Multiagent Learning

Foundations and Recent Trends

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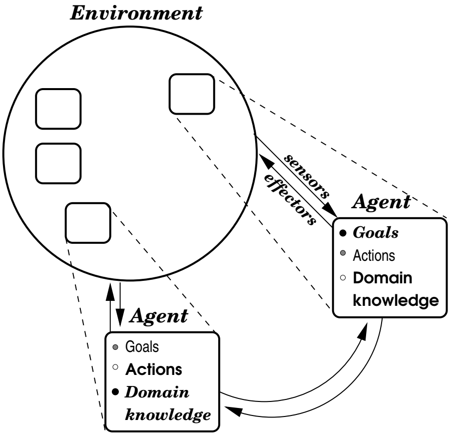
Tutorial at IJCAI 2017 conference:
http://www.cs.utexas.edu/~larg/ijcai17_tutorial

Overview

Multiagent Systems

- Multiple agents interact in common environment
- Each agent with own sensors, effectors, goals, ...
- Agents have to coordinate actions to achieve goals

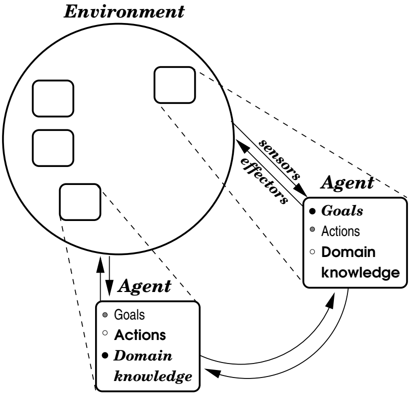


Environment defined by:

- state space
- available actions
- effects of actions on states
- what agents can observe

Agents defined by:

- domain knowledge
- goal specification
- policies for selecting actions



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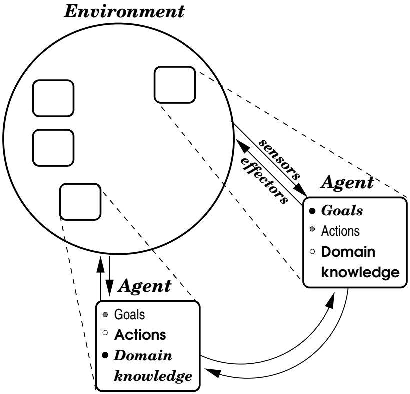
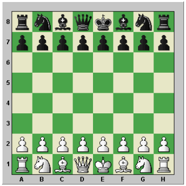


Many problems can be modelled as multiagent systems!

Chess

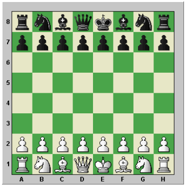


Poker

Starcraft

Multiagent Systems – Applications

Chess



Poker

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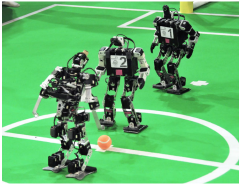
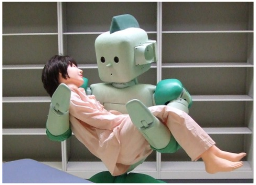
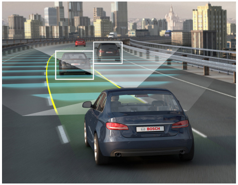
Robot soccer



Home assistance



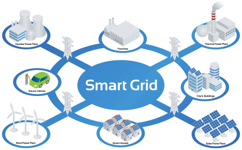
Autonomous cars



Negotiation

Wireless networks

Smart grid



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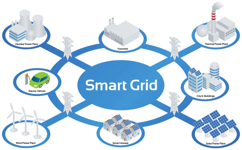
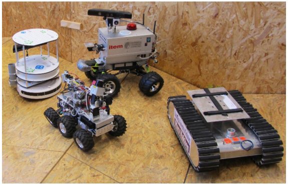


User interfaces

Multi-robot rescue



Multiagent learning

- Learning is process of improving performance via experience
- Can agents learn to coordinate actions with other agents?
- What to learn?

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  $\Rightarrow$ How to select own actions

  $\Rightarrow$ How other agents select actions

  $\Rightarrow$ Other agents' goals, plans, beliefs, ...

Why learning?

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- Other agents may learn too
  $\Rightarrow$ Have to adapt continually!
  "*Moving target problem*" central issue in multiagent learning

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Multiagent learning studied in different communities

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  $\Rightarrow$ Very large + growing body of work!

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- Many algorithms proposed to address different assumptions (constraints), learning goals, performance criteria, ...

Tutorial

This tutorial:

- Introduction to basics of multiagent learning:
    - Interaction models & assumptions
    - Learning goals
    - Selection of learning algorithms
- Plus some recent trends

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Further reading:

- AIJ Special Issue *"Foundations of Multi-Agent Learning"*
  Rakesh Vohra, Michael Wellman (eds.), 2007
- Surveys: Tuyls and Weiss (2012); Busoniu et al. (2008); Panait and Luke (2005); Shoham et al. (2003); Alonso et al. (2001); Stone and Veloso (2000); Sen and Weiss (1999)
- Our own upcoming survey on agents modelling other agents!

Overview

- Introduction
- Multiagent Models & Assumptions
- Learning Goals
- Learning Algorithms
- Recent Trends

Overview

Multiagent Models & Assumptions

Standard multiagent models:

- Normal-form game
- Repeated game
- Stochastic game

Assumptions and other models

Normal-Form Game

Normal-form game consists of:

- Finite set of agents $N = \{1, ..., n\}$
- For each agent $i \in N$:
  - Finite set of actions A_i
  - Utility function $u_i : A \to \mathbb{R}$, where $A = A_1 \times ... \times A_n$

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Each agent i selects policy $\pi_i : A_i \rightarrow [0, 1]$, takes action $a_i \in A_i$ with probability $\pi_i(a_i)$, and receives utility $u_i(a_1, ..., a_n)$

Given policy profile $(\pi_1, ..., \pi_n)$, expected utility to i is

$$U_i(\pi_1, ..., \pi_n) = \sum_{a \in A} \pi_1(a_1) * ... * \pi_n(a_n) * u_i(a)$$

$\Rightarrow$ Agents want to maximise their expected utilities

Normal-Form Game: Prisoner's Dilemma

Example: Prisoner's Dilemma

- Two prisoners questioned in isolated cells
- Each prisoner can Cooperate or Defect
- Utilities (row = agent 1, column = agent 2):

	C	D
C	-1,-1	-5,0
D	0,-5	-3,-3

Example: Chicken

- Two opposite drivers on same lane
- Each driver can **Stay** on lane or **Leave** lane
- Utilities:

	S	L
S	0,0	7,2
L	2,7	6,6

Normal-Form Game: Rock-Paper-Scissors

Example: Rock-Paper-Scissors

- Two players, three actions
- **Rock** beats **Scissors** beats **Paper** beats **Rock**
- Utilities:

	R	P	S
R	0,0	-1,1	1,-1
P	1,-1	0,0	-1,1
S	-1,1	1,-1	0,0

Repeated Game

Learning requires experience

- Normal-form game is single interaction

  $\Rightarrow$ No experience!

