15-780: Graduate AI Lecture 8. Games

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Last time, on Grad AI

Optimization

- \circ Unconstrained optimization: gradient = 0
- Equality-constrained optimization
 - Lagrange multipliers
- Inequality-constrained: either
 - o nonnegative multipliers (last W), or
 - search through bases (simplex, on M)

Duality

- How to express path planning as an LP
- Dual of path planning LP

Optimization in ILPs

- o DFS, with pruning by:
 - constraint propagation
 - best solution so far
 - dual feasible solution
 - dual feasible solution for relaxation of ILP with some variables set (branch and bound)

Optimization in ILPs

- o Duality gap and Slater's condition
- Cutting planes (how to use, how to find)
 - o generally, e.g., Gomory
 - problem specific, e.g., subtour elimination for TSPs
- Branch and cut

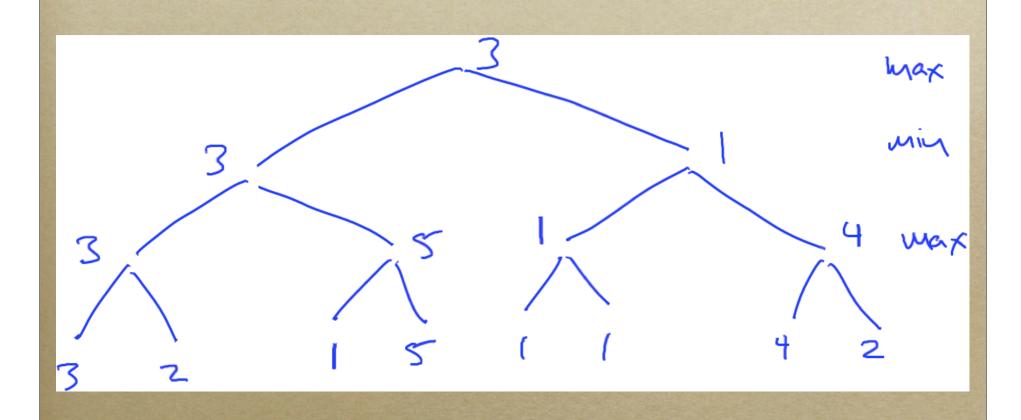
Historical note

- o Gomory's cuts weren't the first poly-time cuts: e.g., Dantzig in 1959
- But they were first to guarantee finite termination of cutting plane method for ILPs
- Proven by Gomory in 1963

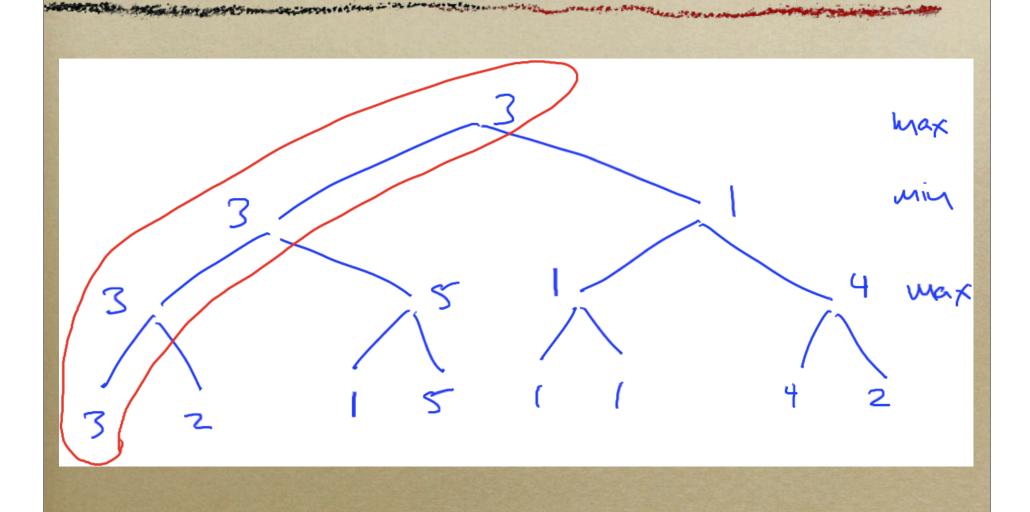
Game search



Synthetic example



Principal variation



Making it work

- Minimax is all well and good for small games
- But what about bigger ones? 2 answers:
 - cutting off search early (big win)
 - o pruning (smaller win but still useful)

