Computing Solution Concepts of Normal-Form Games

- Can no longer be represented even as an LCP
 - Impractical to solve exactly
- Unclear how to best formulate the problem as input to an algorithm

- There has been some success approximating the solution using a sequence of linear complementarity problems (SLCP)
 - Each LCP is an approximation of the problem, and its solution is used to create the next approximation in the sequence
 - Can be thought of as a generalization to Newton's method of approximating the local maximum of a quadratic equation
 - Although not globally convergent, it is possible to try a number of different starting points because of its relative speed

- Another approach is to formulate the problem as a minimum of a function
 - Starting from a strategy profile s, let c_i (s) be the change in utility to player i if he switches to playing action a_i as a pure strategy
 - . Then, define $d_i^j(s)$ as $c_i^j(s)$ bounded from below by zero

$$c_i^j(s) = u_i(a_i^j, s_{-i}) - u_i(s)$$
$$d_i^j(s) = \max(c_i^j(s), 0)$$

$$c_i^j(s) = u_i(a_i^j, s_{-i}) - u_i(s)$$
$$d_i^j(s) = \max(c_i^j(s), 0)$$

- Note that $d_i^j(s)$ is positive if and only if player i has an incentive to deviate to action $a_i^j(s)$
- Thus, strategy profile s is a Nash equilibrium if and only if $d_i^j(s) = 0$ for all players i, and all actions j for each player

$$\begin{array}{ll} \text{minimize} & f(s) = \sum_{i \in N} \sum_{j \in A_i} \left(d_i^j(s) \right)^2 & & \text{makes the function differentiable everywhere} \\ \\ \text{subject to} & \sum_{j \in A_i} s_i^j = 1 & & \forall i \in N \\ \\ s_i^j \geq 0 & & \forall i \in N, \forall j \in A_i \end{array}$$

- This function has one or more global minima at 0, and the set of all s such that f(s) = 0 is exactly the set of Nash equilibria
- We can now apply any method for constrained optimization

 For an unconstrained optimization method, we can roll the constraints into the objective function

 We still have a differentiable function that is zero if and only if s is a Nash equilibrium

- :(Both optimization problems have local minima which do not correspond to Nash equilibria
- Considering the commonly-used optimization methods
 - : (hill-climbing gets stuck in local minima
 - :(<u>simulated annealing</u> often converges globally only for parameter settings that yield an impractically long running time

- Alternative algorithms
 - Scarf's algorithm
 - Govindan and Wilson
 - . SEM

- Computational uses for identifying dominated strategies
- Computational complexity of this process

- Iterated removal of <u>strictly</u> dominated strategies
 - The same set of strategies will be identified regardless of the elimination order
 - All Nash equilibria of the original game will be contained in this set
 - Can be used to narrow down the set of strategies to consider before attempting to identify a sample Nash equilibrium
 - In the worst case this procedure will have no effect
 - In practice, it can make a big difference

- Iterated removal of <u>weakly</u> dominated strategies
 - The elimination order does make a difference
 - the set of strategies that survive iterated removal can differ depending on the order in which dominated strategies are removed
 - Removing weakly dominated strategies can eliminate some equilibria of the original game
 - No new equilibria are ever created by this elimination
 - Since every game has at least one equilibrium, at least one of the original equilibria always survives
 - Will often produce a smaller game

Algorithm for determining whether s_i is strictly dominated by any <u>pure strategy</u>

 How to change this algorithm to determine whether s_i is weakly dominated by any <u>pure</u> <u>strategy?</u>

```
forall pure strategies a_i \in A_i for player i where a_i \neq s_i do dom \leftarrow true, flag = false forall pure-strategy profiles a_{-i} \in A_{-i} for the players other than i do i if u_i(s_i, a_{-i}) > u_i(a_i, a_{-i}) then dom \leftarrow false else if u_i(s_i, a_i) < u_i(a_i, a_i) then flag \leftarrow true if dom = true and flag = true then c return true
```

