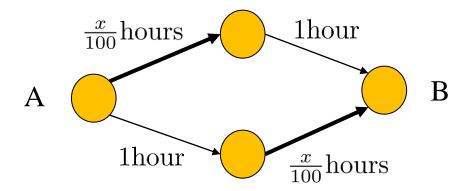
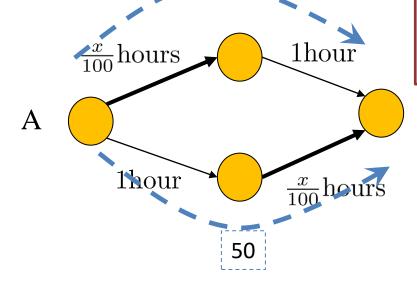
#### L07 Price of Anarchy

CS 295 Introduction to Algorithmic Game Theory Ioannis Panageas

Suppose 100 drivers commute from A to B. Drivers want to minimize the time.



Suppose 100 drivers commute from A to B. Drivers want to minimize the time 50



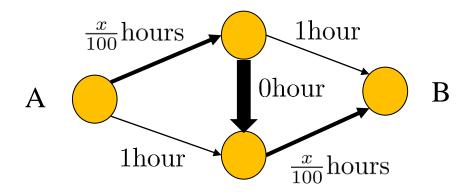
Delay is 1.5 hours for everybody at the unique Nash equilibrium.

В

Suppose 100 drivers commute from A to B.

Drivers want to minimize the time.

Question: What if we add a new link?



Suppose 100 drivers commute from A to B.

Drivers want to minimize the time.

100

Delay is now 2 hours for everybody at the unique Nash equilibrium.

Braess's paradox

B

1hour

A

B

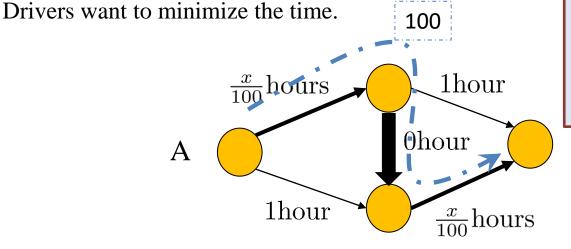
B

B

 $\frac{x}{100}$  hours

Adding a fast link is not always a good idea!

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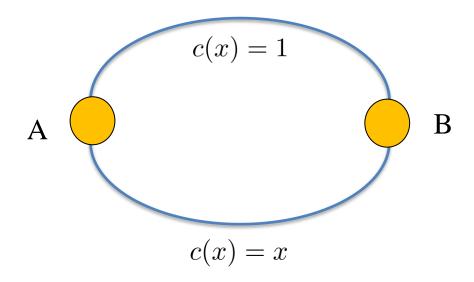
Adding a fast link is not always a good idea!

PoA = performance of worst case NE optimal performance if agents do not decide on their own

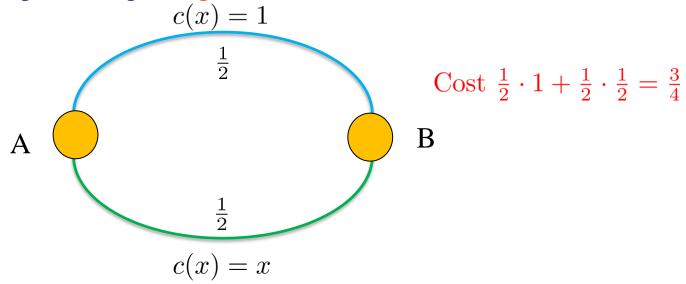
Price of Anarchy (Koutsoupias, Papadimitriou 99').

4/3!!

