

# Networks Games:

the price of anarchy, stability, and learning

Éva Tardos  
Cornell University

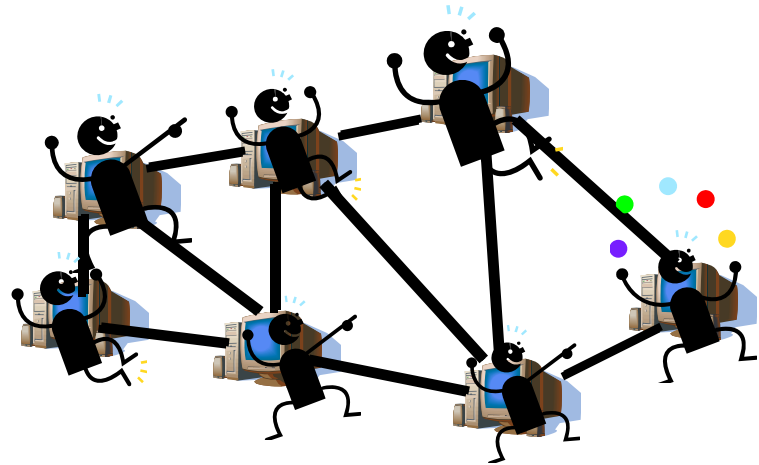
# Why care about Games?

Users with a multitude of diverse economic interests sharing a Network (**Internet**)

- browsers
- routers
- servers

Complex Networks in all aspects of life :

- social networks,
- financial networks,
- buyer-seller networks



Selfishness:

Parties deviate from their protocol if it is in their interest

Model Resulting Issues as **Games on Networks**

# Main question:

## Quality of Selfish outcome

Well known: Central design can lead to better outcome than selfishness.

e.g.: Prisoner Dilemma

Question: how much better?

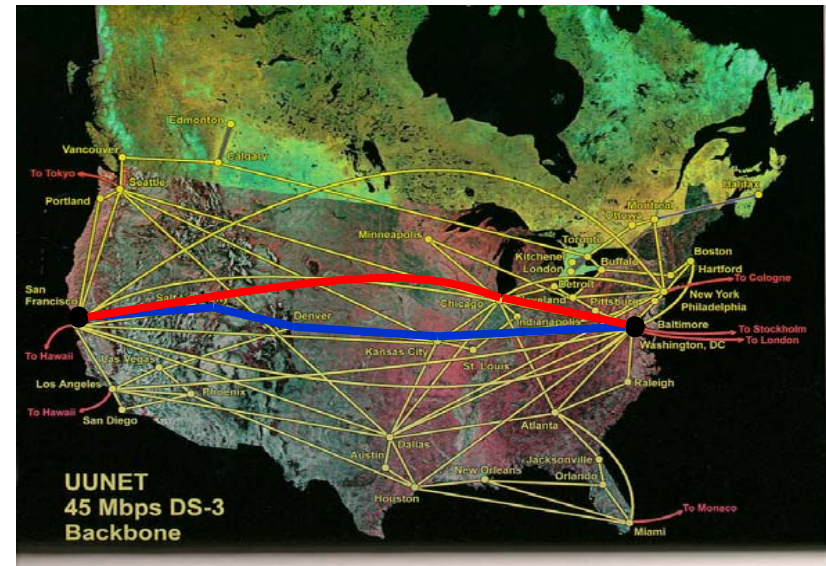
	C	D
C	2 2	1 99
D	99 1	98 98

## Our Games

- Routing, Network formation: Users select paths that connects their terminals to minimize their own delay or cost
- Selling of goods: implicit network
- Contagion of financial risk

Congestion games

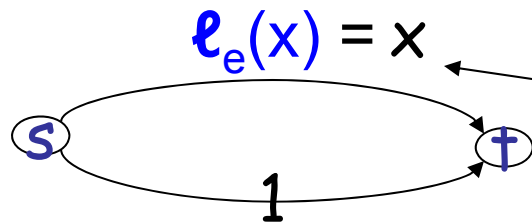
# Example: Routing Game



- Traffic subject to congestion delays
  - cars and packets follow shortest path
- Large number of participants!!

# Congestion sensitive load balancing

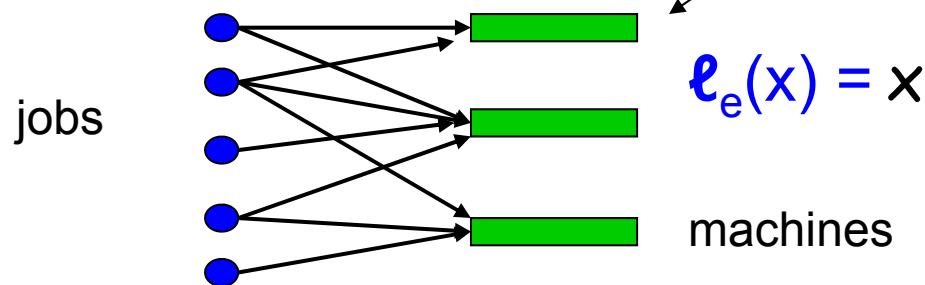
Routing network:



Cost/Delay/Response time as a fn of load:

$x$  unit of load  $\rightarrow$   
causes delay  $\ell_e(x)$

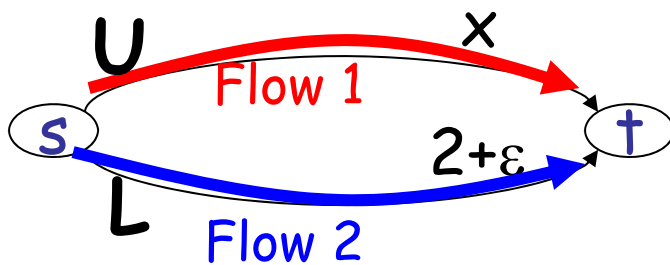
Load balancing:



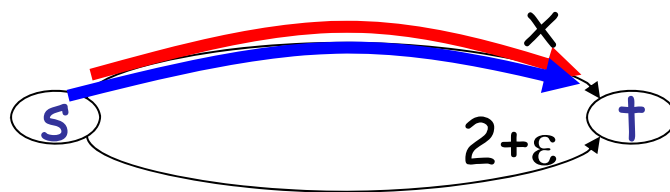
**A congestion game**

# Examples on two links: load balancing

Two players each have one unit of flow to send



An envy free solution:

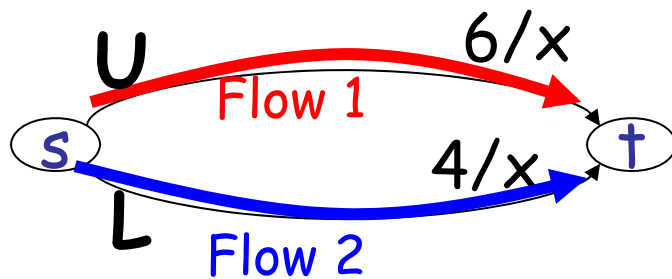


	U	L
U	2	$2+\epsilon$
L	$2+\epsilon$	$2+\epsilon$

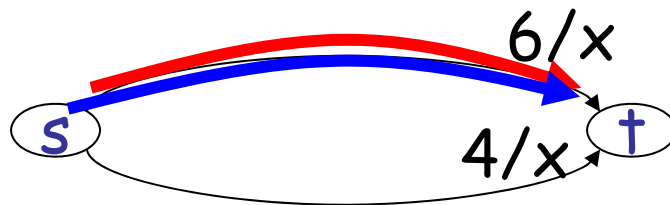
Cost increasing  
with congestion

# Examples on two links: coordination game

Two players each have one unit of flow to send



An envy free solution:



Two solutions of  
different value

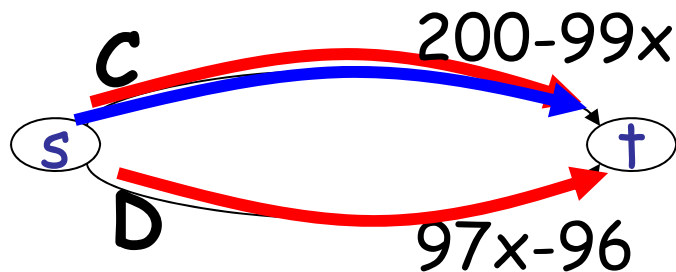
	U	L
U	3	4
L	3	2

Payoff matrix for the coordination game. The top-left cell (3, 3) is circled in green. The bottom-right cell (2, 2) is circled with a dashed green line.

