

# Optimization Meets Smart Networks

## Research and Technological Challenges in Systems and Control

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<http://opt4smart.eu>

Tavola Rotonda Automatica.it 2017 - Milano

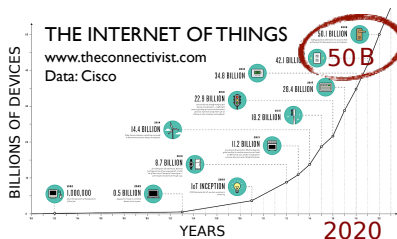
RESEARCH FUNDED BY



## Ubiquitous Smart Devices

### Massive

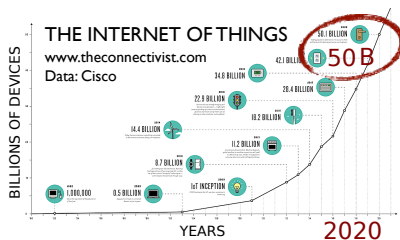
embedded computation  
communication  
sensing/control



## Ubiquitous Smart Devices

### Massive

embedded computation  
communication  
sensing/control



SPATIALLY-DISTRIBUTED and UNSTRUCTURED

## Sunway TaihuLight

(fastest supercomputer as of 2016)

Processing pwr: 105 PFLOPS

Memory: 1.31 PB

Storage: 20 PB



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Processing pwr: 105 PFLOPS

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## Iphone 7

(active since 2016)

Processing pwr: 10 GFLOPS

Memory: 2 GB

Storage: 256 GB



## Sunway TaihuLight

(fastest supercomputer as of 2016)

Processing pwr: 105 PFLOPS

Memory: 1.31 PB

Storage: 20 PB



## 1.4M smartphones

(Milan population)

Processing pwr: 14 PFLOPS

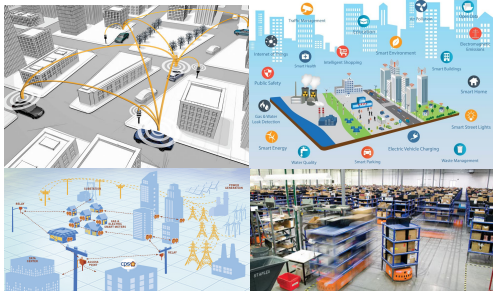
Memory: 2.8 PB

Storage: 360 PB



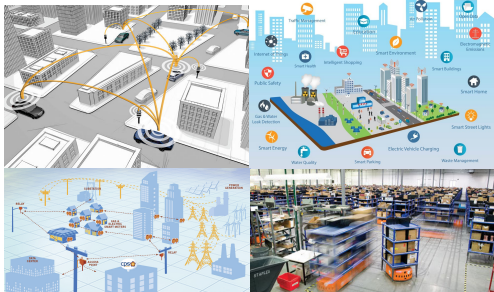
## Turn smart devices into **Cooperative Intelligent Systems**

- car-2-x systems
- smart cities
- smart grids
- automated factories
- ...



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*This is “our” (Control Engineers’) job!*



Optimization is a building block for many problems in Engineering  
but also Economics, Social Sciences, Biology, ...

- **ESTIMATION and LEARNING**

traffic estimation, localization, classification, clustering, ...

- **DECISION and CONTROL**

cooperative robotics, smart grid control, resource/task allocation ...