- Experience comes from repeated interactions

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Repeated game:

- Repeat same normal-form game: at each time t, each agent i chooses action a_i^t and gets utility $u_i(a_1^t, ..., a_n^t)$
- Policy $\pi_i : \mathbb{H} \times A_i \to [0,1]$ assigns action probabilities based on history of interaction

$$\mathbb{H} = \cup_{t \in \mathbb{N}^0} \mathbb{H}^t, \quad \mathbb{H}^t = \left\{ H^t = (a^0, a^1, ..., a^{t-1}) \mid a^\tau \in A \right\}$$

Repeated Game

What is expected utility to i for policy profile $(\pi_1, \ldots, \pi_n)$?

- Repeating game $t \in \mathbb{N}$ times:

$$U_i(\pi_1, \ldots, \pi_n) \;=\; \sum_{H^t \in \mathbb{H}^t} P(H^t | \pi_1, \ldots, \pi_n) \sum_{\tau=0}^{t-1} u_i(a^\tau)$$

$$P(H^t | \pi_1, \ldots, \pi_n) \;=\; \prod_{\tau=0}^{t-1} \prod_{j \in N} \pi_j(H^\tau, a_j^\tau)$$

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$$U_i(\pi_1, ..., \pi_n) = \lim_{t \to \infty} \sum_{H^t} P(H^t | \pi_1, ..., \pi_n) \sum_{\tau} \gamma^\tau u_i(a^\tau)$$

Discount factor $0 \leq \gamma < 1$ makes expectation finite

Interpretation: low γ is "myopic", high γ is "farsighted"
(Or: probability that game will end at each time is $1 - \gamma$)

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  Can also define expected utility as limit average

Repeated Game: Prisoner's Dilemma

Example: Repeated Prisoner's Dilemma

	C	D
C	-1,-1	-5,0
D	0,-5	-3,-3

Example policies:

- At time t, choose C with probability $(t+1)^{-1}$
- Grim: chose C until opponent's first D, then choose D forever
- Tit-for-Tat: begin C, then repeat opponent's last action

Example: Repeated Rock-Paper-Scissors

	R	P	S
R	0,0	-1,1	1,-1
P	1,-1	0,0	-1,1
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Example policy:

- Compute empirical frequency of opponent actions over past 5 moves

$$P(a_j) = \frac{1}{5} \sum_{\tau=t-5}^{t-1} [a_j^\tau = a_j]_1$$

and take best-response action $\max_{a_i} \sum_{a_j} P(a_j)\, u_i(a_i, a_j)$

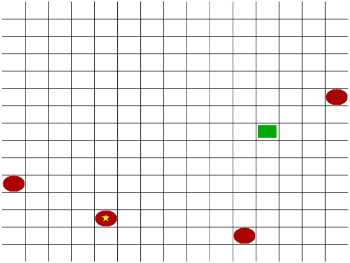
Stochastic Game

Agents interact in common environment

- Environment has states, actions have effect on state
- Agents choose actions based on state-action history

Example: Pursuit (e.g. Barrett et al., 2011)

- Predator agents must capture prey
- State: agent positions
- Actions: move to neighbouring cell



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Generalises **Markov decision process (MDP)** to multiple agents

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Game starts in initial state $s^0 \in S$

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  - receives utility $u_i(a_1^t, ..., a_n^t)$
- Game transitions into next state $s^{t+1} \in S$ with probability $T(s^t, a^t, s^{t+1})$

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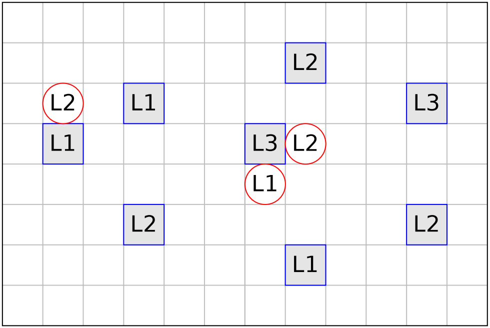
Process repeated finite or infinite number of times, or until terminal state is reached (e.g. prey captured).

Stochastic Game: Level-Based Foraging

Example: Level-Based Foraging (Albrecht and Ramamoorthy, 2013)

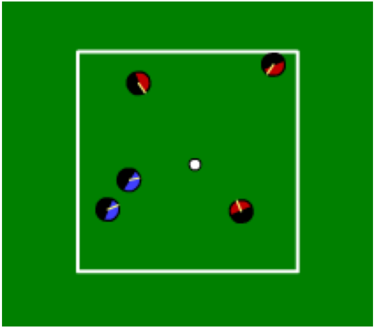
- Agents (circles) must collect all items (squares)
- State: agent positions, item positions, which items collected
- Actions: move to neighbouring cell, try to collect item



Stochastic Game: Soccer Keepaway

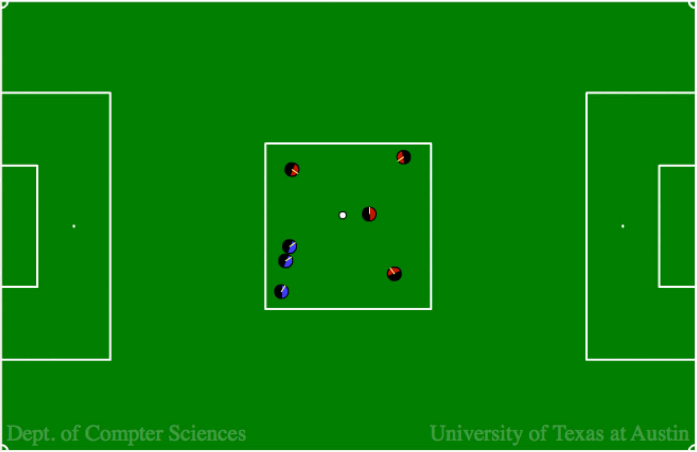
Example: Soccer Keepaway (Stone et al., 2005)

- "Keeper" agents must keep ball away from "Taker" agents
- State: player positions & orientations, ball position, ...
- Actions: go to ball, pass ball to player, ...



Stochastic Game: Soccer Keepaway

Video: 4 vs 3 Keepaway



Source: `http://www.cs.utexas.edu/~AustinVilla/sim/keepaway`

Assumptions

Models and algorithms make assumptions, e.g.

- What do agents know about the game?
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Many learning algorithms designed for repeated/stochastic game with full observability

- But assumptions may vary and other models exist!

Other Models

Other assumptions & models:

- Assumption: elements of game unknown
  - Bayesian game, stochastic Bayesian game

    AAAI'16 tutorial "Type-based Methods for Interaction in Multiagent Systems"

    `http://thinc.cs.uga.edu/tutorials/aaai-16.html`

- Assumption: partial observability of states and actions
  - Extensive-form game with imperfect information
  - Partially observable stochastic game (POSG)
  - Multiagent POMDPs: Dec-POMDP, I-POMDP, ...

