The Price of Anarchy and Stability

Aaron Roth

University of Pennsylvania

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- What can we say about the quality of the outcome that has been reached?
- This is where the *price of anarchy* and *price of stability* come in. They measure how bad things *can* and *must* get respectively
- We'll study this question for Nash equilibria, but more generally its sensible to study for any of the equilibrium concepts we have seen.

The Designer's Goal

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5. More generally we could be interested in other things. Note in this case, smaller values are better.

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Definition

The *price of anarchy* of a game G is:

$$PoA = \max_{a : a \text{ is a Nash equilibrium of } G} \frac{\mathrm{Objective}(a)}{\mathrm{OPT}}$$

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4. We have defined Price of Anarchy (POA) and Price of Stability (PoS) for Nash equilibria, but we could have defined them for any of our equilibrium concepts. Observe:

$$PoA(PSNE) \leq PoA(MSNE) \leq PoA(CE) \leq PoA(CCE)$$

(why?)

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4. The social cost in this case is the total cost of resources built:

$$\text{Objective}(a) = \sum_{i=1}^{n} c_i(a) = \sum_{j \in a_1 \cup \ldots \cup a_n} w_j$$

Fair Cost Sharing Games

Theorem

For fair cost sharing games:

$$PoS(PSNE) \geq H_n = \Omega(\log n)$$

where $H_n = \sum_{i=1}^{n} 1/i$ *is the n'th harmonic number.*

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To prove an upper bound, we need a more sophisticated argument because we need to show something for *all* such games.

Proof

1. Recall that congestion games have an exact potential function:

$$\phi(a) = \sum_{j:n_j(a)\geq 1} \sum_{k=1}^{n_j(a)} \ell_j(k)$$

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&\leq \sum_{j\in a_1\cup\ldots\cup a_n} w_j \cdot H_n \\
&= H_n \cdot \mathrm{Objective}(a)
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2. Thus:
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3. So lets conduct a thought experiment...
4. Let a^* be a state such that $\mathrm{Objective}(a^*) = \mathrm{OPT}$.

A Thought Experiment

$$\text{Objective}(a) \leq \phi(a) \leq H_n \cdot \text{Objective}(a)$$

1. Imagine starting at state a^* and then running best response dynamics until it converges to a PSNE a'.

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3. Tada!

The Price of Anarchy

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In fair cost sharing games:

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Once again, to prove a lower bound we just need an example...

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Let a^* be an action profile such that $\mathrm{Objective}(a^*) = \mathrm{OPT}$. We claim that for every pure strategy Nash equilibrium a:

$$c_i(a) \leq n \cdot c_i(a^*)$$

Why?

Proof

By the Nash equilibrium condition, for every player i:

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Since this holds term by term: $\sum_{i=1}^n c_i(a) \le n \sum_{i=1}^n c_i(a^*)$.

Thanks!

See you next class — stay healthy!