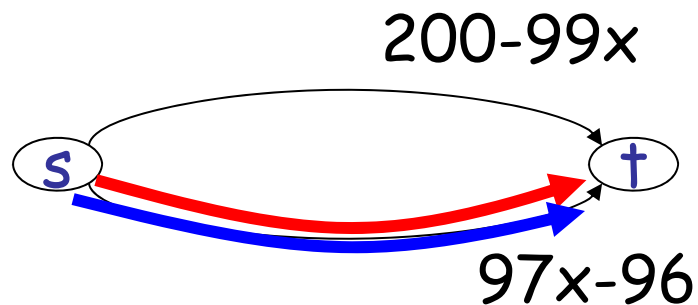
Cost-sharing:  
cost decreasing  
with congestion

# Examples on two links: Prisoner's Dilemma

Two players each have one unit of flow to send



An envy free solution:



	$C$	$D$
$C$	2	1
$D$	101	98

$C$  has decreasing,  
 $D$  has increasing  
congestion cost



# Today:

focus on: pure equilibria  
very small and same sized jobs  
social welfare

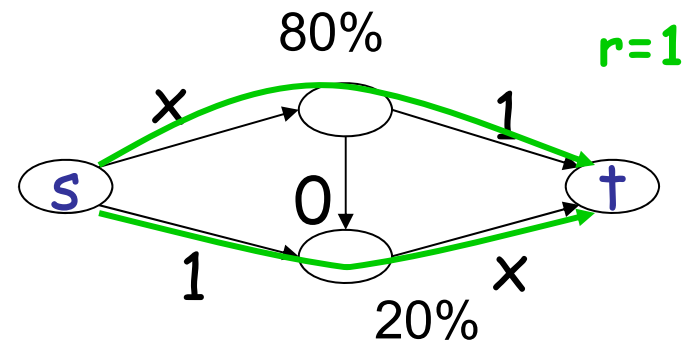
- Does a pure equilibria exists?
- Does a high quality equilibria exists?
- Are all equilibria high quality?

some of the results extend to **expected**  
social welfare

# Atomic vs. Non-atomic Game

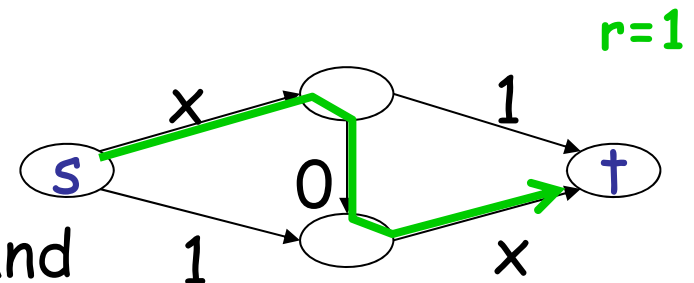
## Non-atomic game:

- Users control an infinitesimally small amount of flow
- **equilibrium**: all flow paths carrying flow are minimum total delay



## Atomic Game:

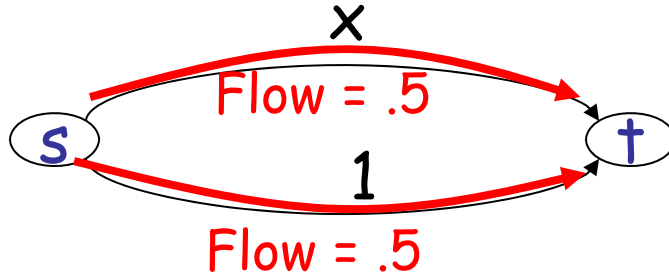
- Each user controls a unit of flow, and
- selects a single path or machine



Both **congestion games**: cost on edge  $e$  depends on the congestion (number of users)

# Example of nonatomic flow on two links

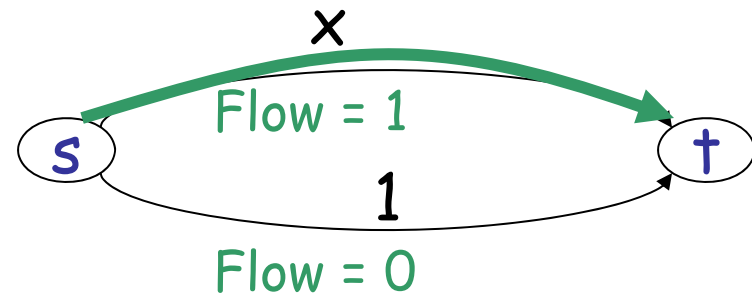
- One unit of flow sent from  $s$  to  $t$



Traffic on lower edge is envious.

An envy free solution:

No-one is better off

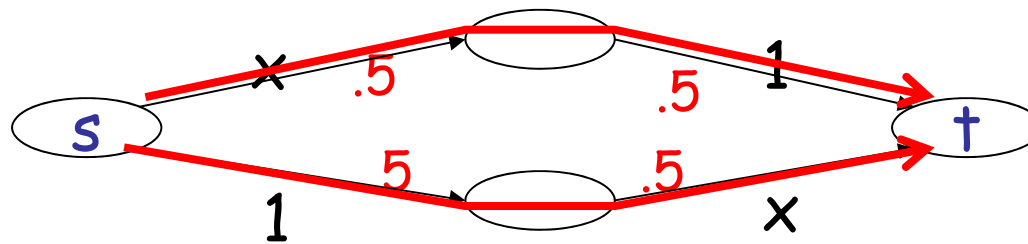


Infinite number of players

- will make analysis cleaner by continuous math

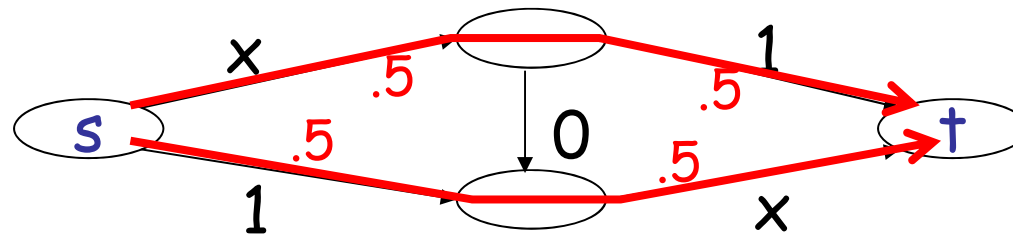
# Braess's Paradox

## Original Network



Cost of **Nash flow**  
 $= 1.5$

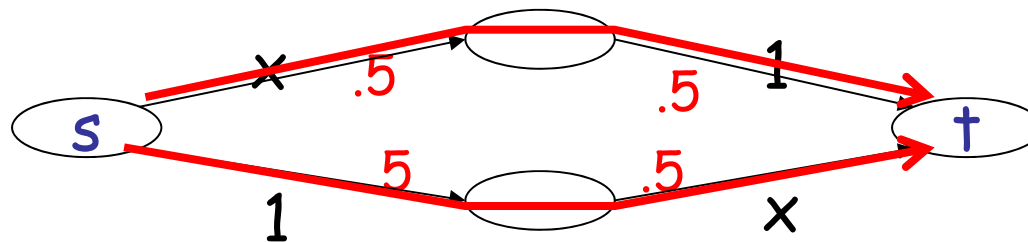
Added edge:



Effect?