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Learning Goals

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Many learning goals proposed:

- Minimax/Nash/correlated equilibrium
- Pareto-optimality
- Social welfare & fairness
- No-regret
- Targeted optimality & safety

… plus combinations & approximations

Maximin/Minimax

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Policy profile (π_i, π_j) is maximin/minimax profile if

$$U_i(\pi_i, \pi_j) = \max_{\pi_i'} \min_{\pi_j'} U_i(\pi_i', \pi_j') = \min_{\pi_j'} \max_{\pi_i'} U_i(\pi_i', \pi_j') = -U_j(\pi_i, \pi_j)$$

Utility that can be guaranteed against worst-case opponent

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Utility that can be guaranteed against worst-case opponent

- Every two-player zero-sum normal-form game has minimax profile (von Neumann and Morgenstern, 1944)
- Every finite or infinite+discounted zero-sum stochastic game has minimax profile (Shapley, 1953)

Nash Equilibrium

Policy profile $\pi = (\pi_1, ..., \pi_n)$ is Nash equilibrium (NE) if

$$\forall i \; \forall \pi_i' : U_i(\pi_i', \pi_{-i}) \leq U_i(\pi)$$

No agent can improve utility by unilaterally deviating from profile (every agent plays best-response to other agents)

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Every finite normal-form game has at least one NE (Nash, 1950) (also stochastic games, e.g. Fink (1964))

- Standard solution in game theory
- In two-player zero-sum game, minimax is same as NE

Nash Equilibrium – Example

Example: Prisoner's Dilemma

- Only NE in normal-form game is (D,D)
- Normal-form NE are also NE in infinite repeated game
- Infinite repeated game has many more NE ⇒ Folk theorem

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Example: Rock-Paper-Scissors

- Only NE in normal-form game is $\pi_i = \pi_j = (\frac{1}{3}, \frac{1}{3}, \frac{1}{3})$

	R	P	S
R	0,0	-1,1	1,-1
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Correlated Equilibrium

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$(\pi_1, ..., \pi_n)$ is correlated equilibrium (CE) (Aumann, 1974) if no agent can individually improve its expected utility by deviating from recommended actions

- NE is subset of CE $\rightarrow$ no correlation
- CE easier to compute than NE $\rightarrow$ linear program

Correlated Equilibrium – Example

Example: Chicken

Correlated equilibrium:

- $\xi(L, L) = \xi(S, L) = \xi(L, S) = \frac{1}{3}$
- $\xi(S, S) = 0$

Expected utility to both:

$7 * \frac{1}{3} + 2 * \frac{1}{3} + 6 * \frac{1}{3} = 5$

	S	L
S	0,0	7,2
L	2,7	6,6

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Nash equilibrium utilities:

- $\pi_i(S) = 1,\ \pi_j(S) = 0 \ \rightarrow \ (7,2)$
- $\pi_i(S) = 0,\ \pi_j(S) = 1 \ \rightarrow \ (2,7)$
- $\pi_i(S) = \frac{1}{3},\ \pi_j(S) = \frac{1}{3} \ \rightarrow \ \approx 4.66$

The Equilibrium Legacy

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   NE does not specify behaviours for off-equilibrium paths

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1. Non-uniqueness
   Often multiple NE exist, how should agents choose same one?
2. Incompleteness
   NE does not specify behaviours for off-equilibrium paths
3. Sup-optimality
   NE not generally same as utility maximisation

The Equilibrium Legacy

The “Equilibrium Legacy” in multiagent learning:

- Quickly adopted equilibrium as standard goal of learning
- But equilibrium (e.g. NE) has many limitations…

1. Non-uniqueness
   Often multiple NE exist, how should agents choose same one?
2. Incompleteness
   NE does not specify behaviours for off-equilibrium paths
3. Sup-optimality
   NE not generally same as utility maximisation
4. Rationality
   NE assumes all agents are rational (= perfect utility maximisers)

Pareto Optimum

Policy profile $\pi = (\pi_1, ..., \pi_n)$ is Pareto-optimal if there is no other profile π' such that

$$\forall i : U_i(\pi') \geq U_i(\pi) \quad \textbf{and} \quad \exists_i : U_i(\pi') > U_i(\pi)$$

Can't improve one agent without making other agent worse off

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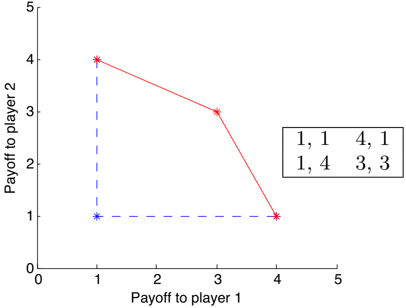

Pareto-front is set of all Pareto-optimal utilities (red line)

Social Welfare & Fairness

Pareto-optimality says nothing about social welfare and fairness

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$$Welfare(\pi) = \sum_i U_i(\pi) \qquad Fairness(\pi) = \prod_i U_i(\pi)$$

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π welfare/fairness-optimal if maximum $Welfare(\pi)$/$Fairness(\pi)$

Any welfare/fairness-optimal π is also Pareto-optimal! (Why?)

No-Regret

Given history $H^t = (a^0, a^1, ..., a^{t-1})$, agent i's regret for not having taken action a_i is

$$R_i(a_i | H^t) = \sum_{\tau=0}^{t-1} u_i(a_i, a_{-i}^\tau) - u_i(a_i^\tau, a_{-i}^\tau)$$

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Policy π_i achieves no-regret if

$$\forall a_i : \lim_{t\to\infty} \frac{1}{t} R_i(a_i|H^t) \leq 0$$

(Other variants exist)

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- Thus, minimising regret not generally same as maximising utility (e.g. Crandall, 2014)

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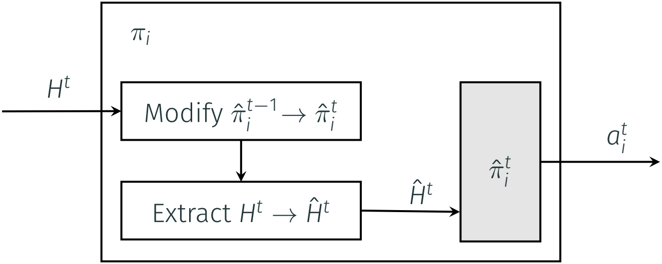
Policy classes: non-learning, memory-bounded, finite automata, ...

How does learning take place in policy π_i?

The internal view:

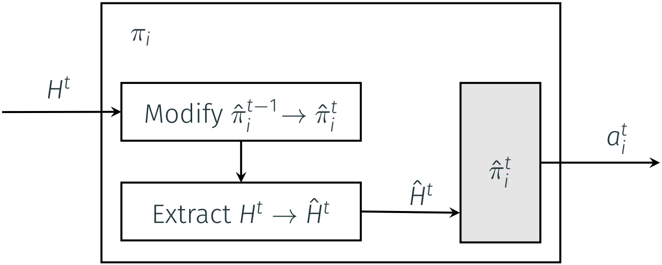
- π_i continually modifies internal policy $\hat{\pi}_i^t$ based on H^t
- $\hat{\pi}_i^t$ has own representation and input format $\hat{H}^t$



Learning Algorithms – The Internal View

Internal policy $\hat{\pi}_i^t$:

- **Representation:** Q-learning, MCTS planner, neural network, ...
- **Parameters:** Q-table, opponent model, connection weights, ...
- **Input format:** most recent state/action, abstract feature vector, ...



