Lecture23:Multi-agent Reinforcement Learning CS486/686 Intro to Artificial Intelligence

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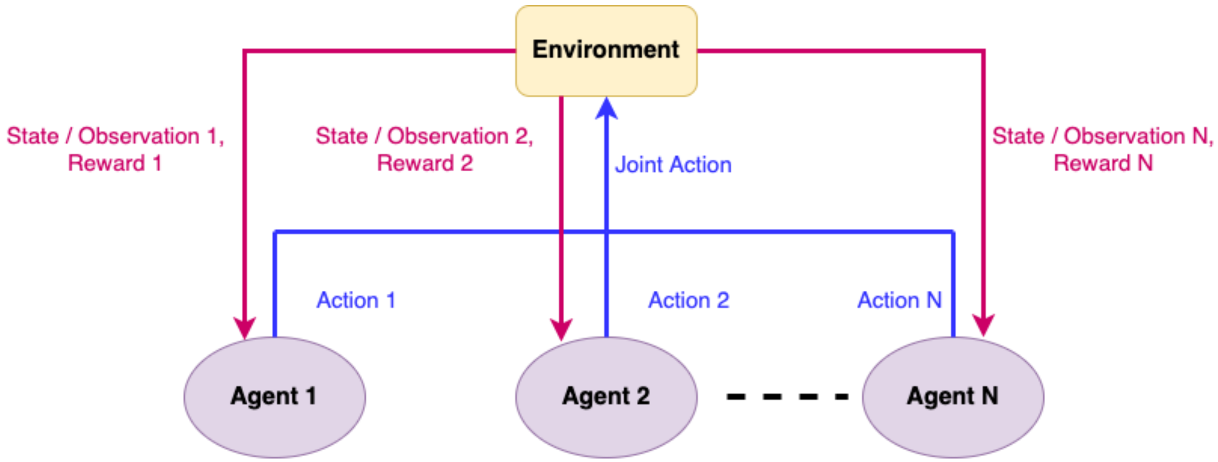
Outline

- Multi-agent Reinforcement Learning (MARL)
- Stochastic Games
- Opponent Modelling
  - Fictitious Play
  - Solving (Unique) Equilibrium
- Cooperative Stochastic Games
  - Joint Q learning
  - Convergence properties
- Competitive Stochastic Games (Zero-sum games)
  - Minimax Q learning
  - Convergence properties
- Mixed Cooperative-Competitive Stochastic Games (General-sum games)
  - Nash Q learning
  - Convergence properties

Multi-agent Reinforcement Learning

Multi-agent Games + Sequential decision making



Newer field with unique challenges and opportunities

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Stochastic Games

- (Simultaneously moving) Stochastic Game (N-agent MDP)
  - Tuple $\langle N, S, A^1, \ldots, A^N, R^1, \ldots, R^N, T, \gamma \rangle$
  - N: Number of agents
  - S: Shared state space $s \in S$
  - A^j: Action space of agent j

    $$\langle a^1, a^2, \ldots, a^N \rangle \in A^1 \times A^2 \times \ldots \times A^N$$

  - R^j: Reward function for agent j - $R^j(s, a^1, \ldots, a^N) = Pr(r^j | s, a^1, \ldots, a^N)$
  - T: Transition function - $Pr(s' | s, a^1, \ldots, a^N)$
  - γ: Discount factor: $0 \leq \gamma \leq 1$
    - Discounted: $\gamma < 1$ Undiscounted: $\gamma = 1$
  - Horizon (i.e., # of time steps): h
    - Finite horizon: $h \in \mathbb{N}$ Infinite horizon: $h = \infty$
  - Policy (strategy) for agent i - $\pi^i : S \rightarrow \Omega(A^i)$

Unknown Models

- Goal: Find optimal policy such that $\boldsymbol{\pi}^* = \{\pi_1^*, \ldots, \pi_N^*\}$, where

$$\pi_i^* = \arg\max_{\pi^i} \sum_{t=0}^{h} \gamma^t \mathbb{E}_{\boldsymbol{\pi}}[r_t^i(s, \boldsymbol{a})], \text{ where } \boldsymbol{a} \triangleq \{a^1, \ldots, a^N\} \text{ and } \boldsymbol{\pi} \triangleq \{\pi^1, \ldots, \pi^N\}$$