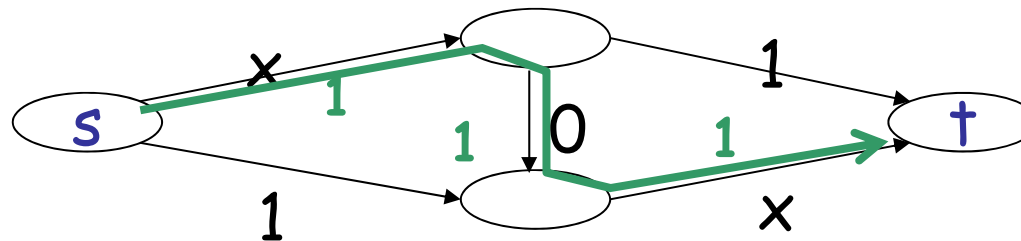
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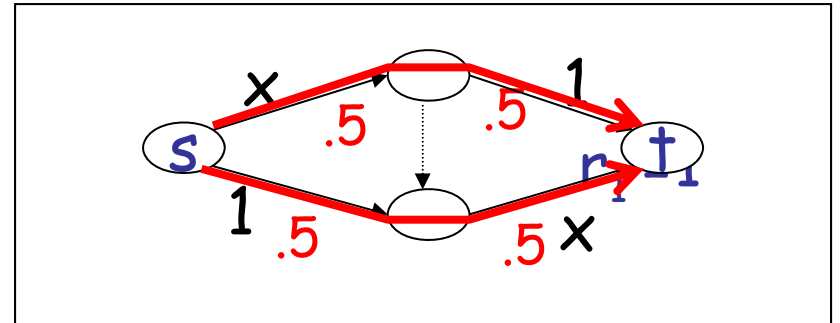


Cost of **Nash flow**  $= 2$

All the flow has increased delay!

# Model of Routing Game

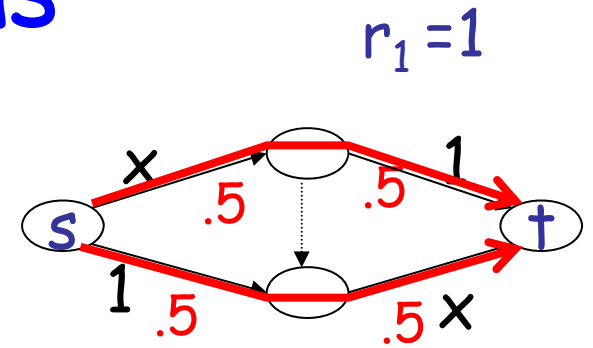
- A directed graph  $G = (V, E)$
- source-sink pairs  $s_i, t_i$  for  $i=1, \dots, k$
- rate  $r_i \geq 0$  of traffic between  $s_i$  and  $t_i$  for each  $i=1, \dots, k$



- Load-balancing jobs wanted min load
- Here want minimum delay:  
 delay adds along path  
 edge-delay is a function  $\ell_e(\cdot)$  of the load on the edge  $e$

# Delay Functions

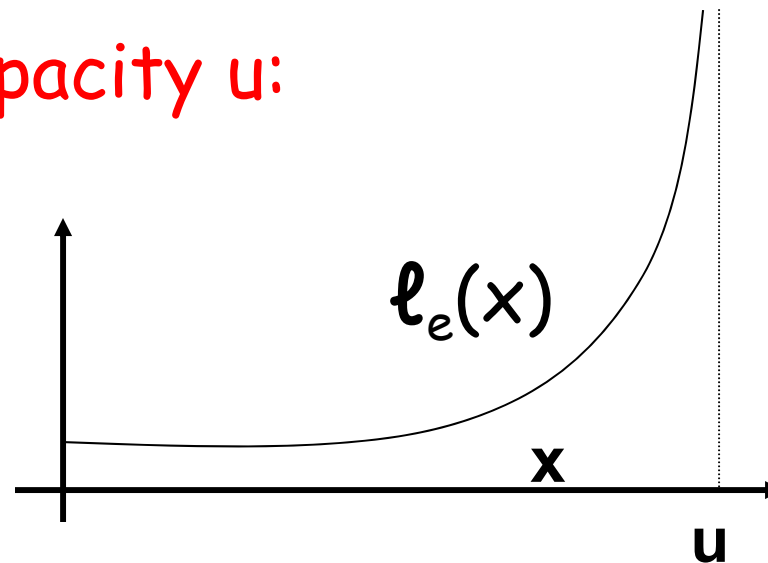
Assume  $\ell_e(x)$  continuous and monotone increasing in load  $x$  on edge



No capacity of edges for now

Example to model capacity  $u$ :

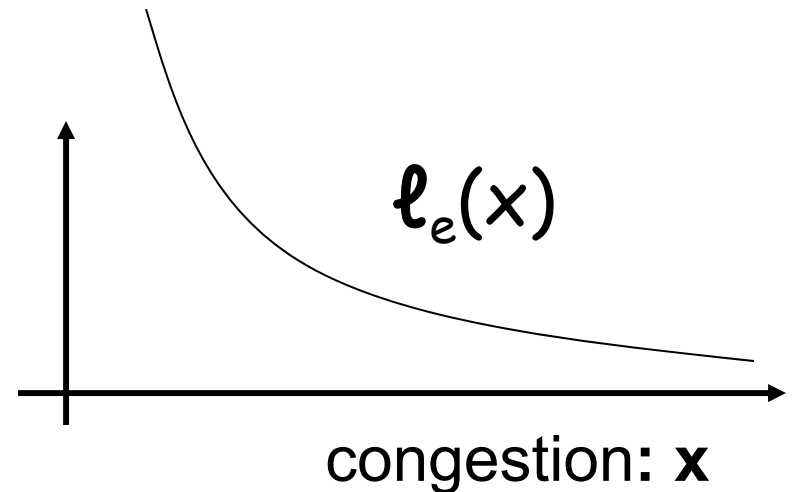
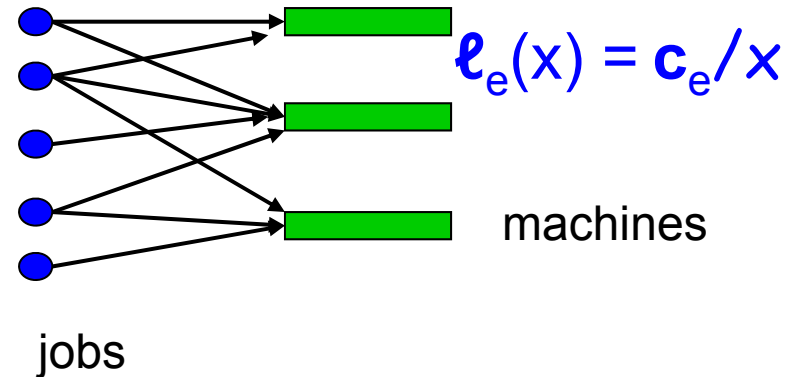
$$\ell_e(x) = a/(u-x)$$



