## Algorithmic game theory

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### 2nd lecture

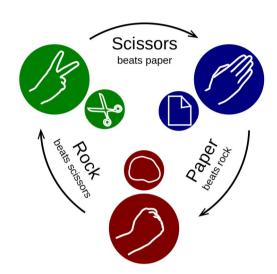
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## Proof of Nash's Theorem

## Nash equilibria in normal-form games

	Rock	Paper	Scissors
Rock	(0,0)	(-1,1)	( <mark>1,-1</mark> )
Paper	<b>(1,-1)</b>	(0,0)	(-1,1)
Scissors	(-1,1)	<b>(1,-1)</b>	(0,0)



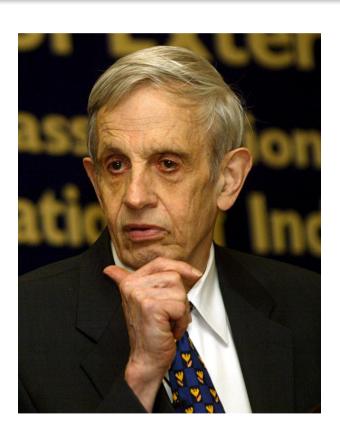
Sources: https://en.wikipedia.org/

- We introduced perhaps the most influential solution concept, which captures a notion of stability.
- The best response of player i to a strategy profile  $s_{-i}$  is a mixed strategy  $s_i^*$  such that  $u_i(s_i^*; s_{-i}) \ge u_i(s_i'; s_{-i})$  for each  $s_i' \in S_i$ .
- For a normal-form game G = (P, A, u) of n players, a Nash equilibrium (NE) in G is a strategy profile  $(s_1, \ldots, s_n)$  such that  $s_i$  is a best response of player i to  $s_{-i}$  for every  $i \in P$ .
- Amazingly, every normal-form game has a Nash equilibrium.

#### Nash's Theorem

Nash's Theorem (Theorem 2.16)

Every normal-form game has a Nash equilibrium.



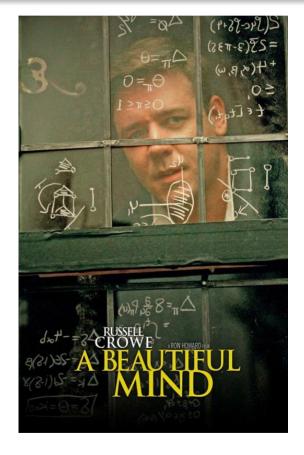


Figure: John Forbes Nash Jr. (1928–2015) and his depiction in the movie A Beautiful mind.

## Preparations for the proof of Nash's theorem

- The proof is essentially topological, as its main ingredient is a fixed-point theorem. We use a theorem due to Brouwer.
- For  $d \in \mathbb{N}$ , a subset X of  $\mathbb{R}^d$  is compact if X is closed and bounded.
- We say that a subset Y of  $\mathbb{R}^d$  is convex if every line segment containing two points from Y is fully contained in Y. Formally: for all x, y from Y,  $tx + (1 t)y \in Y$  for every  $t \in [0, 1]$ .
- For n affinely independent points  $x_1, \ldots, x_n \in \mathbb{R}^d$ , an (n-1)-simplex  $\Delta_n$  on  $x_1, \ldots, x_n$  is the set of convex combinations of the points  $x_1, \ldots, x_n$ . Each simplex is a compact convex set in  $\mathbb{R}^d$ .

#### Lemma (Lemma 2.18)

For  $n, d_1, \ldots, d_n \in \mathbb{N}$ , let  $K_1, \ldots, K_n$  be compact sets, each  $K_i$  lying in  $\mathbb{R}^{d_i}$ . Then,  $K_1 \times \cdots \times K_n$  is a compact set in  $\mathbb{R}^{d_1 + \cdots + d_n}$ .

#### Brouwer's Fixed Point Theorem

• For each  $d \in \mathbb{N}$ , let K be a non-empty compact convex set in  $\mathbb{R}^d$  and  $f: K \to K$  be a continuous mapping. Then, there exists a fixed point  $x_0 \in K$  for f, that is,  $f(x_0) = x_0$ .



Figure: L. E. J. Brouwer (1881–1966).

