

Today

Nash's Theorem

Strategic Games.

N players.

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Vector valued payoff function: $u(s_1, \dots, s_n)$ (e.g., $\in \mathfrak{R}^N$).

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Player 2: { **D**efect, **C**ooperate }.

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Payoff:

	C	D
C	(3,3)	(0,5)
D	(5,0)	(1,1)

Famous because?

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Nash Equilibrium:

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Nash Equilibrium:

neither player has incentive to change strategy.

Proving Nash.

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What is x ?

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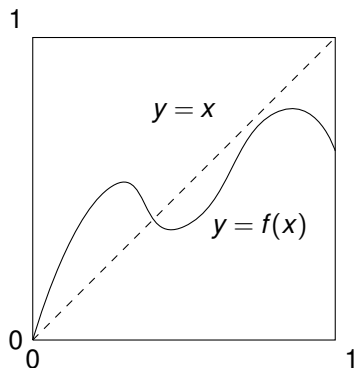
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Theorem: There is a Nash Equilibrium.

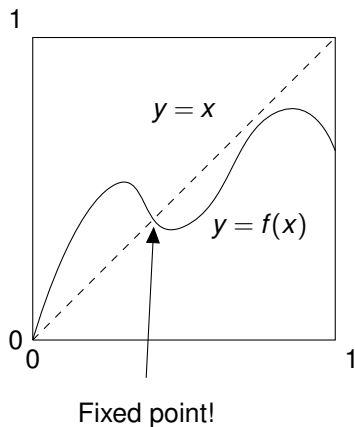
Brouwer Fixed Point Theorem.

Theorem: Every continuous function from a closed compact convex (c.c.c.) set to itself has a fixed point.



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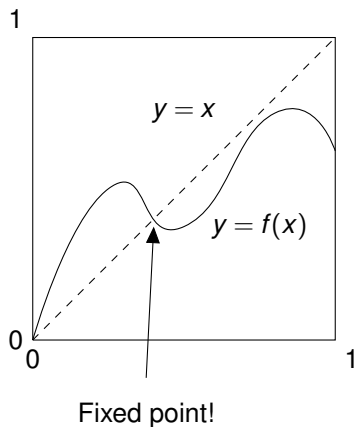
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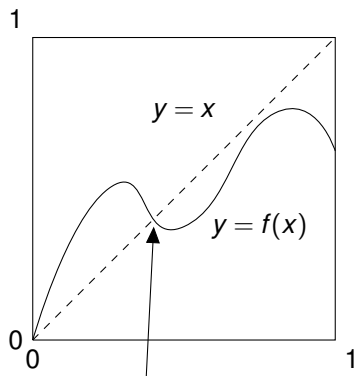
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What is the closed convex set here?
The unit square?

Brouwer Fixed Point Theorem.

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Fixed point!

What is the closed convex set here?

The unit square? Or the unit interval?

Brouwer implies Nash.

The set of mixed strategies x is closed convex set.

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with coefficients being payoffs in game matrix.

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Brouwer: Has a fixed point: $\phi(\hat{z}) = \hat{z}$.

Quick Almost Irrelevant Question.

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Technically: need to project back to feasible set.

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Distribution for each player.

Fixed Point is Nash.

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$$(1 - \alpha)u_i(\hat{z}_{-i}; \hat{y}_i) + \|\hat{z}_i - \hat{y}_i\|^2?$$

$$(1 - \alpha)u_i(\hat{z}) + \alpha(u_i(\hat{z}) + \delta) - \alpha^2\|\hat{z}_i - y_i\|^2$$

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⇒ that the limit point has $f(x)_i = x_i$ for all i .

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For any $n + 1$ -dimensional simplex and a subdivision into smaller simplices.

