Learning How to Behave in an Unfamiliar Society

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Behavior in an Unfamiliar Society

- Suppose you enter an environment that's inhabited by agents who are unfamiliar to you
- You know what actions are *possible*
- But you don't know
 - >> What behaviors and outcomes the agents prefer, and why
 - » How they're likely to react to your actions
 - >>> What collection of behaviors is most likely to elicit the responses you prefer
- How can you decide how to behave?
- First, a simple example

» The game we asked you to play when you registered today





Please help us by playing a game:

- Choose a number in the range from 0 to 100, and write it in the space below.
- We'll take the average of all of the numbers. The winner(s) will be whoever chose a number that's closest to 2/3 of the average.
- Dana Nau will announce the results during his talk this afternoon.

Your number:

Your name (optional):



Please help us by playing a game:

- Choose a number in the range from 0 to 100, and write it in the space below.
- We'll take the average of all of the numbers. The winner(s) will be whoever chose a number that's closest to 2/3 of the average.
 - This game is famous among economists and game theorists
 » It's called the *p*-beauty contest (I used *p* = 2/3)
 - What does game theory tell us about it?
 - First, a very brief review of some game-theoretic concepts

Classical Game Theory

- Consider a game played by a set of agents
 A = {a₁, a₂, ..., a_n}
- An agent's *strategy*: description of what it will do in every possible situation
 - » May be deterministic or probabilistic



- Let S = {s₁, s₂, ..., s_n} be the strategies used by {a₁, a₂, ..., a_n}, respectively
 » Then a_i's expected utility is a_i's average payoff given S
- *S* is a *Nash equilibrium* if *no* agent can get a higher expected utility by *unilaterally* switching to a different strategy
 - » I.e., each agent is doing the best that it can do, *given what the other agents are doing*
- An agent is *rational* if it makes choices that optimize its expected utility
 >> Hence a set of rational agents should gravitate toward a Nash equilibrium

Nash Equilibrium for the *p*-Beauty Contest

- We can find a Nash equilibrium for the *p*-beauty contest by doing *backward induction*
 - » All of the numbers are ≤ 100
 - average $\leq 100 => 2/3$ of the average < 67
 - » If everyone figures this out, they'll choose 67 or less
 - average $\leq 67 => 2/3$ of the average < 45
 - » If everyone figures *this* out, then they'll choose 45 or less
 - average < 45 => 2/3 of the average < 30
 - » ····
- Nash equilibrium strategy: everybody chooses 0
- For those of you who are familiar with evolutionary game theory, this strategy is evolutionarily stable

We aren't game-theoretic "rational" agents

- Huge literature on *behavioral economics* going back to about 1979
 - » Many cases where humans (or aggregations of humans) tend to make different decisions than the gametheoretically optimal ones
 - » Daniel Kahneman received the 2002 Nobel Prize in Economics for his work on that topic



of Guesses

Choosing "Irrational" Strategies

- Why did *you* choose a non-equilibrium strategy?
 - » Limitations in reasoning ability
 - » Hidden payoffs
 - » Opponent modeling

Limitations in Reasoning Ability

- Maybe you didn't calculate the Nash equilibrium correctly, or you didn't know how to calculate it, or you didn't even know the concept
- R. Nagel (1995) "Unravelling in Guessing Games: An Experimental Study." *American Economic Review* 85, 1313–1326
 - » Empirical results compatible with the assertion that
 - 13% of subjects used no backward induction
 - 44% used one level of backward induction
 - 37% used two levels
 - 4% used more than two levels
- Some games are so complicated that even though an optimal strategy exists, it's not feasible to figure out what it is
 - » In chess, the number of possible moves is larger than the number of atoms in the universe
 - The number of possible strategies is even larger

Hidden Payoffs

- "Hidden payoffs" are payoffs not included in the game model
 - » The game model assumed your objective was to *win* the game
- Maybe you participated in the game for a different reason:
 - » Because you thought it would be fun
 - » Because you were curious what would happen
 - » Because you thought it might help me or help the conference
 - » Because the people at the registration desk asked you to
 - » Because you wanted to create mischief
- In these cases, there wouldn't necessarily be any reason for you to choose the Nash equilibrium strategy

Opponent Modeling

- Maybe you predicted that the other players' likely moves made it unlikely that the Nash equilibrium strategy would win
- More generally,
 - » A Nash equilibrium strategy is best for you *if the other agents also use their Nash equilibrium strategies*
 - >>> In many cases, the other agents won't be using Nash equilibrium strategies
 - » In such cases, if you can predict the other agents' likely actions, you may be able to do much better than the Nash equilibrium strategy
- I'll give you several examples ...

