CS 747, Autumn 2023: Lecture 12

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Autumn 2023

Reinforcement Learning

1. Reinforcement learning problem
2. Upcoming topics
3. Applications

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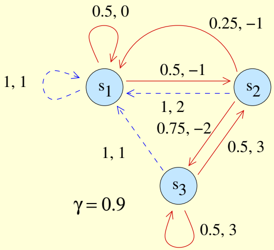
The Learning Setting

Underlying MDP:



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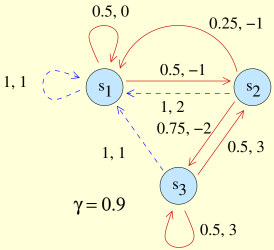

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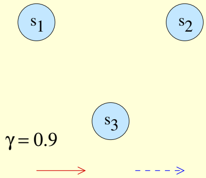

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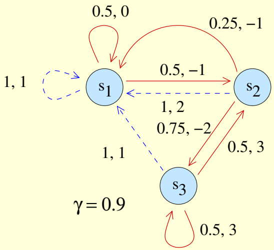

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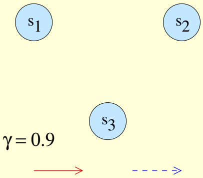

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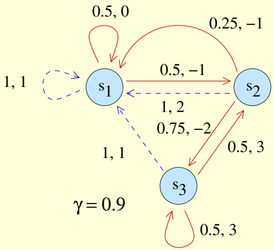

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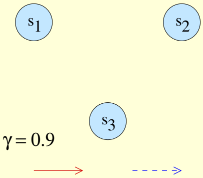

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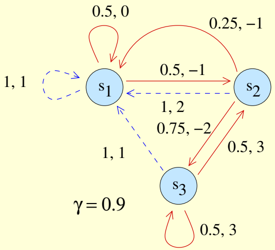

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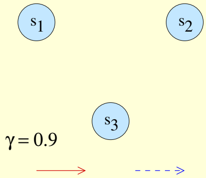

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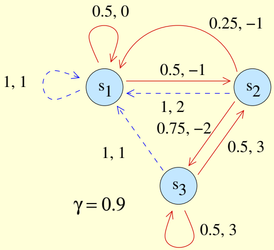

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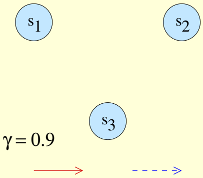

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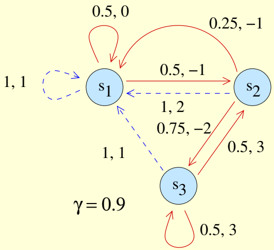

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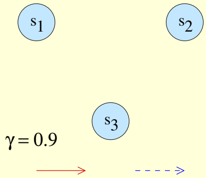

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  Can the agent eventually take optimal actions?

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- **Learning problem**: Can we construct L such that

$$\lim_{H\to\infty} \frac{1}{H}\left(\sum_{t=0}^{H-1} \mathbb{P}\{a^t \sim L(h^t) \text{ is an optimal action for } s^t\}\right) = 1?$$

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- Applications
  - ATARI games (Mnih *et al.* (2015)), Go (Silver *et al.* (2016)).

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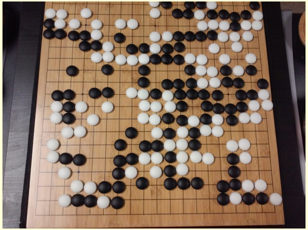
Board Games

Backgammon

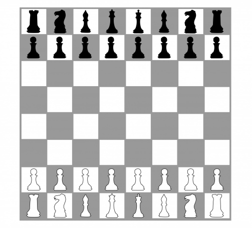
[1]

Go



[2]

Chess



[3]

References: Tesauro (1992), Silver *et al.* (2018).

1. `https://www.publicdomainpictures.net/pictures/60000/velka/backgammon.jpg`.
2. `https://www.publicdomainpictures.net/pictures/170000/velka/finished-go-game.jpg`.
3. `https://www.publicdomainpictures.net/pictures/80000/velka/chess-board-and-pieces.jpg`.

Robotics and Control

[1]

Reference: Ng *et al.* (2003).

1. `https://www.publicdomainpictures.net/pictures/20000/velka/police-helicopter-8712919948643Mk.jpg`.

Video Games

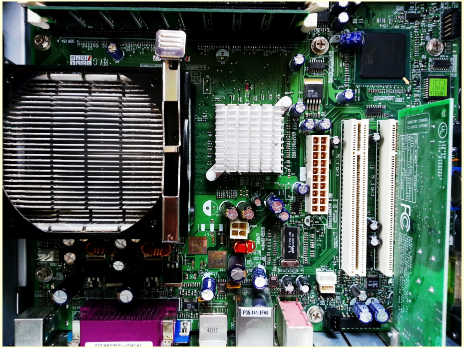
[1]

Reference: Mnih *et al.* (2015).

1. `https://www.publicdomainpictures.net/pictures/30000/velka/arcade-gaming.jpg`.

Computer Systems

Optimising a memory controller



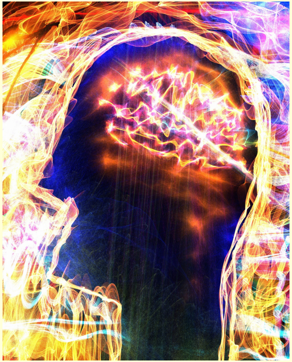
[1]

- Reference: İpek *et al.* (2008).

1. https://www.publicdomainpictures.net/pictures/100000/velka/motherboard.jpg.

Healthcare

Adaptive treatment of epilepsy



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- Reference: Guez *et al.* (2008).

1. https://www.publicdomainpictures.net/pictures/140000/velka/brain-signals.jpg.

Finance

Stock trading

- Reference: Moody and Saffell (2001).

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