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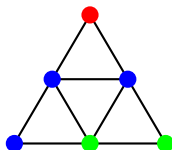
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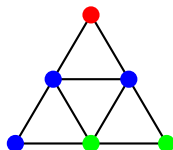
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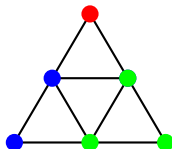
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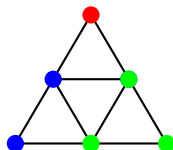
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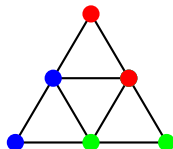
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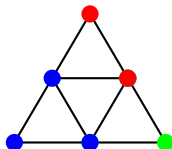
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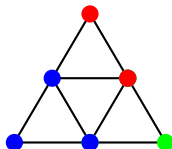
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By induction!

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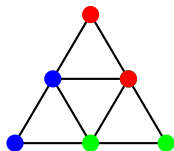
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Two dimensions.



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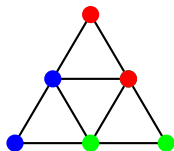
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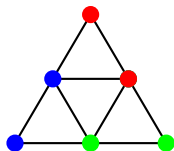
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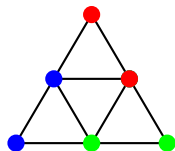
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Dual edge connects regions with r on right.



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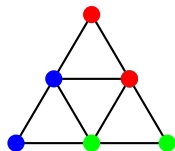
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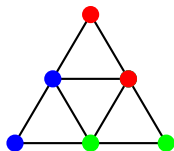
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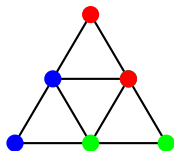
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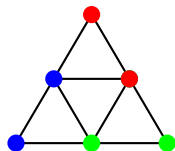


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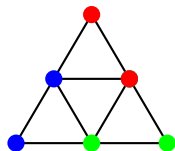
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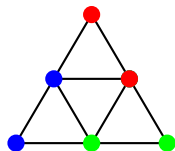
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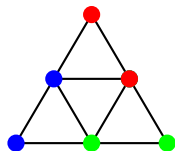
Must be (r, g, b) triangle.

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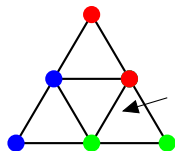
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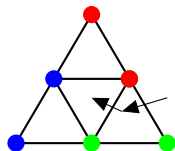
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Number of Rainbow Face to Cell Adjacencies:

$n+1$ -dimensional Sperner.

R : counts “rainbow” cells; has all $n+1$ colors.

Claim: there is an odd number of rainbow cells.

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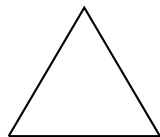
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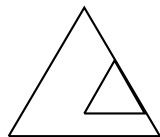
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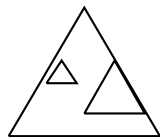
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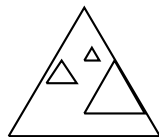
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Thus, $f(x^*)_i \leq x_i^*$ by continuity.

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Thus, $f(x^*)_i \leq x_i^*$ by continuity. Contradiction.

Rainbow Cells to Brower.

Rainbow cell, in \mathcal{S}_j with vertices $x_j^{j,1}, \dots, x_j^{j,n+1}$.

Each set of points $x_j^{j,k}$ is an infinite set in S .

→ This is a convergent subsequence → has limit point.

→ All have same limit point as they get closer together.

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NASH \rightarrow BROUWER \rightarrow SPERNER \rightarrow END OF LINE \in PPAD.

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Assign $d(e)$ for edge $e \in E$ with $\sum_e d(e) = 1$, to maximize $\sum_{i,j} d(i,j)$.

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Theorem: The value of the dual is $O(\frac{\log n}{\alpha})$.

Region Growing: Warmup.

$$\text{Length} \times \text{Width} = \text{Area}.$$

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Width \leq Area/Length at some point in region.

Lemma: If $\exists i, j, d(i, j) \geq \Delta$, then $\exists S$ with $E(S, \bar{S}) \leq \frac{\sum_e d(e)}{\Delta}$.

Length is $d(i, j)$ or Δ .

$d(i, x)$ is distance to x .

S_ℓ with $d(i, x) \leq \ell$ is a cut.

Think Dijkstra's or "Breadth First Search".

Technically fraction of edges inside S_ℓ .

Area is $\sum_e d(e)$.

