Collective Intelligence: a Framework to Explore Complex Systems Biology and Federated AI Medicine

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A "Simple" Collective "Play"

Goal of play:

- Each one of us chooses a number (Participant i chooses x_i^0)

- Compute the average of all our numbers

$$x_{\text{avg}} = \frac{x_1^0 + x_2^0 + \ldots + x_{\text{participants}}^0}{\text{number of participants}}$$

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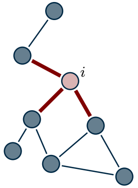
Rules of play:

- Each one of us talks only with some “neighbors”
  (some participants you know)
- You update your guess of x_{avg}

  (Participant i updates x_i^t. At time 0 start with x_i^0)
- You can exchange your guess x_i^t only with your neighbors.



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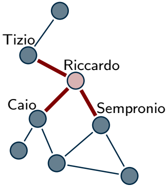
Idea: Suppose Riccardo (Participant 1) has 3 neighbors (Tizio, Caio, Sempronio)

- Collect from them their current guess x_{Tizio}^t, x_{Caio}^t, $x_{\text{Sempronio}}^t$
- Average your guess and the collected ones

$$x_{\text{Riccardo}}^{t+1} = \frac{x_{\text{Riccardo}}^t + x_{\text{Tizio}}^t + x_{\text{Caio}}^t + x_{\text{Sempronio}}^t}{4}$$

- keep doing that!



Distributed Average Consensus in Complex Networks

Group of N individuals, with x_i^t being the opinion of individual i at time t.

Opinions are updated according to

$$x_i^{t+1} = \sum_{j=1}^{N} a_{ij} x_j^t$$

with $a_{ij} \geq 0$ and $\sum_{j=1}^{N} a_{ij} = 1$.

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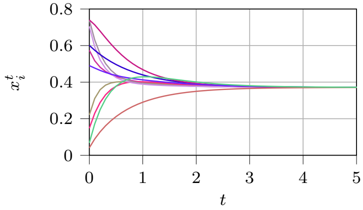


- Do individual opinions converge to a common value ("reach consensus")? Average?
- Under which interaction topology? Do they need to interact synchronously?
- What if there are stubborn individuals ("influencers")?
- What about more complex (nonlinear) dynamics?

Distributed robot coordination

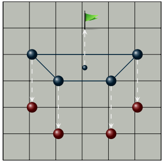
Team of N (mobile) robots aiming at executing complex tasks

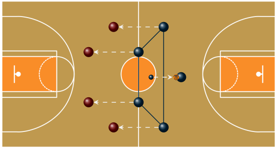
Basic tasks

- rendezvous, containment
- formation, flocking, coverage

Complex tasks

- pickup & delivery
- surveillance, patrolling, exploration





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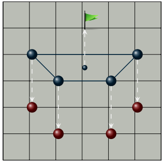
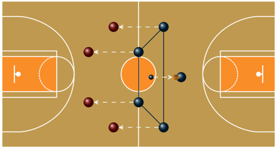
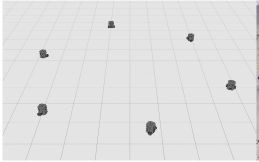
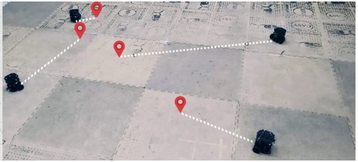




"Simulator (digital twins)"



"Experimental platform"



Tumor growth modeling via evolutionary dynamics

- Model tumor cells (osteosarcoma) with evolutionary dynamics
- Predict response to therapies (doxorubicin, cisplatin)
- Tumor cells adapt to hostile environment in order to survive

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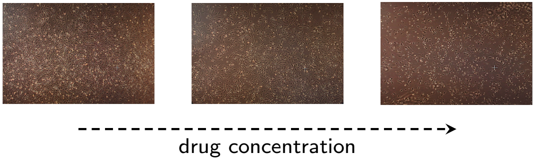
Evolutionary dynamics (single habitat)

$$
\begin{cases}
\dot{x} = xG(\ell, s_1, s_2, x, c_1, c_2) \\
\dot{\ell} = \gamma \dfrac{\partial G(q, v_1, v_2, w, c_1, c_2)}{\partial q} \\
\dot{s}_1 = \gamma \dfrac{\partial G(q, v_1, v_2, w, c_1, c_2)}{\partial v_1} \\
\dot{s}_2 = \gamma \dfrac{\partial G(q, v_1, v_2, w, c_1, c_2)}{\partial v_2} \\
\dot{c}_1 = -z_1 c_1 + u_1 \\
\dot{c}_2 = -z_2 c_2 + u_2
\end{cases}
$$

