Artificial Intelligence & Energy

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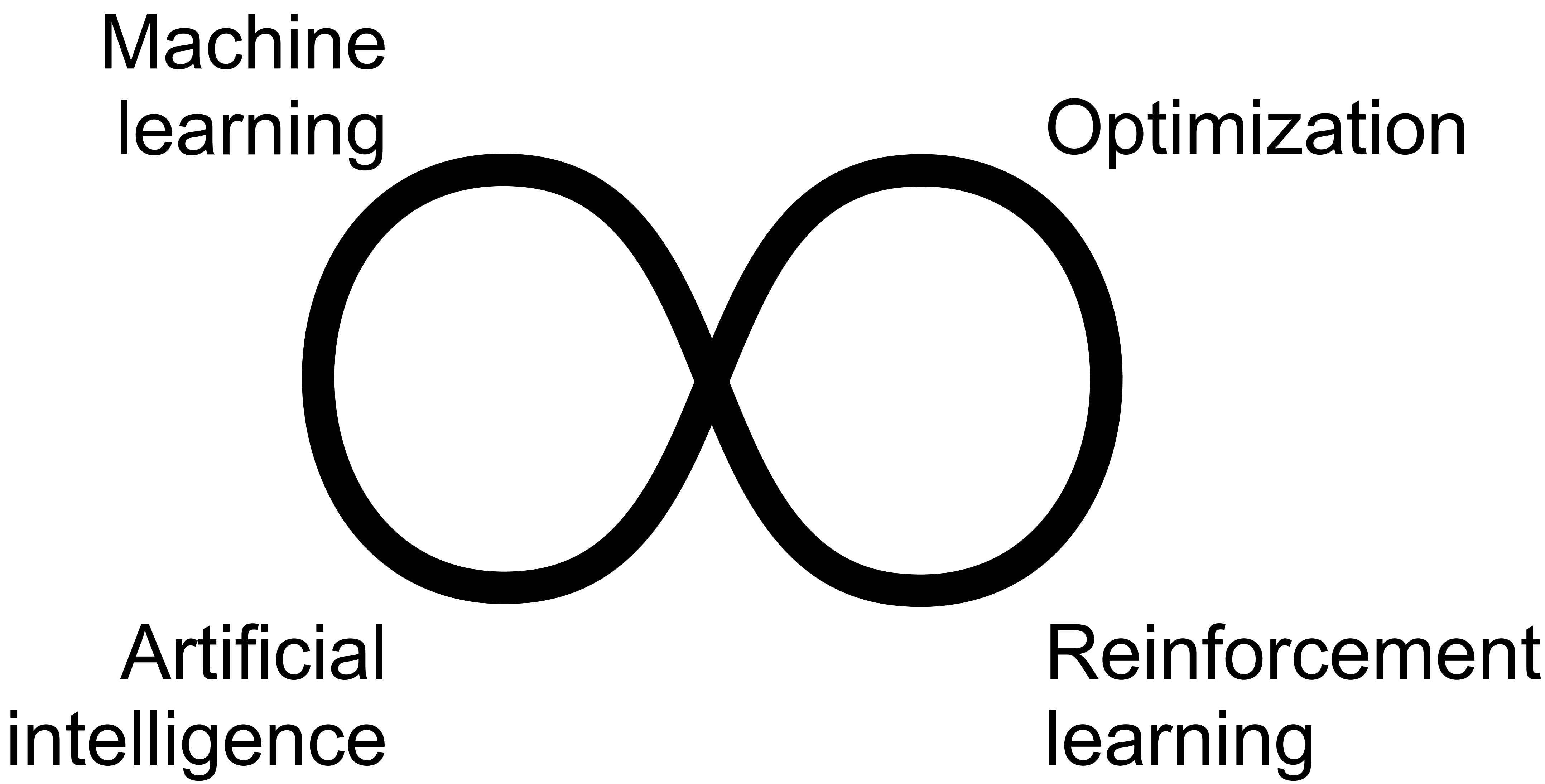
The Smartgrids team is part of the Montefiore Research Unit of the ULg, contains around 15 researchers and is headed by Pr. Damien Ernst

Our vision of Artificial Intelligence

Roadmap


Machine learning
Optimization
Artificial intelligence
Reinforcement learning

Roadmap

Machine
learning

Machine learning is about extracting {patterns, knowledge, information} from data

Cluster images

Google photos

clarifai

Recognize patterns in images

Convert voice signal into sentences

Cortona

SIRI

OK Google

Interpret sentences

Google Now

Make on-line recommandations

NETFLIX

amazon.com

Machine learning studies and builds algorithms that learn from and make predictions on data

Supervised Learning in a nutshell:

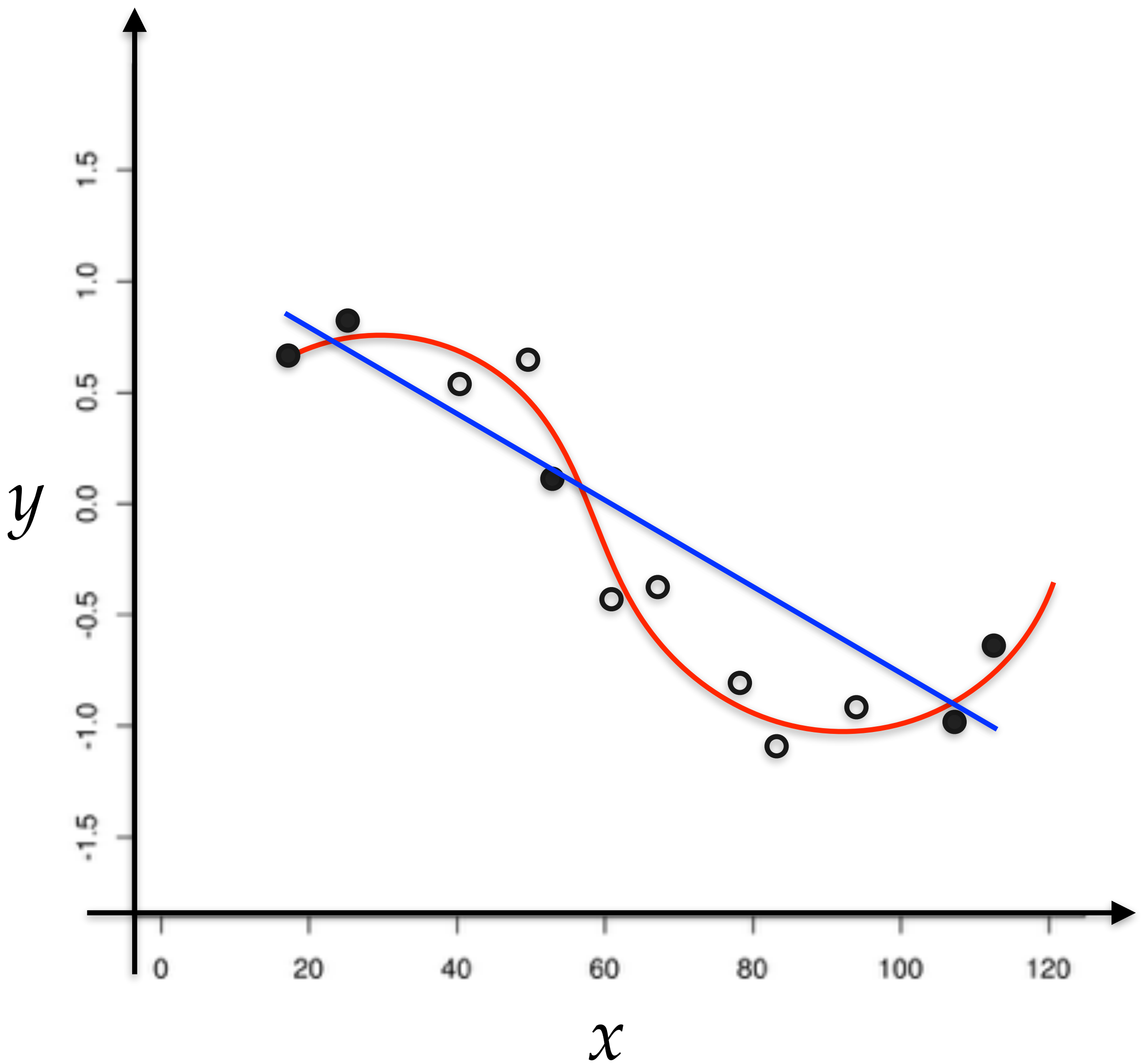
Imagine you have a set of data

$$\{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$$

represented by black points on the figure.

