Computing Solution Concepts – Intro



Solution Concepts

- In single agent settings, there is the notion of *optimal strategy*
- In multiagent setting, situation is more complex. Best strategy depends on the strategies of other agents
- Solution concepts certain subsets of outcomes that are interesting
- Pareto optimality, Nash equilibrium



Computational Concerns

- How to compute a Nash equilibrium?
- Examples we've seen had 2 players, each with 2 actions
- Complexity depends on class of games considered
- 2 player zero-sum games
- 2 player general-sum games
- n players, n > 2
- Other solution concepts



Computing Nash Equilibrium in 2-player, zero-sum games



Setup

• Consider 2-player, zero-sum game:

$$G = (\{1, 2\}, A_1 \times A_2, (u_1, u_2))$$

- Let U_i^* be the equilibrium value of player I
- Recall in a N.E., player 1's value is equal to his maxmin value

Definition 3.4.1 (Maxmin) The maxmin strategy for player i is $\arg\max_{s_i} \min_{s_{-i}} u_i(s_i, s_{-i})$, and the maxmin value for player i is $\max_{s_i} \min_{s_{-i}} u_i(s_i, s_{-i})$.

Use this fact to write an LP



Linear Program

minimize
$$U_1^*$$
 (4.1) subject to $\sum_{k \in A_2} u_1(a_1^j, a_2^k) \cdot s_2^k \leq U_1^*$ $\forall j \in A_1$ (4.2)
$$\sum_{k \in A_2} s_2^k = 1$$
 (4.3)
$$s_2^k \geq 0 \qquad \forall k \in A_2$$
 (4.4)

• Variables: U_i^*, s_2^k



Dual Program

maximize
$$U_1^*$$
 (4.5)

subject to
$$\sum_{j \in A_1} u_1(a_1^j, a_2^k) \cdot s_1^j \ge U_1^*$$
 $\forall k \in A_2$ (4.6)

$$\sum_{j \in A_1} s_1^j = 1 \tag{4.7}$$

$$s_1^j \ge 0 \qquad \forall j \in A_1 \qquad (4.8)$$



Reformulation with Slack Variables

minimize
$$U_1^*$$
 (4.9) subject to $\sum_{k \in A_2} u_1(a_1^j, a_2^k) \cdot s_2^k + r_1^j = U_1^*$ $\forall j \in A_1$ (4.10)
$$\sum_{k \in A_2} s_2^k = 1$$
 (4.11)
$$s_2^k \ge 0 \qquad \forall k \in A_2 \qquad (4.12)$$

$$r_1^j \ge 0 \qquad \forall j \in A_1 \qquad (4.13)$$



Example: Computing Nash Equilibrium in Mixed Pennies



Game Setup: Matching Pennies

```
Payoffs to P1:
U1=[1 -1,
-1 1 ], U2=-U1
```

- If coins match → P1 wins (+1), P2 loses
 (-1)
- If coins differ \rightarrow P2 wins (+1), P1 loses (-1)



Mixed Strategies

Let:

- P1 plays H with probability p, T with probability 1–p
- P2 plays H with probability q, T with probability 1–q
- We'll solve for (p,q) that form a Nash equilibrium.



Indifference Condition, P1

Expected payoff to P1 if they play H:

•
$$u_1(H, q) = 1 \cdot q + (-1) \cdot (1-q) = 2q - 1$$

Expected payoff if they play T:

- $u_1(T, q) = (-1)\cdot q + 1\cdot (1-q) = 1 2q$ Indifference requirement:
- $u_1(H, q) = u_1(T, q)$

•
$$\Rightarrow$$
 2q - 1 = 1 - 2q \Rightarrow q = 1/2



Indifference Condition, P2

By symmetry, if P1 plays H with probability p:

•
$$u_2(H, p) = 1 - 2p$$

•
$$u_2(T, p) = 2p - 1$$

- Indifference:
- 1 2p = 2p 1 ⇒ p = 1/2
 So P1 must also mix equally.



Equilibrium Summary

• Nash Equilibrium: p = 1/2, q = 1/2

- Each player randomizes equally between H and T.
- Expected payoff = 0 to both players.
 Interpretation:
 - Matching Pennies illustrates the need for mixed strategies.
 - Randomization prevents exploitation.