# Congestion Games: Cost-sharing

- jobs  $i=1,\dots,k$
- For each machine  $e$  a cost function  $\ell_e(\cdot)$ 
  - E.g. cloud computing
- Cost decreasing with congestion (decreasing marginal cost)

$$\ell_e(x) = c_e/x$$





# Goal's of the Game: min delay

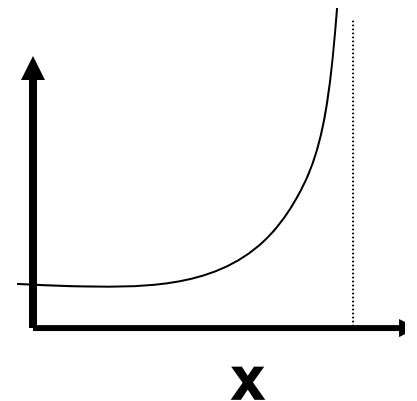
Personal objective: minimize

$\ell_p(f)$  = sum of **delays** of edges along  $P$   
(wrt. flow  $f$ )

Overall objective:

$C(f)$  = total **delay** of a flow  $f$ :  $= \sum_p f_p \cdot \ell_p(f)$

= - social welfare  
or total/average delay



# Goal's of the Game: min cost

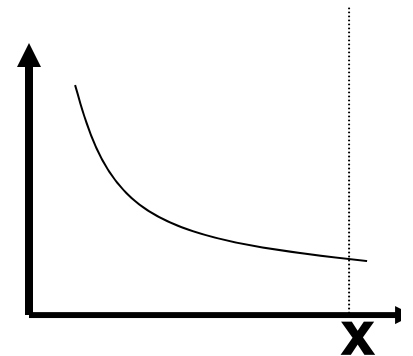
Personal objective: minimize

$\ell_p(f)$  = sum of **costs** of edges along  $P$   
(wrt. flow  $f$ )

Overall objective:

$C(f)$  = total **cost** of a flow  $f$ :  $= \sum_p f_p \cdot \ell_p(f)$

= - **social welfare**  
or **total/average cost**



# What is Selfish Outcome?

We will use: **Nash equilibrium**

- Current strategy “best response” for all players (no incentive to deviate)

**Theorem [Nash 1952]:**

- Always exists if we allow randomized strategies

$$\text{Price of Anarchy} = \frac{\text{cost of worst (pure) Nash}}{\text{“socially optimum” cost}}$$

# Connecting Nash and Opt

- Min-latency flow
  - for one  $s$ - $t$  pair for simplicity
- minimize  $C(f) = \sum_P f_P \cdot \ell_P(f) = \sum_e f_e \cdot \ell_e(f_e)$
- subject to:  $f$  is an  $s$ - $t$  flow
- carrying  $r$  units
- By summing over edges rather than paths  
where  $f_e$  = amount of flow on edge  $e$

# Characterizing the Optimal Flow

Optimality condition (if objective is convex): small change doesn't improve cost

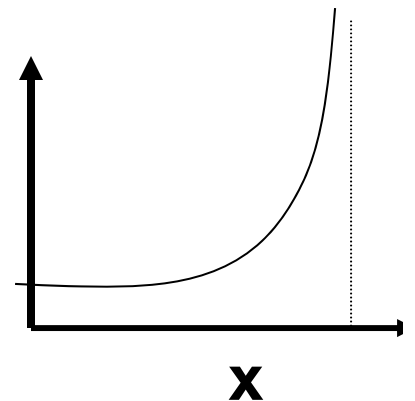
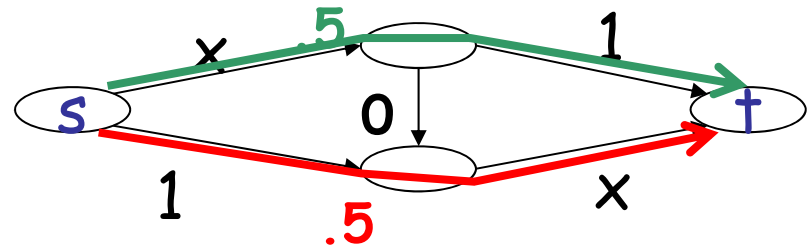
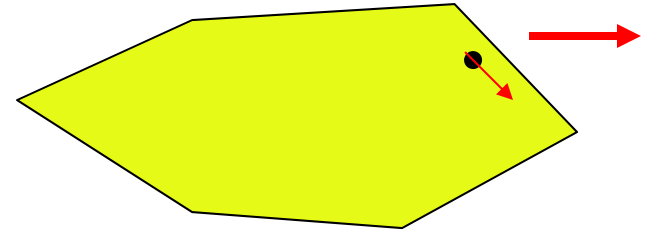
For flows: all flow travels along **minimum-gradient** paths

gradient is:  $(x \ell(x))' = \ell(x) + x \ell'(x)$

selfish part

altruistic term

$(x \ell(x))$  convex if  $\ell(x)$  convex

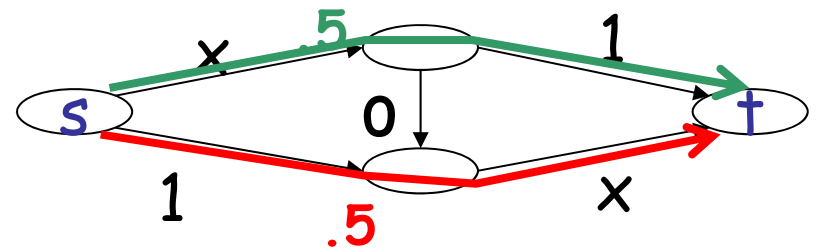


# Optimal versus Nash Flow (convex)

**Optimality condition:** flow  $f$  is at minimum cost iff all flow travels along **minimum-gradient** paths: gradient is  $\ell(x) + x \ell'(x)$

selfish part

altruistic term



**Nash:** flow  $f$  is at **Nash equilibrium** iff all flow travels along **minimum-latency** paths:  $\ell(x)$

selfish part only

# Nash $\leftrightarrow$ Min-Cost

**Corollary 1:** min cost is "Nash" with "delay"

$$\ell(x) + x \ell'(x)$$

**Use of Corollary:** If  $x \ell'(x)$  is changed as tax, selfish users follow optimal paths

# Nash $\leftrightarrow$ Min-Cost

Corollary 2: Nash is "min cost" with "cost"

$$\Phi(f) = \sum_e \int_0^{f_e} \ell_e(x) dx$$

Why?

gradient of  $\Phi(f)$  is delay:

$$\left( \int_0^{f_e} \ell_e(x) dx \right)' = \ell_e(x)$$

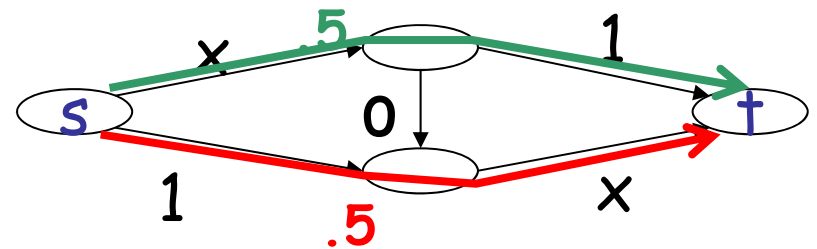


# Optimal versus Nash Flow (not-convex)

**Local optimality condition:** flow  $f$  is at minimum cost **iff** all flow travels along **minimum-gradient** paths: gradient is  $\ell(x) + x \ell'(x)$

selfish part

altruistic term



**Nash:** flow  $f$  is at **Nash equilibrium** iff all flow travels along **minimum-latency** paths:  $\ell(x)$

selfish part only

## Using function $\Phi$

- The solution minimizing  $\Phi$  is Nash

### Theorem (Beckmann'56)

- In a network latency functions  $\ell_e(x)$  that are continuous,
- a deterministic Nash equilibrium exists,
- If  $f$  is monotone increasing then it is essentially unique