To be able to estimate the value of an output y for any input x, You "train" a Machine Learning algorithm using these data. You obtain the blue line.

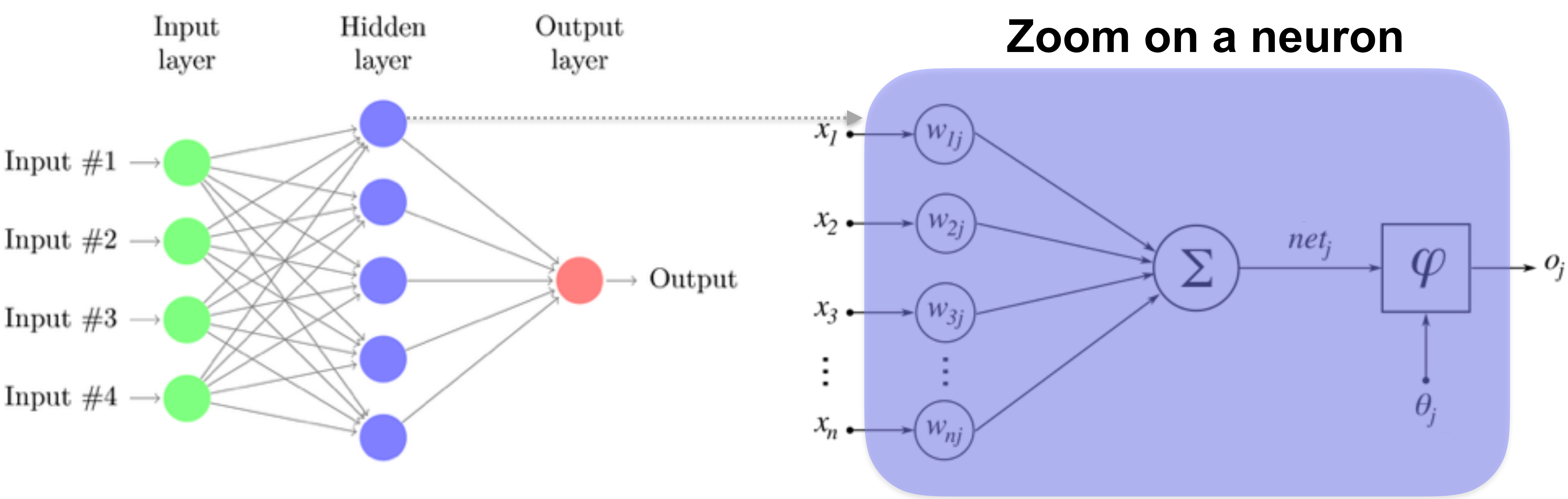
The quality of the estimate depends on data quality/quantity: with more points, e.g. the black circles, you would for instance get the red curve.



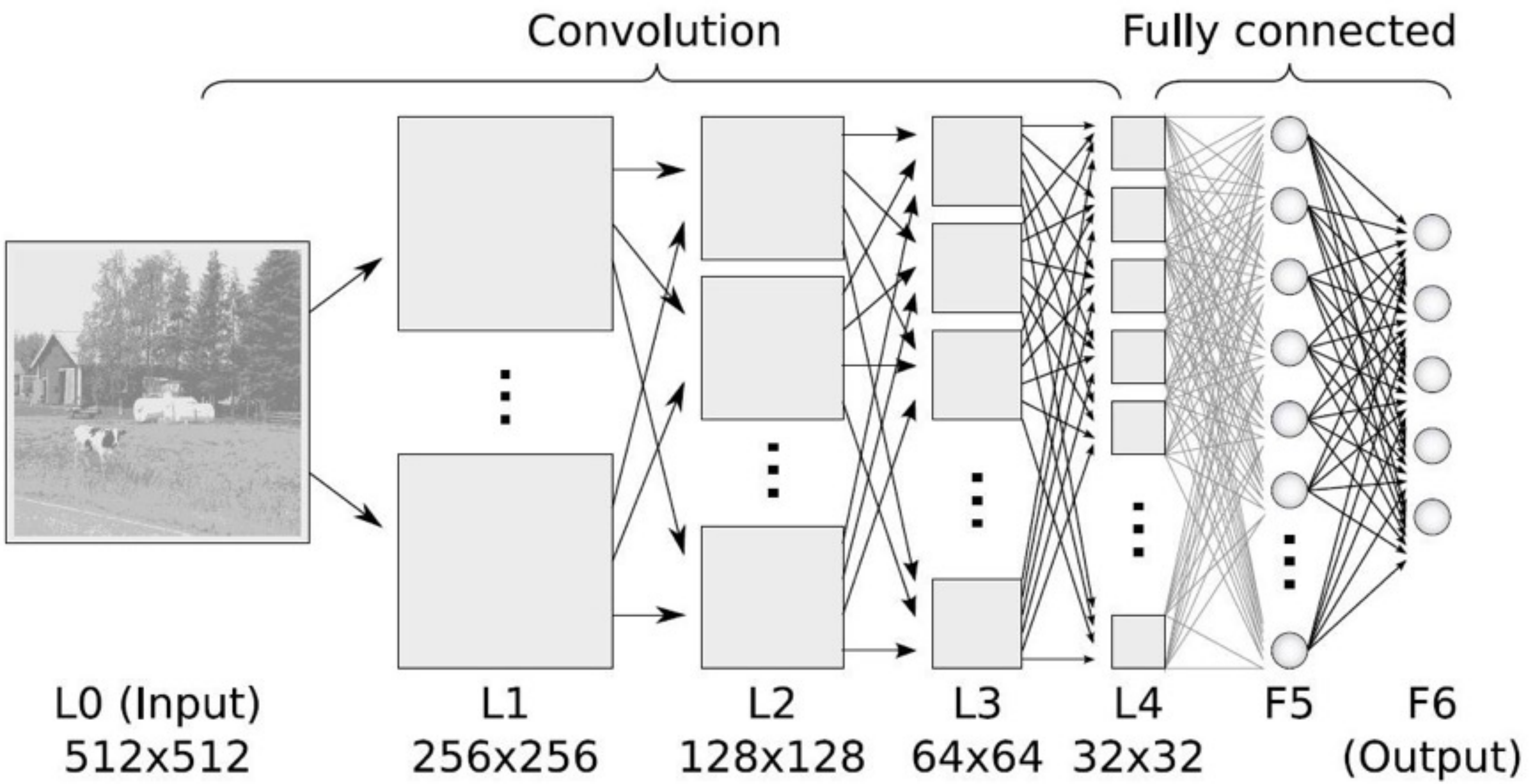
Recent advances in machine learning

Machine learning algorithms have recently shown impressive results, in particular when input data are images: this has led to the identification of a subfield of Machine Learning called **Deep Learning**.

The term "deep" refers to the fact that those learning architectures, mainly **Artificial Neural Networks**, are made of several layers.