Fictitious Play

Simple example: Fictitious Play (FP) (Brown, 1951)

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Self-play: all agents use fictitious play

- If policies converge, policy profile is Nash equilibrium

Learning Algorithms

Many multiagent learning algorithms exist, e.g.

- Minimax-Q (Littman, 1994)
- JAL (Claus and Boutilier, 1998)
- Regret Matching (Hart and Mas-Colell, 2001, 2000)
- FFQ (Littman, 2001)
- WoLF-PHC (Bowling and Veloso, 2002)
- Nash-Q (Hu and Wellman, 2003)
- CE-Q (Greenwald and Hall, 2003)
- OAL (Wang and Sandholm, 2003)
- ReDVaLeR (Banerjee and Peng, 2004)
- GIGA-WoLF (Bowling, 2005)
- CJAL (Banerjee and Sen, 2007)
- AWESOME (Conitzer and Sandholm, 2007)
- CMLeS (Chakraborty and Stone, 2014)
- HBA (Albrecht, Crandall, and Ramamoorthy, 2016)

(Conditional) Joint Action Learning

Joint Action Learning (JAL) (Claus and Boutilier, 1998) and
Conditional Joint Action Learning (CJAL) (Banerjee and Sen, 2007)
learn Q-values for joint actions $a \in A$:

$$Q^{t+1}(a^t) = (1-\alpha)Q^t(a^t) + \alpha\, u_i^t$$

- u_i^t is utility received after joint action a^t
- $\alpha \in [0, 1]$ is *learning rate*

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Use opponent model to compute expected utilities of actions:

$$\text{JAL:} \quad E(a_i) = \sum_{a_j} P(a_j) \, Q^{t+1}(a_i, a_j)$$

$$\text{CJAL:} \quad E(a_i) = \sum_{a_j} P(a_j | a_i) \, Q^{t+1}(a_i, a_j)$$

(Conditional) Joint Action Learning

Opponent models estimated from history H^t:

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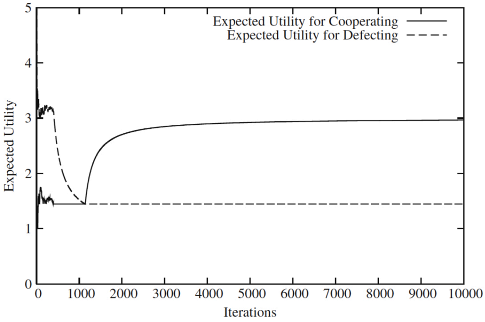
Given expected utilities $E(a_i)$, use some action exploration scheme:

- E.g. ϵ-greedy: choose $\arg\max_{a_i} E(a_i)$ with probability $1 - \epsilon$, else choose random action

(Conditional) Joint Action Learning

JAL and CJAL can converge to Nash equilibrium in self-play

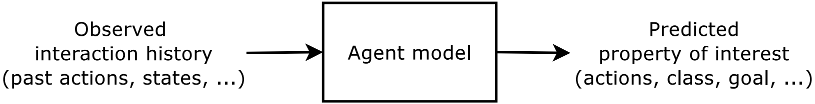
CJAL in variant of Prisoner's Dilemma (from Banerjee and Sen, 2007):



Converging to Pareto-optimal NE (C,C)

FP, JAL, CJAL are simple examples of opponent modelling:

- Use model of other agent to predict its actions, goals, beliefs, ...



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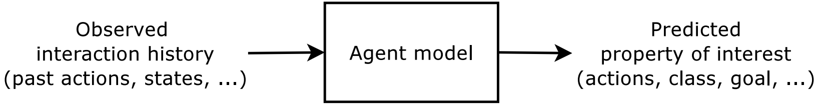

Many forms of opponent modelling exist:

- Policy reconstruction
- Type-based methods
- Classification
- Plan recognition
- Recursive reasoning
- Graphical methods
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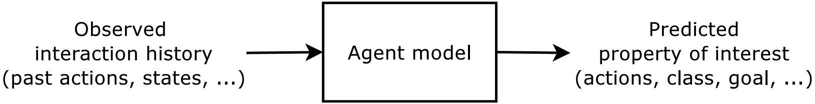

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Upcoming survey by S. Albrecht & P. Stone!

Minimax/Nash/Correlated Q-Learning

Minimax Q-Learning (Minimax-Q) (Littman, 1994) and
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learn joint-action Q-values for each agent $j \in N$:

$$Q_j^{t+1}(s^t, a^t) = (1 - \alpha) Q_j^t(s^t, a^t) + \alpha \left[u_j^t + \gamma E Q_j(s^{t+1}) \right]$$

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- Assumes utilities u_j^t are commonly observed
- $EQ(s^{t+1})$ is expected utility to agent j under equilibrium profile for normal-form game with utility functions $u_j(a) = Q_j^t(s^{t+1}, a)$

  $\Rightarrow$ **Minimax-Q:** use minimax profile (assumes zero-sum game)

  $\Rightarrow$ **Nash-Q:** use Nash equilibrium

  $\Rightarrow$ **CE-Q:** use correlated equilibrium

Minimax/Nash/Correlated Q-Learning

Minimax-Q, Nash-Q, CE-Q can converge to equilibrium in self-play

- E.g. Nash-Q formal proof of convergence to NE
- But based on strong restrictions on Q_j^t!

Assumption 3 *One of the following conditions holds during learning.*[3]

Condition A. *Every stage game* $(Q_t^1(s),\ldots,Q_t^n(s))$*, for all* t *and* s*, has a global optimal point, and agents' payoffs in this equilibrium are used to update their Q-functions.*

Condition B. *Every stage game* $(Q_t^1(s),\ldots,Q_t^n(s))$*, for all* t *and* s*, has a saddle point, and agents' payoffs in this equilibrium are used to update their Q-functions.*

(Hu and Wellman, 2003)

Model-Free Learning

JAL, CJAL, Nash-Q, … learn models of other agents

- Model-based learning

Model-Free Learning

JAL, CJAL, Nash-Q, ... learn models of other agents

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Can also learn without modelling other agents

- Model-free learning
- e.g. WoLF-PHC, Regret Matching

Win or Learn Fast Policy Hill Climbing

Win or Learn Fast Policy Hill Climbing (WoLF-PHC) (Bowling and Veloso, 2002) uses policy hill climbing in policy space:

$$\hat{\pi}_i^{t+1}(s^t, a_i^t) = \hat{\pi}_i^t(s^t, a_i^t) + \begin{cases} \delta & \text{if } a_i^t = \arg\max_{a_i'} Q(s^t, a_i') \\ -\frac{\delta}{|A_i|-1} & \text{else} \end{cases}$$