Playing a stochastic game

- Players choose their actions at the same time
  - No communication with other agents
  - No observation of other player's actions

- Each player chooses a strategy π^i which is a mapping from states to actions and can be either
  - Mixed strategy: Distribution over actions for at least one state
  - Pure strategy: One action with prob 100% for all states

- At each state, all agents face a stage game (normal form game) with the Q values of the current state and joint action of each player being the utility for that player

- The stochastic game can be thought of as a repeated normal form game with a state representation

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Optimal Policy

- In MARL, the optimal policy should correspond to some equilibrium of the stochastic game
- The most common solution concept is the Nash equilibrium
- Let us define a value function for the multi-agent setting

$$v^j_{\boldsymbol{\pi}}(s) \triangleq \sum_{t=0}^{\infty} \gamma^t \mathbb{E}_{\boldsymbol{\pi}}[r^j_t \mid s_o = s, \boldsymbol{\pi}]$$

- Nash equilibrium under the stochastic game satisfies

$$v^j_{(\pi^j_*, \boldsymbol{\pi}^{-j}_*)}(s) \geq v^j_{(\pi^j, \boldsymbol{\pi}^{-j}_*)}(s)$$

$$\forall s \in S; \forall j; \forall \pi^j \neq \pi^j_*$$

Independent learning

- Naive approach: Apply the single agent Q-learning directly
- Each agent would update its Q-values using the Bellman update:

$$Q^j(s, a^j) \leftarrow Q^j(s, a^j) + \alpha\left(r^j + \gamma \max_{a'^j} Q^j(s', a'^j) - Q^j(s, a^j)\right)$$

- Each agent assumes that the other agent(s) are part of the environment

- Merit: Simple approach, easy to apply
- Demerit: Might not work well against opponents playing complex strategies
- Demerit: Non-stationary transition and reward models
- Demerit: No convergence guarantees

Cooperative Stochastic Games

- (Simultaneously moving) Stochastic Game (N-agent MDP)
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  - N: Number of agents
  - S: Shared state space $s \in S$
  - A^j: Action space of agent j

$$\langle a^1, a^2, \ldots, a^N \rangle \in A^1 \times A^2 \times \ldots \times A^N$$

  - R^j: Reward function for agent j - $R(s, a^1, \ldots, a^N) = Pr(r \mid s, a^1, \ldots, a^N), \forall j$
  - T: Transition function - $Pr(s' \mid s, a^1, \ldots, a^N)$
  - γ: Discount factor: $0 \leq \gamma \leq 1$
    - Discounted: $\gamma < 1$ Undiscounted: $\gamma = 1$
  - Horizon (i.e., # of time steps): h
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  - Policy (strategy) for agent i - $\pi^i : S \rightarrow \Omega(A^i)$
- Goal: Find optimal policy such that $\boldsymbol{\pi}^* = \{\pi_1^*, \ldots, \pi_N^*\}$, where

$$\pi_i^* = \arg\max_{\pi^i} \sum_{t=0}^{h} \gamma^t \mathbb{E}_{\boldsymbol{\pi}}[r_t^i(s, \boldsymbol{a})], \text{ where } \boldsymbol{a} \triangleq \{a^1, \ldots, a^N\} \text{ and } \boldsymbol{\pi} \triangleq \{\pi^1, \ldots, \pi^N\}$$

Unknown Models

Optimal Policy

- The equilibrium in the case of cooperative stochastic games is the Pareto dominating (Nash) equilibrium
- Each stage game of this stochastic game faces a coordination game
- There exists a unique Pareto dominating (Nash) equilibrium in utilities

		Bob: Baseball	Bob: Soccer
Alice	Baseball	2,2	0,0
Alice	Soccer	0,0	1,1

Opponent Modelling

- Note that an agent's response requires knowledge of other agent's actions
- This is a simultaneously move game where each agent does not know what the other agents will do
- So each agent should maintain a belief over other agents actions at current state
- This process of maintaining and updating a belief over the next actions of other agents is called opponent modelling

- Types of Opponent Modelling:
  - Fictitious Play
  - Gradient Based Methods
  - Solving Unique Equilibrium (for each stage game)
  - Bayesian Approaches