Deep neural network architectures



Source: http://www.ais.uni-bonn.de/deep_learning/images/Convolutional_NN.jpg

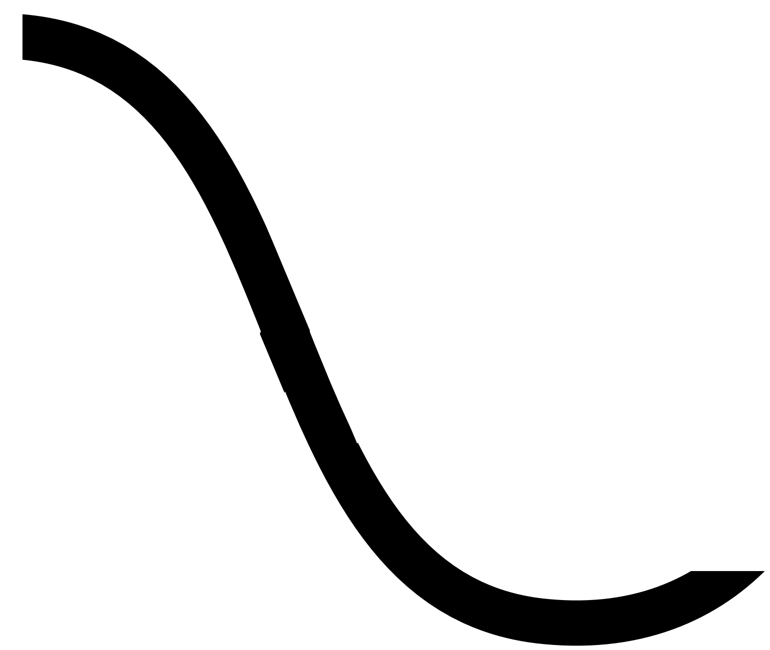
Wait… ANN are not new, right?

ANN date back to the sixties. Training ANN was not an easy task until recently. Recent progress is twofold:

