

# News

- Good news
  - I probably won't use 1:30 hours.
  - The talk is supposed to be easy and has many examples.
  - After the talk you will at least remember how to prove one nice theorem.
- Bad news
  - Concerning algorithmic concepts, this talk (and the part in the book it is about) won't be extraordinary fascinating.
- Ugly news
  - - (none).



# The inefficiency of equilibria

## Chapters 17,18,19 of AGT

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12 April 2010

University of Bergen



# Outline

- 1 Introduction
- 2 Formalization
- 3 Nonatomic Selfish routing
- 4 Congestion
- 5 Atomic selfish routing



# The subject

- Part II of the book is about the question

How inefficient are equilibria?

- Or, still very vague but in more down to earth terminology:

If we let selfish people do what they want without much control, will they be much less happy than if we would impose more rules?

- But, of course the first question only make sense if equilibria do exist.

# A real world example: Street crossing



VS



# A real world example: Street crossing

		P2	
		Cross	Wait
P1	Cross	-100 -100	0 1
	Wait	0 1	0 0

- If we allow mixed strategies, there are at least 3 equilibria:
  - Player 1 lets player 2 cross, the other way around, and
  - both players cross with probability  $\frac{1}{101}$ .
- Note that while the total payoff in the first two equilibria is 1, in the third it is very small and there is a small probability of a car crash.
- So typically in this situation some control is needed.

# Formalization

- Like usual, we consider a game with
  - $n$  players  $\{1, \dots, k\}$ ,
  - sets of strategies  $S_i$  for each player,
  - a utility function  $u_i : S \rightarrow \mathbb{R}$  for each player, where  $S = S_1 \times \dots \times S_k$  is the set of all **strategy vectors**.
- unlike before, we also introduce a social function  $\sigma : S \rightarrow \mathbb{R}$ .
- Denote  $E \subseteq S$  for the set of all equilibria  $s^* \in S$  as the **social optimum** (the strategy vector maximizing  $\sigma$ ).

## Definition

The **price of anarchy** is  $\max_{s \in E} \frac{\sigma(s)}{\sigma(s^*)}$ .

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The **price of stability** is  $\min_{s \in E} \frac{\sigma(s)}{\sigma(s^*)}$ .

# A real world example: Street crossing

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- Social cost function is expectancy of sum of payoffs of both players.

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- Price of stability: 1
- Price of anarchy:



# A real world example: Street crossing

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P1	Cross	-100	0
	Wait	1	0
		0	0

- Social cost function is expectancy of sum of payoffs of both players.
- Price of stability: 1
- Price of anarchy:

$$\frac{2 \frac{1}{101} \frac{100}{101} - 100 \left( \frac{1}{101} \right)^2}{1} \approx 0.01$$



# Our tool: Potential function method

In general, the potential function method is the following:

- Suppose we want prove some property of some implicitly given subset  $E$  of a set  $S$  (for example, it is nonempty).
- Define a potential function  $\phi : S \rightarrow \mathbb{R}$  such that  $E$  are exactly the (global) minima of  $\phi$ .
- Since  $\phi$  has a global minimum,  $E$  is non-empty.
- Algorithmically, this is also useful since an element of  $E$  can be found by minimizing  $\phi$  (but in chapters 17,18 and 19 of the book people don't care).



# Nonatomic Selfish routing

- A directed graph  $G = (V, E)$ , and a source-sink pair  $(s_i, t_i)$  for every player (commodity)  $i$ .
- A **requirement vector**  $r \in \mathbb{R}^k$ , where  $r_i$  represents the traffic of commodity  $i$ , and a nondecreasing, continuous **cost function**  $c_e : \mathbb{R}^+ \rightarrow \mathbb{R}^+$ .
- Let  $\mathcal{P}_i$  be the set of all paths from  $s_i$  to  $t_i$ , and  $\mathcal{P} = \cup_{i=1}^k \mathcal{P}_i$ .
- A **flow**  $f$  is a non-negative vector indexed by  $\mathcal{P}$ .  $f$  is **feasible for  $i$**  if  $\sum_{P \in \mathcal{P}_i} f_P \leq r_i$ .
- Let  $f = (f^1, \dots, f^k)$  be a strategy vector, and  $f_e$  be the total amount of flow of  $f$  on  $e$ ; the cost function  $c_i$  of player  $i$  and social function  $\sigma : S \rightarrow \mathbb{R}^+$  are defined as