- Q is standard Q-learning

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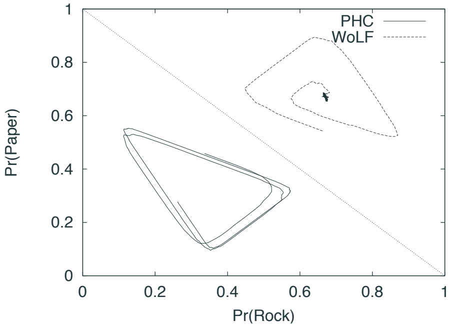
Variable learning rate δ:

$$\delta = \begin{cases} \delta_w & \text{if } \sum_{a_i} \hat{\pi}_i^t(s^t, a_i)\, Q(s^t, a_i) > \sum_{a_i} \bar{\pi}_i(s^t, a_i)\, Q(s^t, a_i) \\ \delta_l & \text{else} \end{cases}$$

- adapt slowly when "winning", fast when "losing" ($\delta_w < \delta_l$)
- $\bar{\pi}_i$ is average policy over past policies $\hat{\pi}_i$

Win or Learn Fast Policy Hill Climbing

WoLF gradient ascent in self-play converges to Nash equilibrium in two-player, two-action repeated game (Bowling and Veloso, 2002)



(b) Rock-Paper-Scissors Game

Targeted optimality: if opponent policy converges, WoLF-PHC converges to best-response against opponent

Regret Matching

Regret Matching (RegMat) (Hart and Mas-Colell, 2000) computes conditional regret for not choosing a_i' whenever a_i was chosen:

$$R(a_i, a_i') = \frac{1}{t+1} \sum_{\tau : a_i^\tau = a_i} u_i(a_i', a_j^\tau) - u_i(a^\tau)$$

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Used to modify policy:

$$\hat{\pi}_i^{t+1}(a_i) = \begin{cases} \frac{1}{\mu} \max[R(a_i^\tau, a_i), 0] & a_i \neq a_i^t \\ 1 - \sum_{a'_i \neq a_i^\tau} \hat{\pi}_i^{t+1}(a'_i) & a_i = a_i^t \end{cases}$$

- $\mu > 0$ is "inertia" parameter

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RegMat converges to correlated equilibrium in self-play

Assumes actions commonly observed and utility functions known

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(plus modified policy normalisation)

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(plus modified policy normalisation)

- Also converges to correlated equilibrium in self-play!

Bonus question: How do algorithms perform in mixed groups?

Empirical study by Albrecht and Ramamoorthy (2012):

- Tested 5 algorithms in mixed groups:
  JAL, CJAL, Nash-Q, WoLF-PHC, Modified RegMat

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- Also tested in 500 random strictly ordinal $2 \times 2 \times 2$ (3 agents) repeated games

Test criteria:

- Convergence rate
- Final expected utilities
- Social welfare/fairness
- Solution rates:
  - Nash equilibrium (NE)
  - Pareto-optimality (PO)
  - Welfare-optimality (WO)
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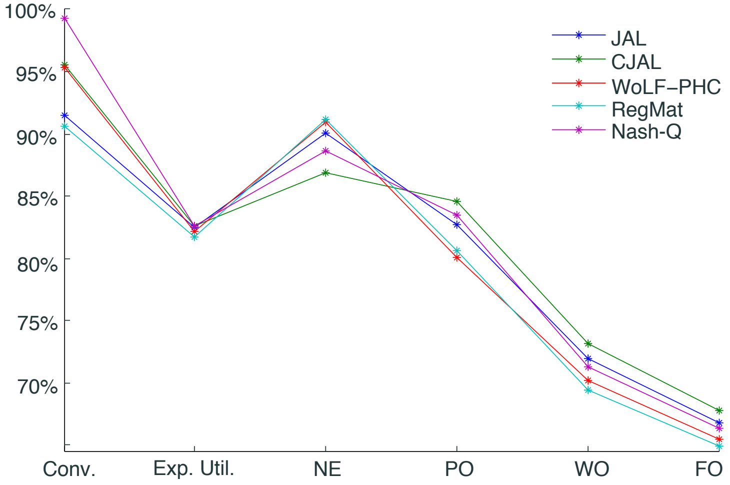
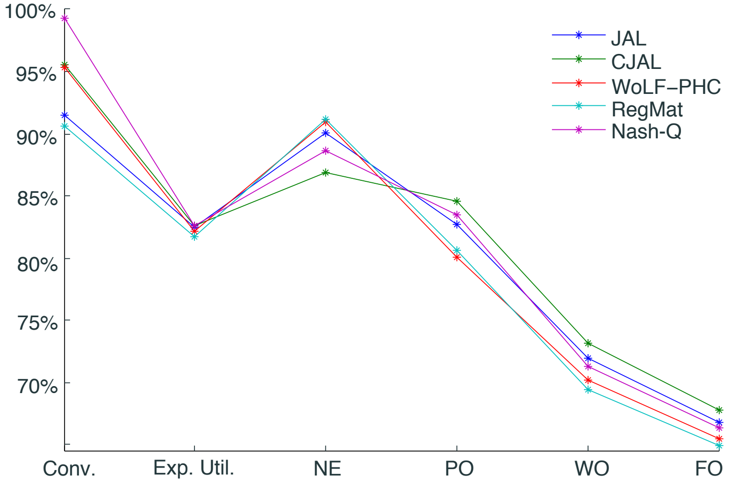
Which algorithm is best?



100% is maximum possible utility/rate

Difficulty: NE < PO < WO < FO

Learning in Mixed Groups



Answer:

No clear winner!

Overview

Introduction

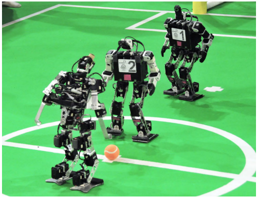
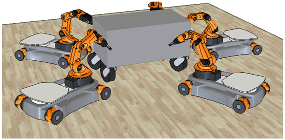
Multiagent Models & Assumptions

Learning Goals

Learning Algorithms

Recent Trends

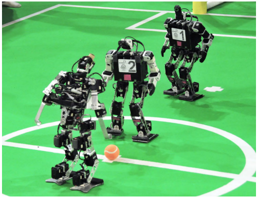
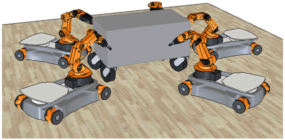
Teamwork

Typical approach:

- Whole team designed and trained by single organisation
- Agents share coordination protocols, communication languages, domain knowledge, algorithms, ...

Teamwork

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  $\Rightarrow$ Pre-coordination!

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Challenge: Ad Hoc Teamwork (Stone et al., 2010)

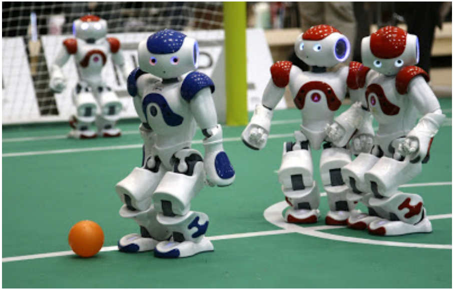
"Create an autonomous agent that is able to efficiently and robustly collaborate with previously unknown teammates on tasks to which they are all individually capable of contributing as team members."

