Robust probabilistic target-oriented exploration with reliability approximation

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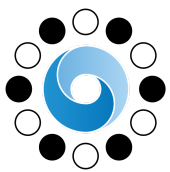
Background

Reinforcement learning (RL) agents have reached superhuman levels in games such as Go and chess.



AlphaGo >

Task complexity

In terms of the complexity of the environment,
real-world tasks are more challenging than games.

>

Reinforcement learning and human learning

[Problem] RL is still too costly to use in the real-world tasks.

- The required amount of sampling time for optimization is not feasible in a realistic time frame.
- The required amount of exploration time for optimization is not feasible in a realistic time frame.

[Idea] Can we solve this by imitating human learning?

- We refer to **satisficing**, which is a learning tendency of humans.
- We introduce the concept of an **aspiration level** into reinforcement learning.
- We generalize the goal of reinforcement learning to satisficing rather than optimization (but optimization is also possible).

We implemented **target-oriented exploration**
in order to achieve the aspiration level through learning.

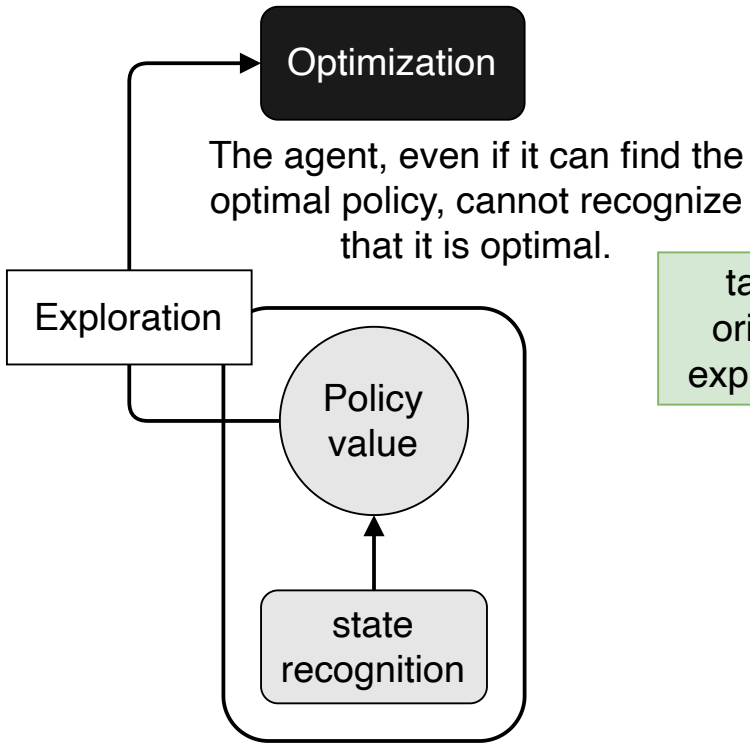
Objectives of this study

[Main objective]
Application of target-oriented exploration to deep reinforcement learning

