

# Game Theory 13-02

## Review: Games of Incomplete Information

BCSE Game Theory

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# Part 1: Static Games of Incomplete Information

## Auctions

# Review: Bayesian Nash Equilibrium

- ▶ **Incomplete Information:** Players do not know opponents' payoff functions (types).
- ▶ **Example:** Auctions (values are private).
- ▶ **Strategy:** A function  $s_i(v_i)$  mapping type to action.
- ▶ **Bayesian Nash Equilibrium (BNE):** Each type  $v_i$  maximizes expected utility given the strategies of others.

# Exercise 1: First-Price Auction (3 Bidders)

## Problem

- ▶ 3 Bidders ( $N = 3$ ).
- ▶ Private values  $v_i$  independently distributed uniform on  $[0, 1]$ .
- ▶ **First-Price Sealed-Bid:** Highest bidder wins and pays their bid.
- ▶ Guess a linear strategy:  $b_i(v_i) = k \cdot v_i$ .

## Task:

1. Determine probability of winning for Bidder 1 with bid  $b$ , assuming Bidders 2 and 3 follow  $b(v) = kv$ .
2. Write down Bidder 1's Expected Payoff function.
3. Solve for the optimal bid  $b^*$  and find the equilibrium constant  $k$ .

## Ex 1: Solution (Probability & Payoff)

**1. Probability of Winning:** Win if  $b_1 > B_j = kv_j \Rightarrow v_j < b_1/k$  for all  $j \neq 1$ . Since  $v_j \sim U[0, 1]$ ,  $\Pr(v_j < x) = x$ .

$$P(\text{Win}) = \left(\frac{b_1}{k}\right)^{N-1}$$

**2. Expected Payoff:**

$$E[\pi_1(b_1, v_1)] = (v_1 - b_1) \cdot \left(\frac{b_1}{k}\right)^{N-1}$$

# Discussion: Bid Shading

## Intuition: Why not bid $v_i$ ?

In a First-Price Auction, your profit is  $v_i - b_i$ .

- ▶ If you bid  $b_i = v_i$ , your profit is **zero** even if you win.
- ▶ To make money, you must bid **below** your value ( $b_i < v_i$ ).
- ▶ **Trade-off:**
  - ▶ Lower bid  $\rightarrow$  Higher Profit Margin (if you win).
  - ▶ Lower bid  $\rightarrow$  Lower Probability of Winning.
- ▶ The equilibrium bid  $b^* = \frac{N-1}{N}v$  balances this trade-off optimally.

## Ex 1: Solution (Equilibrium)

**3. Optimization:** Maximize w.r.t  $b_1$ :

$$\frac{\partial E}{\partial b_1} = -\left(\frac{b_1}{k}\right)^{N-1} + (v_1 - b_1)(N-1)\left(\frac{b_1}{k}\right)^{N-2} \frac{1}{k} = 0$$

Divide by  $(b_1/k)^{N-2}$  and multiply by  $k$ :

$$-b_1 + (v_1 - b_1)(N-1) = 0 \implies b_1 N = v_1(N-1) \implies b^* = \frac{N-1}{N} v_1$$

Comparing to guess  $b(v) = kv$ , we see  $k = \frac{2}{3}$ .

### Result

In an FPSB auction with  $N$  bidders:  $b^*(v) = \frac{N-1}{N}v$ . For  $N = 3$ , bid  $\frac{2}{3}$  of value.

## Part 2: Dynamic Games of Incomplete Information

### Signaling Equilibrium Selection



# Review: Perfect Bayesian Equilibrium (PBE)

In dynamic games of incomplete information, purely strategy-based NE is insufficient. We need to track **Beliefs**.

- ▶ **Belief System  $\mu$** : At every information set, players assign probabilities to nodes (types).
- ▶ **Sequential Rationality**: Strategies are optimal given beliefs  $\mu$ .
- ▶ **Consistency (Bayes' Rule)**: On the equilibrium path, beliefs are derived from strategies using Bayes' Rule.

**PBE** = Strategy Profile + Belief System satisfying these conditions.

## Review: Refining Equilibria (Intuitive Criterion)

PBE places no restriction on **off-equilibrium beliefs**, allowing “unreasonable” equilibria (e.g., pooling sustained by believing any deviator is the “worst” type).

**Intuitive Criterion** (Cho & Kreps):

- ▶ If a deviation is **dominated** for type  $L$  (payoff worse than equilibrium payoff no matter the belief) but **possibly advantageous** for type  $H$ , then...
- ▶ Receivers should NOT believe the deviator is  $L$ . They should believe it is  $H$ .
- ▶ This destroys equilibria relying on “if deviation, believe  $L$ ”.

## Exercise 2: Education Signaling (Spence Model)

### Problem

#### Context:

- ▶ **Worker:** High ( $H$ ) or Low ( $L$ ) Ability. Prior  $\Pr(H) = 0.5$ .
- ▶ **Education:** Years  $e \geq 0$ . Cost:  $c_H = 1$  (High),  $c_L = 2$  (Low).
- ▶ **Employer:** Observes  $e$ , offers wage  $w(e)$  based on expected productivity.
- ▶ **Productivity:**  $\theta_H = 2$ ,  $\theta_L = 1$ .
- ▶ **Payoff:** Worker gets  $w - c_i \cdot e$ . Employer gets  $\theta_i - w$ .