RoboCup Drop-In Competition

RoboCup SPL Drop-In Competition '13, '14, '15 (Genter et al., 2017)

- Mixed players from different teams
- No prior coordination between players

Video: Drop-In Competition



Many learning algorithms not suitable for ad hoc teamwork:

Learning in Ad Hoc Teamwork

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- RL-based algorithms (JAL, CJAL, Nash-Q, ...) need 1000's of iterations in simple games

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- Many algorithms designed for self-play (all agents use same algorithm)

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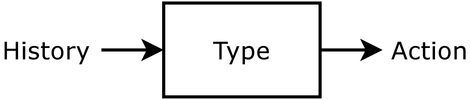
Need method which can learn quickly to interact effectively with unknown other agents!

Type-Based Method

Hypothesise possible types of other agents:

- Each type θ_j is blackbox behaviour specification:



$P(a_j | H^t, \theta_j)$

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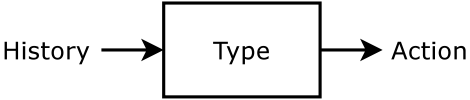


$P(a_j | H^t, \theta_j)$

- Generate types from e.g.
  - experience from past interactions
  - domain and task knowledge
  - learn new types online (opponent modelling)

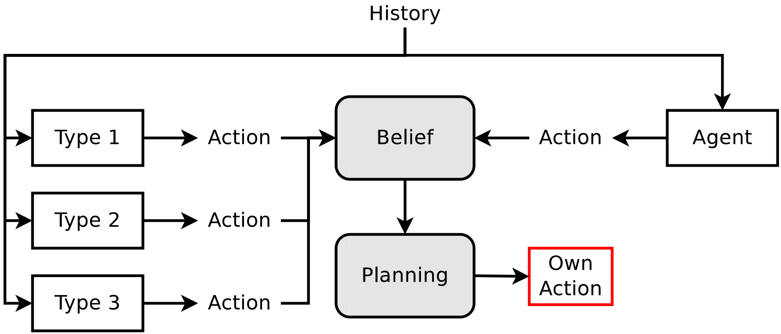
Type-Based Method

During the interaction:

- Compute belief over types based on interaction history H^t:

$$P(\theta_j|H^t) \propto P(H^t|\theta_j)\, P(\theta_j)$$

- Plan own action based on beliefs



Harsanyi-Bellman Ad Hoc Coordination (HBA) (Albrecht et al., 2016)

$$\pi_i(H^t, a_i) \sim \arg\max_{a_i} E_{s^t}^{a_i}(H^t)$$

$$E_s^{a_i}(\hat{H}) = \sum_{\theta_j} P(\theta_j|\hat{H}) \sum_{a_j} P(a_j|\hat{H}, \theta_j)\, Q_s^{(a_i,a_j)}(\hat{H})$$

$$Q_s^a(\hat{H}) = \sum_{s'} T(s, a, s') \left[u_i(s, a) + \gamma \max_{a_i} E_{s'}^{a_i} \left(\langle \hat{H}, a, s' \rangle \right) \right]$$

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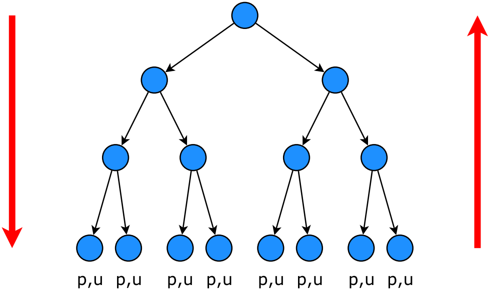
Optimal planning with built-in exploration: Value of Information

Type-Based Method – Planning

Can compute $E_s^{a_i}$ with finite tree-expansion:

- Unfold tree of future trajectories with fixed depth
- Associate each trajectory with **p**robability and **u**tility
- Calculate expected utility of action by traversing to root



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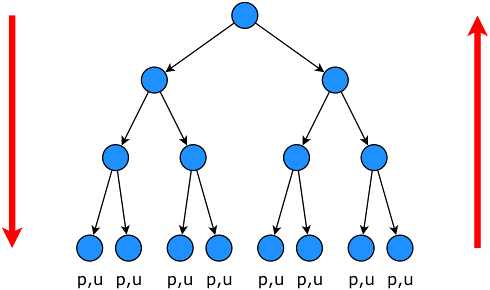
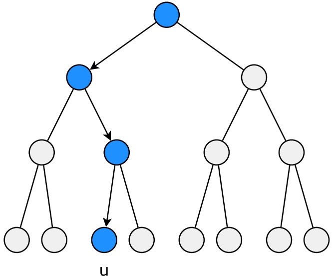


Inefficient: exponential in states, actions, agents

Use Monte-Carlo Tree Search (MCTS) for efficient approximation:

Repeat x times:

1. Sample type $\theta_j \in \Theta_j$ with probabilities $P(\theta_j | H^t)$
2. Sample interaction trajectory using θ_j and domain model T
3. Update utility estimates via backprop on trajectory



E.g. Albrecht and Stone (2017), Barrett et al. (2011)

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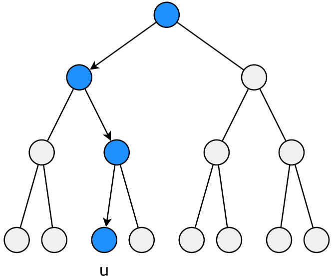


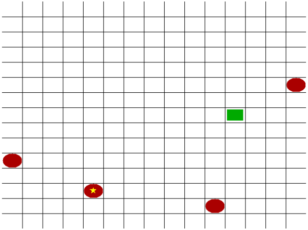
E.g. Albrecht and Stone (2017), Barrett et al. (2011)

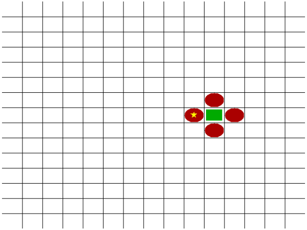
But: loses value of information! (no belief change during planning)

Ad Hoc Teamwork: Predator Pursuit

4 predators must capture 1 prey in grid world (Barrett et al., 2011)

- We control one agent in predator team
- Policies of other predators unknown (prey moves randomly)
- 4 types provided to our agent; online planning using MCTS





Video: 4 types, true type inside

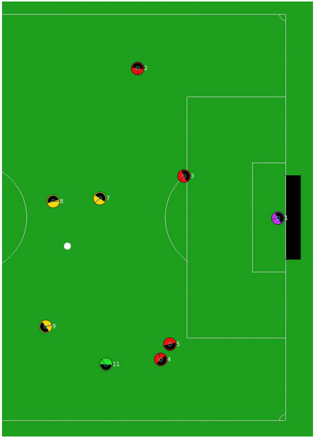
Video: 4 types, true type outside (students)

Source: `http://www.cs.utexas.edu/~larg/index.php/Ad_Hoc_Teamwork:_Pursuit`

Ad Hoc Teamwork: Half Field Offense

4 offense players vs. 5 defense players (Barrett and Stone, 2015)

- We control one agent (green) in offensive team (yellow)
- Policies of teammates unknown (defense uses fixed policies)
- 7 team types provided to our agent; for each team type, plan own policy offline using RL



Video: 4v5 Half Field Offense

Source:
`http://www.cs.utexas.edu/~larg/index.php/Ad_Hoc_Teamwork:_HFO`

Learning Parameters in Types

We can learn more: parameters in types! (Albrecht and Stone, 2017)

$$\text{History} \longrightarrow \boxed{\text{Type + Parameters}} \longrightarrow \text{Action}$$

$$P(a_i | H^t, \theta_j, p)$$

- $p = (p_1, ..., p_k)$ continuous parameter vector
- Complex types can have several parameters

  $\Rightarrow$ learning rate, exploration rate, discount factor, ...