# Using potential $\Phi$ ...

- Nash minimizes the function  $\Phi$
- Hence,

$$\Phi(\text{Nash}) \leq \Phi(\text{OPT}).$$

Suppose that we also know for any solution

$$\Phi \leq \text{cost} \leq A \Phi$$

$$\rightarrow \text{cost}(\text{Nash}) \leq A \Phi(\text{Nash}) \leq A \Phi(\text{OPT}) \leq A \text{cost}(\text{OPT}).$$

→ the Nash solution has good quality

**Example:**  $\Phi \leq \text{cost} \leq \Delta \Phi$

**Example:**  $\ell_e(x) = x^d$  then

- total delay is  $x \cdot \ell_e(x) = x^{d+1}$
- potential is  $\int \ell_e(\xi) d\xi = x^{d+1}/(d+1)$

More generally: delay  $\ell_e(x)$  degree  $d$  polynomial:

- ratio at most  $d+1$

**Sharp bound:** price of anarchy for degree  $d$  polynomials is  $O(d/\log d)$ .

# Sharper results for non-atomic games

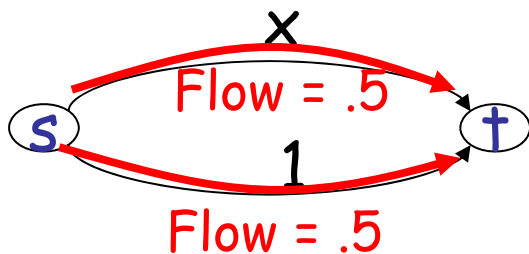
## Theorem 1 (Roughgarden-Tardos)

- In a network with linear latency functions
  - i.e., of the form  $\ell_e(x) = a_e x + b_e$
- the cost of a Nash flow is at most  $4/3$  times that of the minimum-latency flow

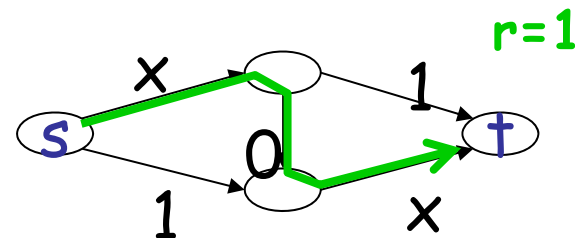
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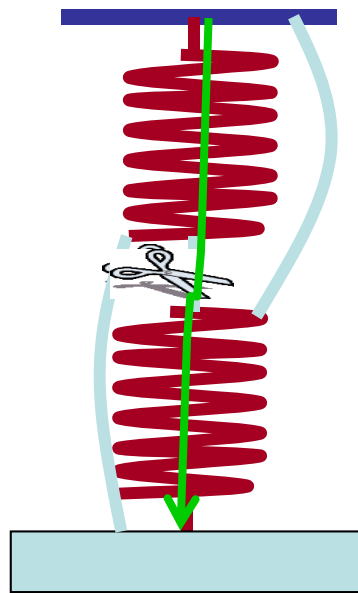


Nash cost 1 optimum  $3/4$

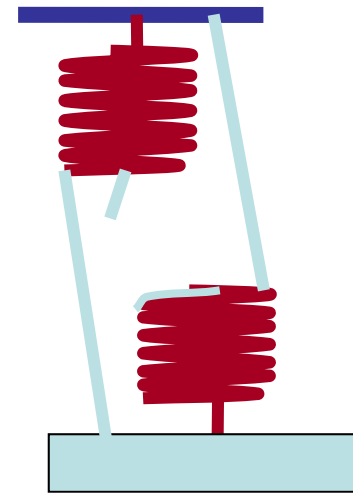


Nash cost 2 optimum 1.5

# Braess paradox in springs (aside)



Cutting  
middle  
string

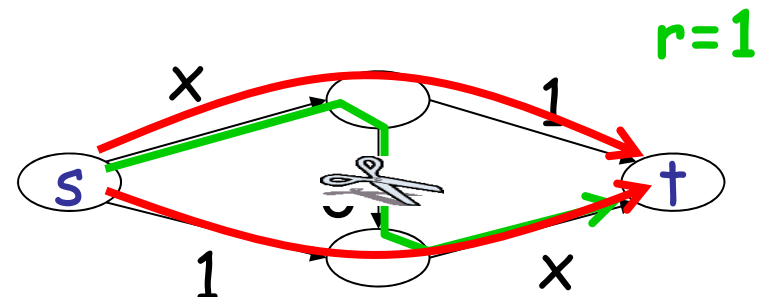


makes the weight **rise**

power flow along springs

Flow=power; delay=distance

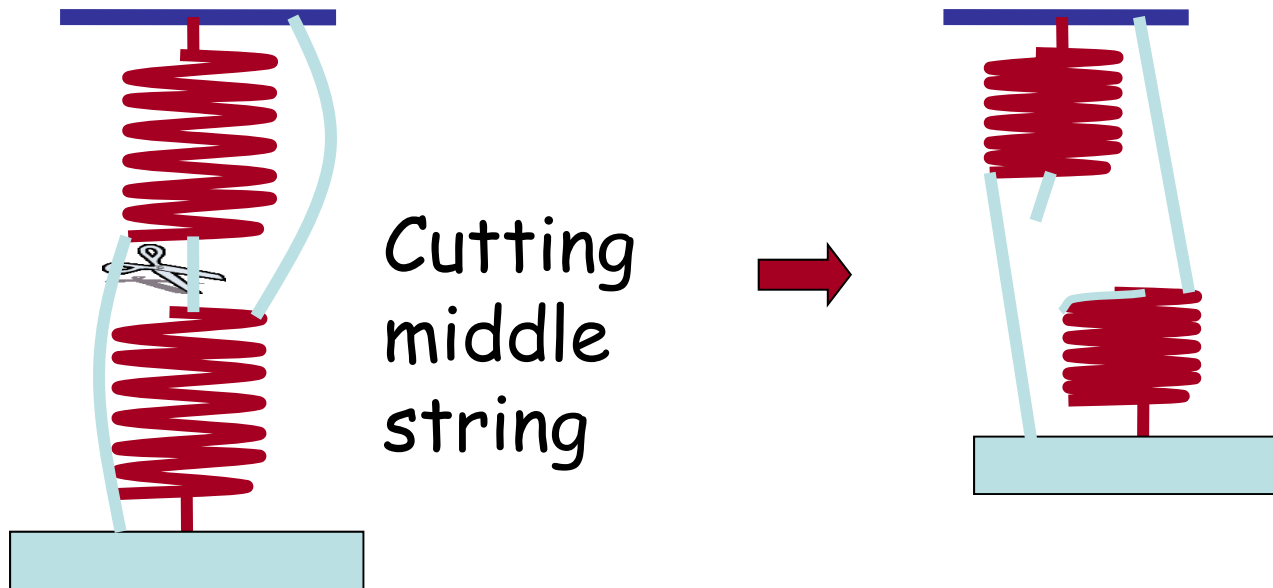
Power conserves,  
transfers only along min path



# Bounds for spring paradox

## Theorem 1' (Roughgarden-Tardos)

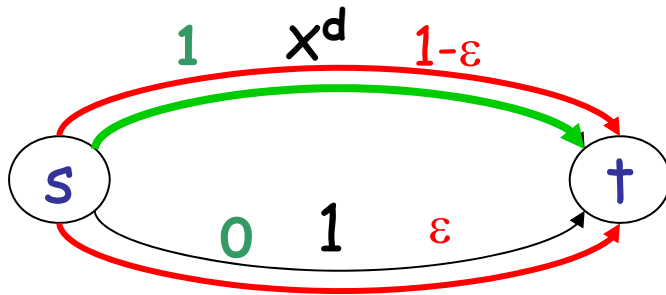
In a network with springs and strings cutting some strings can decrease the stretch by at most a factor of  $4/3$ .





