Reinformcement Learning Theory Learning

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Abstract

a simple note for RL theroy

Keywords:

1. Introduction

RL theory is very long history and these days

- Bullet point one
- Bullet point two
- 1. Numbered list item one
- 2. Numbered list item two

2. Notation and Formatting

some notations:

| \mathcal{S} | the state space | |
|---------------|----------------------------------|--|
| S_t | the state at time t, stochastic | |
| s_t | the state at time t, actual | |
| s | the state, actual | |
| R_t | the reward at time t, stochastic | |
| r_t | the reward at time t, actual | |
| r | the reward, actual | |

| Treatments | Response 1 | Response 2 |
|-------------|------------|------------|
| Treatment 1 | 0.0003262 | 0.562 |
| Treatment 2 | 0.0015681 | 0.910 |
| Treatment 3 | 0.0009271 | 0.296 |

Table 1: Table caption

2.1. Subsection Two

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Placeholder Image

Figure 1: Figure caption

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$$e = mc^2 (1)$$

3. RL algorithms

4. RL convergence theory

4.1. counterexample

In Sutton and Barto [1, chap 11.3] the authors give an intuitive conclusion about when these algorithms will divergence :

the danger of instability and divergence arises whenever we combine three things:

- 1. training on a distribution of trainsition other than that naturally generated by the process whose expectation is being estimated(e.g. off-policy learning)
- 2. scalable function approximation (e.g. li)

4.1.1. counterexample1

In Bertsekas [2] Dimitri [3] $E[\theta_t(t+1)|\theta_t]$

References

- [1] R. S. Sutton, A. G. Barto, Reinforcement learning: An introduction, 2011.
- [2] D. P. Bertsekas, A counterexample to temporal differences learning, Neural Computation 7 (1995) 270–279.
- [3] P. Dimitri, A Counterexample to Temporal Differences Learning, pdf-s.semanticscholar.org (????).