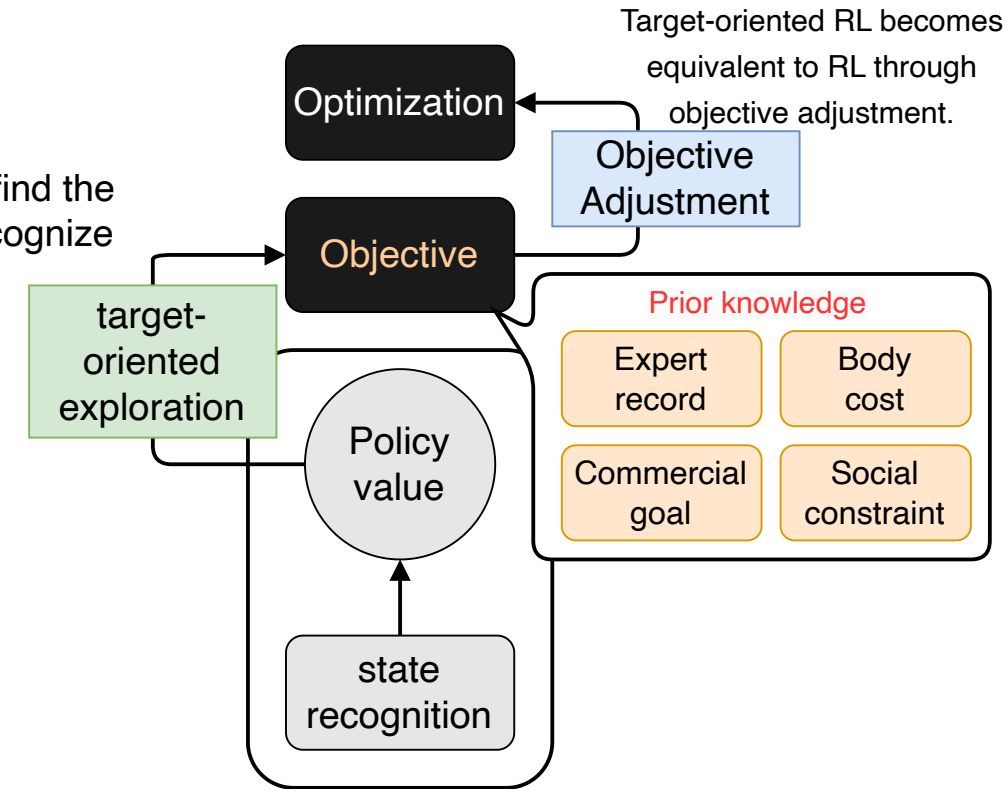
[Sub objective]
Generalization of the action selection of target-oriented exploration methods stochastically

- We generalize the methods that can approximate states.
- We show that the new method can be generalized stochastically without performance degradation.
- We aim to show performance equal to or better than that of representative methods.

Conventional RL



Target oriented RL



Related research

Risk-sensitive Satisficing (RS)

- Overview: RS is a method that incorporates an aspiration level into RL (target-oriented RL).
- Properties: Off-policy, Deterministic action selection
- Features: RS showed better performance than other methods in bandit problems and RL problems.
  - Takahashi et al., 2016
  - Tamatsukiri et al., 2019

Related research

Regional Linear RS (RegLinRS)

- Overview: RegLinRS is one of the RS methods that can identify states.
- Properties: Off-policy, Deterministic action selection
- Features: RegLinRS showed better performance than LinUCB and LinTS in contextual bandit problems.
  - Tsuboya et al., 2023

We want to generalize deterministic action selection to stochastic action selection.

Contextual Bandit Problems

- Experiment task: Linear contextual bandit problems
- Determination of reward expectation value $p_{t,i}$ of each action a_i by context $\mathbf{x}_t$ and weight θ_i
- The agent observes the context $\mathbf{x}_t$ at time t and chooses an action a_i.
  - As a result, the agent observes the reward r_t (in this study, the reward expectation value $p_{t,i}$).
- The calculation method of $p_{t,i}$ is as follows.

$$p_{t,i} = \mathbf{x}_t^T \theta_i + \epsilon_t$$

  - θ_i: The parameter of the reward expectation value
  - ϵ_t: The error term with an expected value of 0

Methods performing well in contextual bandit problems

- LinUCB (Li et al., 2010)
- LinTS (Riquelme et al., 2018)

Regret

- We use **regret** as an evaluation index.
  - Expected reward loss

$$\text{regret} = \sum_{t=1}^{T} (p_{\max} - p_{t,\,\text{chosen}})$$

    - $p_{\max}$: The highest reward expectation value
    - $p_{t,\,\text{chosen}}$: The reward expectation of the action chosen in the t-th step

- Properties of regret
  - Regret is the loss expectation value of the agent, which is a weakly increasing function.
  - The minimum value of regret is 0 (when the agent continues to choose the optimal action).

Subjective regret

Implementation of target-oriented exploration

- If we use target-oriented exploration, we can use a subjective index instead of regret.
  - We call this **subjective regret** (SR).

$$I_i^{\mathrm{SR}} = \sum_{t=1}^{T} (\aleph - p_{t,\,\mathrm{chosen}})$$

  - $\aleph$: Aspiration level
- Properties of SR
  - If the agent newly acquired reward is
    - greater than or equal to $\aleph$ (i.e., sufficient), I_i^{SR} decreases.
    - less than $\aleph$ (i.e., insufficient), I_i^{SR} increases.
  - We can interpret this index as a risk-sensitive value function.