$$c_i(f) = \sum_{P \in \mathcal{P}_i} \sum_{e \in P} c_e(f_e) f_e^i \quad \text{and} \quad \sigma(f) = \sum_{i=1}^k c_i(f^i) = \sum_{e \in \mathcal{P}} c_e(f_e) f_e$$

For a path  $P$ , we shorthand  $c_P(f) = \sum_{e \in P} c_e(f_P)$ .

### Observation

A strategy vector  $f = (f_1, \dots, f_k)$  is an equilibrium if and only if for every commodity  $i$  and every pair  $P, \tilde{P} \in \mathcal{P}_i$  with  $f_P > 0$

$$c_P(f) \leq c_{\tilde{P}}(f)$$

### Proof.

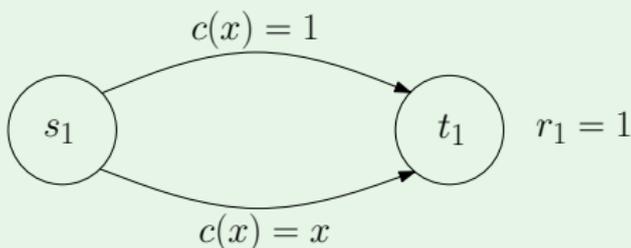
The right to left direction follows from definition of equilibrium. For the other direction, note that since  $c_P$  is "nice", rerouting any amount of flow from  $P$  to  $\tilde{P}$  decreases the costs if the inequality does not hold.  $\square$

## Theorem (Beckmann et al. (1956))

A nonatomic selfish routing game admits at least one equilibrium flow, and if  $f$  and  $\tilde{f}$  are equilibrium flows,  $c_e(f) = c_e(\tilde{f})$  for every edge  $e$ .

Taking the observation into consideration, it is natural to ask whether equilibria and social optima are the same, but:

## Example (Pigou (1920))

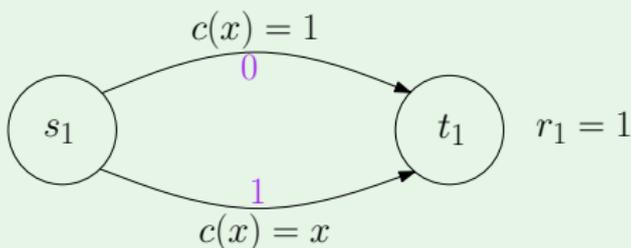


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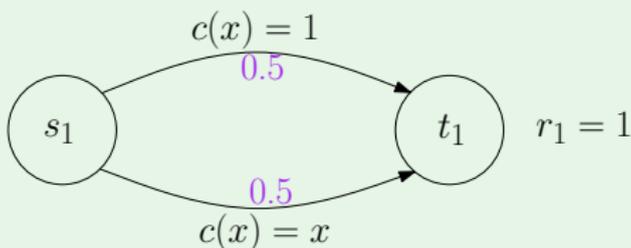


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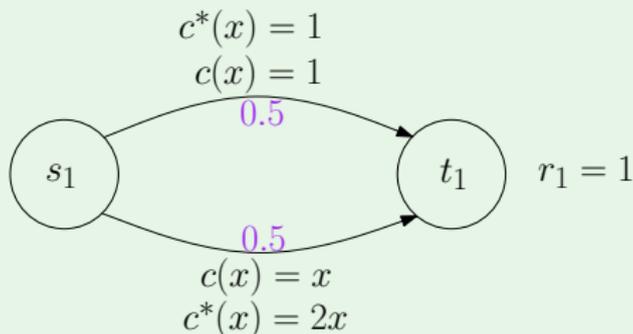


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### Example



## Lemma

Let  $(G, r, c)$  be instance of nonatomic selfish routing, where  $c$  is a nondecreasing, continuous (differentiable) function. Then  $f^*$  is an optimal flow if and only if it is an equilibrium in the instance  $(G, r, c^*)$ .