Fictitious Play

- Each agent assumes that all opponents are playing a stationary mixed strategy
- Agents maintain a count of number of times another agent performs an action

$$n_t^i(s, a_j) \leftarrow 1 + n_{t-1}^i(s, a_j), \ \forall j, \forall i$$

- Agents update and sample from their belief about this strategy at each state according to

$$\mu_{j,t}^i(s) \sim \frac{n_t^i(s, a_j)}{\sum_{a_j'} n_t^i(s, a_j')}$$

- The term $\mu_{j,t}^i(s)$ is sampled from an empirical distribution of past actions of other agent (mixed strategy)
- Agents calculate best responses according to this belief

Learning in cooperative stochastic games

- Algorithm: Joint action learner (JAL) or Joint Q learning (JQL)
- Challenge: Respond to environment as well as opponent(s)
- Same as Q learning but agents also include the opponent action in Q-updates
- Each agent would update its Q-values using the Bellman update:

$$Q^j(s, a^j, a^{-j}) \leftarrow Q^j(s, a^j, a^{-j}) + \alpha\left(r^j + \gamma \max_{a'^j} Q^j(s', a'^j, a'^{-j}) - Q^j(s, a^j, a^{-j})\right)$$

- Need to balance exploration exploitation tradeoff
- Objective for agent: Find the optimal policy for best response
- Objective for system: Find the NE of the stochastic game (or Nash Q function for the game)

- Nash Q function: Agent's immediate reward and discounted future rewards when all agents follow the NE policy

$$Q_*^i(s, \boldsymbol{a}) = r^i(s, \boldsymbol{a}) + \gamma \sum_{s' \in S} P(s' \mid s, \boldsymbol{a}) v^i(s', \pi_*^1, \ldots, \pi_*^n)$$

Joint Q learning

JointQlearning(s, Q)

Repeat

Repeat for each agent i

Select and execute a^i

Observe s', r^i and $\boldsymbol{a}^{-i}$, where $\boldsymbol{a}^{-i} = \{a^1, \ldots, a^{i-1}, a^{i+1}, \ldots, a^N\}$

Update counts: $n(s, \boldsymbol{a}) \leftarrow n(s, \boldsymbol{a}) + 1$

Update counts: $n_t^i(s, a_j) \leftarrow 1 + n_{t-1}^i(s, a_j), \forall j$

Learning rate: $\alpha \leftarrow \dfrac{1}{n(s, \boldsymbol{a})}$

Update Q-value:

$$Q^i(s, a^i, \boldsymbol{a}^{-i}) \leftarrow Q^i(s, a^i, \boldsymbol{a}^{-i}) + \alpha\left(r^i + \gamma \max_{a'^i} Q^i(s', a'^i, \mu_1^i(s'), \ldots, \mu_N^i(s')) - Q^i(s, a^i, \boldsymbol{a}^{-i})\right)$$

$s \leftarrow s'$

Until convergence of Q^i

Convergence of joint Q learning

- If the games is finite (finite agents and finite number of strategies for each agent), then fictitious play will converge to true response of opponent(s) in the time limit in self-play
- Self-play: All agents learn using the same algorithm
- Joint Q-learning converges to Nash Q-values in a cooperative stochastic game if
  - Every state is visited infinitely often (due to exploration)
  - The learning rate α is decreased fast enough, but not too fast (sufficient conditions for α):

$$(1) \sum_n \alpha_n \to \infty \qquad (2) \sum_n (\alpha_n)^2 < \infty$$

- In cooperative stochastic games, the Nash Q-values are unique (guaranteed unique equilibrium point in utilities)

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Joint Q learning

JointQlearning(s, Q)

Repeat

Repeat for each agent i

Select and execute a^i

Observe s', r^i and $\boldsymbol{a}^{-i}$, where $\boldsymbol{a}^{-i} = \{a^1, \ldots, a^{i-1}, a^{i+1}, \ldots, a^N\}$