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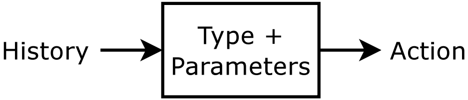


$P(a_i | H^t, \theta_j, p)$

- $p = (p_1, ..., p_k)$ continuous parameter vector
- Complex types can have several parameters

  $\Rightarrow$ learning rate, exploration rate, discount factor, ...

Goal: simultaneously learn type and parameters in type

For each type $\theta_j \in \Theta_j$, maintain parameter estimate $p \in [p^{\min}, p^{\max}]$

Observe action a_j^t of agent j

Select types $\Phi \subset \Theta_j$ for updating

For each $\theta_j \in \Phi$, update estimate $p^t \rightarrow p^{t+1}$

Update beliefs:

$$P(\theta_j | H^{t+1}) \propto P(a_j^t \mid H^t, \theta_j, p^{t+1}) \, P(\theta_j | H^t)$$

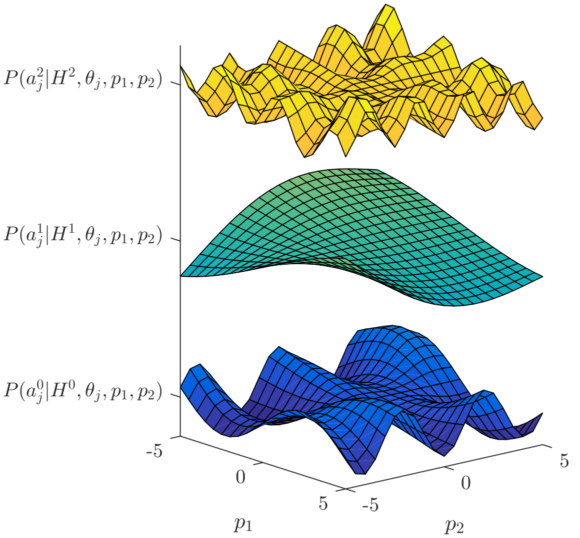
Plan own action

Updating Parameter Estimates

Given type θ_j, update parameter estimate $p^t \rightarrow p^{t+1}$

Type defines action likelihoods

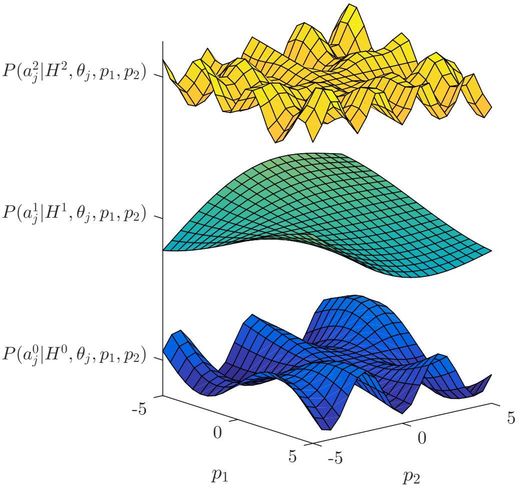
$$P(a_j^t \mid H^t, \theta_j, p)$$



Updating Parameter Estimates

Bayesian updating:

- Approximate $P(a_j^t \mid H^t, \theta_j, p)$ as polynomial with variables p
- Perform conjugate updates through successive layers



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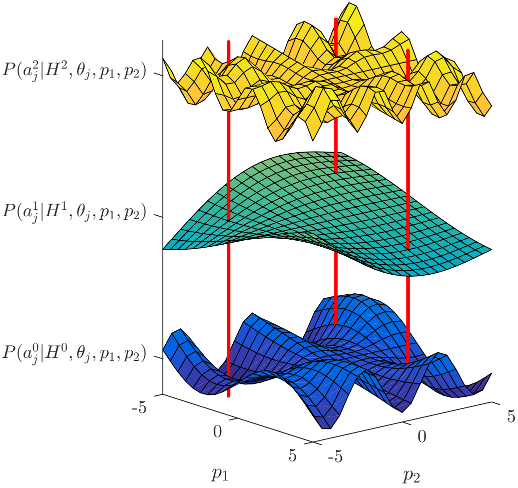
- Perform conjugate updates through successive layers

Global optimisation:

$$\arg\max_p \prod_{\tau=1}^{t+1} P(a_j^{\tau-1} | H^{\tau-1}, \theta_j, p)$$

Solve with Bayesian optimisation

(Albrecht and Stone, 2017)

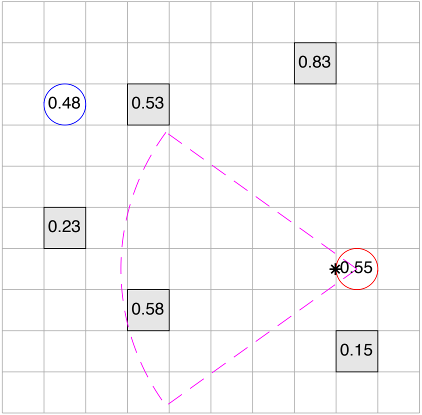


Ad Hoc Teamwork: Level-Based Foraging

Blue = our agent, red = other agents

Goal: collect all items in minimal time

Agents can collect item if
sum of agent levels $\geq$ item level



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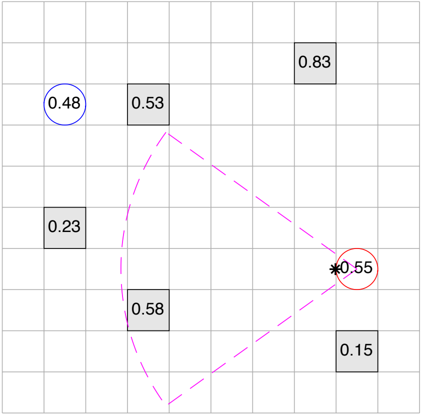
4 possible types for red, e.g.