Maxmin LP for Matching Pennies

- We can solve for Player 1's equilibrium strategy via a linear program.
- Let variables: p_H, p_T ≥ 0 (probabilities for Heads, Tails). v = guaranteed payoff (value of the game)
- Constraints (for each column j of U₁):
- ∑_i p_i · U₁[i,j] ≥ v
 (ensures expected payoff ≥ v against each pure strategy of P2)

Maxmin LP for Matching Pennies

- Constraints (for each column j of U₁):
- $\sum_{i} p_i \cdot U_1[i,j] \ge v$

• Also: p_H + p_T = 1

- Objective: maximize v
- For Matching Pennies, this yields: p_H = 1/2
 p T = 1/2, v = 0

Complexity of Computing a Nash Equilibrium



Computing Nash Equilibria

- 2-player, zero-sum in poly
- 2-player, general sum?
- Cannot be formulated as LP, players not diametrically opposed
- No known reduction from NP-complete problem
- Stumbling block with NP: decision problems. But we always know a NE exists

The PPAD class

- So current knowledge about NE computation is in relation to PPAD class
- PPAD "Polynomial Parity Argument, Directed Version"
- Family of directed graphs G(n)
- Computational task is finding a source or sink node



The family G(n)

- Defined on set N of 2^n nodes, but described in polynomial space
- Just encode set of edges
- *Parent, Child* functions from *N* to *N*: encoded as arithmetic circuits with sizes poly. in *n*
- An edge exists from node j to k iff. Parent(k) = j and Child(j) = k
- There must exist one distinguished node o with exactly zero parents
- Find sink or source other than o in a given grap

Complexity

Theorem 4.2.1 The problem of finding a sample Nash equilibrium of a general-sum finite game with two or more players is PPAD-complete.

- CNE is in PPAD and any other problem in PPAD can be reduced to it
- CNE is in PPAD reduction proceeds quite directly from the proof in the textbook that every game has a NE that uses Sperner's lemma
- Harder part is showing CNE is PPAD-hard. Result was proven in 2005, a culmination of intermediate results achieved over a decade



Complexity

Theorem 4.2.1 The problem of finding a sample Nash equilibrium of a general-sum finite game with two or more players is PPAD-complete.

- Not known if P=PPAD. Generally believed not
- It is known that finding an NE in 2 player games is no easier than finding an NE in n player games
- Finding a NE is no easier than finding an arbitrary Brouwer fixed point



LCP Formulation of 2player NE



Computing Nash Equilibria

- 2-player, zero-sum in poly
- 2-player, general sum?
- Cannot be formulated as LP, players not diametrically opposed
- The LCP formulation



The LCP Formulation

$$\sum_{k \in A_2} u_1(a_1^j, a_2^k) \cdot s_2^k + r_1^j = U_1^* \qquad \forall j \in A_1 \qquad (4.14)$$

$$\sum_{j \in A_1} u_2(a_1^j, a_2^k) \cdot s_1^j + r_2^k = U_2^* \qquad \forall k \in A_2 \qquad (4.15)$$

$$\sum_{j \in A_1} s_1^j = 1, \quad \sum_{k \in A_2} s_2^k = 1 \qquad (4.16)$$

$$s_1^j \ge 0, \quad s_2^k \ge 0 \qquad \forall j \in A_1, \forall k \in A_2 \qquad (4.17)$$

$$r_1^j \ge 0, \quad r_2^k \ge 0 \qquad \forall j \in A_1, \forall k \in A_2 \qquad (4.18)$$

$$r_1^j \cdot s_1^j = 0, \quad r_2^k \cdot s_2^k = 0 \qquad \forall j \in A_1, \forall k \in A_2 \qquad (4.19)$$



The Lemke-Howson Algorithm



Lemke-Howson Algorithm

- 2-player, general sum games
- Algorithm is for solving linear complementarity programs
- Searches vertices of strategy simplices (like the simplex algorithm for solving LPs)



0,1	6,0
2,0	5, 2
3,4	3,3

Figure 4.1: A game for the exposition of the Lemke–Howson algorithm.