Source: https://arxiv.org/pdf/1612.06820.pdf

• https://www.youtube.com/watch?v=csInNn6pfT4&t=268s&ab\_

### Proof of Nash's Theorem I

- Let G = (P, A, u) be a normal-form game of n players. Recall that  $S_i$  is the set of mixed strategies of player i.
- We want to apply Brouwer's theorem, thus we need to find a suitable compact convex body K and a continuous mapping  $f: K \to K$  whose fixed points are NE in G.
- We start with K. Let  $K = S_1 \times \cdots \times S_n$  be the set of all mixed strategies.
  - $\circ$  We verify that K is compact and convex.
  - $\circ$  By definition, each  $S_i$  is, a simplex which is compact and convex.
  - By Lemma 2.18, the set  $K = S_1 \times \cdots \times S_n$  is compact.
  - For any strategy profiles  $s = (s_1, \ldots, s_n), s' = (s'_1, \ldots, s'_n) \in K$  and a number  $t \in [0, 1]$ , the point

$$ts + (1-t)s' = (ts_1 + (1-t)s'_1, \ldots, ts_n + (1-t)s'_n)$$

is also a mixed-strategy profile in K. Thus, K is convex.

#### Proof of Nash's Theorem II

- We now find the continuous mapping  $f: K \to K$ .
- For every player  $i \in P$  and action  $a_i \in A_i$ , we define a mapping  $\varphi_{i,a_i} \colon K \to \mathbb{R}$  by setting

$$\varphi_{i,a_i}(s) = \max\{0, u_i(a_i; s_{-i}) - u_i(s)\}.$$

- $\circ \varphi_{i,a_i}(s) > 0$  iff i can improve his payoff by using  $a_i$  instead of  $s_i$ .
- $\circ$  By the definition of  $u_i$ , this mapping is continuous.
- Given  $s \in K$ , we define a new "improved" strategy profile  $s' \in K$  as

$$s_i'(a_i) = \frac{s_i(a_i) + \varphi_{i,a_i}(s)}{\sum_{b_i \in A_i} (s_i(b_i) + \varphi_{i,b_i}(s))} = \frac{s_i(a_i) + \varphi_{i,a_i}(s)}{1 + \sum_{b_i \in A_i} \varphi_{i,b_i}(s)}.$$

- $\circ$  "Increase probability at actions that are better responses to  $s_{-i}$ ."
- $\circ$   $s' \in K$  as each  $s'_i(a_i)$  lies in [0,1] and  $\sum_{a_i \in A_i} s'_i(a_i) = 1$ .
- We then define f by setting f(s) = s'.

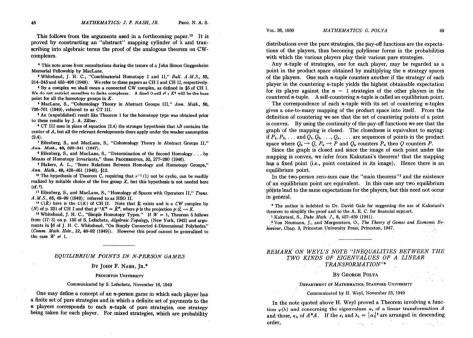
#### Proof of Nash's Theorem III

- Then, f is continuous, since the mappings  $\varphi_{i,a_i}$  are.
- It remains to show that fixed points of f are exactly NE in G. Then, Brouwer's theorem gives us a fixed point of f, which is NE in G.
- First, if s is NE, then all functions  $\varphi_{i,a_i}$  are constant zero functions and thus f(s) = s. So s is a fixed point for f.
- Second, assume that  $s = (s_1, \ldots, s_n) \in K$  is a fixed point for f.
  - For any player i, there is  $a'_i \in A_i$  with  $s_i(a_i) > 0$  such that  $u_i(a'_i; s_{-i}) \le u_i(s)$ . Otherwise,  $u_i(s) < \sum_{a_i \in A_i} s_i(a_i) u_i(a_i; s_{-i})$ , which is impossible by the linearity of the expected payoff.
  - $\circ$  Then,  $\varphi_{i,a_i'}(s)=0$  and we get  $s_i'(a_i')=rac{s_i(a_i')}{1+\sum_{b_i\in A_i}\varphi_{i,b_i}(s)}$ .
  - Since s is a fixed point, we get  $s_i'(a_i') = s_i(a_i')$  and, since  $s_i(a_i') > 0$ , the denominator in the denominator is 1. This means that  $\varphi_{i,b_i}(s) = 0$  for every  $b_i \in A_i$ . It follows that s is NE as

$$u_i(s_i'';s_{-i}) = \sum_{b_i \in A_i} s_i''(b_i)u_i(b_i;s_{-i}) \leq \sum_{b_i \in A_i} s_i''(b_i)u_i(s) = u_i(s).$$

#### Nash's Theorem: remarks

Two pages worth of Nobel prize!



Sources: J. F. Nash: Equilibrium points in *n*-person games (1950).

- Requires finite numbers of players and actions, both assumptions are necessary. (Consider 2-player game "who guesses larger number wins".)
- The proof is non-constructive. How to find NE efficiently?