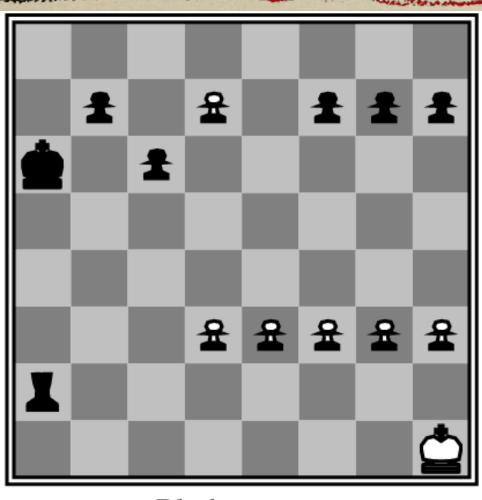
Heuristics

- Quickly and approximately evaluate a position without search
- \circ E.g., Q = 9, R = 5, B = N = 3, P = 1
- Build out game tree as far as we can, use heuristic at leaves in lieu of real value
 - might want to build it out unevenly (more below)

Heuristics

- Deep Blue used: materiel, mobility, king position, center control, open file for rook, paired bishops/rooks, ... (> 6000 total features!)
- Weights are context dependent, learned from DB of grandmaster games then hand tweaked

Quiescence

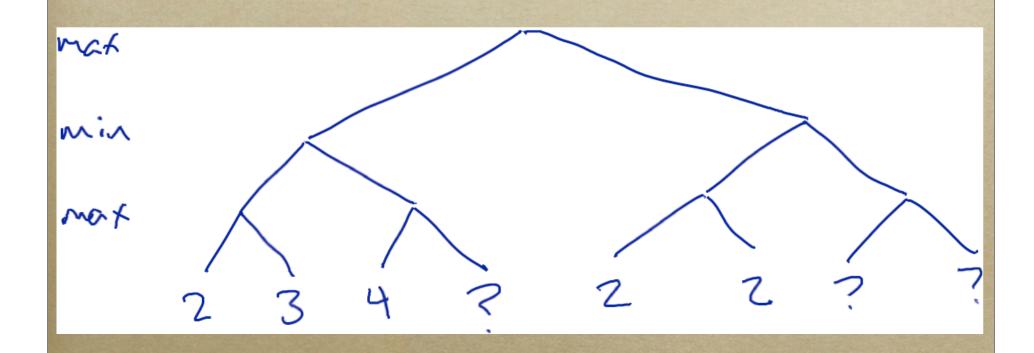


Black to move

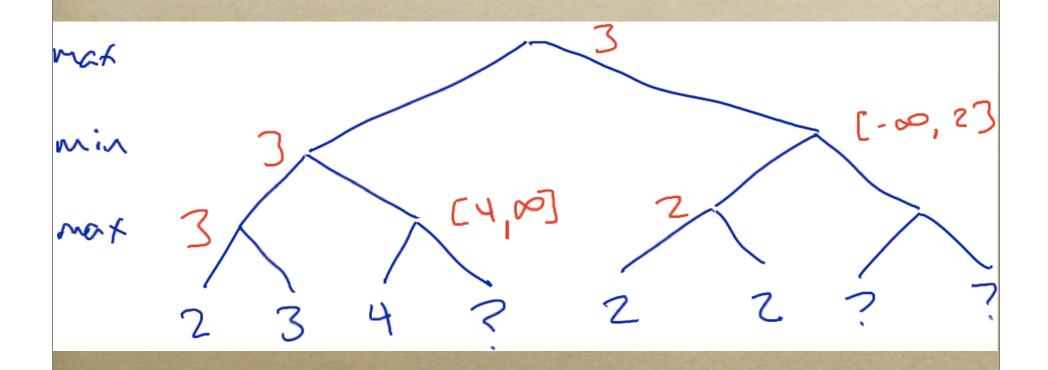
Pruning

 Idea: don't bother looking at parts of the tree we can prove are irrelevant

Pruning example



Pruning example



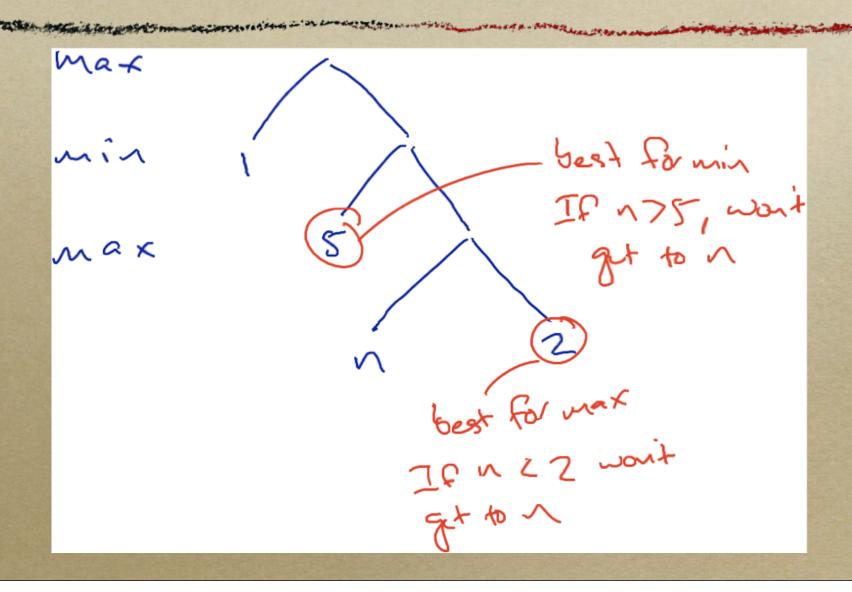
Alpha-beta pruning

- o Do a DFS through game tree
- At each node n on stack, keep bounds
 - α(n): value of best deviation so far for MAX along path to n
 - $\beta(n)$: value of best deviation so far for MIN along path to n