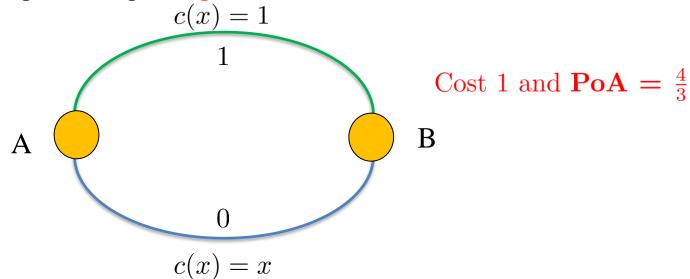
Example: Simpler example. Pigou network.



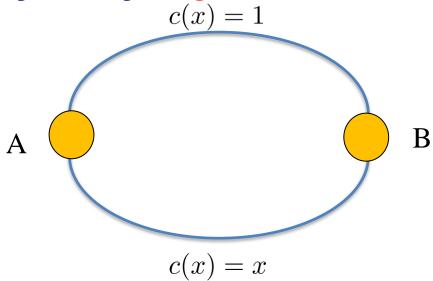
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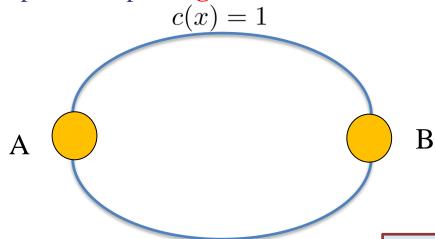
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A non-atomic selfish routing game is defined by:

- Graph G(V, E).
- Source destination pairs  $(s_1, t_1), ..., (s_k, t_k)$ .
- $r_i$  traffic from  $s_i \to t_i$ .
- $c_e(.) \ge 0$  cost function of edge e, continuous and non-decreasing.
- Flow is an equilibrium if all traffic is routed on cheapest paths.

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$$c(x) = x$$

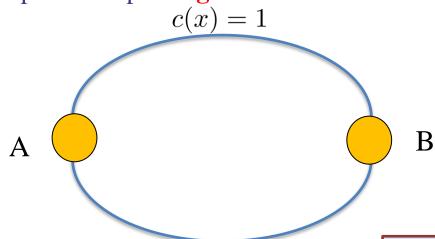
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Social Cost :=  $\sum_{p} f_p c_p(f)$ 

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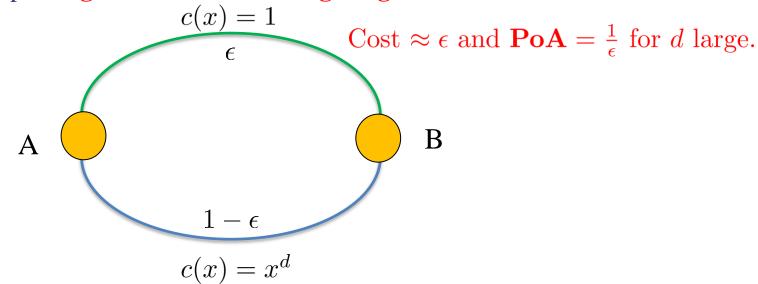
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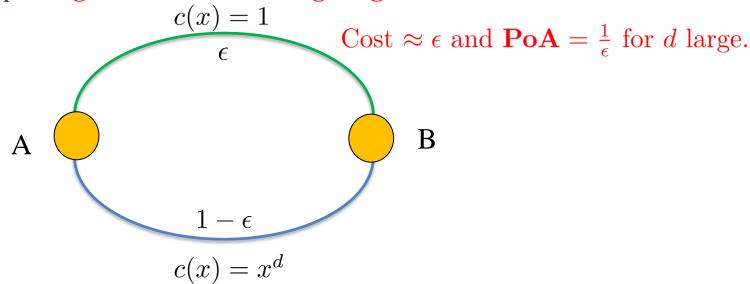
Remark: Equilibrium flow exists and is unique!

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A bad Example. Pigou network with large degree d.



A bad Example. **Pigou network with large degree** *d*.



#### **Questions:**

- 1. When is PoA small (bounded)?
- 2. Can we find bounds on PoA for specific classes of cost functions?