Update counts: $n(s, \boldsymbol{a}) \leftarrow n(s, \boldsymbol{a}) + 1$

Update counts: $n_t^i(s, a_j) \leftarrow 1 + n_{t-1}^i(s, a_j), \forall j$

Learning rate: $\alpha \leftarrow \dfrac{1}{n(s, \boldsymbol{a})}$

Update Q-value:

$$Q^i(s, a^i, \boldsymbol{a}^{-i}) \leftarrow Q^i(s, a^i, \boldsymbol{a}^{-i}) + \alpha\left(r^i + \gamma \max_{a'^i} Q^i(s', a'^i, \mu_1^i(s'), \ldots, \mu_N^i(s')) - Q^i(s, a^i, \boldsymbol{a}^{-i})\right)$$

$s \leftarrow s'$

Until convergence of Q^i

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Common exploration methods

- ϵ-greedy:
  - With probability ϵ, execute random action
  - Otherwise execute best action $a_i^* = \arg\max_{a^i} Q^i(s, a^i, \mu_1^i(s), \ldots, \mu_N^i(s))$

- Boltzmann exploration
  - Increasing temperature T increases stochasticity
  - $$Pr(a) = \frac{e^{\frac{Q^i(s, a^i, \mu_1^i(s), \ldots, \mu_N^i(s))}{T}}}{\sum_a e^{\frac{Q^i(s, a^i, \mu_1^i(s), \ldots, \mu_N^i(s))}{T}}}$$

Competitive Stochastic Games

- (Simultaneously moving) Stochastic Game (N-agent MDP)
  - Tuple $\langle N, S, A^1, A^2, R^1, R^2, T, \gamma \rangle$
  - N: Number of agents
  - S: Shared state space $s \in S$
  - A^j: Action space of agent j

    $$\langle a^1, a^2 \rangle \in A^1 \times A^2$$

  - R^j: Reward function for agent j - $R^j(s, a^1, a^2) = Pr(r_t^j | s_t, a_t^1, a_t^2), \forall j$
  - Condition on Reward function: $r_t^1 + r_t^2 = 0$, $\forall t$
  - T: Transition function - $Pr(s' | s, a^1, a^2)$
  - γ: Discount factor: $0 \leq \gamma \leq 1$
    - Discounted: $\gamma < 1$ Undiscounted: $\gamma = 1$
  - Horizon (i.e., # of time steps): h
    - Finite horizon: $h \in \mathbb{N}$ Infinite horizon: $h = \infty$
  - Policy (strategy) for agent i - $\pi^i : S \rightarrow \Omega(A^i)$
- Goal: Find optimal policy such that $\boldsymbol{\pi}^* = \{\pi_1^*, \ldots, \pi_N^*\}$, where

$$\pi_i^* = \arg\max_{\pi^i} \sum_{t=0}^{h} \gamma^t \mathbb{E}_{\boldsymbol{\pi}}[r_t^i(s, \boldsymbol{a})], \text{ where } \boldsymbol{a} \triangleq \{a^1, a^2\} \text{ and } \boldsymbol{\pi} \triangleq \{\pi^1, \pi^2\}$$

Unknown Models

Optimal Policy

- The equilibrium in the case of competitive stochastic games is the min-max Nash equilibrium
- Each stage game of this stochastic game faces a zero-sum game
- There exists a unique min-max (Nash) equilibrium in utilities
- Optimal min-max value function

$$V_*^j(s) = \max_{a^j} \min_{a^{-j}} [r^j(s, a^j, a^{-j}) + \gamma \sum_{s'} Pr(s' | s, a^j, a^{-j}) V_*^j(s')]$$

- For a competitive stochastic game there exists a unique min-max value function and hence a unique min-max Q-function

Learning in competitive stochastic games

- Algorithm: Minimax Q-Learning
- Q-values for each agent j are over joint actions: $Q^j(s, a^j, a^{-j})$
  - s = state
  - a^j = action
  - a^{-j} = opponent action
- Instead of playing the best $Q^j(s, a^j, a^{-j})$ play min-max Q

$$Q^j(s, a^j, a^{-j}) \leftarrow (1-\alpha)Q^j(s, a^j, a^{-j}) + \alpha(r^j + \gamma V^j(s'))$$

$$V^j(s') \leftarrow \max_{a^j} \min_{a^{-j}} Q^j(s', a^j, a^{-j})$$

Minimax Q learning

Minimax Qlearning($s, \boldsymbol{a}, Q^*$)