Risk-sensitive Satisficing (RS)

Implementation of target-oriented exploration

- The formula for the core metric of target-oriented exploration
  - We define the RS value function by $I_i^{\mathrm{RS}} := -I_i^{\mathrm{SR}}$.
  - The agent chooses an action by taking the argmax from I_i^{RS}.

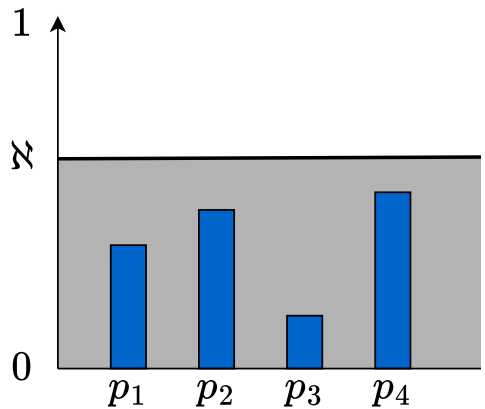
$$I_i^{\mathrm{RS}} = \frac{n_i}{N}(p_i - \aleph) = \frac{n_i}{N}\delta_i$$

  - p_i: Reward expectation value of action a_i
  - n_i: The number of times the agent chose action a_i
  - N: The total number of times the agent chose an action
  - n_i/N: Reliability (Choice propability) of action a_i
- δ_i: Reflection effect of prospect theory → Difference between aspiration level ($p_i - \aleph$)
  - By multiplying the reliability and δ_i, the agent makes optimistic or pessimistic action choices depending on the situation.

Under-archieved and Over-archieved situation

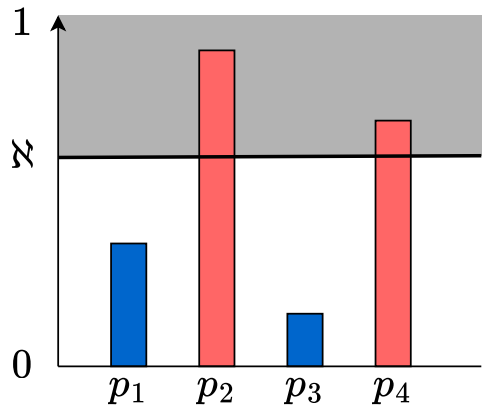
Under-archieved situation

All reward expectation values are less than ℵ.



Over-archieved situation

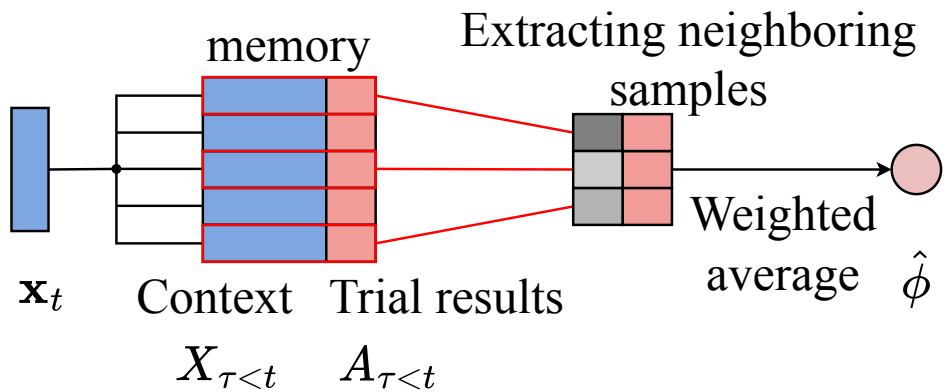
At least one reward expectation value is greater than or equal to ℵ.