Experiment (at IOR)



Experiment courtesy of N. Baldini, S. Avnet, G. di Pompo, T. Fischetti

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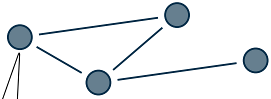
Multi-habitat models for more realistic tumor structures

Combine model-based and AI-trained dynamics
for more precise predictions



$$\dot{x}_i = \underbrace{f_i(x_{\mathcal{N}_i}, u_i)}_{\text{evolutionary model}} + \underbrace{g_i(x_{\mathcal{N}_i}, u_i)}_{\text{learned}}$$

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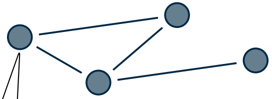
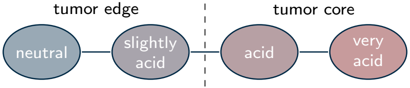


$$\dot{x}_i = \underbrace{f_i(x_{\mathcal{N}_i}, u_i)}_{\text{evolutionary model}} + \underbrace{g_i(x_{\mathcal{N}_i}, u_i)}_{\text{learned}}$$

Example: 4 habitats

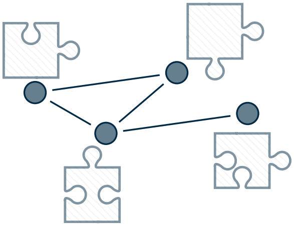


Distributed Optimization

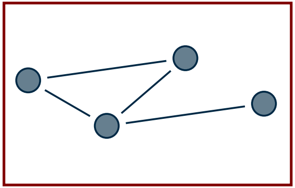
Optimization

$$\min_{x} \; f(x)$$

$$\text{subj.to} \;\; x \in X$$



Network



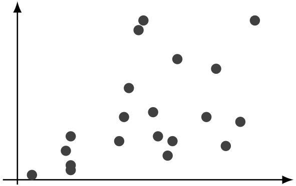
Problem data is spatially distributed and private

Exchange computation rather than data

Distributed Machine Learning: Data Regression

Example: distributed regression

$$\min_{x} \sum_{i=1}^{N} \|b_i - D_i x\|^2$$



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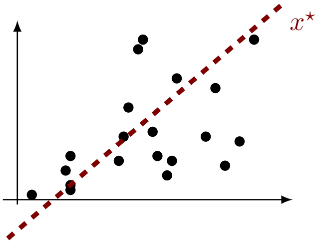

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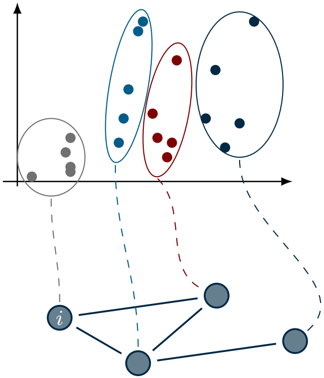

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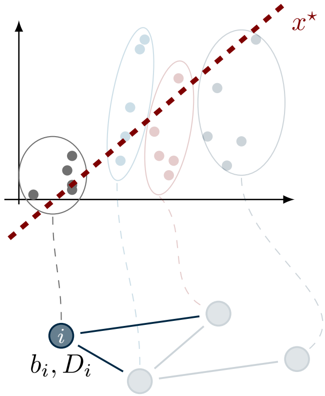
Paradigm