## Proof.

- $f^*$  is optimal iff for every  $i$  and  $P, \tilde{P} \in \mathcal{P}_i$

$$\sum_{e \in P} (f_e^* \cdot c_e(f_e^*))' \leq \sum_{e \in \tilde{P}} (f_e^* \cdot c_e(f_e^*))'$$

- now the equivalence follows from the previous observation.



# Proof of Theorem

Now, we define a **potential function**  $\phi$  such that  $\phi^* = c$  and hence all minimizers of  $\phi$  are exactly the equilibria of the instance  $(G, r, c)$ .

$$\phi(f_e) = \frac{1}{f_e} \int_0^{f_e} c_e(x) dx$$

Then  $\phi^*(f_e) = (f_e \phi(f_e))' = c_e(f_e)$ .



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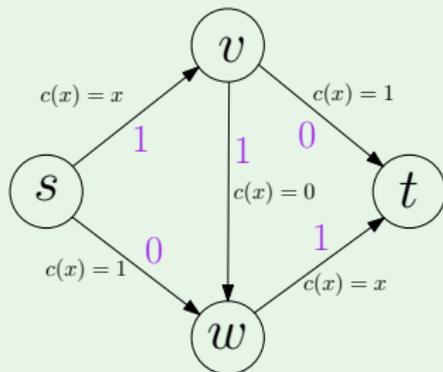
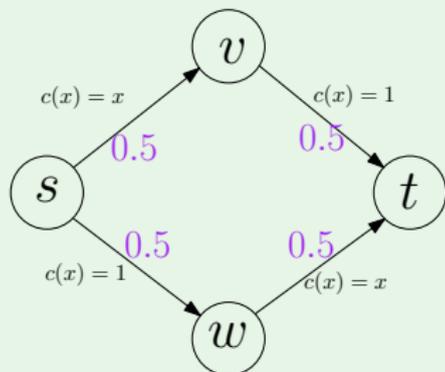
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The proof can probably be used to obtain an equilibrium in polynomial time using convex programming.



# Braess's paradox

## Example



$$t_1 = 1$$

# Congestion game

## Definition

A **congestion game** is a game  $k$  players, a ground set of **resources**  $R$ , a cost function  $c_r : \{1, \dots, k\} \rightarrow \mathbb{R}$  for each  $r \in R$  and each player has a strategy set  $S_i \subseteq R$ . In a strategy profile  $S = (s_1, \dots, s_k)$ , the cost of a player is defined as  $c^i(S) = \sum_{r \in S_i} c_r(n_r)$ , where  $n_r$  is the number of strategies containing  $r$ .

## Theorem (Rosenthal (1973), not in the book.)

*Every congestion game has at least one pure equilibrium.*



**Proof.**

For strategy profile  $S = (s_1, \dots, s_k)$ , denote  $(S_{-i}, s')$  for the strategy vector  $(s_1, \dots, s_{i-1}, s', s_{i+1}, \dots, s_k)$ . Define  $\phi : \mathcal{S} \rightarrow \mathbb{R}^+$ :

$$\phi(s_1, \dots, s_k) = \sum_{r \in R} \sum_{i=1}^{n_r} c_r i$$

then

$$\begin{aligned} c^i((S_{-i}, s')) - c(S) &= \sum_{r \in s' \setminus s_i} c_r (n_r + 1) - \sum_{r \in s_i \setminus s'} c_r (n_r) \\ &= \phi((S_{-i}, s')) - \phi(S) \end{aligned}$$