Alpha-beta pruning

- Deviation = way of leaving the path to n
- So, to get α,
 - o take all MAX nodes on path to n
 - look at all their children that we've finished evaluating
 - best (highest) of these children is α
- Lowest of children of MIN nodes is β

Example of alpha and beta



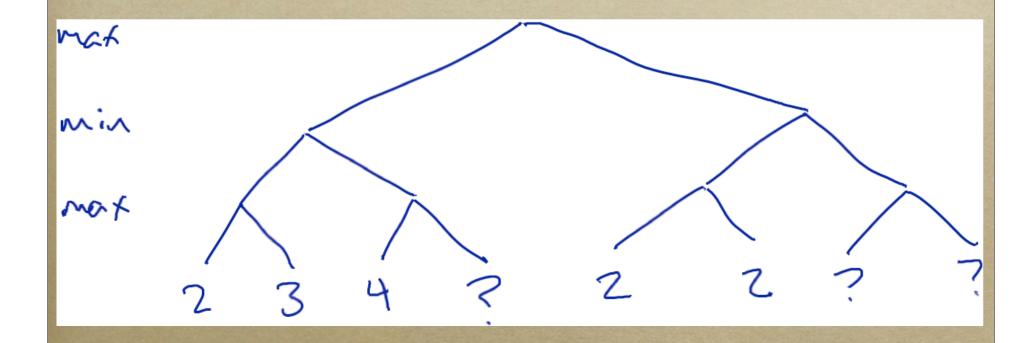
Alpha-beta pruning

- At max node:
 - o receive α and β values from parent
 - expand children one by one
 - o update a as we go
 - o if α ever gets higher than β, stop
 - won't ever reach this node (return α)

Alpha-beta pruning

- At min node:
 - o receive α and β values from parent
 - expand children one by one
 - update β as we go
 - o if β ever gets lower than α, stop
 - won't ever reach this node (return β)

Example



How much do we save?

- Original tree: bd nodes
 - \circ b = branching factor
 - \circ d = depth
- If we expand children in random order, pruning will touch $b^{3d/4}$ nodes
- Lower bound (best node first): $b^{d/2}$
- Can often get close to lower bound w/ move ordering heuristics

Matrix

games

Matrix games

- Games where each player chooses a single move (simultaneously with other players)
- Also called normal form games
- Simultaneous moves cause uncertainty: we don't know what other player(s) will do

Acting in a matrix game

- One of the simplest kinds of games; we'll get more complicated later in course
- o But still will make us talk about
 - negotiation
 - cooperation
 - threats, promises

Matrix game: prisoner's dilemma

	C	D		C	D
C	-1	-9	C	-1	0
D	0	-5	D	-9	-5

payoff to Row

Payoff to Col

Matrix game: prisoner's dilemma

	C	D	
C	-1, -1	-9, 0	
D	0, -9	-5, -5	

Can also have n-player games

	Н	T		Н	T
Н	0, 0, 1	0, 0, 1	Н	1, 1, 0	0, 0, 1
T	0, 0, 1	1, 1, 0	T	0, 0, 1	0, 0, 1

if Layer plays H

if Layer plays T

Analyzing a game

- What do we want to know about a game?
- Value of a joint action: just read it off of the table
- Value of a mixed joint strategy: almost as simple

Value of a mixed joint strategy

	C	D	
C	.6*.3*w	.4*.3*x	
D	.6*.7*y	.4*.7*z	

Suppose Row plays 30-70, Col plays 60-40

Payoff of joint strategy

- Just an average over elements of payoff matrices M_R and M_C
- If x and y are strategy vectors like (.3, .7)' then we can write x' M_R y and x' M_C y

What else?

- Could ask for value of a strategy x under various weaker assumptions about other players' strategies y, z, ...
- Weakest assumption: other players might do absolutely anything!
- How much does a strategy guarantee us in the most paranoid of all possible worlds?

Safety value

- Worst-case value of a row strategy x in 2player game is
 - \circ miny $x' M_R y$
- More than two players, min over y, z, ...
- Best worst-case value is safety value or minimax value of game
 - \circ $max_x min_y x' M_R y$

What else?

- If the world really is out to get us, the safety value is the end of the story
- This is the case in...