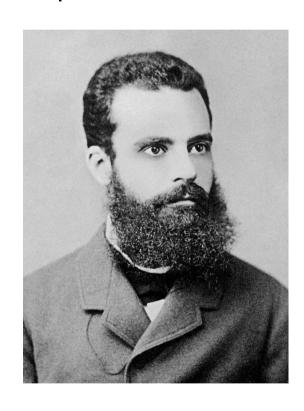
# Pareto optimality

## Pareto optimality

- A brief detour: another example of an interesting solution concept, other than NE.
- We want to capture "the best" state of a game. Might be difficult, consider the Battle of sexes.
- A strategy profile s in G Pareto dominates s', written  $s' \prec s$ , if, for every player i,  $u_i(s) \geq u_i(s')$ , and there exists a player j such that  $u_j(s) > u_j(s')$ .
  - $\circ$  The relation  $\prec$  is a partial ordering of the set S of all strategy profiles of G.
  - $\circ$  The outcomes of G that are considered best are the maximal elements of S in  $\prec$ .
- A strategy profile  $s \in S$  is Pareto optimal if there does not exist another strategy profile  $s' \in S$  that Pareto dominates s.
  - o In zero-sum games, all strategy profiles are Pareto-optimal.
  - Not all NE are Pareto-optimal (the NE in Prisoner's dilemma)

#### Vilfredo Pareto

• an Italian engineer, sociologist, economist, political scientist, and philosopher.



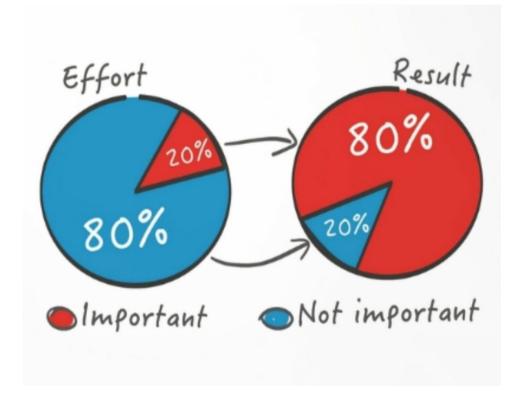


Figure: Vilfredo Pareto (1848–1923).

Sources: https://en.wikipedia.org and https://medium.com/

• Pareto principle: for many outcomes roughly 80% of consequences come from 20% of the causes.

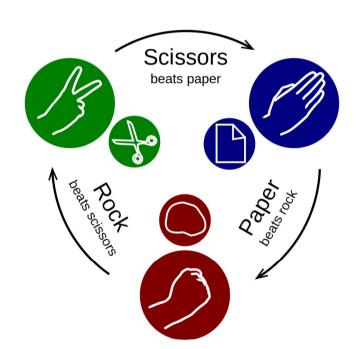
## Finding Nash equilibria

- We know that NE exist in every normal-form game (Nash's theorem).
- However, we do not have any algorithm for how to find them yet.
- We start with a simple class of 2-player games, so-called zero-sum games.
- We show that we can find NE efficiently in this case. In fact, we show that NE "solves" zero-sum games completely.
- Historically, zero-sum games were considered first in game game theory (by Morgenstern and Von Neumann in the 1940s).

## Zero-sum games

• Two-player games (P, A, u) where  $u_1(a) = -u_2(a)$  for every  $a \in A$ .

	Rock	Paper	Scissors
Rock	(0,0)	(-1,1)	( <mark>1,-1</mark> )
Paper	(1,-1)	(0,0)	(-1,1)
Scissors	$\left(-1,1\right)$	<b>(1,-1)</b>	(0,0)



Sources: https://en.wikipedia.org/

## Zero-sum games examples: chess



Source: https://edition.cnn.com/

## Zero-sum games examples: table tennis



Source: https://www.reddit.com/

## Zero-sum games examples: derivative trading



Source: https://www.linkedin.com/

## Zero-sum games examples: elections



Source: https://youtube.com/

## Zero-sum games examples: many more



Source: https://lhongtortai.com/collection/what-is-a-non-zero-sum-game

### Representing zero-sum games

- With zero-sum games, our notation simplifies.
- Let  $G = (P, A = A_1 \times A_2, u)$  be a zero-sum game. That is,  $u_1(a) + u_2(a) = 0$  for every  $a \in A$ .
- If  $A_1 = \{1, ..., m\}$  and  $A_2 = \{1, ..., n\}$ , then G can be represented with an  $m \times n$  payoff matrix M where  $M_{i,j} = u_1(i,j) = -u_2(i,j)$ .
- For a strategy profile  $(s_1, s_2)$ , we write  $x_i = s_1(i)$  and  $y_j = s_2(j)$ , representing  $(s_1, s_2)$  with mixed strategy vectors  $x = (x_1, \ldots, x_m)$  and  $y = (y_1, \ldots, y_n)$  that satisfy  $\sum_{i=1}^m x_i = 1$  and  $\sum_{j=1}^n y_j = 1$ .
- The expected payoff of player 1 then equals

$$u_1(s) = \sum_{a=(i,j)\in A} u_1(a)s_1(i)s_2(j) = \sum_{i=1}^m \sum_{j=1}^n M_{i,j}x_iy_j = \mathbf{x}^\top M\mathbf{y} = -u_2(s).$$