 For all of the definitions of domination, the complexity of the procedure is O(|A|), linear in the size of the normal-form game

- We cannot use the previous simple algorithm to test whether a given strategy s_i is dominated by a mixed strategy because these strategies cannot be <u>enumerated</u>
- However, it turns out that we can still answer the question in <u>polynomial time</u> by solving a linear program
 - Each flavor of domination requires a somewhat different linear program

Another solution concept

Reminder:

	L	С	
U	3,1	0,3	Why is the dominated
M	1,5	1,1	
В	0,½	4,2	

action

 Q: What does this <u>feasibility program</u> give us for a given strategy s_i?

$$\sum_{j \in A_i} p_j u_i(a_j, a_{-i}) \ge u_i(s_i, a_{-i}) \qquad \forall a_{-i} \in A_{-i}$$

$$p_j \ge 0 \qquad \forall j \in A_i$$

$$\sum_{j \in A_i} p_j = 1$$

A: Very weakly dominance!

 $j \in A_i$

Matlab code:

•
$$A = [-3 \ 0; \ 0 \ -4]$$

•
$$b = [-1 \ -1];$$

•
$$Aeq = [1 1];$$

• beq =
$$1$$
;

•
$$1b = [0 \ 0];$$

•
$$f = [];$$

• z = linprog(f, A, b, Aeq, beq, lb)

$$z = 0.3349$$
 0.6651

$$\sum_{j \in A_i} p_j u_i(a_j, a_{-i}) \ge u_i(s_i, a_{-i}) \qquad \forall a_{-i} \in A_{-i}$$

$$p_j \ge 0 \qquad \forall j \in A_i$$

$$\sum_{j \in A_i} p_j = 1$$

	L	С
U	3,1	0,3
M	1,5	1,1
В	0,½	4,2

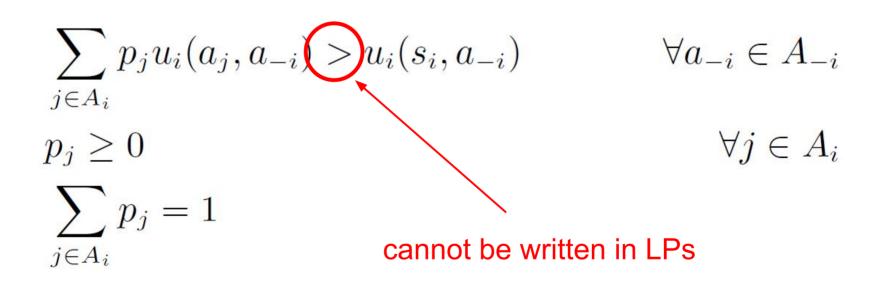
- Then, let us consider <u>strict domination</u> by a mixed strategy
- This would seem to have the following straightforward LP formulation (indeed, a mere feasibility program)

$$\sum_{j \in A_i} p_j u_i(a_j, a_{-i}) > u_i(s_i, a_{-i}) \qquad \forall a_{-i} \in A_{-i}$$

$$p_j \ge 0 \qquad \forall j \in A_i$$

$$\sum_{j \in A_i} p_j = 1$$

 The problem is that the constraints in linear programs must be weak inequalities



Instead, we must use the LP that follows

minimize
$$\sum_{j\in A_i} p_j$$
 subject to
$$\sum_{j\in A_i} p_j u_i(a_j,a_{-i}) \geq u_i(s_i,a_{-i}) \qquad \forall a_{-i}\in A_{-i}$$

$$p_j\geq 0 \qquad \qquad \forall j\in A_i$$

 This LP simulates the strict inequality of constraint through the objective function

minimize
$$\sum_{j\in A_i}p_j$$
 subject to
$$\sum_{j\in A_i}p_ju_i(a_j,a_{-i})\geq u_i(s_i,a_{-i}) \qquad \forall a_{-i}\in A_{-i}$$

