

F. Zanella, D. Varagnolo, A. Cenedese, G. Pillonetto, L. Schenato

Department of Information Engineering, University of Padova

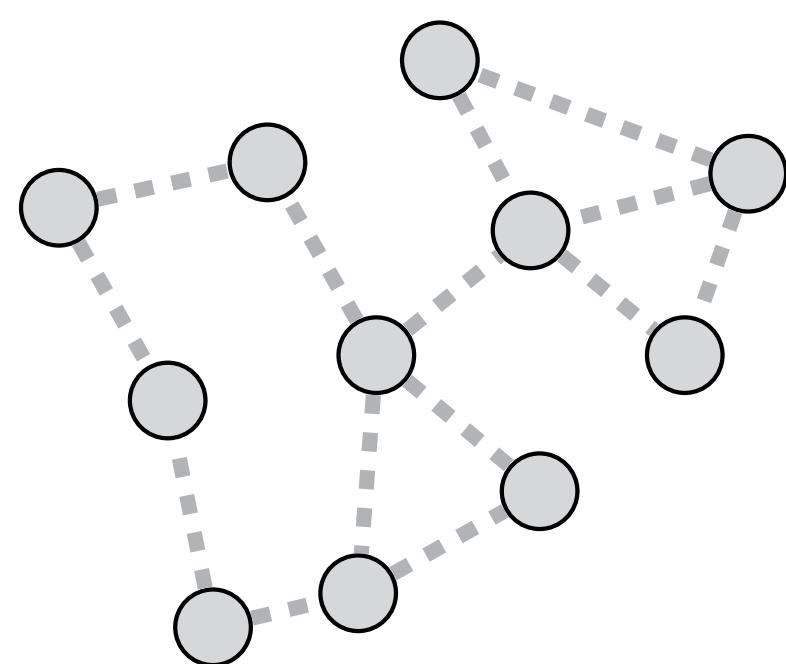
KTH Royal Institute of Technology

## Problem description

Aim:

- develop a **distributed convex optimization algorithm** suitable for

$$x^* := \arg \min_x f(x) \quad \text{with} \quad f(x) = \sum_{i=1}^N f_i(x)$$



Multi-Agents Scenario:

- use only local information
- exchange messages only with neighbors
- use asynchronous communications

**Assumption:**  $f_i : \mathbb{R} \mapsto \mathbb{R}$  smooth, closed, proper and strictly convex

## Derivation of the algorithm

Simplified case – quadratics:

$$f_i(x) = \frac{1}{2} a_i (x - b_i)^2 \quad \Rightarrow \quad x^* = \frac{\sum_{i=1}^N a_i b_i}{\sum_{i=1}^N a_i} = \frac{\frac{1}{N} \sum_{i=1}^N a_i b_i}{\frac{1}{N} \sum_{i=1}^N a_i}$$