## Centralized Methods

- Small-size problems
- Sequential computations



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## Parallel (and “Classical Distributed”) Methods

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## Parallel (and “Classical Distributed”) Methods

- Large-scale problems
- Several computations simultaneously
- Main goal: computation speedup
- Network topology is a design parameter



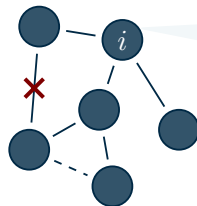
# Main Challenges in Distributed Optimization

Structured optimization problem

$$\min_x \sum_{i=1}^N f_i(x)$$

$$\text{subj. to } x \in \bigcap_{i=1}^N X_i$$

cost  
coupled

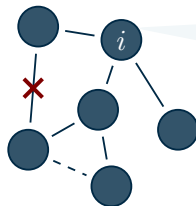


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Structured optimization problem

$$\begin{aligned} \min_{\{x_i \in X_i\}} & \sum_{i=1}^N f_i(x_i) \\ \text{subj. to} & \sum_{i=1}^N g_i(x_i) \leq 0 \end{aligned}$$

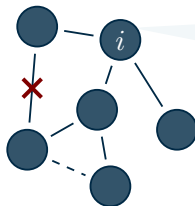
constraint  
coupled



# Main Challenges in Distributed Optimization

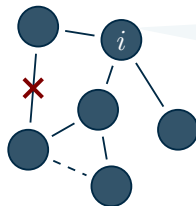
## GOAL

solve (given!) problem via  
Distributed Algorithm



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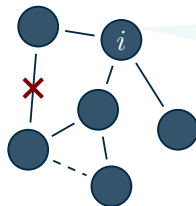
- processors know only a portion of the problem
- ASYNCHRONOUS and unreliable communication
- large-scale and BIG-DATA problems
- possibly NONCONVEX (mixed-integer, combinatorial)
- ... to be solved in REALTIME!



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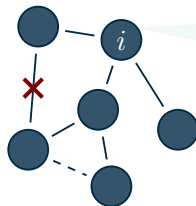


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NO central coordinator!

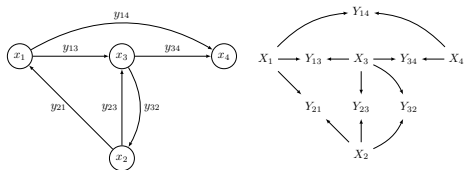
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network topology NOT a design parameter!



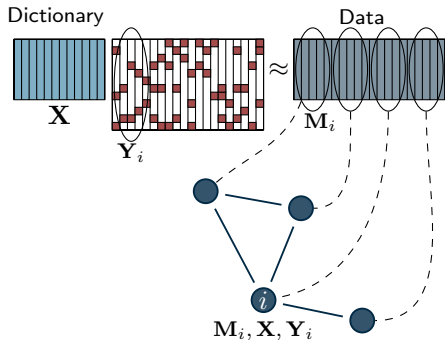
- users mutually evaluate themselves
- local interaction and cooperation
- GOAL: cooperative self-profiling

Empirical Bayes (relaxed) Estimator

$$(\hat{\theta}, \hat{\gamma}) = \operatorname{argmax}_{(\theta, \gamma) \in \mathcal{S}_{\Theta} \times \mathcal{S}_{\Gamma}} \sum_{i=1}^N g(\theta, \gamma; n_i)$$

$(\theta, \gamma)$  unknown “world” parameters

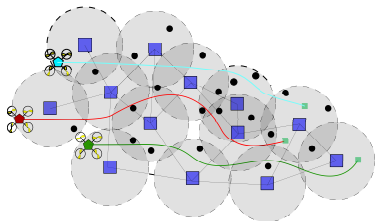
$n_i$  aggregate statistics at node  $i$



- inpainting
- denoising
- collaborative filtering (recommender systems)

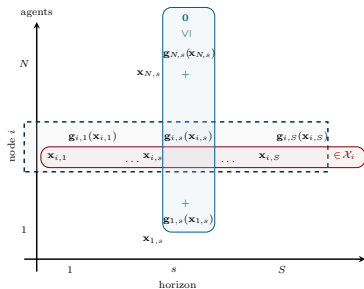
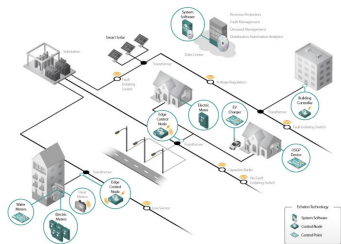
$$\min_{\mathbf{X}, \mathbf{Y}_1, \dots, \mathbf{Y}_N} \sum_{i=1}^N \|\mathbf{M}_i - \mathbf{X}\mathbf{Y}_i\|_F^2 + \lambda \|\mathbf{Y}_i\|_1$$

subj. to  $\mathbf{X} \in \mathcal{X}$



- smart environment  
(sensors, processors, mobile robots)
- local processing and communication
- GOAL: assign tasks in realtime  
(e.g., paths that minimize time)