$$p_j\geq 0 \qquad \qquad \forall j\in A_i$$

no constraints restrict the p_j 's from above: this LP will always be feasible

In the optimal solution, the p_j 's may be smaller or greater to 1

- A strictly dominating mixed strategy therefore exists iff the optimal solution to the LP has objective function < 1
- In this case, we can add a positive amount to each p_j in order to cause constraint to hold in its strict version everywhere while achieving the condition $\Sigma_i p_i = 1$

minimize
$$\sum_{j\in A_i} p_j$$
 subject to
$$\sum_{j\in A_i} p_j u_i(a_j,a_{-i}) \geq u_i(s_i,a_{-i}) \qquad \forall a_{-i}\in A_{-i}$$

$$p_j\geq 0 \qquad \qquad \forall j\in A_i$$

• Matlab code:

minimize
$$\sum_{j \in A} p_j$$

• A =
$$[-3 \ 0; \ 0 \ -4]$$
 subject
• b = $[-1 \ -1];$

• A = [-3 0; 0 -4] subject to
$$\sum_{j \in A_i} p_j u_i(a_j, a_{-i}) \ge u_i(s_i, a_{-i})$$
 $\forall a_{-i} \in A_{-i}$ • b = [-1 -1]; $\forall j \in A_i$

- Aeq = [];
- beq = [];
- $1b = [0 \ 0];$
- f = [1 1];
- z = linprog(f, A, b, Aeq, beq, lb)
- Z =
- 0.3333
- 0.2500

	L	С
U	3,1	0,3
M	1,5	1,1
В	0,1/2	4,2

 How to identify if strategy s_i is weakly dominated by a mixed strategy?

• If the optimal solution > 0 (not \geq), the mixed strategy given by the p_j 's achieves strictly positive expected utility for at least one $a_{-i} \in A_{-i}$, meaning that s_i is <u>weakly dominated</u> by this mixed strategy

$$\begin{aligned} & \text{maximize} & & \sum_{a_{-i} \in A_{-i}} \left[\left(\sum_{j \in A_i} p_j \cdot u_i(a_j, a_{-i}) \right) - u_i(s_i, a_{-i}) \right] \\ & \text{subject to} & & \sum_{j \in A_i} p_j u_i(a_j, a_{-i}) \geq u_i(s_i, a_{-i}) \\ & & & \forall a_{-i} \in A_{-i} \\ & & & p_j \geq 0 \\ & & & \forall j \in A_i \end{aligned}$$

Iterated dominance

- For all three flavors of domination, it requires only polynomial time to iteratively remove dominated strategies until the game has been maximally reduced
- A single step of this process consists of checking whether every pure strategy of every player is dominated by any other mixed strategy, which requires us to solve at worst $\Sigma_{i \in N} |A_i|$ linear programs
- Each step removes one pure strategy for one player, so there can be at most $\Sigma_{i \in N}(|A_i|-1)$ steps

Iterated dominance

- Some forms of dominance can produce different reduced games
- Some computational questions
 - (Strategy elimination) Does there exist some elimination path under which the strategy s; is eliminated?
 - (Reduction identity) Given action subsets $A_i' \subseteq A_i$ for each player i, does there exist a maximally reduced game where each player i has the actions A_i' ?
 - (Reduction size) Given constants k_i for each player i, does there exist a maximally reduced game where each player i has exactly k_i actions?

Iterated dominance

. Theorem

- (i) For iterated strict dominance, the strategy elimination, reduction identity, uniqueness and reduction size problems are in *P*. (ii) For iterated weak dominance, these problems are *NP-complete*
 - (i) it follows from the fact that iterated strict dominance always arrives at the same set of strategies regardless of elimination order
 - (ii) Gilboa et al. [1989] and Conitzer and Sandholm [2005]