a well known structure:  
**parallel of two average consensus**

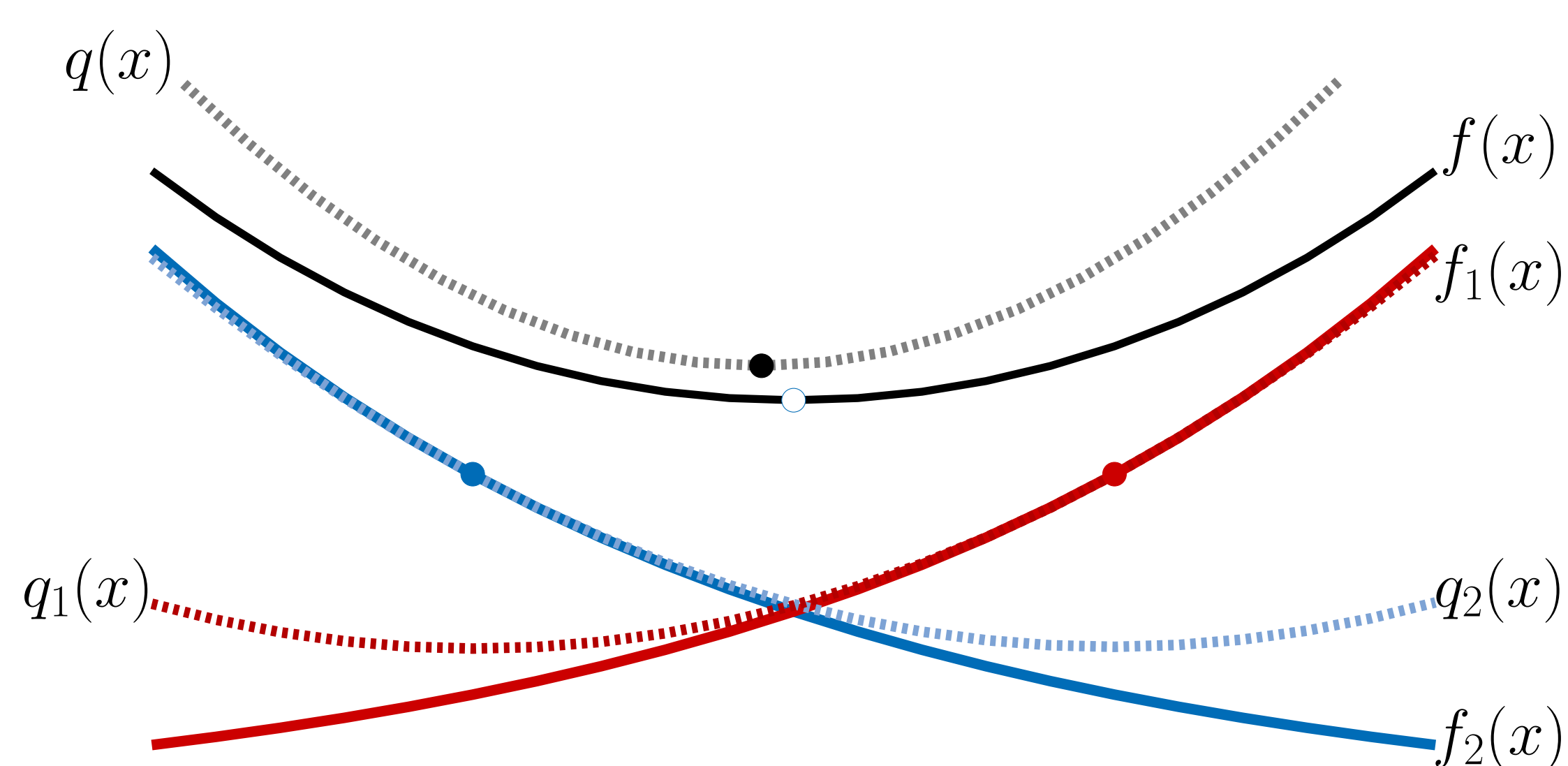
Question: *how to extend this to the general case?* First attempt:

### Prototype

let  $P$  = average consensus matrix

- initialize as follows:  
randomly select the  $x_i(0)$ 's  
compute  $y_i(0) = f_i''(x_i(0))x_i(0) - f_i'(x_i(0))$  and  $z_i(0) = f_i''(x_i(0))$
- run the average consensus  
 $\mathbf{y}^+ = P\mathbf{y}$   
 $\mathbf{z}^+ = P\mathbf{z}$
- when converged, compute  $\mathbf{x} = \frac{\mathbf{y}}{\mathbf{z}}$

**Proposition:** the  $\mathbf{x}$  computed by the previous algorithm corresponds to the exact Newton direction  $\Rightarrow$  *the previous procedure indicates where to move*  
 $\Rightarrow$  updating  $\mathbf{x}$  through  $\frac{\mathbf{y}}{\mathbf{z}}$  gets us closer to  $x^*$ :



$\rightarrow$  **directions for generalizations:**

- track the changing  $x_i(k)$
- make the local estimation step  $\mathbf{x}(k+1) = \frac{\mathbf{y}(k+1)}{\mathbf{z}(k+1)}$  milder
- make communications asynchronous

## The main algorithm: NRC

let

$$g_i(k) := f_i''(x_i(k))x_i(k) - f_i'(x_i(k))$$

$$h_i(k) := f_i''(x_i(k))$$

let also  $S(k)$ ,  $E(k)$ ,  $P(k)$  be, e.g.,

$$S(k) = \begin{bmatrix} 0 & & & \\ 1 & & & \\ & 0 & & \\ & & 0 & \\ & & & 0 \end{bmatrix} \quad E(k) = \begin{bmatrix} 0 & & & \\ 1 & & & \\ & 0 & & \\ & & 1 & \\ & & & 0 \end{bmatrix} \quad P(k) = \begin{bmatrix} 1 & & & \\ 1-\alpha & & \alpha & \\ & 1 & & \\ \alpha & & 1-\alpha & \\ & & & 1 \end{bmatrix}$$