Roshambo (Rock-Paper-Scissors)

A_1	Rock	Paper	Scissors
A ₂			
Rock	0, 0	-1, 1	1, -1
Paper	1, -1	0, 0	-1, 1
Scissors	-1, 1	1, -1	0, 0

- Rock beats scissors
- Scissors beats paper
- Paper beats rock
- Nash equilibrium strategy:
 - » Choose randomly, probability 1/3 for each move
 - \gg Expected utility = 0



Roshambo (Rock-Paper-Scissors)

• International roshambo programming competitions

» 1999 and 2000, Darse Billings, U. of Alberta

- » http://www.cs.unimaas.nl/ICGA/games/roshambo
- The 2000 competition
 - » First phase: round-robin
 - 64 programs competed
 - For each program, 1000 iterations against each of the programs (including itself)
 - Hence 64000 points possible per program
 - » Results averaged over 100 trials
 - Highest score: 9268
 - Lowest score: -52074



Poker

- Sources of uncertainty
 - » The card distribution
 - » The opponents' betting styles
- Lots of recent AI work on the most popular variant of poker
 - » Texas Hold 'Em
- The best AI programs are starting to approach the level of human experts
 - » Construct a statistical model of the opponent
 - What kinds of bets the opponent is likely to make under what kinds of circumstances
 - » Combine with game-theoretic reasoning
 - Billings, Davidson, Schaeffer, and Szafron (2002). "The challenge of poker." *Artificial Intelligence* (Vol. 134, Issue 1-2)



Kriegspiel Chess

• Kriegspiel: an imperfect-information variant of chess

- » Developed by a Prussian military officer in 1824
- » Became popular as a military training exercise
- » Progenitor of modern military wargaming

• Like chess, but

- » You don't know where your opponent's pieces are, because you can't observe most of their moves
- Only ways to observe:
 - » You take a piece, they take a piece, they put your king in check, you make an illegal move
- Size of belief state (set of all states you *might* be in):
 - » Texas hold'em: 10^3 (one thousand)
 - \gg bridge: 10⁷ (ten million)
 - » kriegspiel: 10^{14} (ten trillion)



Monte-Carlo Information-Set Search

- Recursive formulas for computing expected utilities of belief states
 - » Explicitly incorporates an opponent model
- Infeasible computation, due to belief-space size
- Monte Carlo approximations of the belief states
 - » Reduces the computation to sort-of feasible

• Results:

- » One of the world's best kriegspiel programs
- The *minimax* opponent model
 (Nash equilibrium in ordinary chess)
 is *not* the best opponent model for kriegspiel
- » A better model is an "overconfident" one that assumes the opponent won't play very well
- Parker, Nau, and Subrahmanian (2006). Overconfidence or paranoia? search in imperfect-information games. *Proc. National Conf. on Artificial Intelligence (AAAI)*
 - » http://www.cs.umd.edu/~nau/papers/parker06overconfidence.pdf



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- What collection of behaviors is most likely to elicit the responses you prefer ______ your best strategy
- How can you decide how to behave?



- their payoffs

Technical Approach

- Work by my recent PhD graduate, Tsz-Chiu Au
 - Finished his PhD this August
 - Now at University of Texas
- For technical details, see
 - » T.-C. Au, D. Nau, and S. Kraus. Synthesis of strategies from interaction traces. *International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS)*, 2008
 - » http://www.cs.umd.edu/~nau/papers/au08synthesis.pdf

Learning from Interaction Traces



- Suppose the other agents are competent members of their society
 - Even without knowing their payoffs, we can guess that many of their interactions produce payoffs that at least are acceptable to them
- So let's see if we can use those interactions ourselves
 - » Observe agents' interactions, collect *interaction traces*
 - » Look at what interaction traces produce outcomes that *we* prefer

i.e., high payoff for us if we interact with those agents

» Synthesize a *composite strategy* that combines those traces



Necessary and sufficient conditions

» for combining interaction traces into a composite strategy

• The CIT algorithm

» selects the best set (i.e., highest expected utility) of combinable interaction traces, and combines them