maximize:
$$\sum_{a \in A} p(a) \sum_{i \in N} u_i(a)$$



 $a \in A$

probability of suggesting strategy profile a

$$\sum_{a \in A \mid a_i \in a} p(a)u_i(a) \ge \sum_{a \in A \mid a_i \in a} p(a)u_i(a'_i, a_{-i}) \quad \forall i \in N, \, \forall a_i, a'_i \in A_i$$

$$p(a) \ge 0 \qquad \qquad \forall a \in A$$

$$\sum p(a) = 1$$

maximize: $\sum_{a \in A} p(a) \sum_{i \in N} u_i(a)$



$$\sum_{a \in A \mid a_i \in a} [u_i(a) - u_i(a_i', a_{-i})] p(a) \ge \mathbf{p}$$



$$p(a) \ge 0$$
$$\sum_{a \in A} p(a) = 1$$

$$\forall a \in A$$

• max [6p(D,D) + 6p(D,H) + 6p(H,D) + 0p(H,H)]

. s.t.

•
$$p(D,D)(3-5) + p(D,H)(1-0) ≥ 0$$

•	p(H,D)	(5-3)	+ p	(H,H))(0-1)	≥ 0
						7

	p(D	,D)	(3-5)	+p((H,D)	(1-0)	$) \geq 0$
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•	p(<mark>D,H</mark>)(5-3)) + <i>p</i> ((H,H)	(0-1)	≥ 0
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•
$$p(D,D) + p(D,H) + p(H,D) + p(H,H) = 1$$

• p(D,D), p(D,H), p(H,D), p(H,H) ≥ 0

	D	Н
D	3,3	1,5
Н	5,1	0,0

•
$$max [6p(D,D) + 6p(D,H) + 6p(H,D)]$$

. s.t.

.
$$-2 p(D,D) + p(D,H) ≥ 0$$

• 2 $p(H,D)$ - $p(H,H)$ ≥ 0	•	2 p	(H,D)) - p	(H,H	$) \geq 0$
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. $-2 p(D,D) + p(H,D) ≥ 0$	2	2 01	D.	D) +	D	H	.D) ≥	0
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•	2	D	(D.	H	_	D	H	H) ≥	0
				/				,		

•
$$p(D,D) + p(D,H) + p(H,D) + p(H,H) = 1$$

• p(D,D), p(D,H), p(H,D), p(H,H) ≥ 0

	D	Н
D	3,3	1,5
Н	5,1	0,0

•
$$min - [6p(D,D) + 6p(D,H) + 6p(H,D)]$$

. s.t.

.
$$2 p(D,D) - p(D,H) ≤ 0$$

•	-2	p	H,	D) +	p	(H,	H_{j}) ≤	0	1
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•	2	D	(D	D) -	D	H	D) ≤	0
							,			

2	? p(D,H	+p	(H,H)	≤ 0
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•	p(D,D) +	p(D,H) +	p(H,D)	+ p(H,H) = 1
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• p(D,D), p(D,H), p(H,D), p(H,H) ≥ 0

	D	Н
D	3,3	1,5
Н	5,1	0,0

	D	Н
D	3,3	1,5
Н	5,1	0,0

- . min [6p(D,D) + 6p(D,H) + 6p(H,D)]
- . s.t.
- . 2 p(D,D) p(D,H) ≤ 0
- . -2 p(H,D) + p(H,H) ≤ 0
- $2 p(D,D) p(H,D) \le 0$
- . $-2 p(D,H) + p(H,H) \le 0$
- p(D,D) + p(D,H) + p(H,D) + p(H,H) = 1
- p(D,D), p(D,H), p(H,D), p(H,H) ≥ 0

Matlab code:

```
f = [-6 -6 -6 0];
A = \begin{bmatrix} 2 & -1 & 0 & 0 & ; 0 & 0 & -2 & 1 & ; & 2 & 0 & -1 & 0 & ; \end{cases}
0 - 2 0 1 1;
b = [0 \ 0 \ 0 \ 0];
Aeq = [1 \ 1 \ 1 \ 1];
beq = 1;
1b = [0 \ 0 \ 0 \ 0];
z = linprog(f, A, b, Aeg, beg, lb)
z =
      0.1220
      0.4390
      0.4390
      0.0000
```