Repeat

Repeat for each agent

Select and execute action a^j

Observe s', a^{-j} and r

Update counts: $n(s, \boldsymbol{a}) \leftarrow n(s, \boldsymbol{a}) + 1$

Learning rate: $\alpha \leftarrow \frac{1}{n(s, \boldsymbol{a})}$

Update Q-value:

$$Q_*^j(s, a^j, a^{-j}) \leftarrow (1 - \alpha) Q_*^j(s, a^j, a^{-j}) + \alpha(r^j + \gamma \max_{a'^j} \min_{a'^{-j}} Q_*^j(s', a'^j, a'^{-j})))$$

$s \leftarrow s'$

Until convergence of Q^*

Return Q^*

Opponent Modelling

- In a competitive game rational agents always take a min-max action
- There is no requirement for a separate opponent modelling strategy in self-play
- However:
  - Other agents could use different algorithms
  - Computing the min-max action can be time consuming
- Alternative: Fictitious play
  - Theorem: Fictitious play also converges in competitive zero-sum games
  - Theorem: Fictitious play converges to the min-max action in self-play

Convergence of Minimax Q learning

- Convergence in self-play
- Minimax Q-learning converges to min-max equilibrium in a competitive stochastic game if:
  - Every state is visited infinitely often (due to exploration)
  - The learning rate α is decreased fast enough, but not too fast (sufficient conditions for α):

$$(1)\ \sum_n \alpha_n \rightarrow \infty \qquad (2)\ \sum_n (\alpha_n)^2 < \infty$$

- In a competitive stochastic games, the Nash Q-values are unique (guaranteed unique min-max equilibrium point in utilities)

Exploration vs Exploitation Tradeoff

- Same as Q-learning and Joint Q learning
- ϵ-greedy
  - Play random action with probability ϵ
  - Play min-max action with probability $1 - \epsilon$

    (or)
  - Play max action based on fictitious belief

(Mixed) Stochastic Games/ General-sum Stochastic Game

- (Simultaneously moving) Stochastic Game (N-agent MDP)
  - Tuple $\langle N, S, A^1, \ldots, A^N, R^1, \ldots, R^N, T, \gamma \rangle$
  - N: Number of agents
  - S: Shared state space $s \in S$
  - A^j: Action space of agent j

    $$\langle a^1, a^2, \ldots, a^N \rangle \in A^1 \times A^2 \times \ldots \times A^N$$

  - R^j: Reward function for agent j - $R^j(s, a^1, \ldots, a^N) = Pr(r^j | s, a^1, \ldots, a^N)$
  - Rewards of all agents can be related arbitrarily
  - T: Transition function - $Pr(s' | s, a^1, \ldots, a^N)$
  - γ: Discount factor: $0 \le \gamma \le 1$
    - Discounted: $\gamma < 1$ Undiscounted: $\gamma = 1$
  - Horizon (i.e., # of time steps): h
    - Finite horizon: $h \in \mathbb{N}$ Infinite horizon: $h = \infty$
  - Policy (strategy) for agent i - $\pi^i : S \rightarrow \Omega(A^i)$
- Goal: Find optimal policy such that $\boldsymbol{\pi}^* = \{\pi_1^*, \ldots, \pi_N^*\}$, where

$$\pi_i^* = \arg\max_{\pi^i} \sum_{t=0}^{h} \gamma^t \mathbb{E}_{\boldsymbol{\pi}}[r_t^i(s, \boldsymbol{a})], \text{ where } \boldsymbol{a} \triangleq \{a^1, \ldots, a^N\} \text{ and } \boldsymbol{\pi} \triangleq \{\pi^1, \ldots, \pi^N\}$$

Unknown Models

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Optimal Policy

- The equilibrium in the case of competitive stochastic games is the (mixed strategy) Nash equilibrium for the stochastic game
- Nash theorem guarantees at-least one mixed strategy NE exists
- There could be multiple Nash equilibria
- Objective for agent: Find the optimal policy for best response
- Objective for system: Find the NE of the stochastic game (or Nash Q function for the game)
- Nash Q function: Agent's immediate reward and discounted future rewards when all agents follow the NE policy

$$Q_*^i(s, \boldsymbol{a}) = r^i(s, \boldsymbol{a}) + \gamma \sum_{s' \in \mathcal{S}} P(s' \mid s, \boldsymbol{a}) v^i(s', \pi_*^1, \ldots, \pi_*^n)$$

- Problem: Which NE should we converge to?