- Smart(er) training approaches
- GPU calculus

Roadmap

Machine
learning



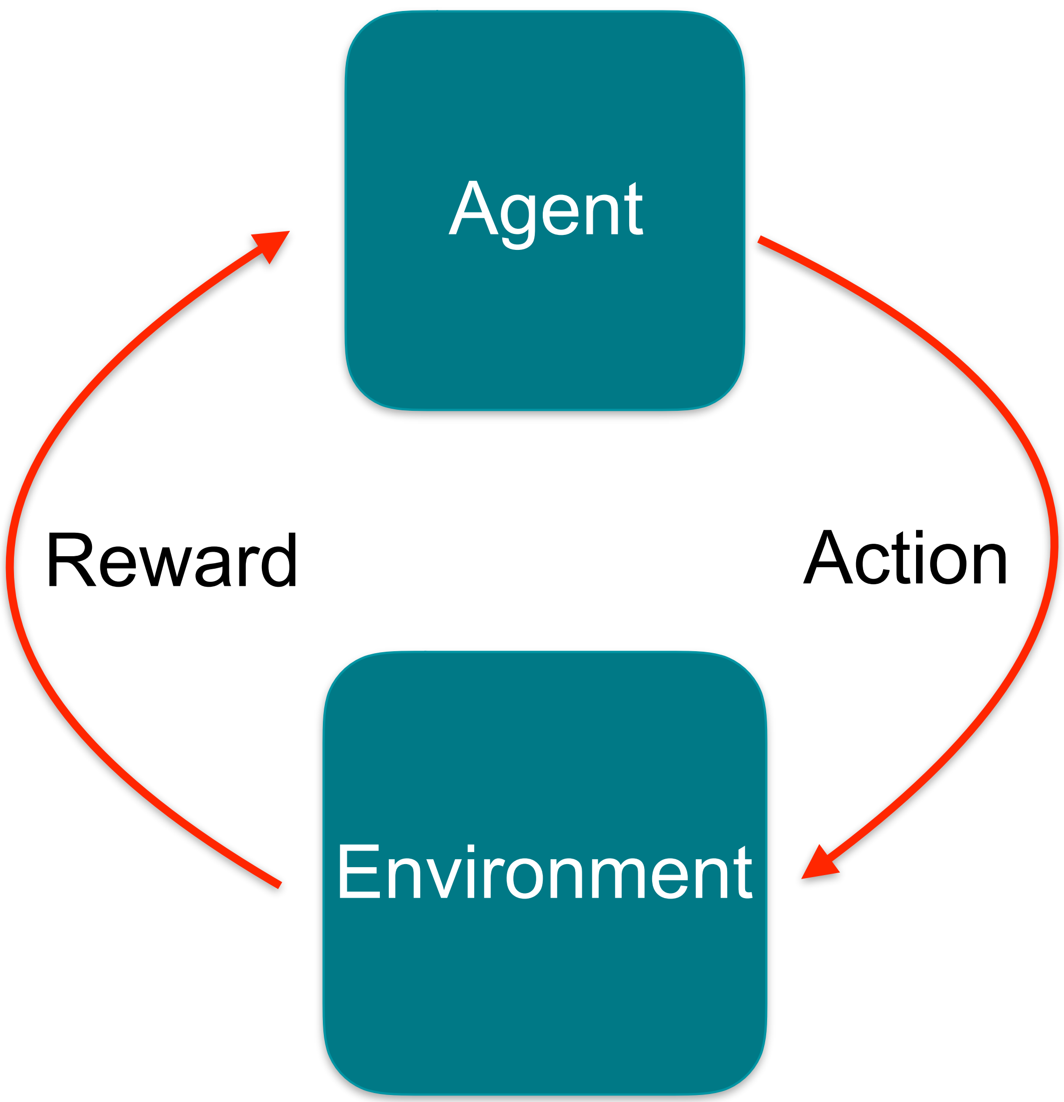
Reinforcement
learning

From supervised learning to reinforcement learning

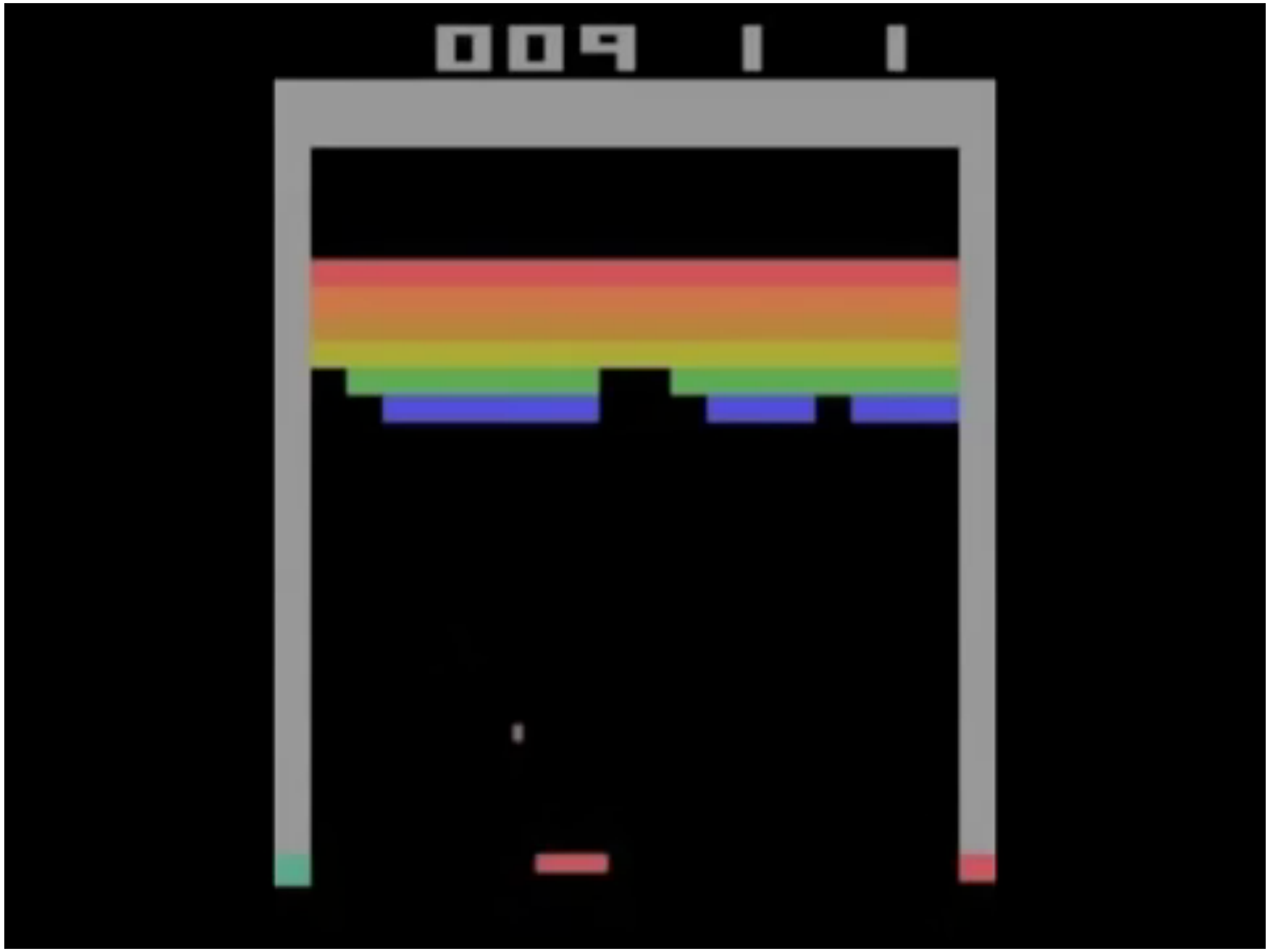
Supervised learning techniques (in particular (deep) convolutional networks) may be used as a block in a more complex structure, in particular in Dynamic Programming (DP) or Model Predictive Control (MPC) schemes.

This connects to **reinforcement learning**, an area of machine learning originally inspired by behaviorist psychology, concerned with how software agents ought to take actions in an environment so as to maximize some notion of cumulative reward.

Deep reinforcement learning combines deep learning with reinforcement learning (and, consequently, in DP / MPC schemes).



Playing Atari with deep reinforcement learning



At Google Deepmind

At ULg

Human-level control through deep reinforcement learning. Nature, 2015.
Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A. Rusu, Joel Veness, Marc G. Bellemare, Alex Graves, Martin Riedmiller, Andreas K. Fidjeland, Georg Ostrovski, Stig Petersen Charles Beattie, Amir Sadik, Ioannis Antonoglou, Helen King, Dharshan Kumaran, Daan Wierstra, Shane Legg & Demis Hassabis

Breaking news

Recent breakthroughs in the field of AI for the game of GO have been done by Google Deepmind.

These results have been obtained by combining Deep Convolutional Networks with Monte Carlo Tree Search techniques.

The resulting agent, AlphaGo, achieved 99.8% winning rate against other GO AI, and defeated the European Go champion by 5 games to 0.

Mastering the game of Go with deep neural networks and tree search. Nature, 2016.
David Silver, Aja Huang, Chris J. Maddison, Arthur Guez, Laurent Sifre, George van den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, Sander Dieleman, Dominik Grewe, John Nham, Nal Kalchbrenner, Ilya Sutskever, Timothy Lillicrap, Madeleine Leach, Koray Kavukcuoglu, Thore Graepel & Demis Hassabis

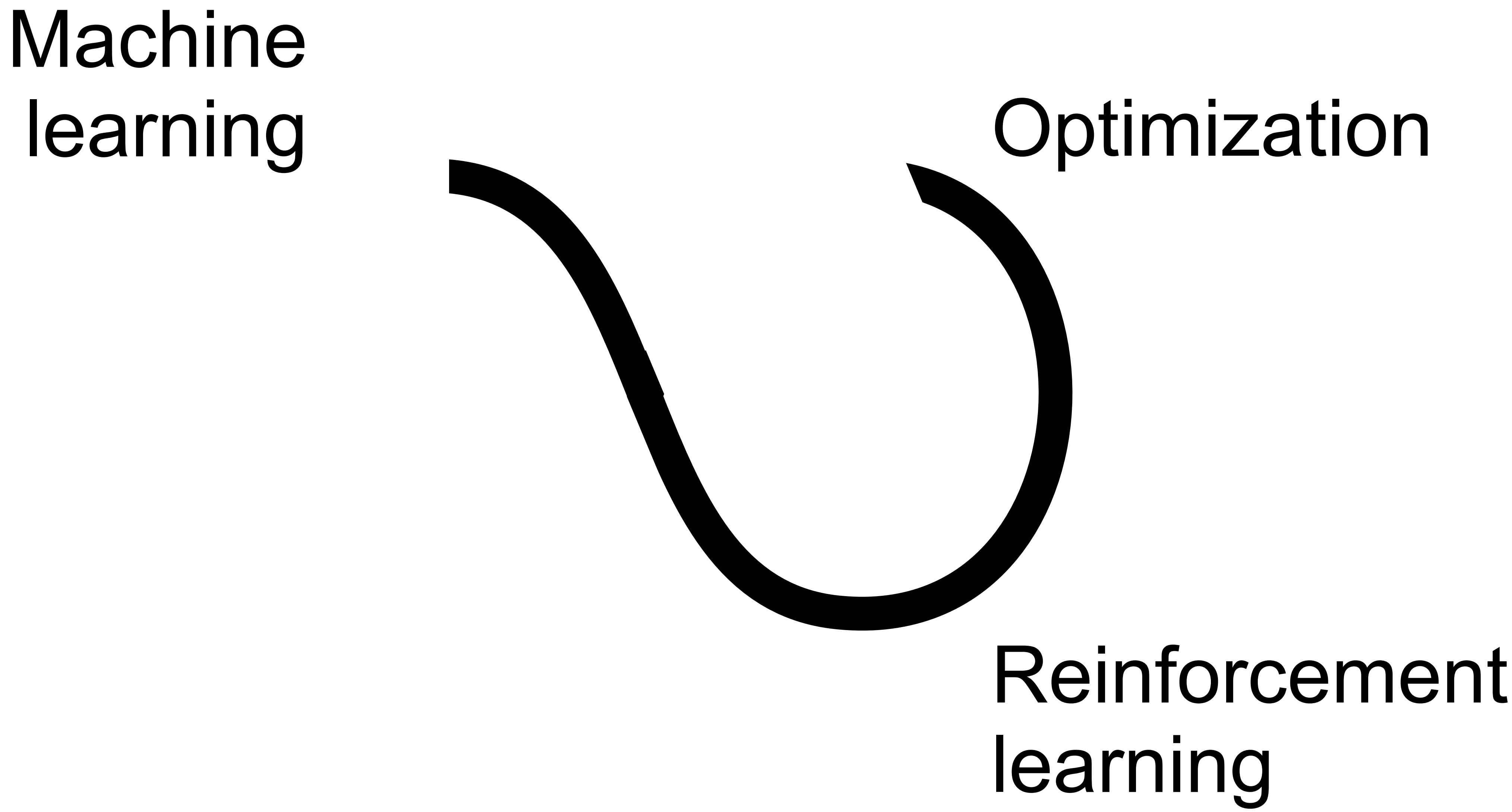
Want to know more?