1: initialize as follows:

randomly select the  $x_i(0)$ 's

set  $y_i(0) = z_i(0) = g_i(-1) = h_i(-1) = 0$

(main algorithm)

2: **for**  $k = 1, 2, \dots$  **do**

$$3: \quad \mathbf{y}(k+1) = P(k) \left( \mathbf{y}(k) + E(k) (\mathbf{g}(k) - \mathbf{g}(k-1)) \right)$$

$$4: \quad \mathbf{z}(k+1) = P(k) \left( \mathbf{z}(k) + E(k) (\mathbf{h}(k) - \mathbf{h}(k-1)) \right)$$

$$5: \quad \mathbf{x}(k+1) = \mathbf{x}(k) + \varepsilon S(k) \left( -\mathbf{x}(k) + \frac{\mathbf{y}(k+1)}{\mathbf{z}(k+1)} \right)$$

6: **end for**

**Why the algorithm works** (for sufficiently small  $\varepsilon$ ):

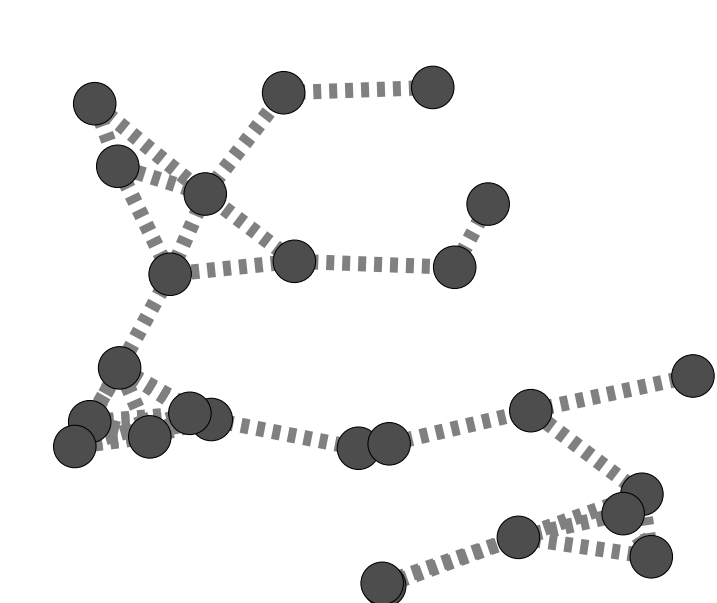
- $y_i(k) \approx \frac{1}{N} \sum_{i=1}^N (f_i''(x_i) x_i - f_i'(x_i))$
- $z_i(k) \approx \frac{1}{N} \sum_{i=1}^N f_i''(x_i)$
- $\hat{x}_{\text{ave}} \approx -\frac{f'(x_{\text{ave}})}{f''(x_{\text{ave}})}$