Exploration area

Local approximation of the reliability

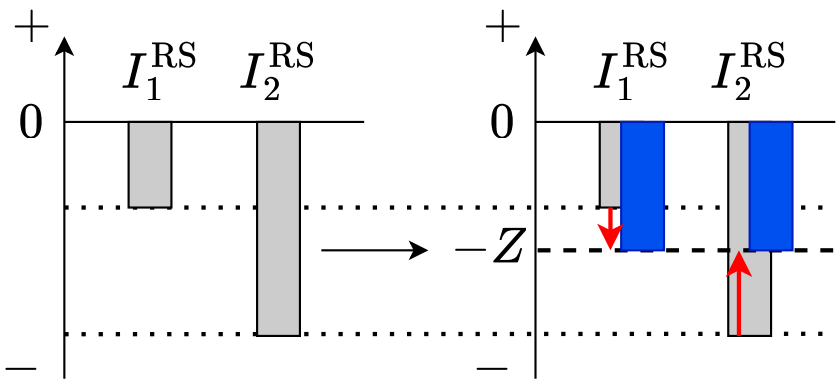
- The agent approximates and estimates the reliability using episodic memory and k-nearest neighbor.
- **Regional Linear RS** (RegLinRS)
  - Tsuboya et al., 2023



Inversely calculating of the choice distribution in RS

- RS is estimable for internal choice ratio in under-archieved situation.
- The agent generates a probability distribution from the difference between the estimated reliability and the actual reliability.
  - The agent generates the estimated reliability ρ_i^z using the RS equilibrium value $-Z$.
- **Stochastic RS** (SRS)

RS equilibrium value $-Z$



$$I_i^{\mathrm{RS}} = -Z$$

$$\rho_i = n_i/N = Z/(\aleph - p_i)$$

$$\sum_{i=1}^{K} \rho_i = \sum_{i=1}^{K} Z/(\aleph - p_i) = 1$$

$$Z = 1/\sum_{i=1}^{K} \frac{1}{\aleph - p_i}$$

Calculate policy of SRS

Under-archieved situation

- We can calculate $-Z$.

$$
\begin{aligned}
b_i &= \frac{n_i}{\rho_i^z} - N + \epsilon \\
I_i^{\mathrm{SRS}} &= (N + \max_i(b_i))\rho_i^z - n_i > 0 \\
\pi_i &= I_i^{\mathrm{SRS}} / \sum_{i=1}^{K} I^{\mathrm{SRS}_i}
\end{aligned}
$$

- b: Adjustment parameter for preventing negative ratios
- ϵ: An extremely small value to prevent zero division

Over-achieved situation

- We cannot calculate $-Z$.
- We calculate the probability of selecting an action that has a reward expectation value greater than $\aleph$.

$$
\begin{aligned}
I_i^{\mathrm{RS}'} &= \begin{cases} I_i^{\mathrm{RS}} + \epsilon, & \text{if } p_i \geq \aleph \\ 0, & \text{if } p_i < \aleph \end{cases} \\
\pi_i &= I_i^{\mathrm{RS}'} / \sum_{j=1}^{K} I_j^{\mathrm{RS}'}
\end{aligned}
$$

Regional Linear SRS

- **New method**
- This method is a combination of the reliability estimation part of RegLinRS and SRS.
  - The formula of SRS contains n_i and N.
  - We can approximate n_i/N, but we cannot approximate n_i and N.

Transformation of the equations in SRS

$$\frac{b_i}{N_x} = \frac{1}{\rho_i^z} \cdot \frac{n_i}{N_x} - 1 + \epsilon = \frac{\rho_i}{\rho_i^z} - 1 + \epsilon$$

$$\begin{aligned}\frac{I_i^{\mathrm{SRS}}}{N_x} &= \left(\frac{N_x + \max_i(b_i)}{N_x}\right) \\ &= \left\{\max_i\left(\frac{\rho_i}{\rho_i^z}\right) + \epsilon\right\}\rho_i^z - \rho_i\end{aligned}$$

$$\frac{I_i^{\mathrm{SRS}}}{N_x} = \left\{\max\left(\frac{\hat{\phi}_i}{\rho_i^z}\right) + \epsilon\right\}\rho_i^z - \hat{\phi}_i$$

$$\pi_i = \frac{I_i^{\mathrm{SRS}}}{N_x} \Big/ \sum_{j=1}^{K} \frac{I_j^{\mathrm{SRS}}}{N_x} = I_i^{\mathrm{SRS}} \Big/ \sum_{j=1}^{K} I_j^{\mathrm{SRS}}$$

→ We can extend SRS to RegLinSRS.

Artificial dataset

- We created an artificial dataset in which the aspiration level $\aleph$ is always constant.
  - The reason is to compare RegLinRS, RegLinSRS with other methods using the same evaluation index.