# General Latency Functions

- **Question:** what about more general edge latency functions?
- **Bad Example:** ( $r = 1$ ,  $d$  large)



A **Nash flow** can cost arbitrarily more than the **optimal (min-cost) flow**

# For non-atomic games

## Theorem 3 (Roughgarden-Tardos):

- In any network with continuous, nondecreasing latency functions

cost of Nash with  
rates  $r_i$  for all  $i$

$\leq$

cost of opt with  
rates  $2r_i$  for all  $i$

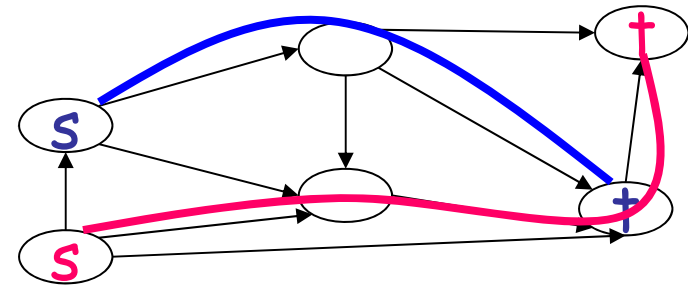
## Proof idea:

Opt may cost very little, but **marginal cost** is as high as latency in Nash

→ Augmenting to double rate costs at least as much as Nash

# Atomic (discrete) Analog

- Each user controls **one** unit of flow, and
- selects a single path



**Theorem** Change in potential is same as function change perceived by one user

[Rosenthal'73, Monderer Shapley'96,]

$$\Phi(\mathbf{f}) = \sum_e (\ell_e(1) + \dots + \ell_e(f_e)) = \sum_e \Phi_e$$

Even though moving player ignores all other users

[Recall continuous potential:  $\Phi(\mathbf{f}) = \sum_e \int_0^{f_e} \ell_e(x) dx$ ]

**Corollary:** Nash equilibria are local min. of  $\Phi(\mathbf{f})$

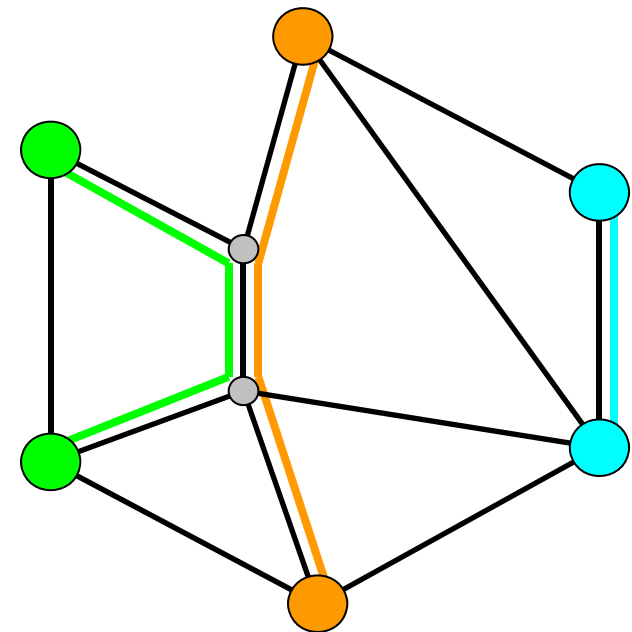
# Network Design as Potential Game

Given:  $G = (V, E)$ ,  
costs  $c_e(x)$  for all  $e \in E$ ,  
 $k$  terminal sets (colors)

Have a player for each color.

Each player wants to build a network in which his nodes are connected.

Player strategy: select a tree connecting his set.



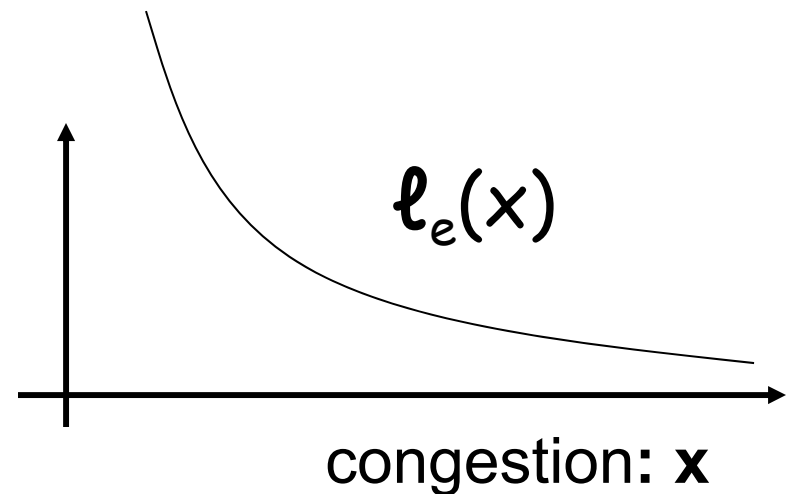
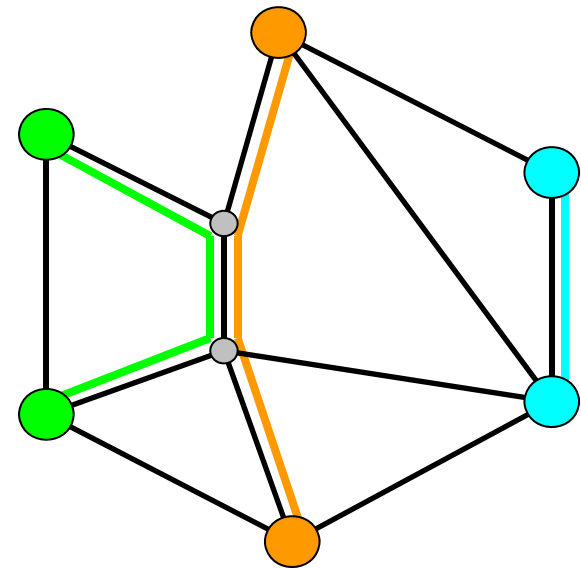
# Costs in Connection Game

Players pay for their trees,  
want to minimize payments.