#### Questions:

1. Find Pooling equilibria (both choose  $e = 0$ ).
2. Find Separating equilibria ( $H$  chooses  $e^*$ ,  $L$  chooses 0).
3. Apply Intuitive Criterion to refine equilibria.

## Ex 2: Pooling Equilibrium ( $e = 0$ )

**Candidate:** Both types choose  $e = 0$ .

- ▶ **Employer's Belief:**  $\mu(H|e = 0) = 0.5$  (prior).
- ▶ **Wage:**  $w(0) = E[\theta] = 0.5 \times 2 + 0.5 \times 1 = 1.5$ .
- ▶ **Payoffs:**  $H$  gets  $1.5 - 0 = 1.5$ .  $L$  gets  $1.5 - 0 = 1.5$ .

**Deviation Check:** Would  $H$  deviate to  $e > 0$ ?

- ▶ If employer believes deviator is  $L$  (worst case):  $w(e) = 1$ .
- ▶  $H$ 's payoff from deviation:  $1 - 1 \cdot e < 1.5$  for all  $e > 0.5$ .
- ▶ So  $H$  won't deviate if off-equilibrium belief is pessimistic.

**Result:** Pooling at  $e = 0$  is a PBE (with pessimistic off-equilibrium beliefs).

## Ex 2: Separating Equilibrium

**Candidate:**  $H$  chooses  $e^*$ ,  $L$  chooses 0.

- ▶ **Wages:**  $w(e^*) = 2$  (employer knows it's  $H$ ),  $w(0) = 1$  (employer knows it's  $L$ ).
- ▶ **Payoffs:**  $H$  gets  $2 - 1 \cdot e^* = 2 - e^*$ .  $L$  gets  $1 - 0 = 1$ .

**Incentive Constraints:**

1.  $H$  prefers  $e^*$  over 0:  $2 - e^* \geq 1 \implies e^* \leq 1$ .
2.  $L$  prefers 0 over  $e^*$ :  $1 \geq 2 - 2e^* \implies e^* \geq 0.5$ .

**Result:** Any  $e^* \in [0.5, 1]$  supports a separating PBE.

# Discussion: Why Multiple Equilibria?

## Intuition: Education as a Signal

- ▶ **Separating** ( $e^* \in [0.5, 1]$ ): Education is costly but signals ability. High-ability workers can afford it (lower cost), low-ability cannot. The exact level  $e^*$  is arbitrary as long as it's "expensive enough" to deter mimicking.
- ▶ **Pooling** ( $e = 0$ ): If employers are pessimistic about deviators (believe  $e > 0$  means Low ability), then High types won't signal. Everyone pools at  $e = 0$  and gets average wage.

## Ex 2: Intuitive Criterion Application

### Intuitive Criterion (Cho & Kreps):

- ▶ If deviation is **equilibrium-dominated** for type  $L$  (worse than equilibrium payoff under any belief),
- ▶ but **potentially beneficial** for type  $H$  (better under some belief),
- ▶ then receiver should believe deviator is  $H$ , not  $L$ .

**Test Pooling at  $e = 0$ :** Can  $H$  profitably deviate to  $e \in [0.5, 1]$ ?

Consider  $e = 0.6$ :

- ▶ **For  $L$ :** Best case (believed  $H$ ):  $2 - 2(0.6) = 0.8 < 1$  (pooling).
  - ▶ Deviation is **equilibrium-dominated** for  $L$ .
- ▶ **For  $H$ :** If believed  $H$ :  $2 - 0.6 = 1.4 < 1.5$  (pooling).
  - ▶ Not beneficial for  $H$  either. Try smaller  $e$ .

Try  $e = 0.4$ : Both types would deviate! Pooling is unstable.

**Conclusion:** Pooling fails IC. Separating ( $e^* \in [0.5, 1]$ ) survives.

## Ex 2: Key Insights

### Summary

- ▶ **Multiple PBE:** Pooling and Separating both exist.
- ▶ **Intuitive Criterion:** Eliminates Pooling.
  - ▶ Reasoning: "Why would a Low-ability worker get expensive education?"
  - ▶ If we see deviation to  $e \in [0.5, 1]$ , it must be High ability.
- ▶ **Least-Cost Separating:**  $e^* = 0.5$  minimizes waste (education has no productive value here, it's pure signaling).
- ▶ **Welfare:** Separating is inefficient (education is costly but doesn't increase productivity), but it's the only "reasonable" equilibrium.



# Why Game Theory for Computer Science? (1/2)

## Course Reflection

Game Theory provides essential tools for computational systems:

### 1. Algorithm Design & Mechanism Design

- ▶ Auctions (Google Ads, eBay), Matching Markets (Residency, School Choice)
- ▶ Incentive-compatible protocols (Blockchain, Voting Systems)

### 2. Multi-Agent Systems & AI

- ▶ Nash Equilibrium in multi-agent learning (AlphaGo, Poker AI)
- ▶ Adversarial ML: Attacker-Defender games (Security, Robustness)

# Why Game Theory for Computer Science? (2/2)

## 3. Network Economics & Platform Design

- ▶ Pricing strategies (Cloud services, SaaS)
- ▶ Network effects and competition (Social networks, Marketplaces)

## 4. Strategic Thinking

- ▶ Analyzing incentives, Understanding user behavior