- We used the same dataset as Tsuboya et al., 2023.
- We designed the dataset so that the optimal action would not be biased in order to properly evaluate the balance between exploration and exploitation.

Configuration Item	Configuration Value
Feature vector dimension d	128
Number of actions K	8
Optimal Aspiration level $\aleph_{\mathrm{opt}}$	0.7
Data size N	100,000

※ $\aleph_{\mathrm{opt}}$ is the reference value set between the optimal and suboptimal.

Experiment 1

Comparison methods

LinUCB, LinTS, RS methods (RegLinRS, RegLinSRS)

Experiment settings

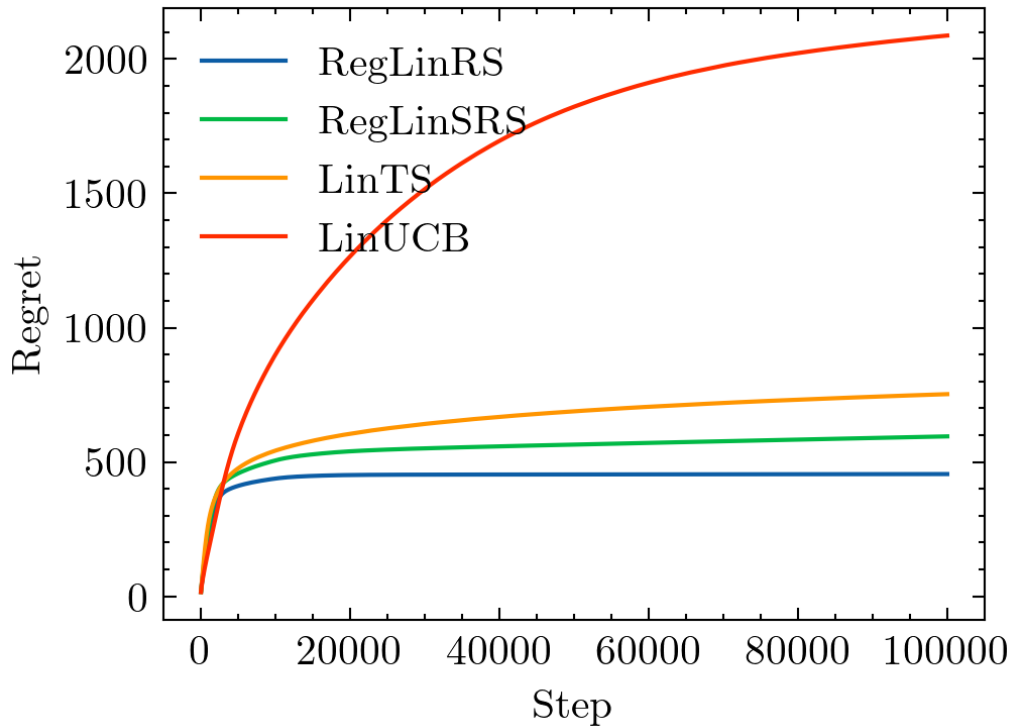
- We ran 1,000 simulations with 100,000 steps per simulation.
  - We calculated the average value and used it as the result.
- The agent initially selects each action 10 times.
  - This setting is necessary for parameter initialization.
- We set the batch size to 20 for all methods.

Value Name	Value
ϵ	sys.float_info.epsilon in Python
episodic memory size	10,000
k of K-nearest neighbors	50
$\aleph$	0.6
α of LinUCB	0.1
λ of LinTS	0.25
α of LinTS	6
β of LinTS	6
$\mathbf{b}_i$	All 0
$\mathbf{A}_i$	Identity matrix $\mathbf{I}$