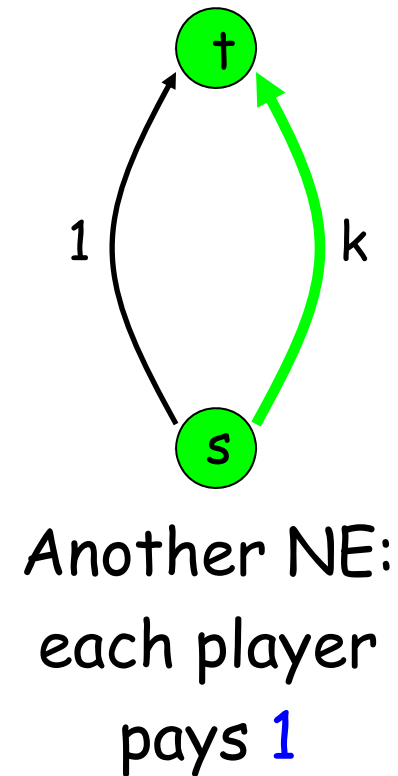
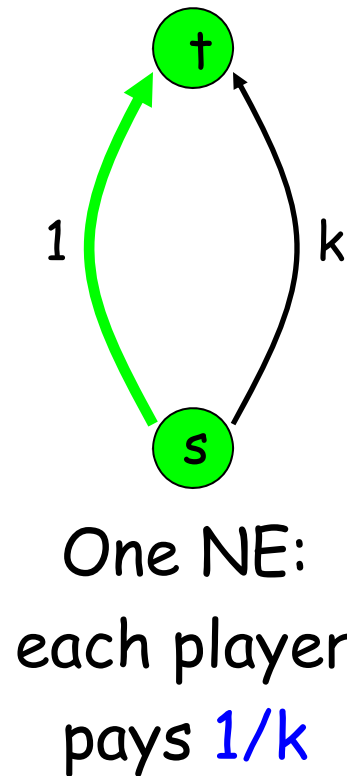
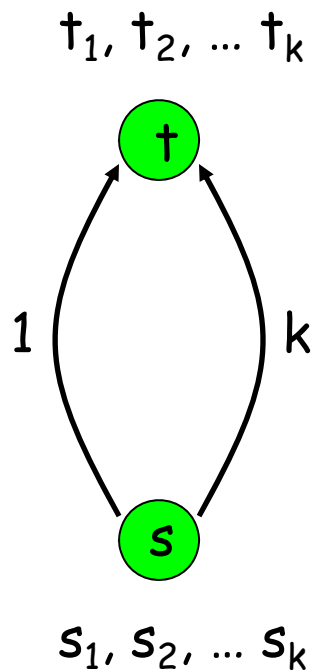
What is the cost of the edges?  
 $c_e(x)$  is cost of edge  $e$  for  $x$  users.

Assume economy of scale and fair  
sharing:

e.g.:  $\ell_e(x) = c_e(x) / x$



# A Simple Example



# Results for Network Design

**Theorem** [Anshelevich, Dasgupta, Kleinberg, Tardos, Wexler, Roughgarden FOCS'04]

There exists equilibrium with  $\text{cost} \leq O(\log k) \text{Opt}$   
for  $k$  players (bound sharp)

**Proof**

$$\text{cost} \leq \Phi \leq \text{cost} \cdot O(\log k)$$

Why? cost  $c$  while  $\Phi = c + c/2 + c/3 + \dots = c H_k$

$$\text{Price of Stability} = \frac{\text{cost of best selfish outcome}}{\text{“socially optimum” cost}}$$

# Summary: Potential games and the Price of Anarchy

Potential games: Player best response improves a potential function  $\Phi$

$\Rightarrow$  Nash are local optima of the potential function  $\Phi$

$\Rightarrow$  potential function's true optima is high quality Nash.

But why care about Best Nash/Opt ratio?



# Best Nash is good quality...

Price of Stability =  $\frac{\text{cost of best selfish outcome}}{\text{“socially optimum” cost}}$

Price of Anarchy =  $\frac{\text{cost of worst selfish outcome}}{\text{“socially optimum” cost}}$

---

Potential argument  $\Rightarrow$  Low price of stability

But do we care?

# Atomic Game: Price of Anarchy?

Non-atomic game: Nash is unique...

Atomic Nash not unique! Design with constraint  
for stability

What about other Nash equilibria?

- Discrete routing
- Cost sharing

**Theorem:** Can be bounded for some classes of delay functions

e.g., polynomials of degree at most  $d$  at most exponential in  $d$ :  $O(2^d d^{d+1})$  **Awerbuch-Azar-Epstein, Christodoulou-Koutsoupias STOC'05**

# Proof technique

- bounds price of anarchy (not stability)
- Tight bounds in many games

A game is  $(\lambda, \mu)$ -**smooth** if, for every pair  $f, f^*$  outcomes ( $\lambda > 0; \mu < 1$ ):

$$\sum_e f_e^* \cdot \ell_e(f_e) \leq \lambda \sum_e f_e^* \cdot \ell_e(f_e^*) + \mu \sum_e f_e \cdot \ell_e(f_e)$$

Cost of  $f^*$

Cost of  $f$

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or for all  $f, f^* \geq 0$

$$f^* \cdot \ell(f) \leq \lambda f^* \cdot \ell(f^*) + \mu f \cdot \ell(f)$$

# Discrete version

Smooth for flows:

$$\sum_e f_e^* \cdot \ell_e(f_e) \leq \lambda \sum_e f_e^* \cdot \ell_e(f_e^*) + \mu \sum_e f_e \cdot \ell_e(f_e)$$

A game is  $(\lambda, \mu)$ -smooth if, for every pair  $s, s^*$  outcomes

$$\sum_i C_i(s_i^*, s_{-i}) \leq \lambda \text{cost}(s^*) + \mu \text{cost}(s)$$

Where  $\text{cost}(s) = \sum_i C_i(s)$

$s_i$  strategy of user  $i$

$s_{-i}$  strategies of all users

# Discrete version

Smooth for flows:

$$\sum_e f_e^* \cdot \ell_e(f_e) \leq \lambda \sum_e f_e^* \cdot \ell_e(f_e^*) + \mu \sum_e f_e \cdot \ell_e(f_e)$$

A game is  $(\lambda, \mu)$ -smooth if, for every pair  $s, s^*$  outcomes

$$\sum_i C_i(s_i^*, s_{-i}) \leq \lambda \text{cost}(s^*) + \mu \text{cost}(s)$$

Cost of  $s^*$

Cost of  $s$

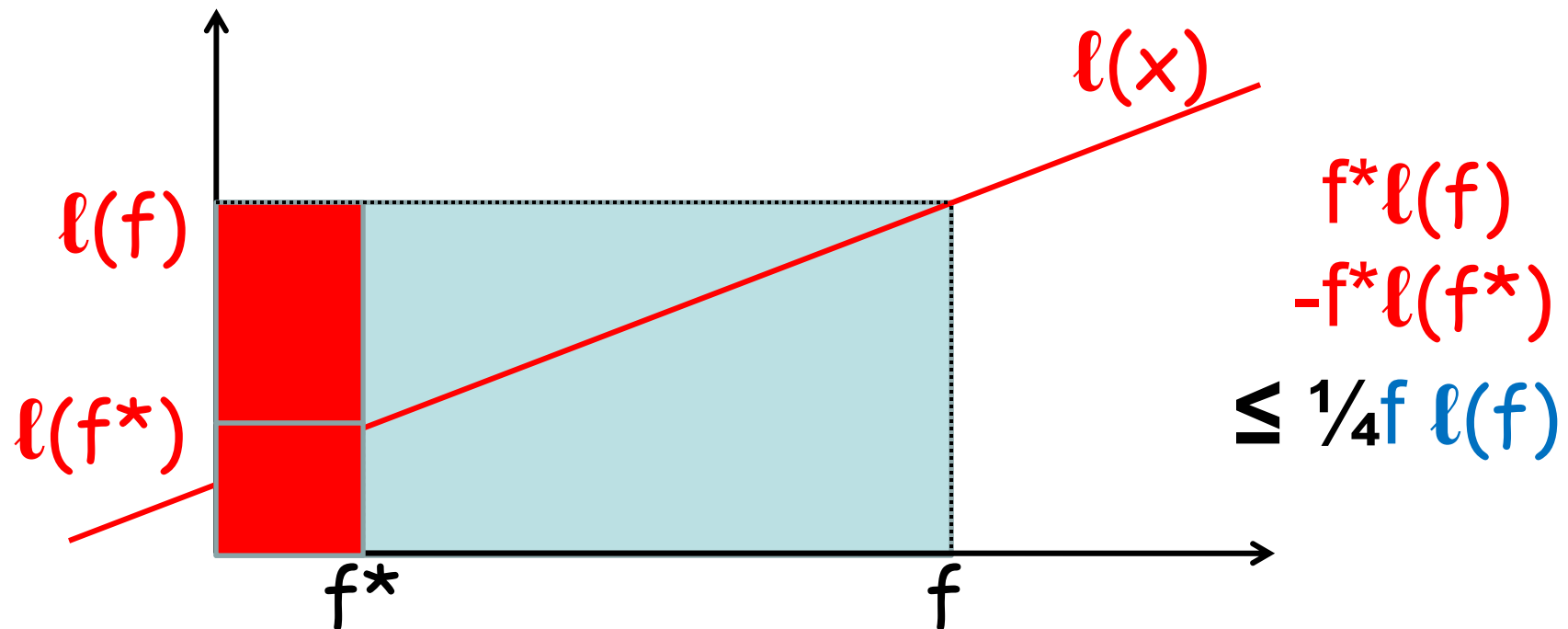
If  $s^*$  has a lot smaller cost than  $s$  then  
single player moves capture the improvement

