CS344M
Autonomous Multiagent Systems

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Good Afternoon, Colleagues

Are there any questions?
Logistics

• Readings
Logistics

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  – Specify which papers you read!
Logistics

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  - 2 case studies and 1 TDP
Logistics

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• How to read a research paper

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Logistics

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- How to read a research paper
  - Some have too few details...
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● How to read a research paper
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  – Others have too many.
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• Next week’s readings posted
Logistics

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  - 2 case studies and 1 TDP

- How to read a research paper
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  - Others have too many.

- Next week’s readings posted

- Use the undergrad writing center!
  - Friday afternoon workshops (3 p.m.)
Overview of the Readings

- *Darwin: genetic programming approach*
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- *Darwin*: genetic programming approach
- *Stone and McAllester*: Architecture for action selection
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- *Riley et al*: Coach competition, extracting models
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- *Withopf and Riedmiller*: Reinforcement learning
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• *MacAlpine et al*: UT Austin Villa 2011
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- *Kuhlmann et al*: Learning for coaching
- *Withopf and Riedmiller*: Reinforcement learning
- *MacAlpine et al*: UT Austin Villa 2011
- *Barrett et al*: SPL Kicking strategy
Evolutionary Computation

- Motivated by biological evolution: GA, GP
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- Search through a space
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  - Probabilistically apply search operators to set of points in search space
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- Randomized, parallel hill-climbing through space
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- Learning is an optimization problem (fitness)
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  - Need a **representation, fitness function**
  - Probabilistically apply search operators to set of points in search space
- Randomized, parallel hill-climbing through space
- Learning is an optimization problem (fitness)

Some slides from *Machine Learning* (Mitchell, 1997)
Darwin United

- More ambitious follow-up to Luke, 97 (made 2nd round)
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- Success of the method, but not pursued
Architecture for Action Selection

- (other slides, video)
Architecture for Action Selection

- (other slides, video)
- downsides
Architecture for Action Selection

- (other slides, video)
- downsides
- Keepaway
Coaching

• Learn best strategy to play a fixed team
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• Give high level advice to players at low frequency
Coaching

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• Focus on learning formations
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- Learn when successful teams passed/kicked
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• What if players switch roles?
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- Why just imitate another team?
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- Why just imitate another team?
- Other slides
Reinforcement Learning

- RL Slides
Reinforcement Learning

- RL Slides
- Extend to grid soccer
Reinforcement Learning

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- Large state space, joint actions
Reinforcement Learning

- RL Slides
- Extend to grid soccer
- Large state space, joint actions
• Other slides
- Other slides
- Why not use CMA-ES on role positions as well?
• Other slides

• Why not use CMA-ES on role positions as well?

• Changes for 2012?
Kicking Under Uncertainty

- Used by our SPL team
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- Kick engine to kick at various distances/headings
Kicking Under Uncertainty

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- Kick engine to kick at various distances/headings
- Adjust to seen ball location
Kicking Under Uncertainty

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- Kick engine to kick at various distances/ headings
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- Select first kick that moves ball up field
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- Figure
Kicking Under Uncertainty

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- Emphasis on quickness
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- Now: Better model of opponents -> Know if we have more time
Kicking Under Uncertainty

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- Figure
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Learning Commentary

• David Chen and Ray Mooney
Coordination Graphs

- $n$ agents, each choose an action $A_i$
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- $A = A_1 \times \ldots \times A_n$
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- $R_i(A) \mapsto \mathbb{R}$
Coordination Graphs

- \( n \) agents, each choose an action \( A_i \)
- \( A = A_1 \times \ldots \times A_n \)
- \( R_i(A) \mapsto \mathbb{R} \)
- Coordination problem: \( R_1 = \ldots = R_n = R \)
Coordination Graphs

- $n$ agents, each choose an action $A_i$

- $A = A_1 \times \ldots \times A_n$

- $R_i(A) \mapsto \mathbb{R}$

- Coordination problem: $R_1 = \ldots = R_n = R$

- Nash equilibrium: no agent could do better given what others are doing.
Coordination Graphs

- $n$ agents, each choose an action $A_i$
- $A = A_1 \times \ldots \times A_n$
- $R_i(A) \rightarrow \mathbb{R}$
- Coordination problem: $R_1 = \ldots = R_n = R$
- Nash equilibrium: no agent could do better given what others are doing.
- May be more than one (chicken)
Example from the paper

- Understand the rule syntax
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- Form the coordination graph
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- First eliminate rules based on context
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- What does it mean for $G_3$ to collect all relevant rules?
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- What does it mean for $G_3$ to maximize over all actions of $a_1$ and $a_2$?
Example from the paper

- Understand the rule syntax
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- First eliminate rules based on context
- What does it mean for $G_3$ to collect all relevant rules?
- What does it mean for $G_3$ to maximize over all actions of $a_1$ and $a_2$?
- How are the results propagated back?
Example from the paper

- Understand the rule syntax
- Form the coordination graph
- First eliminate rules based on context
- What does it mean for $G_3$ to collect all relevant rules?
- What does it mean for $G_3$ to maximize over all actions of $a_1$ and $a_2$?
- How are the results propagated back?
- Let’s try again with $G_1$ eliminated first
Application to soccer

- Make the world discrete by assigning roles, using high-level predicates

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Application to soccer

- Make the world discrete by assigning roles, using high-level predicates
- Assume global state information
Application to soccer

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- Assume global state information
- Finds pass sequences and starts players moving ahead of time.
Application to soccer

• Make the world discrete by assigning roles, using high-level predicates

• Assume global state information

• Finds pass sequences and starts players moving ahead of time.

• Note the results: with and without coordination.
Reactive Deliberation

- A hybrid approach
- Executor: carry out reactive behaviors
- Deliberator: evaluate possible high-level schema with parameters; generate bids
- Deliberator takes time, but something keeps happening always.
- In effect: deliberator commits to schema for some time