Al over networks: when decisions shall be taken together

Damiano Varagnolo

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Who am I?

Purposes of this seminar

- discuss about some technological problems and potential solutions
- connect with you

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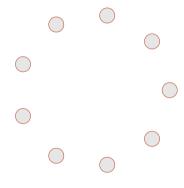
- discuss about some technological problems and potential solutions
- connect with you

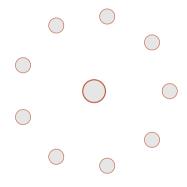
today's cut: divulgation

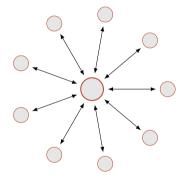
Roadmap

- centralized vs. distributed
- how shall we share information?
- consensus
- taking decisions over networks

centralized vs. distributed

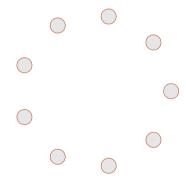




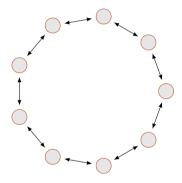


What does distributed mean?

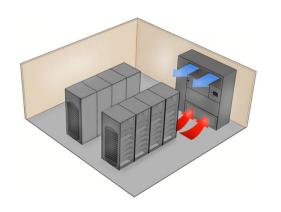
What does distributed mean?



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Different paradigms for different applications





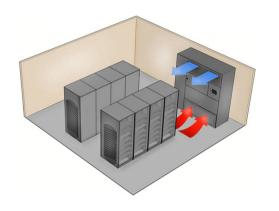
Summary of the pros and cons

logical simplicity vs. practical feasibility

main problems: what to exchange, and how

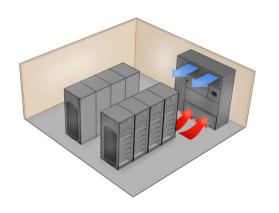
how shall we share information? (in the distributed paradigm case)

Fixed vs. dynamic topologies



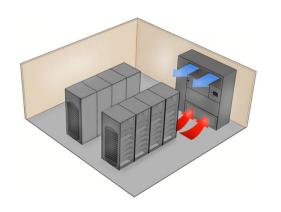


Wired vs. wireless communications



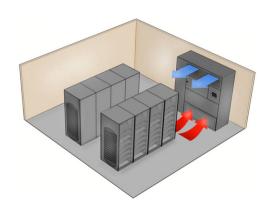


Synchronous vs. asynchronous communications





Lossless vs. lossy channels

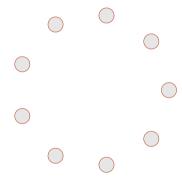


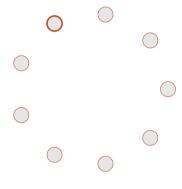


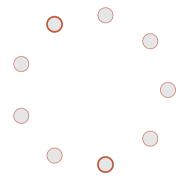
Summarizing, what are the main characteristics?

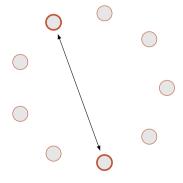
- do the connections change in time?
- what is the communication medium?
- is there a shared knowledge of time?
- may the communications fail?

towards consensus: the basic strategies for exchanging information





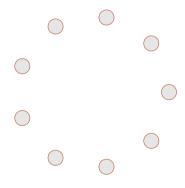




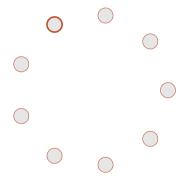
Byzantine generals, and their problems



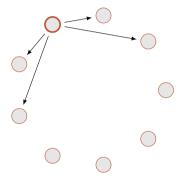
Broadcast communications



Broadcast communications



Broadcast communications



Summarizing, how can we be robust?

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- broadcast
- asynchronous
- tolerating packet losses

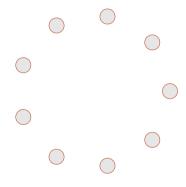
Summarizing, how can we be robust?

- broadcast
- asynchronous
- tolerating packet losses

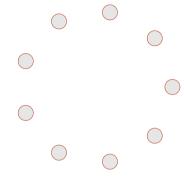
remember: there is no free lunch!

consensus

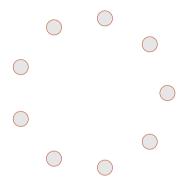
What does *consensus* mean?



Why is it important?



Why is it important?



example of a collective decision: if in average colder than 18°, then turn the heaters on

Average consensus

$$\begin{cases} \text{ local state:} & \theta_i, \quad i=1,\dots,n \\ \\ \text{ desired quantity:} & \frac{1}{n}\sum_{i=1}^n\theta_i \end{cases}$$
 (1

Max consensus

$$\begin{cases} \text{local state:} & \theta_i, \quad i=1,\ldots,n \\ \\ \text{desired quantity:} & \max\left\{\theta_1,\ldots,\theta_n\right\} \end{cases} \tag{2}$$

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example of a collective decision: randomly select a leader

Max consensus: how?