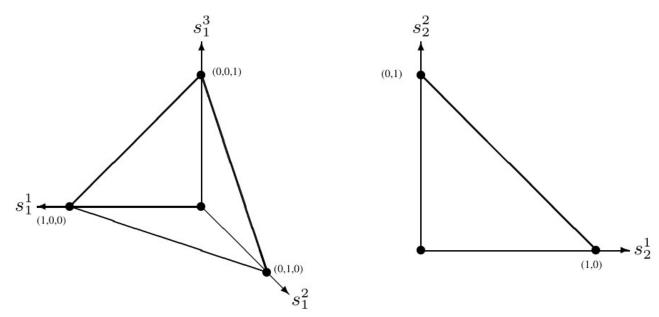


Figure 4.2: Strategy spaces for player 1 (left) and player 2 (right) in the game from Figure 4.1.



Our next step in defining the Lemke–Howson algorithm is to define a labeling on the strategies. Every possible mixed strategy s_i is given a set of labels $L(s_i^j) \subseteq A_1 \cup A_2$ drawn from the set of available actions for both players. Denoting a given player as i and the other player as -i, mixed strategy s_i for player i is labeled as follows:

- with each of player i's actions a_i^j that is *not* in the support of s_i ; and
- with each of player -i's actions a_{-i}^{j} that is a best response by player -i to s_{i} .



Our next step in defining the Lemke–Howson algorithm is to define a labeling on the strategies. Every possible mixed strategy s_i is given a set of labels $L(s_i^j) \subseteq A_1 \cup A_2$ drawn from the set of available actions for both players. Denoting a given player as i and the other player as -i, mixed strategy s_i for player i is labeled as follows:

- with each of player i's actions a_i^j that is *not* in the support of s_i ; and
- with each of player -i's actions a_{-i}^j that is a best response by player -i to s_i .
- A strategy profile is a Nash equilibrium iff. it is completely labeled

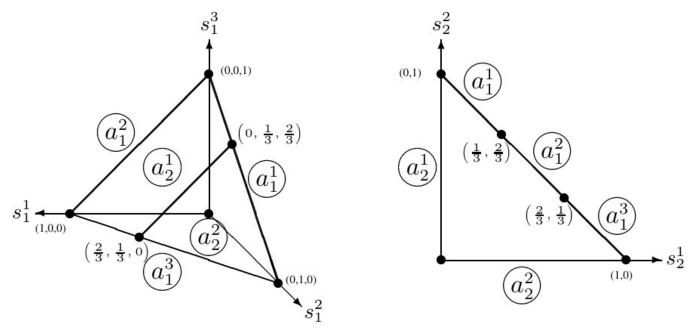
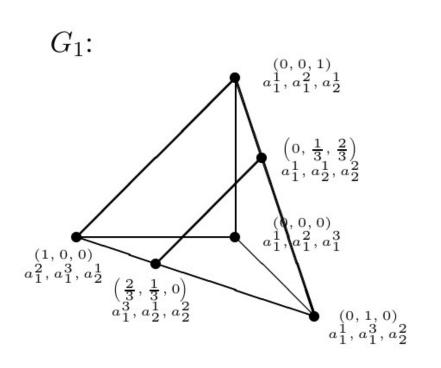
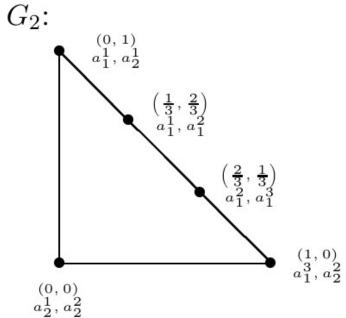


Figure 4.3: Labeled strategy spaces for player 1 (left) and player 2 (right) in the game from Figure 4.1.







Lemke-Howson – Properties

- Guaranteed to find a NE
- Alternative proof of the existence of NE
- Path after initial move is unique. Only nondeterminism is in first move
- All paths from the starting point to a NE can be exponential (algorithm is provably exponential)
- No way to assess how close we are to a NE