assuming  $\mu < 1$

# Linear delay is smooth

Claim:  $f^* \cdot \ell(f) \leq f^* \cdot \ell(f^*) + \frac{1}{4} f \cdot \ell(f)$

assuming  $\ell(f)$  linear:  $\lambda = 1; \mu = \frac{1}{4}$





# Smooth $\Rightarrow$ Price of Anarchy

## [Roughgarden]

Use smooth for  $s = \text{Nash}$  and  $s^* = \text{opt}$

$$\sum_i C_i(s_i^*, s_{-i}) \leq \lambda \text{cost}(s^*) + \mu \text{cost}(s)$$

$$\begin{aligned} \text{cost}(s) &= \sum_i C_i(s_i, s_{-i}) \\ &\leq \sum_i C_i(s_i^*, s_{-i}) && [s \text{ a Nash eq}] \\ &\leq \lambda \text{cost}(s^*) + \mu \text{cost}(s) && [\text{smooth}] \end{aligned}$$

$$\text{Then: } \text{cost}(s) \leq \lambda / (1 - \mu) \text{cost}(s^*)$$

**Note:** used for  $s^* = \text{opt}$  only!



# Atomic Smoothness Bound

atomic linear delay smooth

$$\sum_i C_i(f^*_i, f_{-i}) \leq \lambda \text{cost}(f^*) + \mu \text{cost}(f)$$

Consider edge by edge:

(nonatomic version):

$$f^* \cdot \ell(f) \leq \lambda f^* \cdot \ell(f^*) + \mu f \cdot \ell(f)$$

Atomic version

$$f^* \cdot \ell(f+1) \leq \lambda f^* \cdot \ell(f^*) + \mu f \cdot \ell(f)$$

$$\text{basic inequality: } y(z+1) \leq (5/3)y^2 + (1/3)z^2$$

# Implicit Smoothness Bounds

Examples: selfish routing, **linear cost fns.**

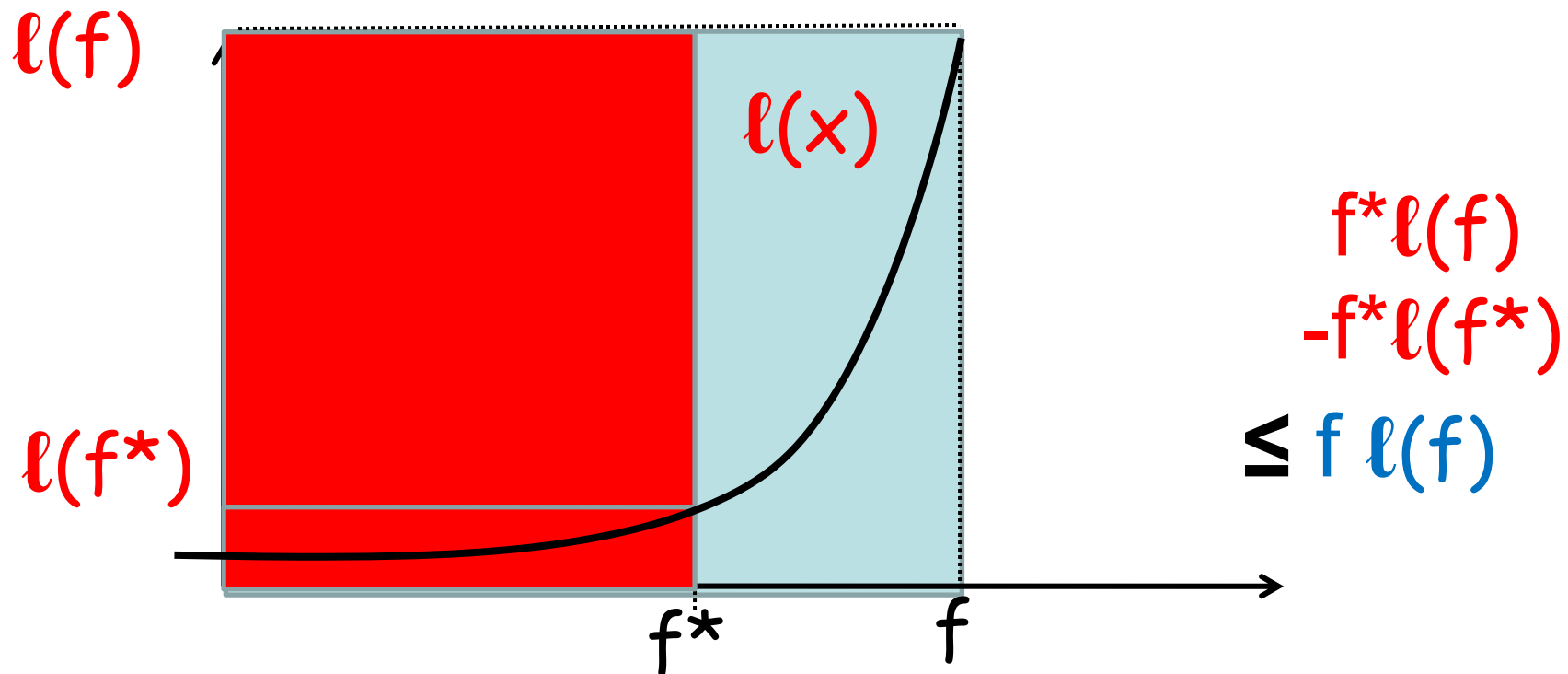
- every nonatomic game is  $(1, 1/4)$ -smooth
  - follows directly from analysis in [\[Correa/Schulz/Stier Moses 05\]](#)
  - Implies a  $\frac{3}{4} = 1/(1 - \frac{1}{4})$  bound on Price of Anarchy
- every atomic game is  $(5/3, 1/3)$ -smooth
  - follows directly from analysis in [\[Awerbuch/Azar/Epstein 05\]](#), [\[Christodoulou/Koutsoupias 05\]](#)
  - Implies a  $5/2$  bound on Price of Anarchy

**Theorem** [\[Roughgarden 09\]](#) for congestion game the best such bound tight

# General increasing delay?

Any increasing function is (1,1)-smooth

$$f^* \cdot l(f) \leq f^* \cdot l(f^*) + f \cdot l(f)$$



# Summary

Congestion games are potential games

- $\exists$  Pure equilibria (min of potential)
- Min of potential has OK quality
- Price of stability (or anarchy when unique)
- Smoothness and stronger Price of anarchy bounds
  - Applies to some other games also

Tomorrow:

- Learning in games (why and how?)
- solutions reached via learning