0.39	-

Iowa Gambling Task

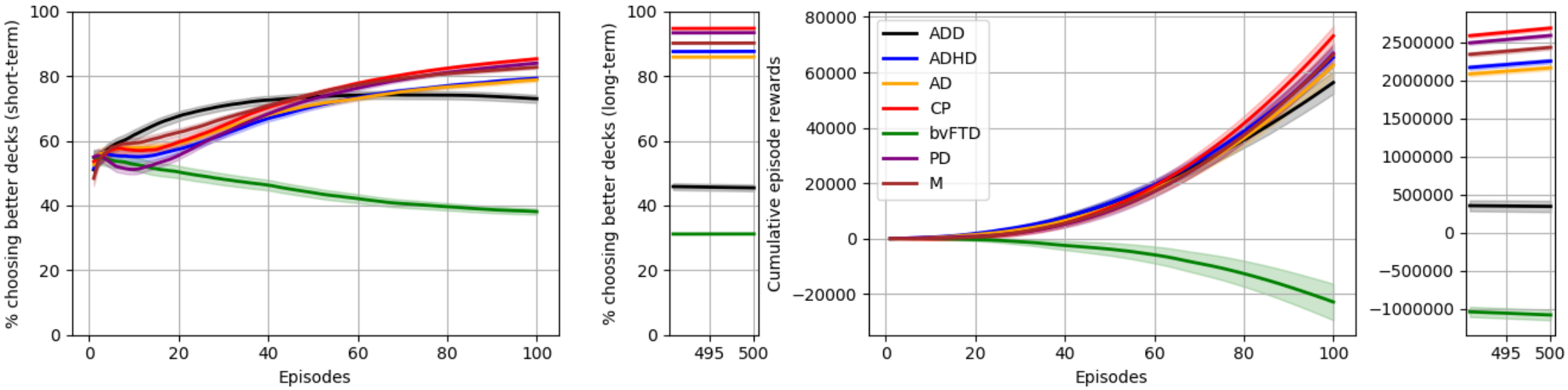
Table 4: Iowa Gambling Task schemes

Decks	win per card	loss per card	expected value	scheme
A (bad)	+100	Frequent: -150 (p=0.1), -200 (p=0.1), -250 (p=0.1), -300 (p=0.1), -350 (p=0.1)	-25	1
B (bad)	+100	Infrequent: -1250 (p=0.1)	-25	1
C (good)	+50	Frequent: -25 (p=0.1), -75 (p=0.1),-50 (p=0.3)	+25	1
D (good)	+50	Infrequent: -250 (p=0.1)	+25	1
A (bad)	+100	Frequent: -150 (p=0.1), -200 (p=0.1), -250 (p=0.1), -300 (p=0.1), -350 (p=0.1)	-25	2
B (bad)	+100	Infrequent: -1250 (p=0.1)	-25	2
C (good)	+50	Infrequent: -50 (p=0.5)	+25	2
D (good)	+50	Infrequent: -250 (p=0.1)	+25	2





Iowa Gambling Task



Ongoing directions

- Investigate the optimal reward bias parameters computer games evaluated on different criteria, e.g., longest survival time vs. highest final score.
- Explore the multi-agent interactions given different reward processing bias.
- Tune and extend the proposed model to better capture observations in literature.
- Learn the parametric reward bias from actual patient data.
- Test the model on both healthy subjects and patients with specific mental conditions.
- Evaluate the merit in two-stream processing in deep Q networks.

Acknowledgements

Feel free to check out the full version at arxiv.org/abs/1906.11286

Reinforcement Learning Models of Human Behavior: Reward Processing in Mental Disorders

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Thanks! Questions?

- Feel free to also check out my other talk at IJCAI HBAI Workshop:

Neural Networks as Model Selection with Incremental MDL Normalization

in area **2403** today at **16:15**