Google is launching a new deep learning course (in collaboration with Udacity):
https://www.udacity.com/course/deep-learning--ud730

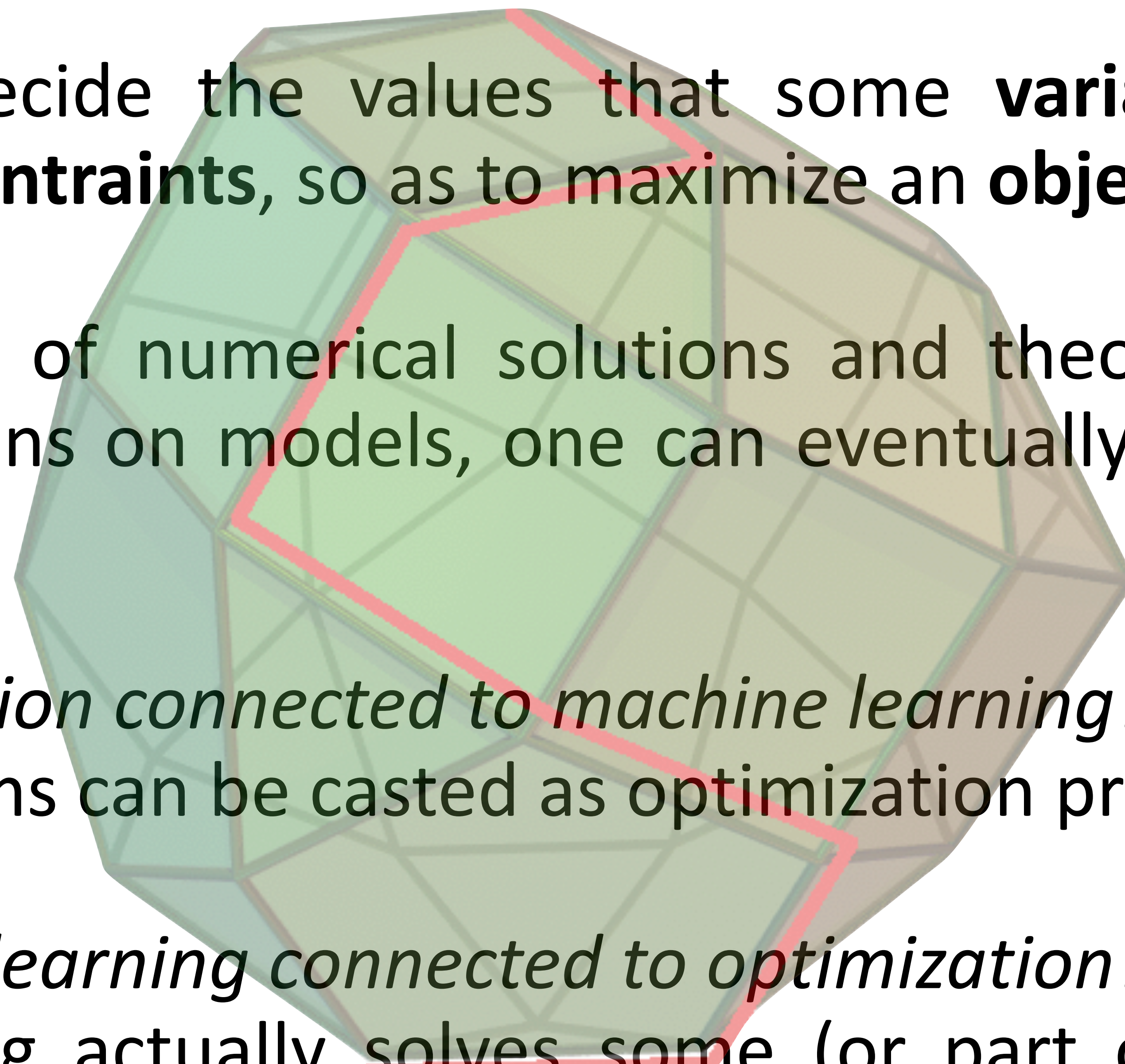
You may also be interested in NVidia Deep Learning course:
https://developer.nvidia.com/deep-learning-courses

Or even Stanford Mooc about Machine Learning:
https://www.coursera.org/learn/machine-learning

Roadmap



Machine learning is tightly coupled to optimization



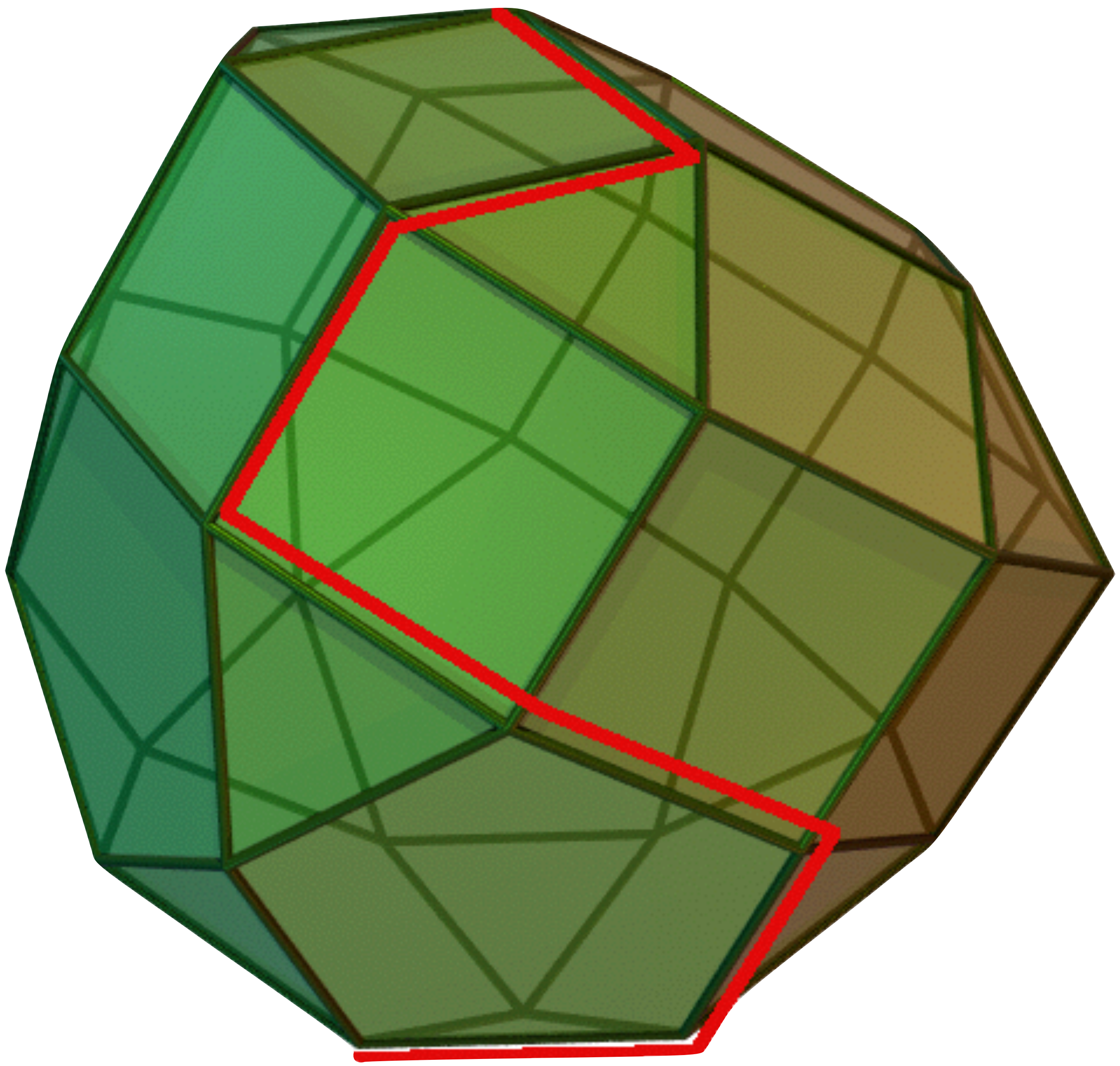
Optimization: decide the values that some **variables** can take, under a set of **contraints**, so as to maximize an **objective**.