Result

Experiment 1

Good



Result

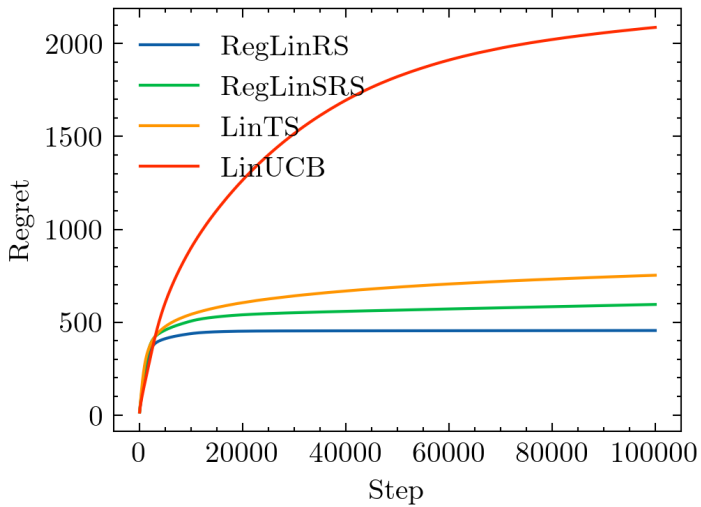
Experiment 1

- RegLinRS, RegLinSRS, LinTS, LinUCB performed well in that order.
- LinTS, LinUCB have a logarithmic increase in regret.
- RegLinRS, RegLinSRS have almost converged regret.

- LinTS is one of the state-of-the-art methods (Agrawal et al., 2019).
- LinTS is inferior to RegLinRS, RegLinSRS in the initial rise of regret.

↓

RegLinRS, RegLinSRS can stop learning faster than LinTS and can select the truly optimal action even in situations where accurate approximation has not yet been achieved?

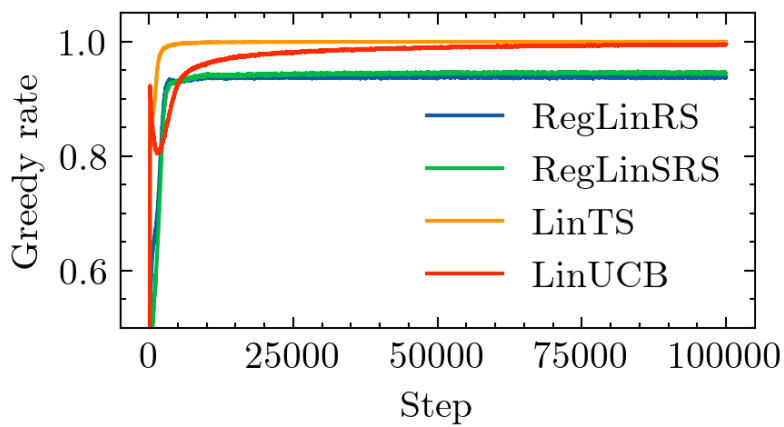


Discussions

Experiment 1

- LinTS, LinUCB have reached a Greedy rate of 1.0.
- RegLinRS, RegLinSRS have stopped at a Greedy rate of over 0.9.
  - Not greedy about 1 in 10 times

→ RegLinRS, RegLinSRS can choose the truly optimal action even if the action is overestimated.



Hypothesis

Experiment 1

[Fact] RegLinRS, RegLinSRS can partially mitigate the effects of approximation errors.

- These methods can choose the truly optimal action even if the action is overestimated due to approximation errors.

[Hypothesis] Are RegLinRS and RegLinSRS achieving this by reliability?

- RS does not necessarily make greedy action selection due to the reflection effect of reliability.
- This property is rational in the sense that the agent can choose a satisfactory action with certainty.

→ We conducted an experiment to verify this property
by intentionally adding noise to the reward expectation value.

Experiment 2

Experimental purpose

- **To verify the robustness of RS to approximation errors**
  - We added noise to the estimated reward expectation value.
  - We intentionally created a situation where it is easy to select a non-optimal action.