Modified composite agent

- » augments an agent to use the composite strategy to enhance its performance
- Cross-validated experimental results

Repeated Games

- Used by game theorists, economists, social and behavioral scientists as simplified models of various real-world situations
- Some well-known examples
 - » Roshambo
 - » Iterated Prisoner's Dilemma
 - » Iterated Battle of the Sexes
 - » Iterated Chicken Game
 - » Repeated Stag Hunt
 - » Repeated Ultimatum Game
 - » Repeated Matching Pennies
- I'll describe three of them



Iterated Prisoner's Dilemma

Prisoner's Dilemma

- » Each prisoner can *cooperate* with the other or *defect* (incriminate them)
- Iterated Prisoner's Dilemma (IPD)
 - » Iterations => incentive to cooperate
- Widely used to study emergence of cooperative behavior among agents
- IPD tournaments [Axelrod, *The Evolution of Cooperation*, 1984]
 - » Tit-for-Tat (TFT)
 - On 1st move, cooperate. On *n*th move, repeat the other player's (*n*-1)-th move
 - » Could establish and maintain advantageous cooperations with many other players
 - » Could prevent malicious players from taking advantage of it

Prisoner's Dilemma: a_2 CooperateDefect a_1 CooperateDefectCooperate3, 30, 5Defect5, 01, 1

Nash equilibrium



Iterated Chicken Game

• Chicken Game:

- » Made famous in *Rebel Without a Cause*
- » Two people drive toward a cliff
- » The first one to turn away loses face
- » If neither turns away, both will be killed

• Example

- » Two groups need to divide a piece of land between them
- » If they can't agree how to divide it, they'll fight
- Nash equilibria (with no iteration):
 - » Do the opposite of what the other agent does
- Iterated Chicken Game (ICG)
 - » Mutual cooperation does not emerge
 - Each player wants to establish him/herself as the defector



Chicken game:



Iterated Battle of the Sexes

Battle of the Sexes:

- » Two players need to coordinate their actions to achieve some goal
- » They each prefer different actions
- Original scenario: husband prefers football, wife prefers opera
- Another scenario:
 - >>> Two nations must act together to deal with an international crisis
 - » They prefer different solutions
- Iterated Battle of the Sexes (IBS)
 - » Two players repeatedly play the Battle of the Sexes
 - » Not very much is known about what strategies work well in this game





T (take): choose your preferred activity G (give): choose the other's preferred activity

Example: Two Interaction Traces

- Suppose an observer sees the following two interaction traces
- The game is the IBS, but the observer doesn't necessarily know that

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Someone interacting with an agent who is using a "fair" strategy:
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» Behavior: alternately *Take & Give*



Someone interacting with an agent who is using a "selfish" strategy:

» Behavior: always *Take*



How Should We Behave?

- In the games that I described, prejudice is impossible
- The agents don't have *tags*
 - » a_2 doesn't know a_1 's name, reputation, ethnicity, gender, social status, ...
 - » a₂'s only information about a₁ is how a₁ behaves toward a₂
 - if we interact with a₂ and we behave like a₁, then a₂ should behave like it did with a₁
- This also could happen in a game where prejudice is possible, if a₂ had the same prejudice toward both a₁ and us



How Should We Behave?

- If a_1 and a_3 are both competent members of their society, we might want to
 - » Emulate a_1 's behavior if we're playing with a_2
 - » Emulate a_3 's behavior if we're playing with a_4
- Problem: how do we know whether the other agent is a_2 or a_4 ?
 - » Recall that the agents don't have tags
 - >> The only way we can find out is by observing how the agent acts
- Solution:
 - » Combine the behaviors of a₁ and a₃ to get a strategy that tells how to act with both of them
 - >> We can do this because the interaction traces have a property called *compatibility*



Compatible Interaction Traces Example



• These two traces are *compatible*

because

- ← The point where the other agents' actions differ
- ← is *before* the point where *our* actions must differ
 - We can identify the other agent's behavior soon enough to decide what to do

Compatible Interaction Traces Example



- Combine the behaviors of a_1 and a_3 into a *composite strategy*
 - » The decision tree shown here

Compatible Interaction Traces General Case

T = **compatible** set of interaction traces



Theorem: If a set of interaction traces T is compatible, then we can combine T into a composite strategy C

- If *T* includes an interaction trace for every pure strategy, then *C* will be a *total* strategy
 - » I.e., it will specify an action for every situation we might encounter
- Otherwise *C* will be a *partial* strategy
 - » In some cases it won't tell us what action to perform

Incompatible Interaction Traces Example



• Must choose between two incompatible moves *before* we have enough information to see how the opponent is going to behave

>> Which move to choose?