. Theorem

The following problems are in the complexity class
 P when applied to correlated equilibria: uniqueness,
 Pareto optimal, guaranteed payoff, subset inclusion,
 and subset containment

. Problem:

- Interpersonal comparison of utility
 - Depends upon the ability to aggregate, or sum up, individual preferences into a combined social welfare function
- In the previous example, if you make cell (H,D) = (1000, 1), the correlated equilibrium will give probability 1 to this state

	D	Н
D	3,3	1,6
Н	5,1	0,0

- . min [6p(D,D) + 7p(D,H) + 6p(H,D)]
- . s.t.
- $2 p(D,D) p(D,H) \le 0$
- $-2 p(H,D) + p(H,H) \le 0$
- $3 p(D,D) p(H,D) \le 0$
- -3 p(D,H) + p(H,H) ≤ 0
- p(D,D) + p(D,H) + p(H,D) + p(H,H) = 1
- p(D,D), p(D,H), p(H,D), p(H,H) ≥ 0

Python code:

```
f = [-6, -7, -6, 0]
A = [[2, -1, 0, 0], [0, 0, -2, 1],
[3, 0, -1, 0], [0, -3, 0, 1]]
b = [0, 0, 0, 0]
Aeq = [[1, 1, 1, 1]]
bea = [1]
x0 bounds = (0, None)
x1 \text{ bounds} = (0, \text{None})
x2 bounds = (0, None)
x3 bounds = (0, None)
res = linprog(f, A ub=A, b ub=b,
bounds=(x0 bounds, x1 bounds,
x2 bounds, x3 bounds), A eq=Aeq,
b eq=beq)
x: array([0., 1., 0., 0.])
fun: -7.0
```

	D	Н
D	3,3	1,6
Н	5,1	0,0

- . min [6p(D,D) + 7p(D,H) + 6p(H,D)]
- . s.t.
- $2 p(D,D) p(D,H) \le 0$
- $-2 p(H,D) + p(H,H) \le 0$
- $3 p(D,D) p(H,D) \le 0$
- -3 p(D,H) + p(H,H) ≤ 0
- p(D,D) + p(D,H) + p(H,D) + p(H,H) = 1
- . p(D,D), p(D,H), p(H,D), p(H,H) ≥ 0
- p(D,H) p(H,D) = 0

Python code:

```
f = [-6, -7, -6, 0]
A = [[2, -1, 0, 0], [0, 0, -2, 1],
[3, 0, -1, 0], [0, -3, 0, 1]
b = [0, 0, 0, 0]
Aeq = [[1, 1, 1, 1], [0, 1, -1, 0]]
beg = [1, 0]
x0 bounds = (0, None)
x1 \text{ bounds} = (0, \text{None})
x2 bounds = (0, None)
x3 bounds = (0, None)
res = linprog(f, A ub=A, b ub=b,
bounds=(x0 bounds, x1 bounds,
x2 bounds, x3 bounds), A eq=Aeq,
b eq=beq)
x: array([0., 0.5, 0.5, 0.])
fun: -6.5
```

- Q: Why can we express the definition of a correlated equilibrium as a linear constraint, while we cannot do the same with the definition of a Nash equilibrium, even though both definitions are quite similar?
- A: The difference is that a correlated equilibrium involves a single randomization over action profiles, while in a Nash equilibrium agents randomize separately

Software

- GAMBIT [McKelvey et al., 2006] (http://www.gambit-project.org/) is a library of game-theoretic algorithms for finite normal-form and extensive-form games
- GAMUT [Nudelman et al., 2004]
 (http://gamut.stanford.edu) is a suite of game generators designed for testing game-theoretic algorithms
- NASHPY [Knight. 2017]
 (https://nashpy.readthedocs.io/en/stable/) is a Python library used for the computation of equilibria in 2 player strategic form games.