Width is cut-size. Rate of growth at each $d(S_\ell)$.

Or with natural numbers:

Breadth first search tree of depth D .

Each level is a cut.

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Claim: Exists a cut, S , where $d(S_\ell) \geq D_i$ and $E(S, \bar{S}) \leq \frac{2D_i \log n}{\Delta}$

Proof: Interval i : has length $\frac{\Delta}{2^{\log n}}$ and area $\leq D_i$

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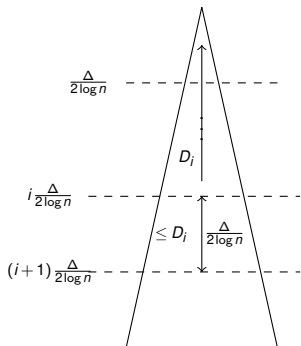
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Width $\frac{2D_i \log n}{\Delta}$.



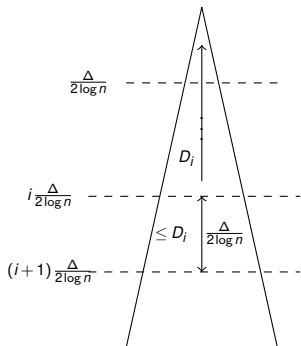
Again with a picture.



Claim:

Exists cut, S , such that $E(S, \bar{S}) \leq \frac{2D(S) \log n}{\Delta}$

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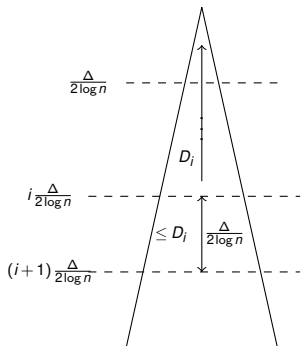


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Call $d(e)$ weight.

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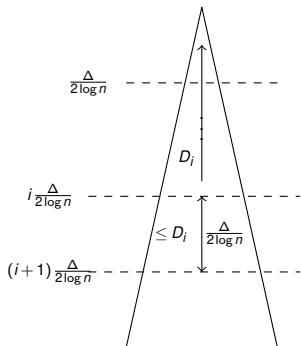
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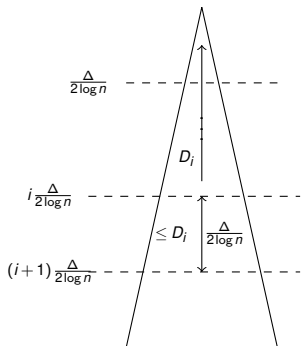
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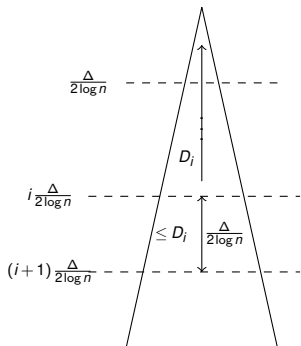
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Cut-size \leq Area/length $= \frac{D_i}{\Delta/2 \log n}$

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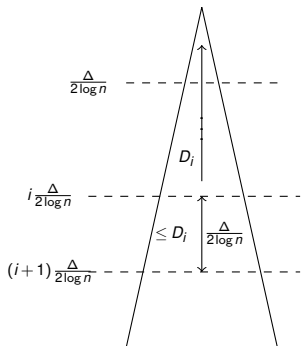
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Done.

Approximation Algorithm

Claim: $\frac{E(S, \bar{S})}{D(S)} \leq \frac{2 \log n}{\Delta}$.

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Scenario: $D(S) = \Omega(1)$ and $|S| = \Omega(n)$.

Finds cut of sparsity $O(\log n/\alpha)$.

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$O(\log n)$ approximation.

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$O(\log n)$ approximation.

Do some averaging to get real result.

A structure.

Low diameter decomposition.

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Procedure produces cluster of Diameter $O(\Delta)$.

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$O(\frac{\log n}{\Delta})$ fraction of edges in between.

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Repeat until every vertex in a cluster.

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$\tilde{O}(\cdot)$ hides log factors.