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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  (Example: Riccardo is Participant 1 and chooses $x_1^0 = 25$)

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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 $x_{\text{avg}}$
  (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 $x_{Tizio}^t$, $x_{Caio}^t$, $x_{Sempronio}^t$
- Average your guess and the collected ones

\[ x_{\text{Riccardo}}^{t+1} = \frac{x_{\text{Riccardo}}^t + x_{Tizio}^t + x_{Caio}^t + x_{Sempronio}^t}{4} \]
- keep doing that!
Distributed Average Consensus in Complex Networks

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

Opinions are updated according to

$$x^{t+1}_i = \sum_{j=1}^{N} a_{ij} x^t_j$$

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

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Distributed Average Consensus in Complex Networks

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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)

\[
\begin{align*}
\dot{x} &= xG(\ell, s_1, s_2, x, c_1, c_2) \\
\dot{\ell} &= \gamma \frac{\partial G(q, v_1, v_2, w, c_1, c_2)}{\partial q} \\
\dot{s}_1 &= \gamma \frac{\partial G(q, v_1, v_2, w, c_1, c_2)}{\partial v_1} \\
\dot{s}_2 &= \gamma \frac{\partial G(q, v_1, v_2, w, c_1, c_2)}{\partial v_2} \\
\dot{c}_1 &= -z_1 c_1 + u_1 \\
\dot{c}_2 &= -z_2 c_2 + u_2
\end{align*}
\]

Experiment (at IOR)

Experiment courtesy of N. Baldini, S. Avnet, G. di Pompo, T. Fischetti
Tumor growth modeling via evolutionary dynamics

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Multi-habitat models for more realistic tumor structures
Combine model-based and AI-trained dynamics for more precise predictions

\[ \dot{x}_i = f_i(x_{N_i}, u_i) + g_i(x_{N_i}, u_i) \]

- Evolutionary model
- Learned
Tumor growth modeling via evolutionary dynamics

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Multi-habitat models for more realistic tumor structures

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

Example: 4 habitats

\[ \dot{x}_i = f_i(x_{N_i}, u_i) + g_i(x_{N_i}, u_i) \]

- tumor edge
- neutral
- slightly acid
- acid
- very acid
- tumor core
Distributed Optimization

Optimization

\[
\min_x f(x)
\]
subj.to \( x \in X \)

Problem data is spatially distributed and private
Exchange computation rather than data
Distributed Machine Learning: Data Regression

Example: distributed regression

$$\min_x \sum_{i=1}^{N} \|b_i - D_ix\|^2$$
Example: distributed regression

\[ \min_{x} \sum_{i=1}^{N} \| b_i - D_i x \|^2 \]
**Example:** distributed regression

\[
\min_x \sum_{i=1}^{N} \| b_i - D_i x \|^2
\]
Distributed Machine Learning: Data Regression

Example: distributed regression

\[
\min_x \sum_{i=1}^{N} \|b_i - D_i x\|^2
\]

Paradigm

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

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Distributed Machine Learning: Training of Neural Networks

**General** optimization set-up embraces also training of neural networks

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

**Paradigm**
- dataset split among processors

\[\mathcal{D} = \mathcal{D}_1 \cup \cdots \cup \mathcal{D}_N\]
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\[
\min_x \sum_{i=1}^{N} f_i(x)
\]

Paradigm

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

Common model for \( \mathcal{D} = \mathcal{D}_1 \cup \cdots \cup \mathcal{D}_N \)
In-Network Optimization

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

- \(N\) agents communicate over graph \(G\)
- agent \(i\) knows \(f_i\) only
- \(x^t_i\) solution estimate of \(i\)
In-Network Optimization

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

\[ \sum_{i=1}^{N} f_i(x), \ x \in \mathbb{R}^2 \]

agent 1 estimate \( x_1^t \)

agent \( N \) estimate \( x_N^t \)

optimal solution \( x^* \)

t \( \to \) \( \infty \)

consensus
DISROPT: A Python Package for Distributed Optimization

DISROPT
Toolbox for distributed optimization in 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...

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G. di Pompo (Researcher)
T. Fischetti (PhD student)
Distributed Optimization Methods for Smart Cyber-Physical Networks

Methodological framework for distributed optimization

Numerical tools for machine learning and control

Experimental testbed and toolbox
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”!