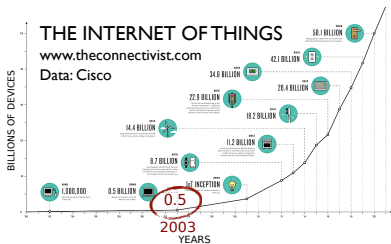
$$\begin{aligned} \min_{x,y} \quad & c_x^\top x + y \\ \text{subj. to} \quad & a_i^\top x \leq y, \forall i = 1, \dots, d_Z \\ & A_T x \leq -\mathbf{1}_{N_T} w \\ & P x = \mathbf{1}_{N_v} \\ & x \in \{0, 1\} \text{ (binary)}, y \in \mathbb{R} \end{aligned}$$



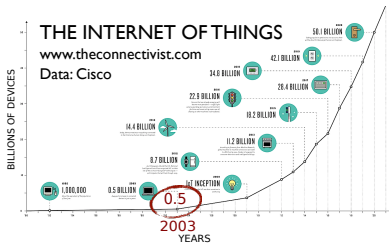
- smart generators/accumulators/loads
- local processing and communication
- GOAL: cooperatively optimize generation/consumption

$$\begin{aligned}
 & \min_{\{x_{i,s}\}} \sum_{i=1}^N \sum_{s=1}^S f_{i,s}(x_{i,s}) \\
 & \text{subj. to } \sum_{i=1}^N g_{i,s}(x_{i,s}) \leq 0, \quad s \in \{1, \dots, S\} \\
 & \quad x_i \in X_i, \quad i \in \{1, \dots, N\}
 \end{aligned}$$

Start of  
exponential growth  
2002/2003



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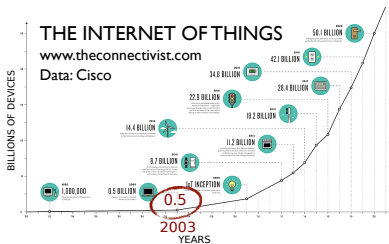
## What happened in those years in our Controls Community?

Jadbabaie, Lin, Morse, “Coordination of groups of mobile autonomous agents using nearest neighbor rules”, CDC 2002, TAC 2003.

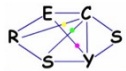
new distributed “control” research started



Start of  
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What about Italian community? (Personal experience!)



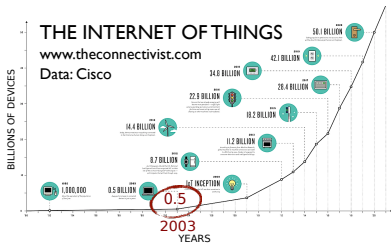
RECSYS - FP5 (09/2002 - 08/2005)

Real-Time Emb. Control of Mobile Systems w/ Distributed Sensing

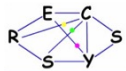
Coordinator: G. Picci (UNIPD)

Partners: UNIPI (A. Bicchi), S. Anna, EPFL, KTH, Intecs

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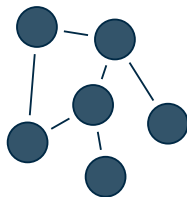
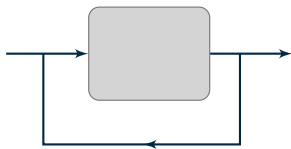
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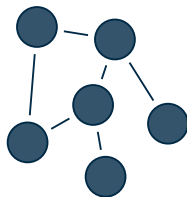
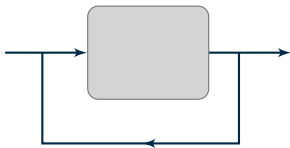
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### OBJECTIVES

"... new paradigms and methods for control design of embedded systems with distributed sensing, limited communication and computational resources ..."