Zero-sum

games

Zero-sum game

- o A 2-player matrix game where
- (payoff to A) = -(payoff to B) for all combinations of actions
- Note: 3-player games are never called zero-sum, even if payoffs add to 0
- But if (payoff to A) = 7 (payoff to B) we
 sometimes fudge and call it zero-sum

Zero-sum: matching pennies

	Н	T	
Н	1	-1	
T	-1	1	

Minimax

- In zero-sum games, safety value for Row is negative of safety value for Col (famous theorem of Nash)
- A strategy that guarantees minimax value is a minimax strategy
- If both players play such strategies, we are in a minimax equilibrium
 - o no incentive for either player to switch

Finding minimax

o min_x max_y x'My subject to

$$1'x = 1$$

$$1$$
'y = 1

$$x, y \ge 0$$

For example

Finding minimax

- Eliminate x's equality constraint:
- \circ min_x max_{y, z} z(1 1'x) + x'My subject to

$$1'y = 1$$

$$x, y \ge 0$$

Finding minimax

• Gradient wrt x is

o maxy, z z subject to

$$My - 1z \ge 0$$

$$1'y = 1$$

$$y \ge 0$$

For example

JH & BT = 1

Interpreting LP

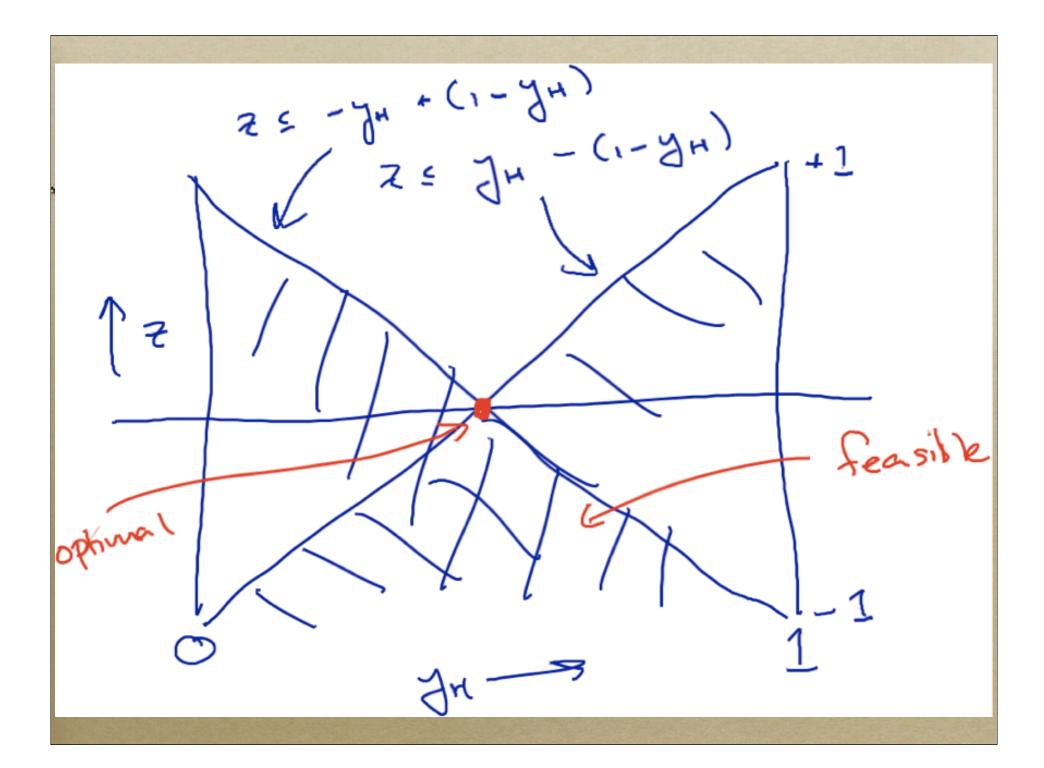
o maxy, z z subject to

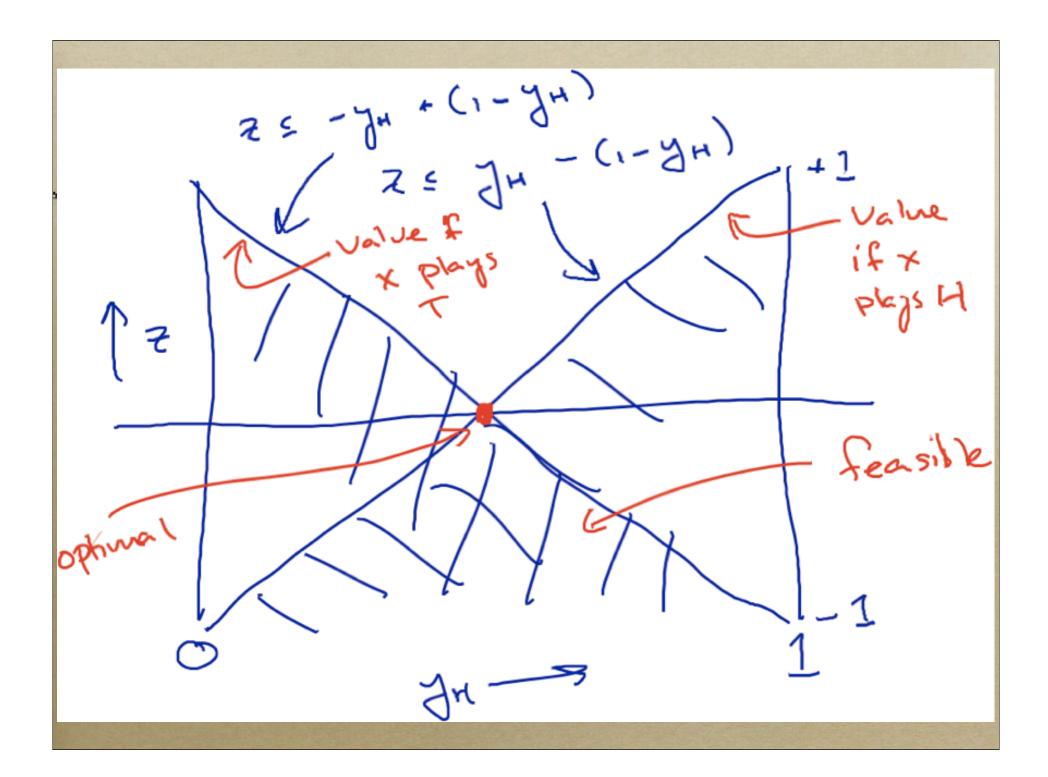
$$My \ge 1z$$

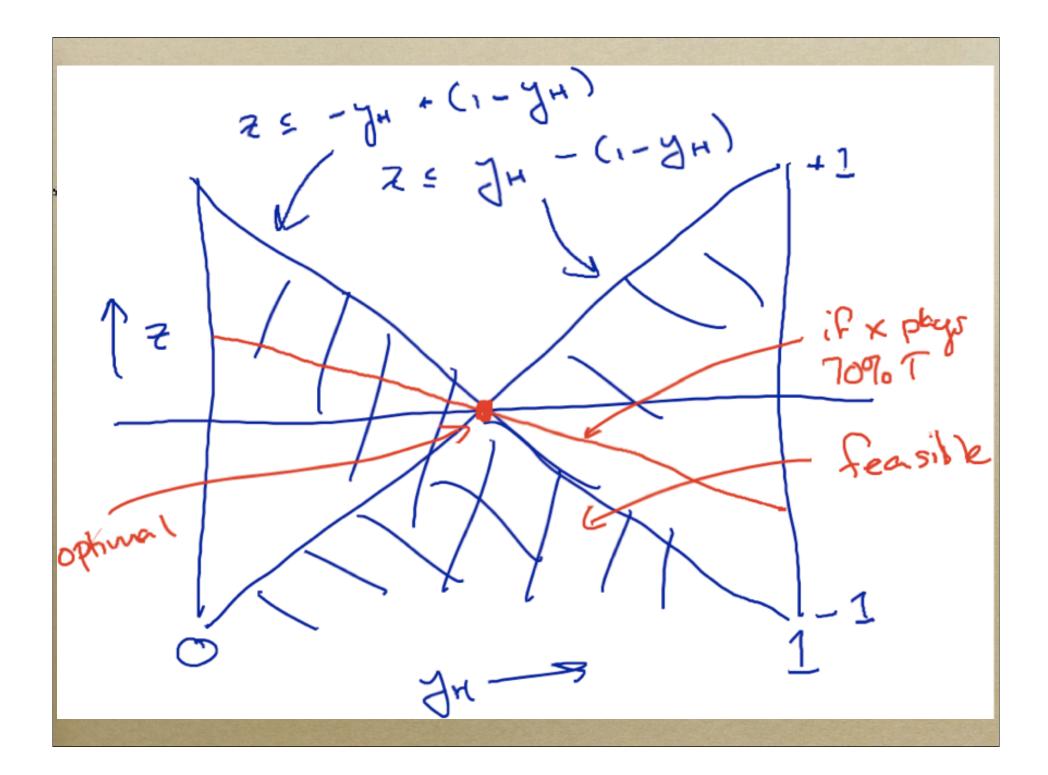
$$1'y = 1$$

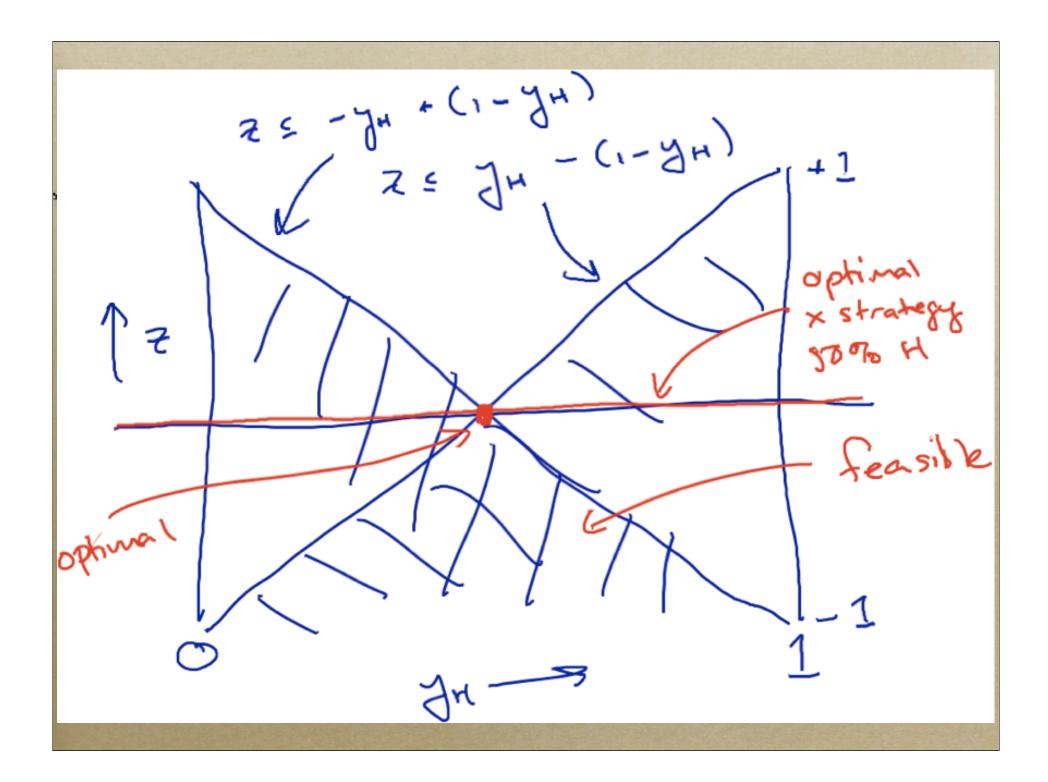
$$y \ge 0$$

 y is a strategy for Col; z is value of this strategy









Duality

- x is dual variable for $My \ge 1z$
- Complementarity: Row can only play strategies where My = 1z
- Makes sense: others cost more
- Dual of this LP looks the same, so Col can only play strategies where x'M is maximal

Back to general-sum

- What if the world isn't really out to get us?
- Minimax strategy is unnecessarily pessimistic

General-sum equilibria

Lunch

	\boldsymbol{A}	U	
A	3, 4	0, 0	