A long tradition of numerical solutions and theoretical analysis. Given assumptions on models, one can eventually get guarantees about solutions.

How is optimization connected to machine learning?
Learning problems can be casted as optimization problems

How is machine learning connected to optimization?
Machine learning actually solves some (or part of) optimization problems (e.g: RL, or tuning of an algo, or proxy to an algo)

Machine learning is tightly coupled to optimization



An illustration of the simplex algorithm. The simplex algorithm was invented by G. Dantzig. It dates back to the second world war.

This can be used to solve many practical optimization problems.

Optimization relies on an analytical model ...

Example: Building the lunch menu, a first application of AI for energy ;)

```
set NUTRIENT ordered;
set FOOD ordered;

param cost {FOOD} >= 0;
param minNutrient {NUTRIENT} >= 0;
param maxNutrient {i in NUTRIENT} >= minNutrient[i];
param amount {NUTRIENT,FOOD} >= 0;

# Variables
var Buy {j in FOOD} integer;

# Objective
minimize Total_Cost:  sum {j in FOOD} cost[j] * Buy[j];

(or minimize nutrient_amount {i in NUTRIENT}: sum {j in FOOD} amount[i,j] * Buy[j];)

# Constraints
subject to Diet {i in NUTRIENT}:
   minNutrient[i] <= sum {j in FOOD} amount[i,j] * Buy[j] <= maxNutrient[i];
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```
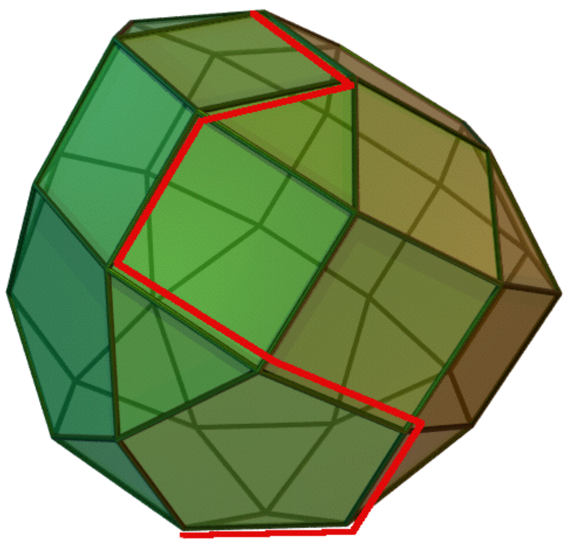
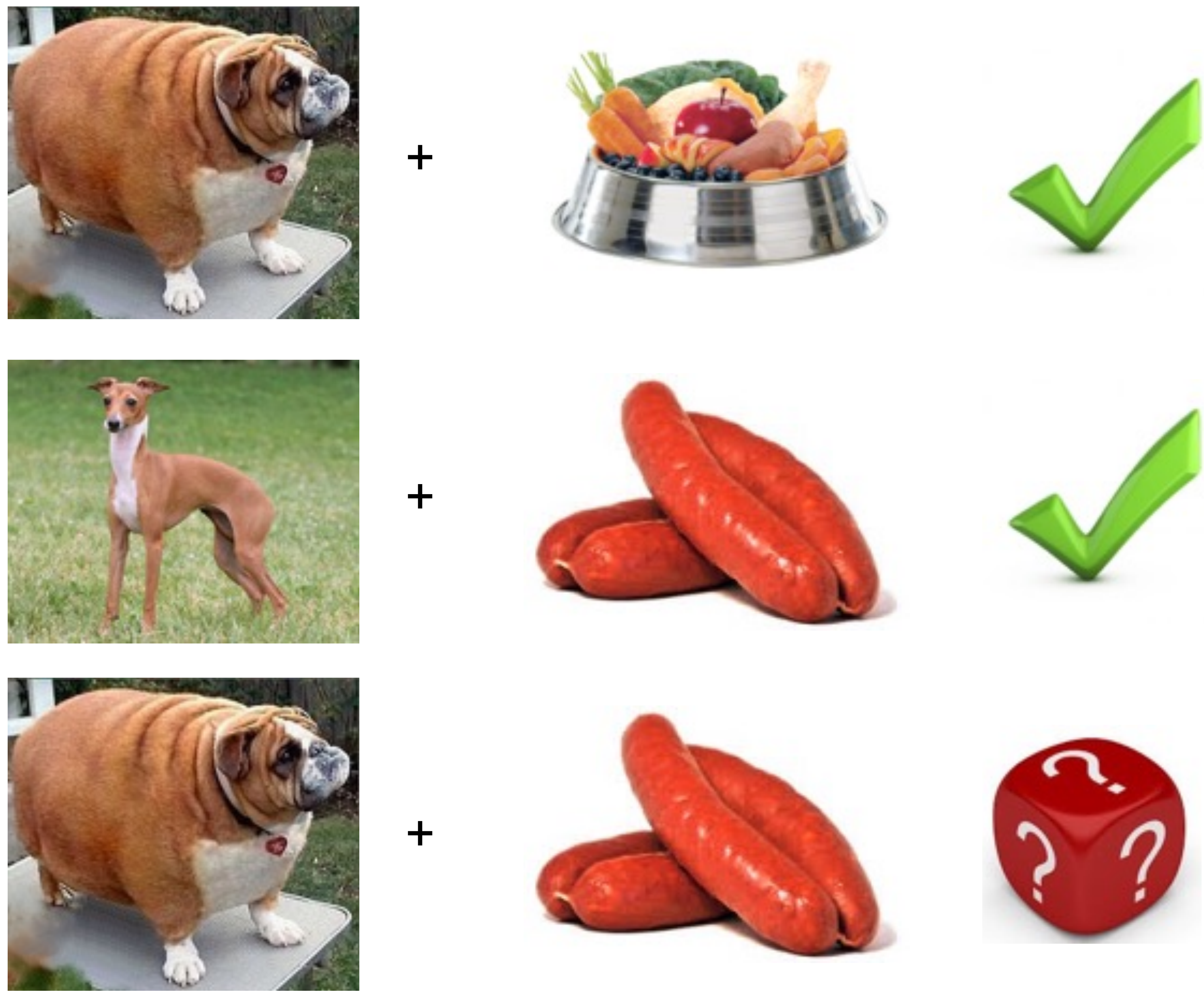

+ Data →



↓

Your lunch menu

Optimization relies on an analytical model, machine learning may not

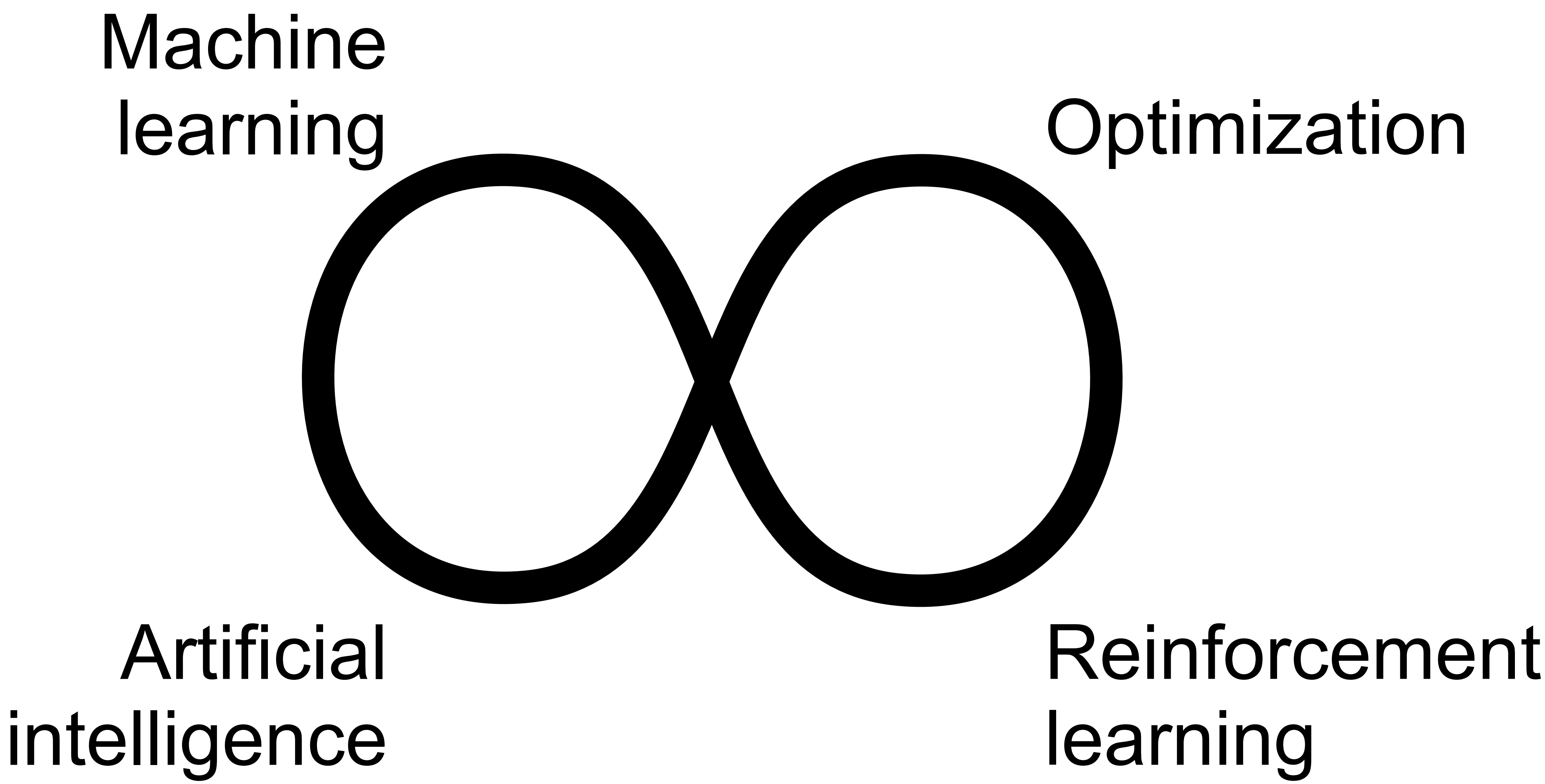


Optimization and Machine learning have different aims

In the **optimization** world, a method targets one problem class, or even an instance of a problem, and a theory is obsessed by optimality (can I prove it mathematically?) and efficiency (can I compute it efficiently?)

Machine learning is focused on statistical significance (reaching a trade off between overfitting and “misrepresentation”), replicability to other problems with few adaptation, and interpretability of results

Roadmap


Machine learning
