### Reinforcement Learning, Tutorial 03

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# Outline

- 1. Announcements
- 2. Solutions
- 3. Outlook

### Announcements

- ▶ Points for exercise sheet in ilias
- ► Next exercise sheet is available

### Admin

- From now on, submissions in the wrong file format will give 0 points. Allowed is: one single pdf and one single .py. If you want to compress upload as a single .zip file! (not allowed is anything else: .doc, .txt, .odt, .rar, .ipynb, ...)
- ▶ If you send me files after the deadline they will not be graded
- Advice: Upload early and verify that your files are the correct ones
- The exercises do not influence your final grade, only the final exam does. But: you need 50% of the points in the exercises to participate in the exam.

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#### 1a

**Task:** Show that the Bellman optimality operator  ${\mathcal T}$  is a  $\gamma$ -contraction

$$\begin{split} \left\| \mathcal{T}v - \mathcal{T}v' \right\|_{\infty} &= \left\| \max_{a} \sum_{s',r} p(s',r \mid s,a) \left[ r + \gamma v(s') \right] - \max_{a} \sum_{s',r} p(s',r \mid s,a) \left[ r + \gamma v'(s') \right] \right\|_{\infty} \\ &\leq \left\| \max_{a} \left( \sum_{s',r} p(s',r \mid s,a) \left[ r + \gamma v(s') \right] - \sum_{s',r} p(s',r \mid s,a) \left[ r + \gamma v'(s') \right] \right) \right\|_{\infty} \\ &= \left\| \max_{a} \left( \gamma \sum_{s',r} p(s',r \mid s,a) \left[ v(s') - v'(s') \right] \right) \right\|_{\infty} \\ &\leq \left\| \max_{a} \left( \gamma \sum_{s',r} p(s',r \mid s,a) \| v - v' \|_{\infty} \right) \right\|_{\infty} \\ &= \left\| \gamma \| v - v' \|_{\infty} \max_{a} \sum_{s',r} p(s',r \mid s,a) \right\|_{\infty} \\ &= \gamma \| v - v' \|_{\infty} \end{split}$$

- $\blacktriangleright$  Even if all inequalities are equalities it converges for  $\gamma < 1$
- ► This proof shows convergence of value iteration, in the lecture it was for policy evaluation!

## 1b

**Task:** With bounded rewards, show:  $\frac{r_{\min}}{1-\gamma} \leq v(s) \leq \frac{r_{\max}}{1-\gamma}$ 

$$\begin{split} v(s) &= \mathbb{E}\left[G_t \mid S_t = s\right] \\ &= \mathbb{E}\left[\sum_{i=0}^{\infty} \gamma^i R_{t+i+1} \mid S_t = s\right] \\ &\leq \mathbb{E}\left[\sum_{i=0}^{\infty} \gamma^i r_{\max} \mid S_t = s\right] \\ &= \sum_{i=0}^{\infty} \gamma^i r_{\max} \\ &= \frac{r_{\max}}{1-\gamma} \end{split}$$

ightharpoonup Similar for  $r_{min}$ 

## 1b cont.

**Task:** Show: 
$$|v(s) - v(s')| \le \frac{r_{\max} - r_{\min}}{1 - \gamma}$$

Use equation previous slide:

$$|v(s) - v(s')| \le v_{\mathsf{max}} - v_{\mathsf{min}} = \frac{r_{\mathsf{max}}}{1 - \gamma} - \frac{r_{\mathsf{min}}}{1 - \gamma} = \frac{r_{\mathsf{max}} - r_{\mathsf{min}}}{1 - \gamma}$$

2a

**Task:** Compute optimal value function with value iteration.

number iterations: 43

0.02685371 0. 0.05978021 0.

 $0.0584134 \quad 0.13378315 \quad 0.1967357 \quad 0.$ 

0. 0.2465377 0.54419553 0.

## 2b

#### **Task:** Compute optimal policy

► Multiple optimal policies:

Down/Right	Up	Right	Up
Left	Н	Left/Right	Н
Up	Down	Left	Н
Н	Right	Down	G

▶ Why action "Right" in state 2?

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## Next exercise sheet

- Next exercise sheet available
- ▶ It is about Monte-Carlo Methods
- Programming part is on the blackjack environment that we also had in the lecture
- Sourcecode on github https://github.com/humans-to-robots-motion/rl-course