U	0, 0	4, 3	

A = Ali Baba, U = Union Grill

Pessimism

- In Lunch, safety value is 12/7 < 2
- Could get 3 by suggesting less-preferred restaurant
- Any halfway-rational player will cooperate with this suggestion

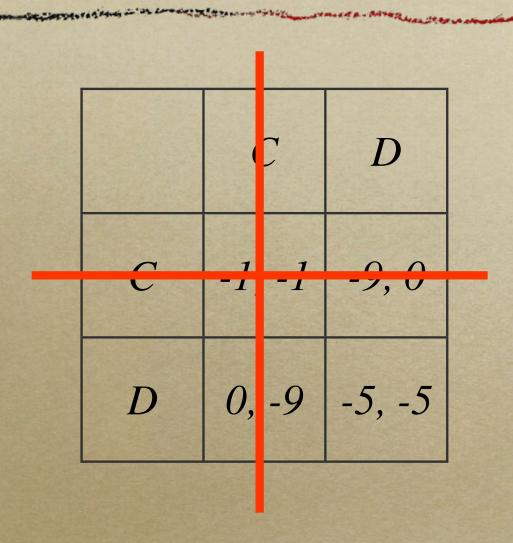
Rationality

- Trust the other player to look out for his/ her own best interests
- Stronger assumption than "s/he might do anything"
- Results in possibility of higher-than-safety payoff

Dominated strategies

- First step towards being rational: if a strategy is bad no matter what the other player does, don't play it!
- Such a strategy is (strictly) dominated
- Strict = always worse (not just the same)
- Weak = sometimes worse, never better

Eliminating dominated strategies



Do we always get a unique answer?

- No: try Lunch
- What can we do instead?
- Well, what was special about Row offering to play A?