**Definition** (Linear costs). Linear costs are of the form  $c_e(x) = a_e \cdot x + b_e$ .

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Observe that

 $f^*$  equilibrium flow  $\Rightarrow$  if  $f_p^* > 0$  then  $c_p(f^*) \leq c_{p'}(f^*)$  for all paths p'.

Proof cont. Therefore all paths p so that  $f_p^* > 0$  have same cost say L. Hence  $\sum_p f_p^* c_p(f^*) = L \cdot F$  where  $F = \sum_p f_p^*$  is the total flow.

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Since  $c_p(f^*) \geq L$  we conclude

$$\sum_{p} f_p c_p(f^*) \ge L \sum_{p} f_p = L \cdot F$$

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Combining the above

$$\sum_{e} f_e c_e(f^*) = \sum_{p} f_p c_p(f^*) \ge L \cdot F = \sum_{p} f_p^* c_p(f^*) = \sum_{e} f_e^* c_e(f^*)$$

$$\sum_{e} f_{e} c_{e}(f^{*}) \ge \sum_{e} f_{e}^{*} c_{e}(f^{*}).$$

*Proof cont.* We get that

$$\sum_{e} f_e^* c_e(f^*) \le \sum_{e} f_e c_e(f) + \sum_{e} f_e(c_e(f^*) - c_e(f))$$

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$$\left| \sum_{e} f_e(c_e(f^*) - c_e(f)) \right| \le \frac{1}{4} \sum_{e} f_e^* c_e(f^*)$$

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- Case  $c_e(f^*) \ge c_e(f) \Rightarrow f_e^* \ge f_e$ . Linear costs  $\Rightarrow$  LHS =  $a_e f_e(f_e^* f_e)$  and RHS  $\ge \frac{1}{4} a_e f_e^{*2}$ .

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$$\sum_{e} f_e^* c_e(f^*) \le \frac{4}{3} \sum_{e} f_e c_e(f).$$

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Intro to AGT

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$$\sum_{e \in P_i} c_e(l_e^*) \le \sum_{e \in P_i \cap \tilde{P}_i} c_e(l_e^*) + \sum_{e \in \tilde{P}_i \setminus P_i} c_e(l_e^* + 1)$$

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$$\sum_{i \in [n]} \sum_{e \in P_i} c_e(l_e^*) \le \int_{e} \text{Since } y(z+1) \le \frac{5}{3}y^2 + \frac{1}{3}z^2 \text{ for naturals } y, z$$

$$= \underbrace{\frac{1}{2} m_e \tilde{l}_e(l_e^* + 1) + b_e \tilde{l}_e}_{e}.$$

$$\le \sum_{e} a_e \left(\frac{5}{3}\tilde{l}_e^2 + \frac{1}{3}l_e^{*2}\right) + b_e \tilde{l}_e.$$

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$$C(l^*) \le \frac{5}{3}C(\tilde{l}) + \frac{1}{3}\sum_{e} a_e l_e^{*2}$$

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$$Proof cont. \text{ Ob}$$

$$\frac{5}{3}C(\tilde{l}) = C(l^*) \le \frac{5}{2}C(\tilde{l}).$$

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#### Remark:

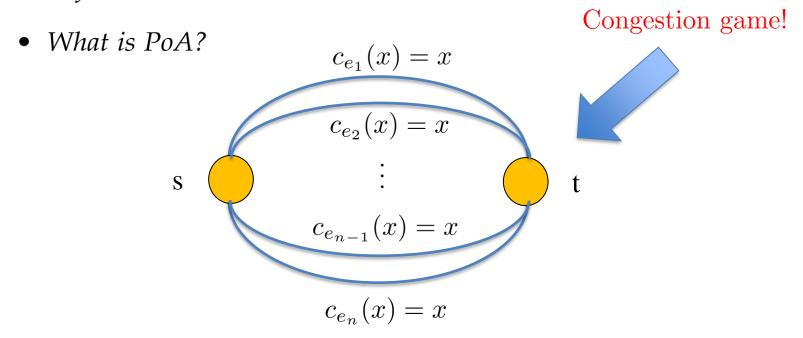
- 1. The above bound is tight!
- 2. For polynomial cost functions the PoA is exponential in d.