Learning in General-sum stochastic games

- Algorithm: Nash Q-learning
- Assumption: Self-play
- Every agent maintains the Q values of all other agents
- At each state, every agent face a stage (normal form) game
- Utilities of the normal form game are the Q values for each action for each agent
- Need to calculate NE of the normal form game $\pi^1(s')\cdots\pi^n(s')$
- Each agent would update its Q-values using the Bellman update:

$$Q^j(s, a^j, a^{-j}) \leftarrow (1-\alpha)Q^j(s, a^j, a^{-j}) + \alpha\Big(r^j + \gamma NashQ^j(s')\Big)\Big)$$

where

$$NashQ^j(s') = \pi^1(s')\cdots\pi^n(s') \cdot Q^j(s')$$

- Here, $\pi^j(s')$ is a vector containing distribution of probability of each action (mixed strategy)
- Here, $Q^j(s')$ is a vector containing Q values for all actions of the agent j

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Nash Q learning

NashQ learning($s, \boldsymbol{a}, Q*$)

Repeat

Repeat for each agent

Select and execute action a^j

Observe s', a^{-j} and $\boldsymbol{r} \triangleq r^1, \ldots, r^N$

Update counts: $n(s, \boldsymbol{a}) \leftarrow n(s, \boldsymbol{a}) + 1$

Learning rate: $\alpha \leftarrow \dfrac{1}{n(s, \boldsymbol{a})}$

Update Q-value for every $j = 1, \ldots, n$:

$$Q_*^j(s, \boldsymbol{a}) \leftarrow (1 - \alpha) Q_*^j(s, \boldsymbol{a}) + \alpha(r^j + \gamma NashQ_*^j(s'))$$

$s \leftarrow s'$

Until convergence of $Q*$

Return $Q*$

Opponent Modelling

- Note: Each agent is maintaining Q-values of all agents
- Solution 1: Agents can take equilibrium action if unique
  - Problem: Non-unique equilibria in practice
  - Problem: Equilibrium computation can take a long time
  - Problem: Convergence only under strong assumptions (unique equilibrium)
- Solution 2: Fictitious play
  - Problem:Convergence only under strong assumptions (unique equilibrium)
- Solution 3: Assume every agent is playing independent learning
  - Problem: No convergence guarantees

Convergence of Nash Q-learning

- Convergence in self-play (under strong assumptions)
- Nash Q-learning converges to the NE in a general sum stochastic game if
  - Every state is visited infinitely often (due to exploration)
  - The learning rate α is decreased fast enough, but not too fast (sufficient conditions for α):

$$(1) \sum_n \alpha_n \rightarrow \infty \qquad (2) \sum_n (\alpha_n)^2 < \infty$$

  - The NE can be considered as a global optimum or a saddle point in each stage game of the stochastic game
    - (Important qualification) Can only be one of global optimum or saddle point (cannot alternate)
    - Extremely rare to hold in practice
    - Convergence observed even when the condition is violated
    - Guarantees unique convergence point in utilities and hence unique Nash Q function

Exploration vs Exploitation Tradeoff

- In practice, same as JAL, Minimax Q-learning and Q-learning
- ϵ-greedy
  - Play random action with probability ϵ
  - Play max action based on fictitious belief with probability $1 - \epsilon$

    (Or)
  - Play equilibrium action with probability $1 - \epsilon$

Alternative approaches

- A NE is not always the best solution
- NE is attractive because it is unrestrictive (all agents can be independent) and Nash theorem guarantees existence
- Can consider other equilibria as well:
  - Pareto-optimality
  - Regret
  - Correlated equilibrium
  - Dominant strategy equilibrium

- Function approximation techniques
- Model-based techniques

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Summary

- Multi-agent Reinforcement Learning (MARL)
- Stochastic Games
- Opponent Modelling
  - Fictitious Play
  - Solving (Unique) Equilibrium
- Cooperative Stochastic Games
  - Joint Q learning
  - Convergence properties
- Competitive Stochastic Games (Zero-sum games)
  - Min-max Q learning
  - Convergence properties
- Mixed Cooperative-Competitive Stochastic Games (General-sum games)
  - Nash Q learning
  - Convergence properties