Incompatible Interaction Traces General Case



- If *T* isn't compatible, we can find a compatible subset *T*' of *T* and construct a composite strategy *C*' from *T*'
 - >> Want to choose T' so as to maximize our expected utility
 - » Don't need to know other agents' payoffs and utilities, just ours
- Problem 1: exponentially many possibilities for *T'*
 - » Reduce to polynomial using divide-and-conquer
- Problem 2: to compute expected utility, need probability of each trace
 - » Get this from how many times the trace occurs in T

The CIT Algorithm

- Let *T* be a set of interaction traces
- Let C = {all composite strategies that can be formed from compatible subsets of T}
- The CIT algorithm
 - Finds an optimal composite strategy (highest expected utility of any strategy in C)
 - » Divide-and-conquer algorithm
 - » Running time
 - $= O(|T| \times \text{length of game})$



Using a Composite Strategy to Enhance an Agent's Performance

- Given an agent φ and a composite strategy C,
- Modified Composite Agent $MCA(\varphi, C)$
 - » If *C* specifies a move for the current situation, then make that move
 - » Otherwise make whatever move φ would normally make





Experimental Evaluation

- Evaluated in three games:
 - » Iterated Prisoner's Dilemma (IPD)
 - » Iterated Chicken Game (ICG)
 - » Iterated Battle of the Sexes (IBS)
- Sources of agents:
 - » Asked students in advanced AI classes to contribute agents to play in tournaments
 - » Also added the usual "standard" agents:
 - ALLC, ALLD, GRIM, NEG, PAVLOV, RAND, STFT, TFT, TFTT

	IPD	ICG	IBS
No. of deterministic agents	34	22	17
No. of probabilistic agents	18	24	29
Total no. of agents	52	46	46

Experimental Setup

For each game, a five-fold cross-validation experiment:

- $A = \{ all the agents we have for the game \} \}$
- Divide A into 5 subsets A_1, A_2, A_3, A_4, A_5
- For i = 1, 2, 3, 4, 5
 - » Create optimal composite strategy C from the interaction traces of the agents *not* in A_i
 - » For each agent φ in A_i , play φ and MCA(φ ,C) against the agents in A_i
 - Which does better: MCA(φ,C) or φ?
 - How often does MCA(φ,C) use C?



Experimental Results



• In nearly every case MCA(φ ,*C*)'s score and rank were much higher than φ 's

» Especially in cases where the strategy φ was weak

• Smallest improvement in the IPD

» Reason: most IPD agents already are very good to begin with

• Using composite strategies can greatly enhance an agent's performance

Is This Work Generalizable?

• Limitations of this work

- » Repeated games
- » All interactions were among pairs of agents
- » In each interaction, an agent had only two available actions
 - cooperate or defect, give or take
- What about
 - » Sequential games
 - \gg Interactions among *n* agents at once
 - » More than two available actions
- The number of possible strategies could increase exponentially
 - » Would the same approach have any realistic chance of working?
- I think that in many cases, the answer may be yes
 - » We only needed to use a very small fraction of the possible strategies



How Often the Composite Strategies Were Used

- Each game lasted 200 iterations,
 - » Hence, 2²⁰⁰ possible behaviors (sequences of actions) the other agent might use
- On average, C contains only about 200 traces
 - » C only tells us how to behave against 200 of the 2^{200} possible behaviors
- If we play MCA(φ ,*C*) against a random agent *a*
 - » Pr[C gives us a behavior to use with a] $\approx 200/2^{200} \approx 10^{-58}$
- In our experiments, $MCA(\varphi, C)$ used *C* much more frequently than that
 - » in the IPD, 84% of the time
 - » in the IBS, 48% of the time
 - » in the ICG, 45% of the time

• In other words ...