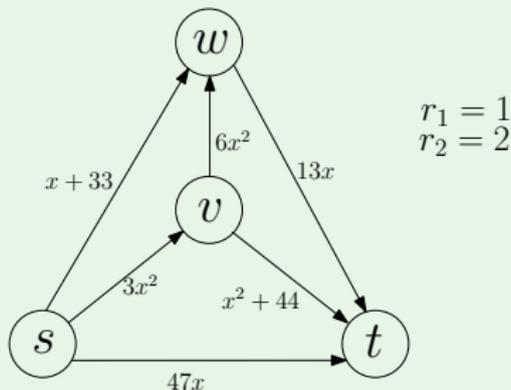
□



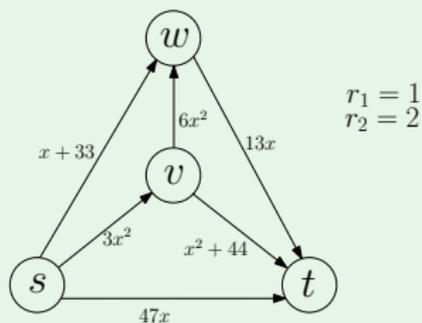
## Atomic selfish routing

- **atomic selfish routing game** is atomic selfish routing restricted to integral flows.
- note that, if the players are restricted to 0 – 1 flows, the existence directly follows from Rosenthals' Theorem. However:

### Example

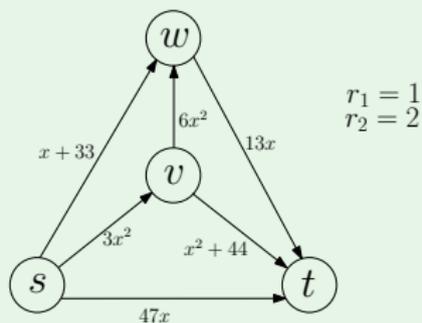


## Example



Let  $P_1, P_2, P_3, P_4$  be respectively  $st, sv, swt, svwt$  then

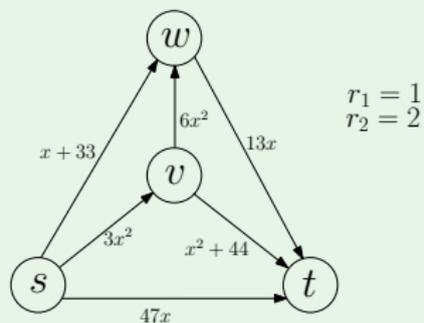
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Let  $P_1, P_2, P_3, P_4$  be respectively  $st, sv, swt, svwt$  then

- player 2  $P_1$  or  $P_2 \rightarrow$  player 1  $P_4$

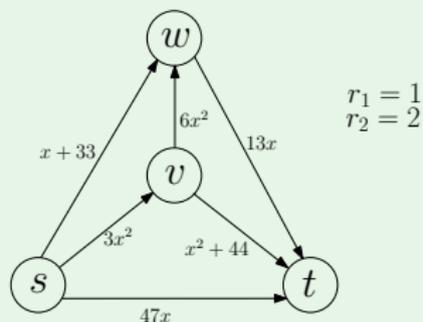
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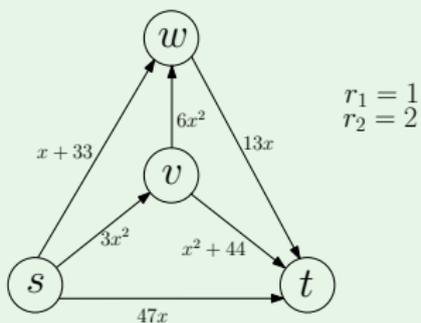
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- player 1  $P_4 \rightarrow$  player 2  $P_3$
- player 1  $P_1 \rightarrow$  player 2  $P_2$

# Cliffhanger

Next time:

- Bounds on the price of anergy.
- Network formation: The same as selfish routing, but with decreasing cost functions.



# Thanks for attending!!!

Any questions?