## Worst-case optimal strategies

- Thus, player's 2 best response to a strategy x of 1, is a vector  $y \in S_2$  that minimizes  $x^\top My$ . Player's 1 best response to a strategy y of 2 is  $x \in S_1$  that maximizes  $x^\top My$ .
- Let  $\beta(x) = \min_{y \in S_2} x^\top My$  be the best expected payoff of 2 against x. Let  $\alpha(y) = \max_{x \in S_1} x^\top My$  be the best expected payoff of 1 to y.
- A strategy profile (x, y) is then a NE if and only if it satisfies  $\beta(x) = x^{\top} M y = \alpha(y)$ .
- Assume player 1 expects player 2 to select a best response to every strategy x he can come up with. Player 1 then chooses a mixed strategy  $\overline{x}$  from  $S_1$  that maximizes his expected payoff under this, rather pessimistic, assumption.
- This worst-case optimal strategy for 1 satisfies  $\beta(\overline{x}) = \max_{x \in S_1} \beta(x)$ . The worst-case optimal strategy for 2 is a mixed strategy  $\overline{y} \in S_2$  that satisfies  $\alpha(\overline{y}) = \min_{y \in S_2} \alpha(y)$ .

## Worst-case optimal strategies and NE

• To achieve NE in a zero-sum game, both players must select their worst-case optimal strategies.

#### Lemma 2.20

- (a) For all  $x \in S_1$  and  $y \in S_2$ , we have  $\beta(x) \leq x^{\top} M y \leq \alpha(y)$ .
- (b) If a strategy profile  $(x^*, y^*)$  is NE, then both strategies  $x^*$  and  $y^*$  are worst-case optimal.
- (c) Any strategies  $x^* \in S_1$  and  $y^* \in S_2$  satisfying  $\beta(x^*) = \alpha(y^*)$  form NE  $(x^*, y^*)$ .
- (a) This follows immediately from the definitions of  $\beta$  and  $\alpha$ .
- (b) Part (a) implies that  $\beta(x) \leq \alpha(y^*)$  for every  $x \in S_1$ . Since  $(x^*, y^*)$  is NE, we have  $\beta(x^*) = \alpha(y^*)$  and thus  $\beta(x) \leq \beta(x^*)$  for every  $x \in S_1$ . Thus,  $x^*$  is a worst-case optimal for 1. Analogously for player 2.
- (c) If  $\beta(x^*) = \alpha(y^*)$ , then (a) implies  $\beta(x^*) = (x^*)^\top M y^* = \alpha(y^*)$ .

#### The Minimax Theorem

#### The Minimax Theorem (Theorem 2.21)

For every zero-sum game, worst-case optimal strategies for both players exist and can be efficiently computed. There is a number v such that, for any worst-case optimal strategies  $x^*$  and  $y^*$ , the strategy profile  $(x^*, y^*)$  is a Nash equilibrium and  $\beta(x^*) = (x^*)^\top M y^* = \alpha(y^*) = v$ .





Figure: John von Neumann (1903–1957) and Oskar Morgenstern (1902–1977).

#### The Minimax Theorem: remarks

- It was a starting point of game theory.
- Proved by Von Neumann in 1928 (predates Nash's Theorem).
- "As far as I can see, there could be no theory of games . . . without that theorem . . . I thought there was nothing worth publishing until the Minimax Theorem was proved." (Von Neumann).
- The Minimax theorem tells us everything about zero-sum games: there is NE and it can be found efficiently. Moreover, there is a unique value of the game  $v = (x^*)^\top M(y^*)$  of the payoff attained in any NE  $(x^*, y^*)$ .
- There are no secrets in zero-sum games: strategies known in advance change nothing, each player can choose a worst-case optimal strategy and get payoff  $\geq v$ . If the opponent chooses his worst-case optimal strategy, then his payoff is always  $\leq v$ .
- The name: the expanded equality  $\beta(x^*) = v = \alpha(y^*)$  becomes

$$\max_{x \in S_1} \min_{y \in S_2} x^\top M y = v = \min_{y \in S_2} \max_{x \in S_1} x^\top M y.$$

• Original proof uses Brouwer's theorem. We will use linear programming.



Source: https://czthomas.files.wordpress.com

# Thank you for your attention.