	A	U	
A	3, 4	0, 0	
U	0, 0	4, 3	

Equilibrium

- If Row says s/he will play A,
 Col's best response is to play
 A as well
- And if Col plays A, then Row's best response is also A
- So (A, A) is a mutually reinforcing pair of strategies an equilibrium

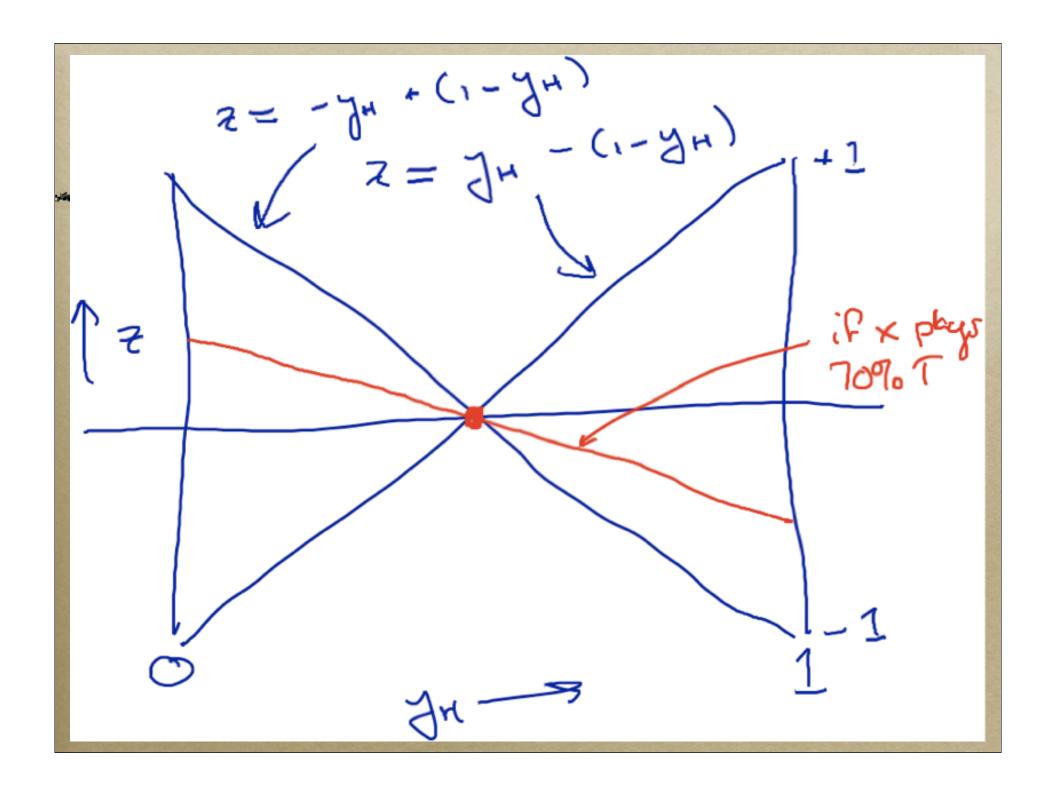
	A	U	
A	3, 4	0, 0	
U	0, 0	4, 3	

Finding equilibria

- The idea of equilibrium allows us to rule out some more joint strategies beyond what dominance gave us
- The particular type of equilibrium we are about to describe is due to Nash
 - his name keeps coming up...

Finding equilibria

- In a Nash equilibrium, we have a (mixed) strategy for each player
- Each strategy is a best response to others
 - o puts zero weight on suboptimal actions
 - therefore zero weight on dominated actions



How good is equilibrium?

- o Does an equilibrium tell you how to play?
- Sadly, no.
- To get further, we'll need additional assumptions

Bargaining

Bargaining

- In the standard model of a matrix game, players can't communicate
- To allow for bargaining, we will extend the model two ways:
 - o first, cheap talk
 - o second, a moderator

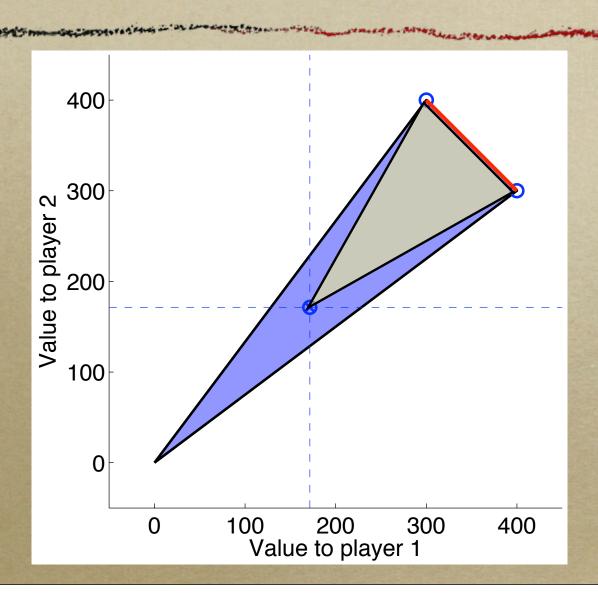
Cheap talk

- Players get a chance to talk to one another before picking their actions
- They cay say whatever they want—lie, threaten, cajole, or even be honest
- What will happen?