- search for item, try to load
- search for agent, load item closest to agent



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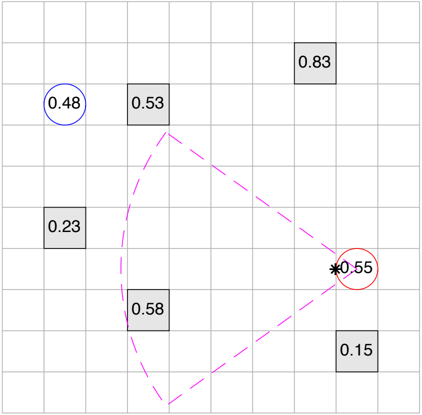
Each type uses 3 parameters:

- skill level, view radius, view angle



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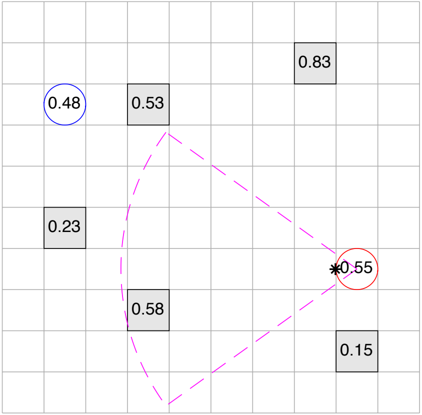
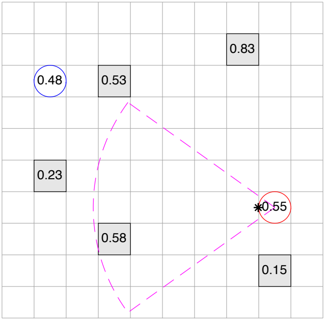
Blue doesn't know true type of red nor parameter values of type

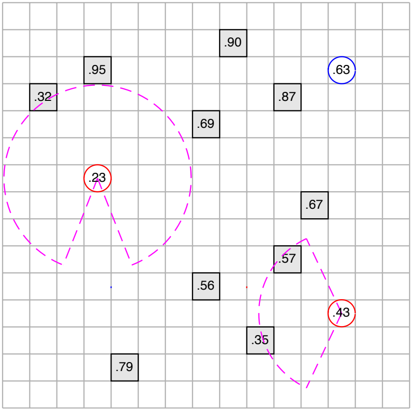


Ad Hoc Teamwork: Level-Based Foraging

Video: 10x10 world, 2 agents



Video: 15x15 world, 3 agents



- AAAI'16 Tutorial on Type-Based Methods:
  `http://thinc.cs.uga.edu/tutorials/aaai-16.html`
- Special Issue on Multiagent Interaction without Prior Coordination (MIPC): `http://mipc.inf.ed.ac.uk/journal`
- MIPC Workshops:
  - AAMAS'17, Sao Paulo, Brazil
  - AAAI'16, Phoenix, Arizona, USA
  - AAAI'15, Austin, Texas, USA
  - AAAI'14, Quebec City, Canada

  `http://mipc.inf.ed.ac.uk`

Standard Q-learning assumes tabular representation:

- One entry in Q for each (s, a)

Deep Reinforcement Learning

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Standard Q-learning assumes tabular representation:

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  $\Rightarrow$ Does not generalise values!

Needs extra engineering to work, including:

- **State abstraction** to reduce state space (usually hand-coded & domain-specific)
- **Function approximation** to store and generalise Q (e.g. linear function approximation in state features)

New problem: extra engineering may limit performance!

- State abstraction may be wrong (e.g. too coarse)
- Function approximator may be inaccurate

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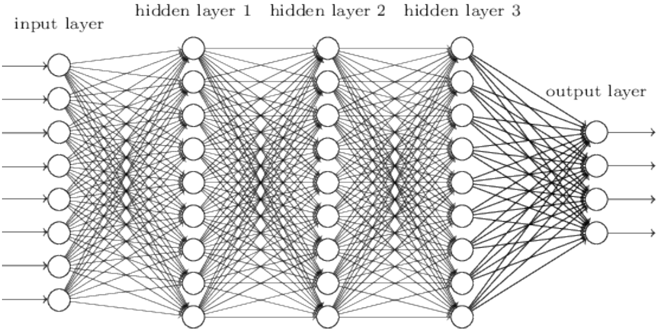
Idea: deep reinforcement learning

- Use "deep" neural network to represent Q
- Learn on raw data (no state abstraction)

$\Rightarrow$ Let network learn good abstraction on its own!

Deep learning: neural network with many layers

- Input layer takes raw data $\rightarrow s$
- Hidden layers transform data
- Output layer returns target scalars $\rightarrow Q(s, \cdot)$
- Train network with back-propagation on labelled data



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Deep Q-Learning (Mnih et al., 2013)

Initialise network parameters Ψ with random weights

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5. Sample random minibatch $D^+ \subset D$

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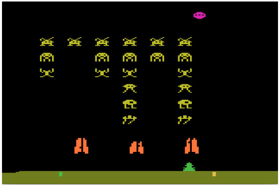
4. Store experience (s^t, a^t, r^t, s^{t+1}) in D
5. Sample random minibatch $D^+ \subset D$
6. For each $(s^\tau, a^\tau, r^\tau, s^{\tau+1}) \in D^+$, perform gradient descent step on

$$(y^\tau - Q(s^\tau, a^\tau; \Psi))^2$$

$$y^\tau = r^\tau + \gamma \max_{a'} Q(s^\tau, a'; \Psi^{fixed})$$

Multiagent Deep Reinforcement Learning



Deep RL very successful at many singe-agent games

- e.g. Atari games, Go, 3D maze navigation, ...

Can we use Deep RL for multiagent learning?

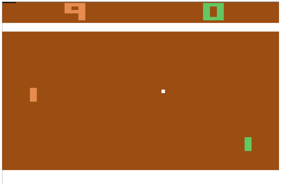
- **Problem:** learning of other agents makes environment non-stationary (breaks Markov property)

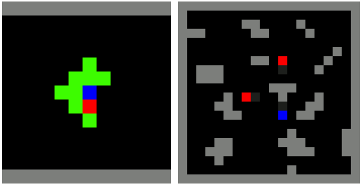
Independent Deep Q-Learners

Video: Cooperative Pong
Video: Competitive Pong

(Tampuu et al., 2017)

`https://www.youtube.com/watch?v=Gb9DprIgdGw`
`https://www.youtube.com/watch?v=nn6_GUVDnVw`





Video: Gathering game
Video: Wolfpack game

(Leibo et al., 2017)

`https://www.youtube.com/watch?v=F97lqqpcqsM`
`https://www.youtube.com/watch?v=kXudpMfecs4`

Video: Starcraft

(Foerster et al., 2017)

`https://www.youtube.com/watch?v=RK7y_uQmwhw`

Multiagent Deep Reinforcement Learning

Some recent works on multiagent deep RL:

- Emergence of cooperative/competitive behaviours
  (Tampuu et al., 2017; Leibo et al., 2017)
- Learning communication protocols
  (Sukhbaatar et al., 2016; Foerster et al., 2016)
- Opponent modelling
  (He et al., 2016)
- Improved minibatch selection
  (Palmer et al., 2017; Foerster et al., 2017)
- Multi-task learning
  (Omidshafiei et al., 2017)
- Learning value decomposition
  (Sunehag et al., 2017)

Concluding Remarks

We covered...

- Multiagent models: normal-form games, repeated games, stochastic games, ...
- Learning goals: equilibria, no-regret, targeted optimality, ...
- Learning algorithms: internal view, model-based, model-free
- Recent trends: ad hoc teamwork, deep RL

Download tutorial slides at:
`http://www.cs.utexas.edu/~larg/ijcai17_tutorial`

Watch out for our upcoming survey on agents modelling other agents!

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