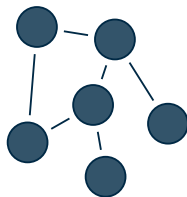
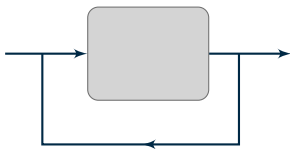


- new research problems ... not even clear which ones!
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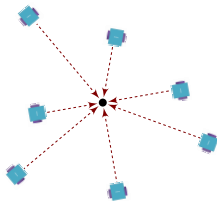
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**Note:** At the beginning “toy” problems ... applications not clear

## Minimum time rendezvous for first order agents

Centralized solution:

move at maximum speed toward the center of the smallest enclosing ball

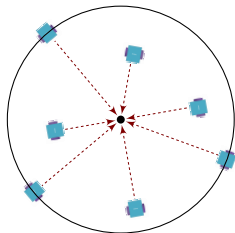


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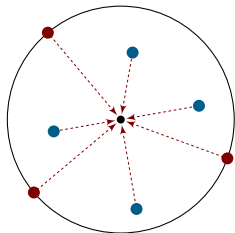
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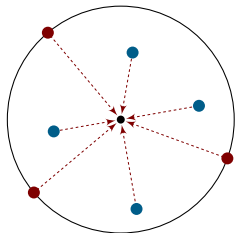
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## Distributed Optimization Problem

# Today's Disruptive Innovations

What is the role of our Control Community in today's innovation challenges?

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MCKINSEY GLOBAL INSTITUTE

## WHAT'S NOW AND NEXT IN ANALYTICS, AI, AND AUTOMATION

BRIEFING NOTE • MAY 2017



“Innovations in digitization, analytics, artificial intelligence, and automation are creating performance and productivity opportunities for business and the economy, even as they reshape employment and the future of work.”

(McKinsey Briefing Note 2017)

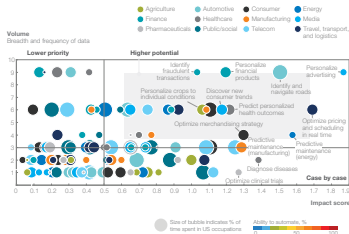
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What is the role of our Control Community in today's innovation challenges?

## Analytics

"Data and analytics are already disrupting business models and bringing performance benefits"

(McKinsey Briefing Note 2017)



## Automation

"AI and Automation will provide a much-needed boost to global productivity"

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courtesy McKinsey Briefing Note 2017

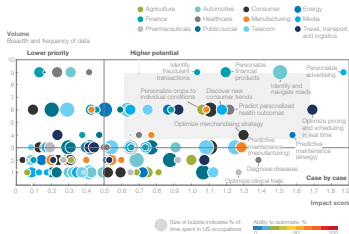
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courtesy McKinsey Briefing Note 2017

this is “Controls” moment!

# What About Keywords?

## Some modern “catchy” keywords

Artificial Intelligence

Machine Learning

(Deep Learning, Reinforcement Learning)

Collective Intelligence

Cognitive Systems

Cyber-Physical Systems

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“[...] It’s probably one of the most difficult AI projects, actually, to work on.”

Tim Cook (Bloomberg, June 2017)

## Opportunities

- new powerful technology with massive computation and communication capability available
- optimization is a building block in many estimation, learning, decision and control problems

## Challenges

- asynchronous, unreliable, directed communication
- complex (optimization) problems in smart networks
- large-scale, dynamic problems to be solved in realtime

RESEARCH FUNDED BY