Order statistics consensus

$$\begin{cases} \text{local state:} & \theta_i, \quad i=1,\dots,n \\ \\ \text{desired quantities:} & \max\left\{\theta_1,\dots,\theta_n\right\} \text{ and } \min\left\{\theta_1,\dots,\theta_n\right\} \end{cases} \tag{3}$$

Order statistics consensus

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example of a collective decision: rapid anonymous statistical counting

Important remarks

max and order statistics consensus protocols can be broadcast, asynchronous, and using lossy media

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... but what about average consensus?

small detour: average consensus in practice

Gossip consensus

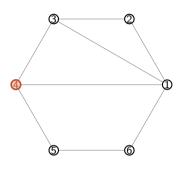
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$$P(k) = \begin{bmatrix} 1/2 & 0 & 0 & 1/2 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 1/2 & 0 & 0 & 1/2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

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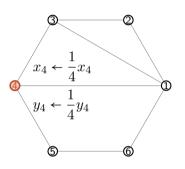
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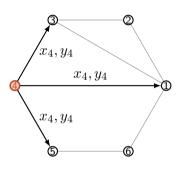
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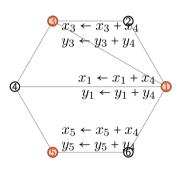
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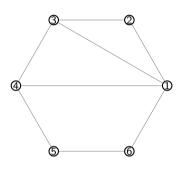
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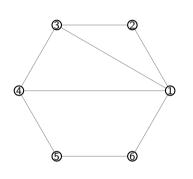
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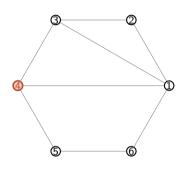


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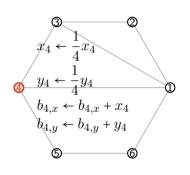
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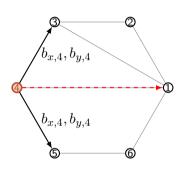
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- $\beta_{i,x}^{(j)}$: j's local estimate of $b_{i,x}$

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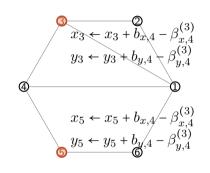
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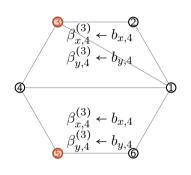
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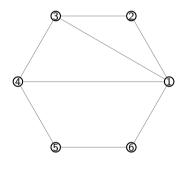


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taking decisions over networks

Numerical optimization: a hidden technology

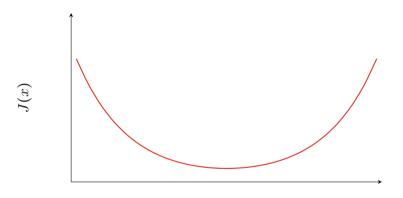
$$x^* = \arg\min_{x \in \mathcal{X}} J(x)$$
s.t. $Ax = b$ (4)
$$g(x) \ge 0$$

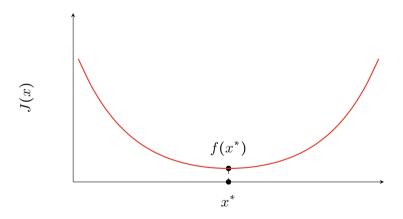
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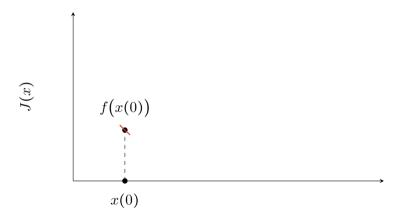
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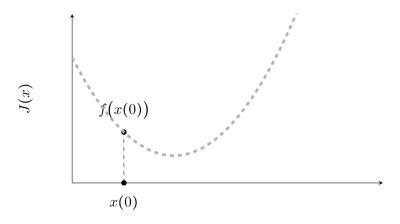
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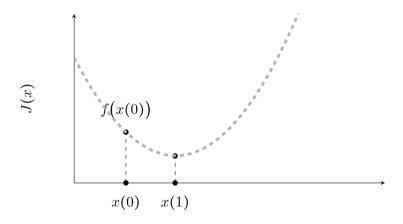
every decision is an optimization!

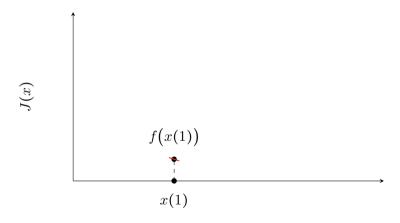


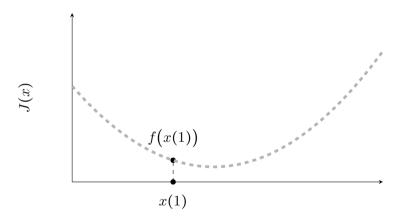












From the centralized NR to its distributed version

Newton update:

$$x^+ = x - \frac{f'(x)}{f''(x)}$$

thus

$$f(x) = \sum_{i=1}^{N} f_i(x) \implies x^+ = x - \frac{\sum_{i=1}^{N} f_i'(x)}{\sum_{i=1}^{N} f_i''(x)}$$

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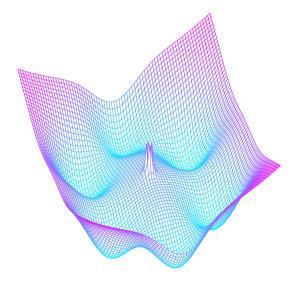
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i.e., parallel of two average consensi

Example: distributed formation control



Example: distributed formation control

video

a look into the future

TODOs

- more general & robust distributed optimization procedures
- develop self-tuning procedures

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- develop self-tuning procedures

• relieve humans from automatable burdens

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