Coordination

- Certainly the players will try to coordinate
- That is, they will try to agree on an equilibrium
 - agreeing on a non-equilibrium will lead to deviation
- But which one?

Pareto dominance



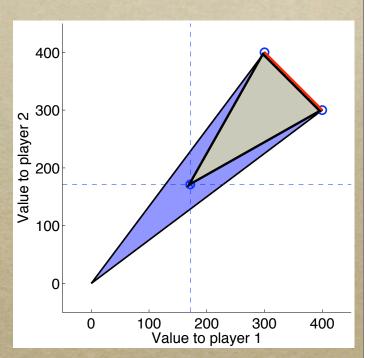
Pareto dominance

- o In Lunch, there are 3 Nash equilibria
- Players could agree on any one, or agree to randomize among them
 - e.g., each simultaneously say a binary number, XOR together, use result to pick equilibrium

Pareto dominance

- Not all equilibria are created equal
- For any in brown triangle's interior, there is one on red line that's better for both players





Beyond Pareto

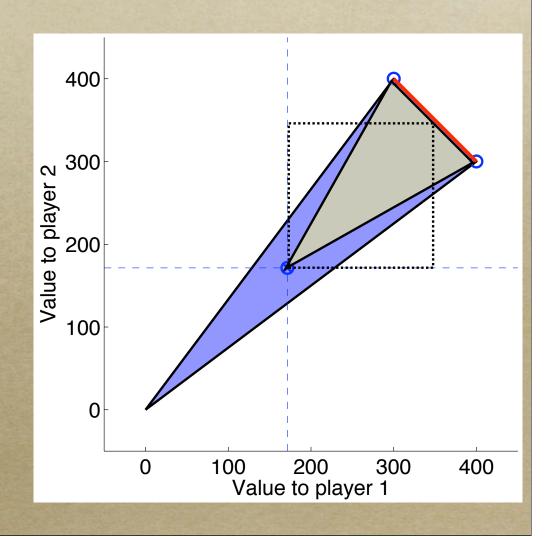
- We still haven't achieved our goal of actually predicting what will happen
- We've narrowed it down a lot: Paretodominant equilibria
- Further narrowing is the subject of much argument among game theorists

Nash bargaining solution

- Nash designed a model of the bargaining process (there's that name again...)
- Rubinstein later made the model more detailed and implementable
- Model includes offers, threats, and impatience to reach an agreement
- o In this model, we finally have a unique answer to "what will happen?"

Nash bargaining solution

- Predicts players
 will agree on the
 point on Pareto
 frontier that
 maximizes product
 of extra utility
- Invariant to axis rescaling, player exchanging



Moderator

- A moderator has a big deck of cards
- Each card has a recommended action for each player
- Moderator draws a card, whispers actions to corresponding players
 - actions may be correlated
 - o only find out your own

- Since players can have correlated actions, an equilibrium with a moderator is called a correlated equilibrium
- Example: 5-way stoplight
- All NE are CE
- At least as many CE as NE in every game (often strictly more)

Realism?

- Moderators are often available
- Sometimes have to be kind of clever
- E.g., can simulate a moderator using cheap talk and some crypto

	A	U		A	U
A	3, 4	0, 0	A	a	b
U	0, 0	4, 3	U	C	d

- Probability that Row is recommended to play A = a + b
- Given recommendation for A, probability that Col also plays A = a / (a + b)
- Rationality: when I'm recommended to play A, I don't want to play B instead

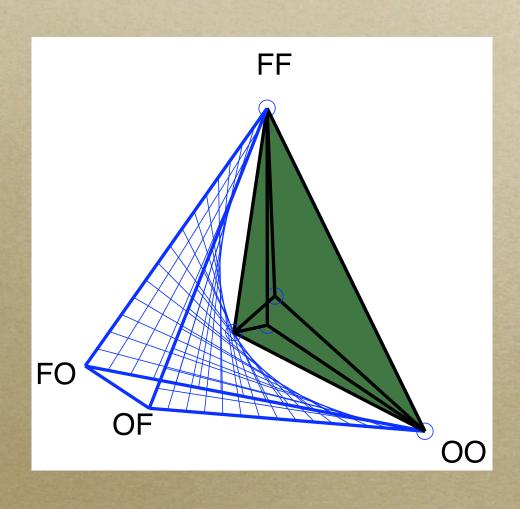
$$4\frac{a}{a+b} + 0\frac{b}{a+b} \ge 0\frac{a}{a+b} + 3\frac{b}{a+b}$$
 if $a+b > 0$

$$4a + 0b \ge 0a + 3b$$

$$0c + 3d \ge 4c + 0d$$

$$0b + 4d \ge 3b + 0d$$

$$3a + 0c > 0a + 4c$$



Bargaining

- Can use Nash bargaining model to select among CE
- Same results hold: unique answer on Pareto frontier (but now Pareto frontier might be better)