**Definition** (Balls and Bins). Consider

- set of n balls and n bins  $\{e_1, ..., e_n\}$ .
- Each ball i chooses a bin j and pays the load of the bin j.
- *Define social cost the maximum load*.
- What is PoA? Is it  $\frac{5}{2}$ ?

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**Theorem** (Koutsoupias-Papadimitriou, PoA for balls & bins). The PoA is

$$\Omega\left(\frac{\ln n}{\ln \ln n}\right).$$

*Proof.* We will use second moment method.

- Set every ball in a different bin. Hence optimal social cost is 1.
- Uniform  $(\frac{1}{n}, ..., \frac{1}{n})$  is a Nash Equilibrium (symmetry).

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Claim 1: Bin i has at least  $k \ll n$  balls with probability at least:

$$\binom{n}{k} \frac{1}{n^k} \left( 1 - \frac{1}{n} \right)^{n-k} \ge \frac{1}{n^k} \left( \frac{n}{k} \right)^k \frac{1}{e} = \frac{1}{ek^k}.$$

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*Proof cont.* Choosing  $k = \frac{\ln n}{3 \ln \ln n}$  we have  $k^k \leq (\ln n)^k = (\ln n)^{\frac{\ln n}{3 \ln \ln n}} = n^{1/3}$ .

Claim 1: Thus bin i has at least  $\frac{\ln n}{3 \ln \ln n}$  balls with probability at least  $\frac{1}{e^{n^{1/3}}}$ .

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Chebyshev's inequality gives  $Pr[|X - E[X]| \ge tE[X]] \le \frac{Var[X]}{t^2E^2[X]}$ ,

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Chebyshev's inequality gives 
$$Pr[|X - E[X]| \ge tE[X]] \le \frac{Var[X]}{t^2E^2[X]}$$
, thus  $Pr[X = 0] \le Pr[|X - E[X]| \ge E[X]] \le \frac{Var[X]}{E^2[X]}$ .

Proof cont. 
$$Pr[X=0] \leq \frac{Var[X]}{E^2[X]}$$
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From negative correlation we have that  $Var[X] \leq \sum_{i} Var[X_i]$ .

Morever 
$$Var[X_i] = E[X_i^2] - E^2[X_i] \le E[X_i^2] = E[X_i] \le 1$$

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We conclude that

$$Pr[X=0] \le \frac{n}{e^2 n^{4/3}} = \frac{n^{-1/3}}{e^2}.$$

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Therefore

$$Pr[X \ge 1] = 1 - Pr[X = 0] \ge 1 - \frac{n^{-1/3}}{e^2} \to 1.$$

#### **Congestion Games**

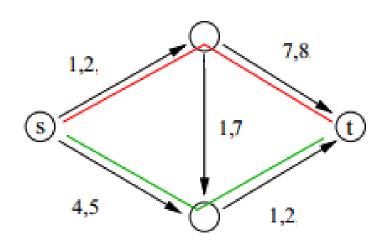
#### A congestion game is defined by:

- n set of players.
- E set of edges/facilities/ bins.
- $S_i \subset 2^E$  the set of strategies of player i.
- $c_e: \{1, ..., n\} \to \mathbb{R}^+ \text{ cost function of edge } e.$

For any 
$$s = (s_1, ..., s_n)$$

- $l_e(s)$  number of players (load) that use edge e.
- $c_i(s) = \sum_{e \in s_i} c_e(l_e)$  the cost function of player i.

#### **Congestion Games**



For this game:

 $n = \{1, 2\}$  (red, green) E are the edges of the network.  $S_i$  is all s - t paths.  $c_e$  on edges.

Remark: Defined by Rosenthal in 1973. Capture atomic routing games!