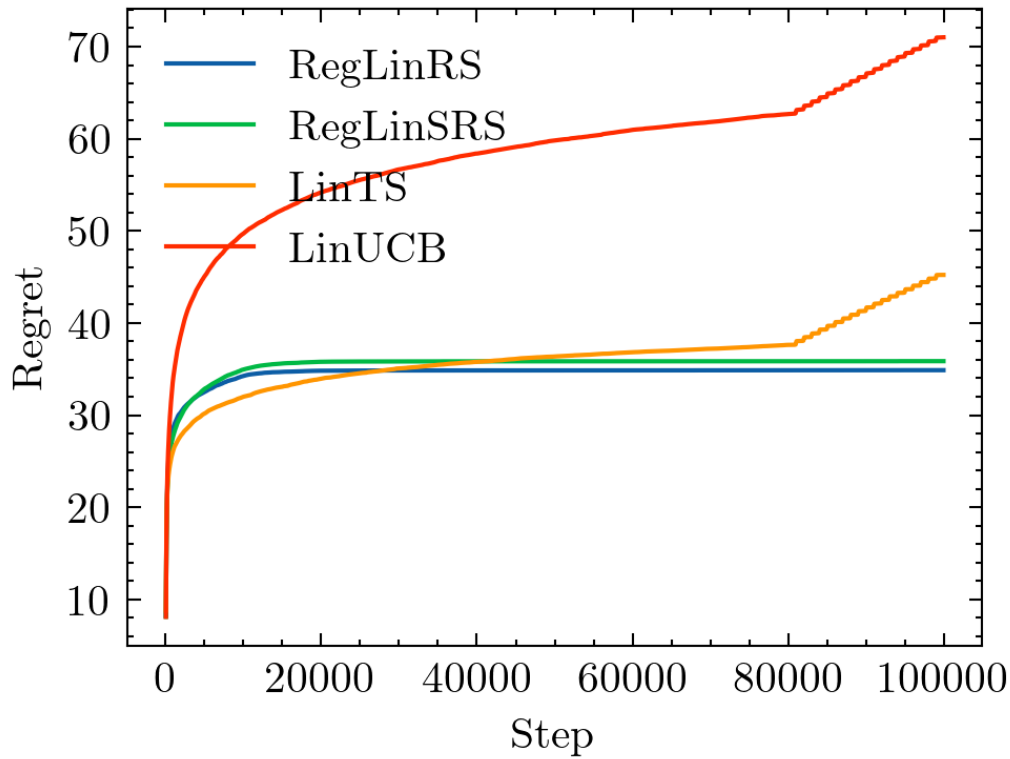
Experimental settings

- We set the number of actions to $K = 2$ to simplify the experiment in Experiment 1.
- We added noise to the estimated reward expectation value at equal intervals after 80,000 steps.
- We set the other settings the same as in Experiment 1.

Result

Experiment 2

Good

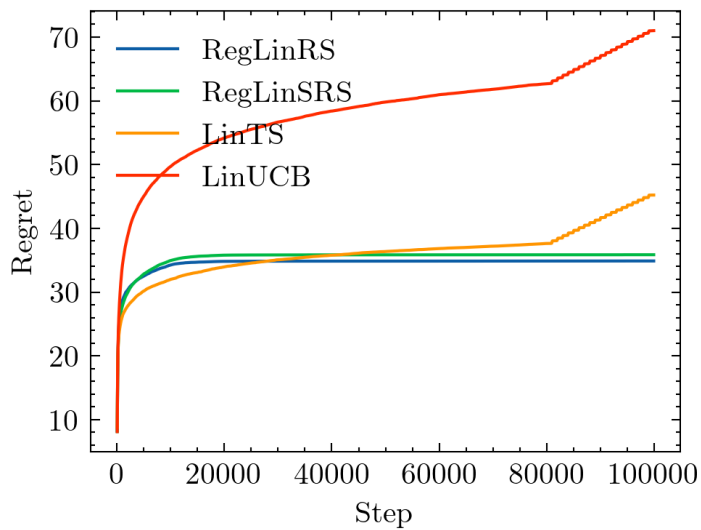


Result

Experiment 2

- After the step on which the noise is added, LinTS, LinUCB have a sharp increase in regret.
- RegLinRS, RegLinSRS have no increase in regret.
  - These methods can partially mitigate the effects of approximation errors by the reflection effect of reliability.

→ We showed the robustness of RS to approximation errors.



Conclusion

- We generalized deterministic action selection (RegLinRS) to **stochastic action selection (RegLinSRS)**.
- We showed that
  - RegLinSRS **does not have a significant performance degradation** compared to RegLinRS.
  - RegLinSRS **has better performance than LinTS and LinUCB**.

- We showed **the robustness of RS to approximation errors**.
  - This property is considered to be useful for extending RS to deep RL in the future.

→ We prepared for the application of RS to deep RL.