- local private data (b_i, D_i)
- cooperate to learn from all data



Distributed Machine Learning: Training of Neural Networks

General optimization set-up embraces also training of neural networks

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

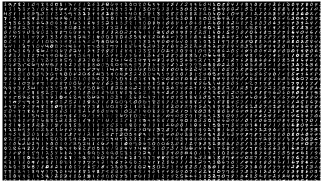
$\mathcal{D}_1$

$\mathcal{D}_2$

$\vdots$

$\mathcal{D}_N$

$\mathcal{D} = \mathcal{D}_1 \cup \cdots \cup \mathcal{D}_N$



Paradigm

- dataset split among processors

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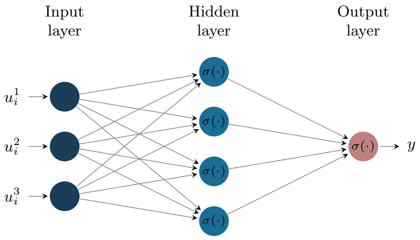
$$\min_{x} \sum_{i=1}^{N} f_i(x)$$

Common model for $\mathcal{D} = \mathcal{D}_1 \cup \cdots \cup \mathcal{D}_N$

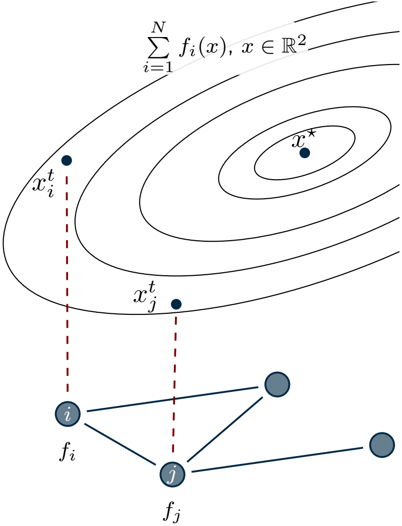


Paradigm

- dataset split among processors
- cooperate to train common neural network

In-Network Optimization

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



- N agents communicate over graph $\mathcal{G}$
- agent i knows f_i only
- x_i^t solution estimate of i

In-Network Optimization

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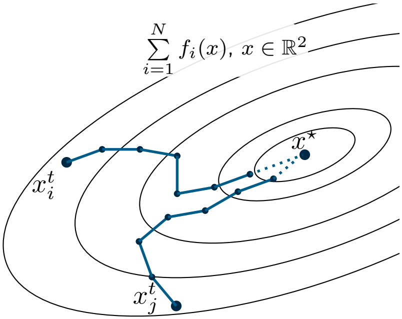


agent 1 estimate
x_1^t

agent N estimate
x_N^t

$t \to \infty$
consensus

optimal solution
$x^\star$

DISROPT: A Python Package for Distributed Optimization

DISROPT

Toolbox for distributed optimization in python™

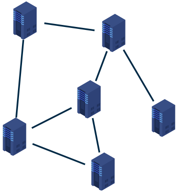
developed by OPT4SMART group

`https://disropt.github.io/disropt/`

Grid computing

High-performance parallel computing units

Model unreliable real networks



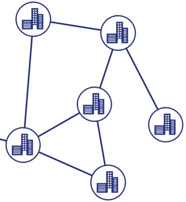
Federated and Distributed Learning from Big-data in Healthcare

Automated decision support systems for healthcare

Collective learning from private big-data databases

Goal: privacy of institutional data

share computation instead of data



Localization of diseases

Personalized treatments

Patient outcome predictions

Thanks to...

Center for Research on Complex Automated Systems (CASY)
Department of Electrical Electronic and Information Engineering "G. Marconi"
Alma Mater Studiorum Università di Bologna

Ivano Notarnicola (junior assistant professor)

Andrea Testa (post-doc)

Andrea Camisa (Ph.D. student)

Guido Carnevale (Ph.D. student)

Lorenzo Sforni (Ph.D. student)

IRCCS Istituto Ortopedico Rizzoli

N. Baldini (Director Rizzoli-RIT)

S. Avnet (Biotechnologist)

G. di Pompo (Researcher)

T. Fischetti (PhD student)

OPT4SMART Project

Distributed Optimization Methods for Smart Cyber-Physical Networks

Methodological framework for distributed optimization

Numerical tools for machine learning and control

Experimental testbed and toolbox

opt4smart.dei.unibo.it

OPT4SMART

European Research Council

Some hints for discussion

- Complex networks theory, large-scale optimization, distributed computing
- In-silico models for complex biological systems
- Distributed federated AI in healthcare (private data & ensemble knowledge)

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Will doctors be AIs with a human touch?

Better... "Human Doctors with an AI touch"!