A Small Set of "Conventional" Behaviors

• One reason why our approach worked well

- » There was a set of "conventional behaviors" that was extremely small compared to the set of all possible behaviors
- » By observing and analyzing the interactions, we synthesized a strategy that utilized these behaviors
- » The strategy worked successfully in many or most circumstances
- We believe that in more complex environments, there again will be a small set of conventional behaviors
 - >>> This provides a reason to believe that learning from observed interactions can be useful there too

Summary

- How to construct a strategy for a new, unfamiliar environment?
- Approach:
 - » Observe the interactions among agents who are familiar with the environment
 - » Combine interaction traces into a *composite strategy*
- Results:
 - » Necessary and sufficient conditions for combining a set of traces
 - » The CIT algorithm: finds an optimal composite strategy
 - » Modified composite agent: uses the composite strategy to enhance the performance of an existing agent
 - » Experimental results in three different non-zero-sum games
 - Our approach greatly enhanced the performance of most agents
 - » Small set of conventional behaviors
 - Observing and learning them gives you a large fraction of what you need in order to do well

Future Work on This Topic

- How to synthesize strategies from interaction traces for *noisy* environments?
 - » Environments in which accidents and miscommunications can happen
 - » Can cause big problems for some strategies
- Game can go on longer than the interaction traces do
 - » Machine-learning techniques such as Q-learning and $TD(\lambda)$ can handle infinite horizons
 - » Can we do the same?
- Other kinds of environments
 - » Zero-sum games
 - » POMDPs
 - » Other multi-agent environments

Ongoing Work on Related Topics

- V. S. Subrahmanian and I codirect the Lab for Computational Cultural Dynamics
- Highly cross-disciplinary partnership
 - » Computer Science
 - » Political science
 - » Psychology
 - » Criminology
 - » Linguistics
 - » Public Policy
 - » Business
 - » Systems Engineering

- LCCD'S active partners include
- Univ. of Pennsylvania (sub)
- Nat. Consortium for the Study of Terrorism and Responses to Terrorism (START)
- Specific regional experts
 - » Minister of S&T, Rwanda
 - » Former Afghan Deputy Minister of the Interior
 - » Former State Dept. officials who served in Pakistan-Afghanistan
 - » Former general involved in busting the Tupac Amaro and Shining Path in Peru



SOMA Rules

- SOMA Rules: predict an agent's behavior under a set of arbitrary conditions
 - » group g will take action a with probability x% to y% when condition c holds
 - » Techniques for extracting such rules automatically from databases (e.g., Minorities at Risk) and from electronic text
 - » Algorithms for using SOMA rules to create forecasts
 - E.g., Aaron Mannes's talk this morning
- V. Subrahmanian, M. Albanese, M. V. Martinez, D. Nau, D. Reforgiato, G. I. Simari, A. Sliva, O. Udrea, and J. Wilkenfeld. CARA: A cultural-reasoning architecture. *IEEE Intelligent Systems*, Mar./Apr. 2007

Social Learning Strategies Tournament

- International competition among computer programs in a evolutionary cultural adaptation environment
 - » Consortium of researchers funded by the European Union
 - » €10,000 prize
 - » http://www.intercult.su.se/cultaptation/tournament.php
- Several of our students have entered programs
- In addition, they have successfully analyzed several simplified versions of the game, to find provably optimal strategies
 - » Carr, Raboin, Parker, and Nau: "When Innovation Matters: An Analysis of Innovation in a Social Learning Game." *ICCCD-2008*
 - Presentation tomorrow
 - » Carr, Raboin, Parker, and Nau: "Balancing innovation and exploitation in a social learning game." *AAAI Fall Symposium on Adaptive Agents in Cultural Contexts*. To appear.

International Planning Competition

• RFF - algorithm for generating plans under uncertainty

- » Guillaume Infantès (ONERA, visitor to our lab)
- » Florent Teichteil-Königsbuch (ONERA, visitor to our lab)
- » Ugur Kuter (research scientist in our lab)
- I just received word today that RFF has won the probabilistic planning track of the 2008 International Planning Competition

Postdoctoral Research Opportunity

- I want to hire a postdoctoral researcher to do research involving game theory
- If you know of anyone who might be suitable, please let me know
 - » Dana S. Nau
 - » nau@cs.umd.edu
 - » 301-405-2684