## Convergence properties

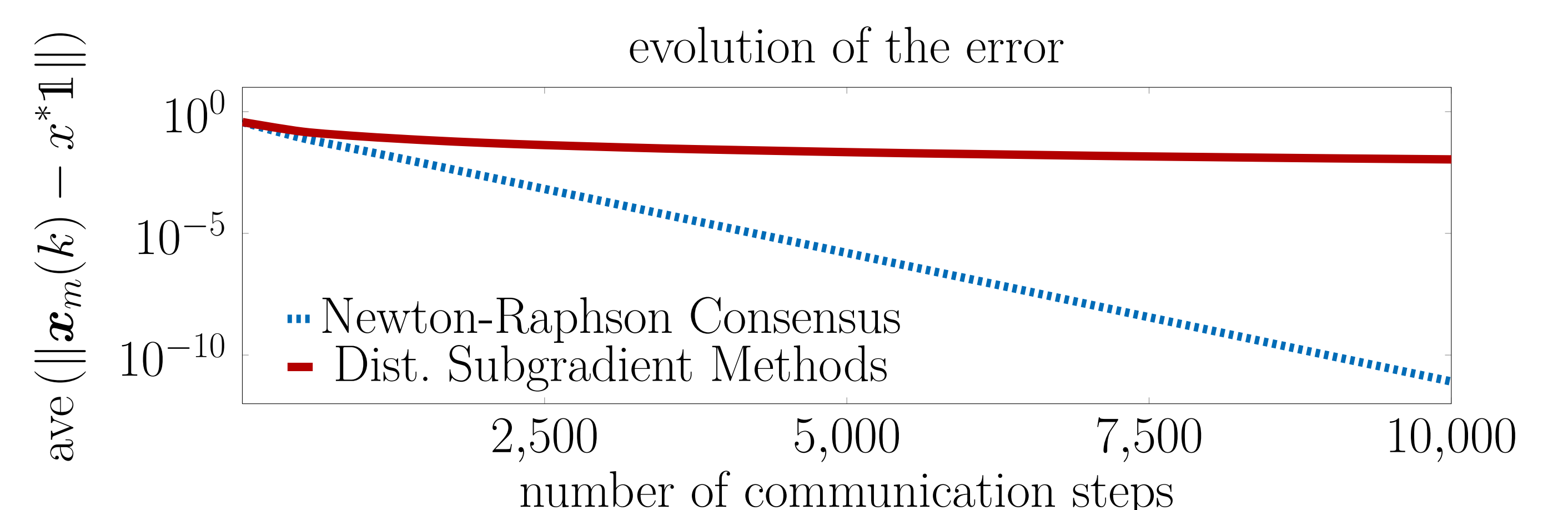
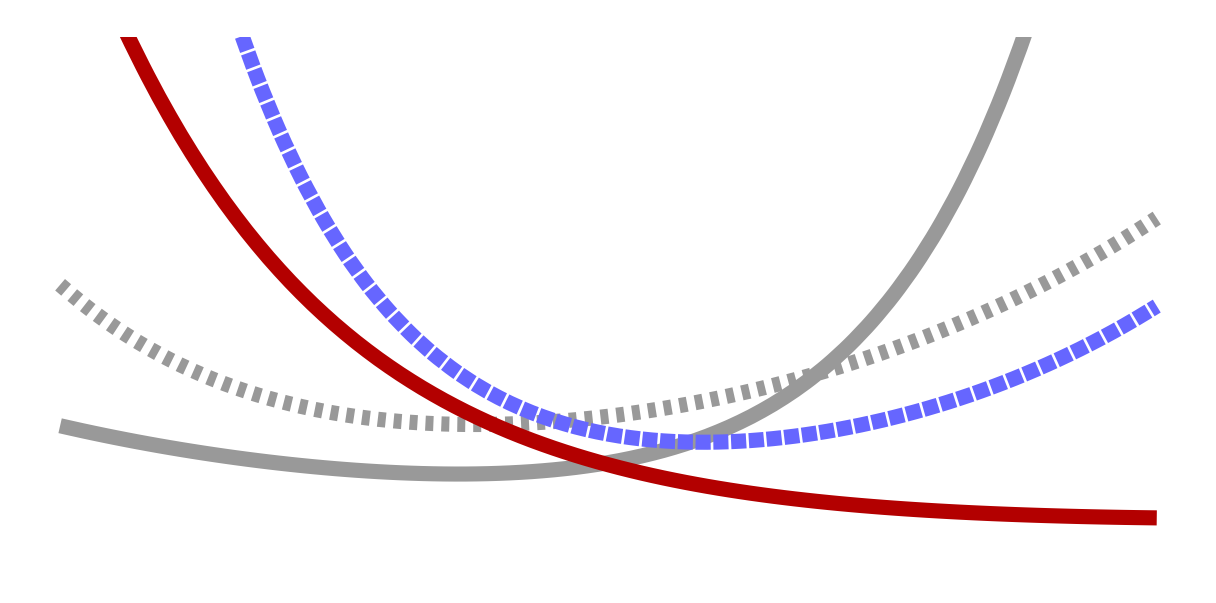
- Theorem: (uniform activation)** if on the long run all the agents are activated the same number of times then NRC is **globally convergent**
- Theorem: (persistent activation)** if every agent is activated at least once in every suff. large time windows then NRC is **locally convergent**

## Performance

communication graph



examples of local costs



## References

- Zanella, Varagnolo, Cenedese, Pillonetto, Schenato, *Newton-Raphson Consensus for Distributed Convex Optimization*, IEEE TAC 2012
- Zanella, Varagnolo, Cenedese, Pillonetto, Schenato, *Asynchronous N.-R. Consensus for Distributed Convex Optimization*, NecSys 2012