Outline

A. Introduction
B. Single Agent Learning
C. Game Theory
D. Multiagent Learning
   - Definition of the Problem: Stochastic Games
   - Equilibrium Learners
   - Best-Response Learners
   - Regret Minimizing Algorithms
   - Learning to Coordinate
E. Future Issues and Open Problems
Equilibrium Learners

Extend Q table to values on joint actions, one for each learner.

Replace “max” with other operators.

Minimax-Q (Littman 94)
- Converges, zero-sum equilibrium (Littman & Szepesvári 96)

Nash-Q (Hu & Wellman 98)
- Applies to general-sum scenarios; works ok sometimes.

Friend-or-Foe-Q (Littman 01)
- Opponents set as friends (use max; Claus & Boutilier 98), foes (use minimax); converges, equilibria if saddlepoint/global optima.

CE-Q (Hall & Greenwald 02)
- Use correlated equilibria.
SG Analogies to MDPs

In the zero-sum case, results analogous to MDPs:

- optimal value function, policy, Q function
- can be found via simulation, search, DP (not LP!)
- can define Q-learning like algorithm

Failed analogies for general-sum games:

- optimal value function need not be unique
- Q-learning like algorithm doesn’t converge
- no efficient algorithm known

Active area of research. What’s the right thing to do?
Grid Game 3  (Hu & Wellman 01)

U, D, R, L, X

No move on collision

Semiwalls (50%)

-1 for step, -10 for collision, +100 for goal

Both can get goal.
Nash in Grid Game

Average total:

- (97, 48)
- (48, 97)
- (-, - ) (not Nash)
- (64, 64) (not Nash)
- (75, 75)?
Collaborative Solution

Average total:
- (96, 96) (not Nash)

A won’t wait.

B changes incentives.

Can we formalize collaboration like this?
Simpler setting: matrix games
Symmetric Markov Game

Episodic
Roles chosen randomly

Algorithm:
- Maximize sum (MDP)
- Security-level (0-sum)
- Choose max if better

Converges to Nash.
Regret Minimizing Algorithms

- Freund and Schapire
- Hart and Mas-Colell
- No internal regret
- No external regret
- Connection to minimax and correlated equilibria