

**CS394R**  
**Reinforcement Learning:**  
**Theory and Practice**  
**Fall 2007**

**Peter Stone**

Department of Computer Sciences  
The University of Texas at Austin

# Good Afternoon Colleagues

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- Are there any questions?

# Logistics

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- Class survey — due Thursday

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- Programming assignments, final project

# TD on week 0 task

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- Equiprobable random policy

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- Compare with MC

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- (book slides)

# SARSA vs. Q

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  - (Remember no access to real model)
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  - Q-learning value function converges to  $Q^*$
  - As long as all state-action pairs visited infinitely
  - And step-size satisfies (2.8)

# R-learning

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- Ergodic: non-zero probability of reaching any state

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- R-learning: why negative in 6.17?
- (Afterstates)