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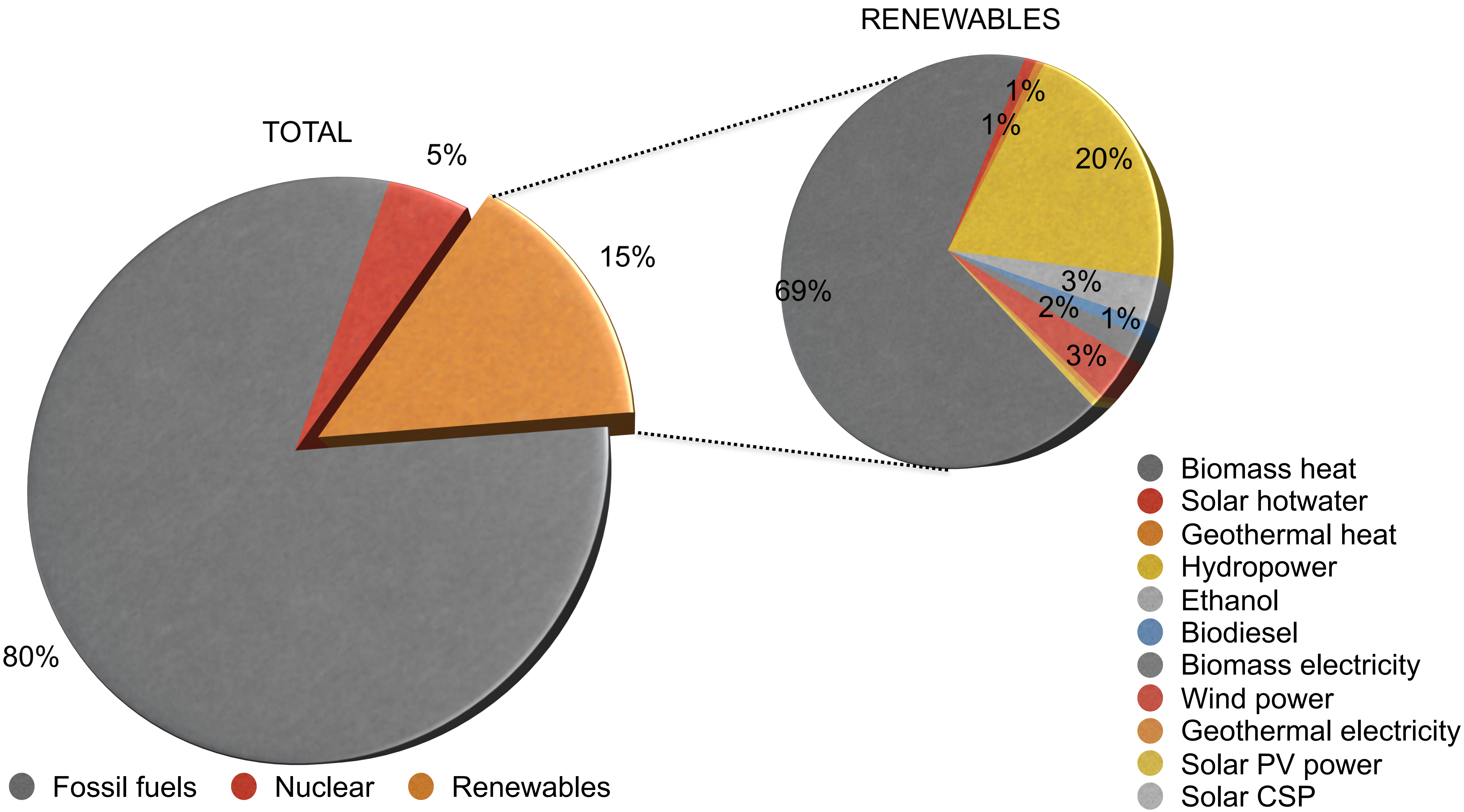
Artificial intelligence
Reinforcement learning

Energetic applications

World energy consumption outlook around 2010



Sources: IEA

Optimization has plenty of applications in the Energy industry

Electrical power systems:

- Production planning: unit commitment
- Managing grid constraints: optimal power flow

Oil and gas industry:

- Where to dig? In which sequence?

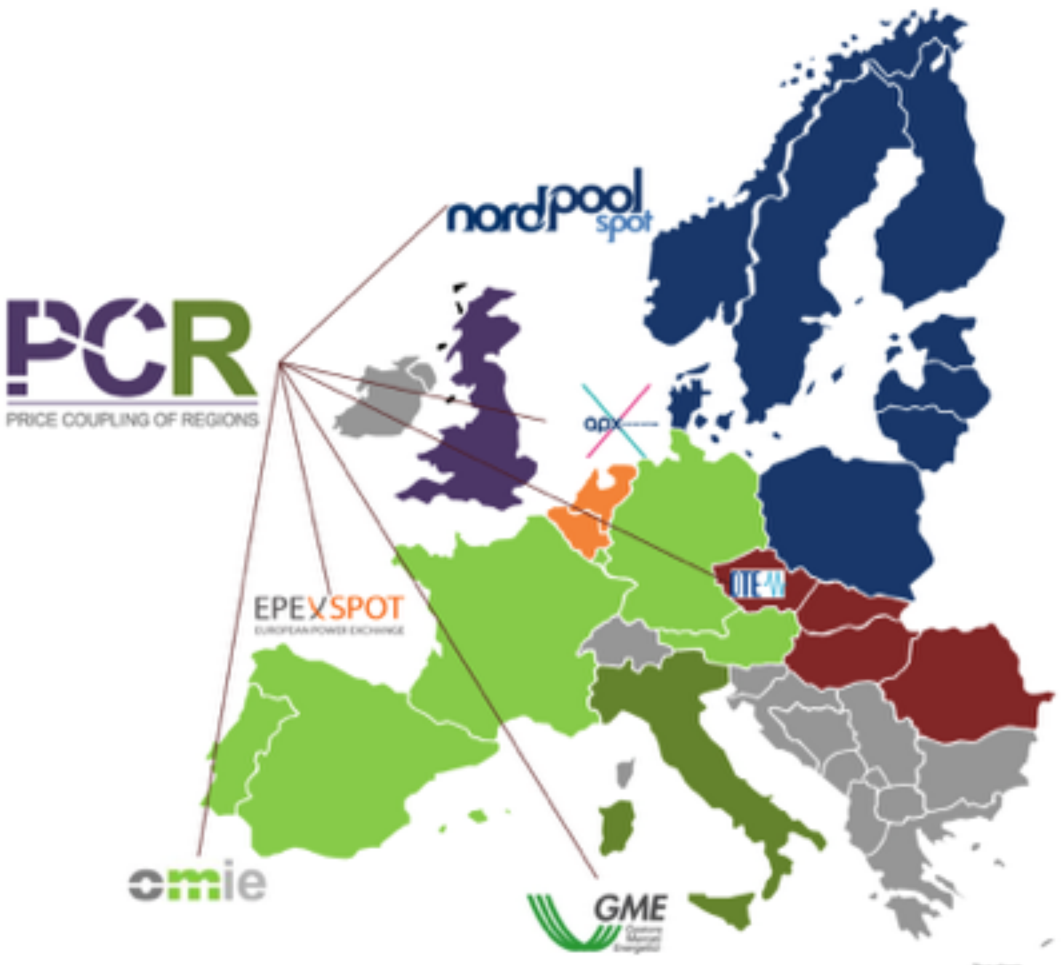
Logistics and transportation:

- Vehicle Routing Problems

Industrial processes:

- Reduction or displacement of energy consumption

Example: Day-ahead electricity prices in Europe are determined by Euphemia



Extension to whole Europe in progress

EUPHEMIA is the market coupling algorithm for European Power exchanges, implemented and developed in-house by N-SIDE, a spin-off of UCL and ULg

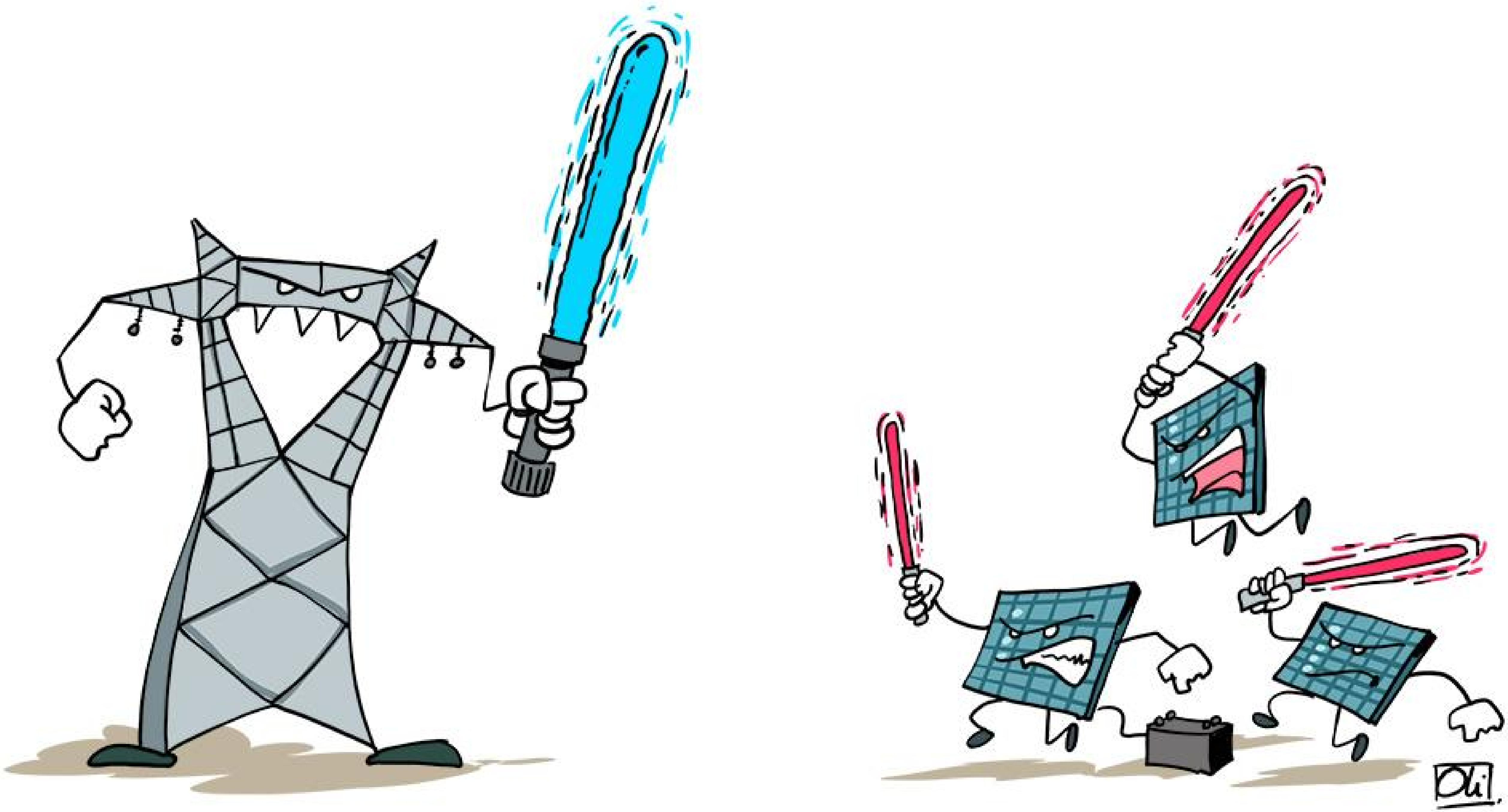
Used daily by Power Exchanges to fix pan-EU day-ahead electricity prices in 19 EU countries.

Computing market prices & volumes by:

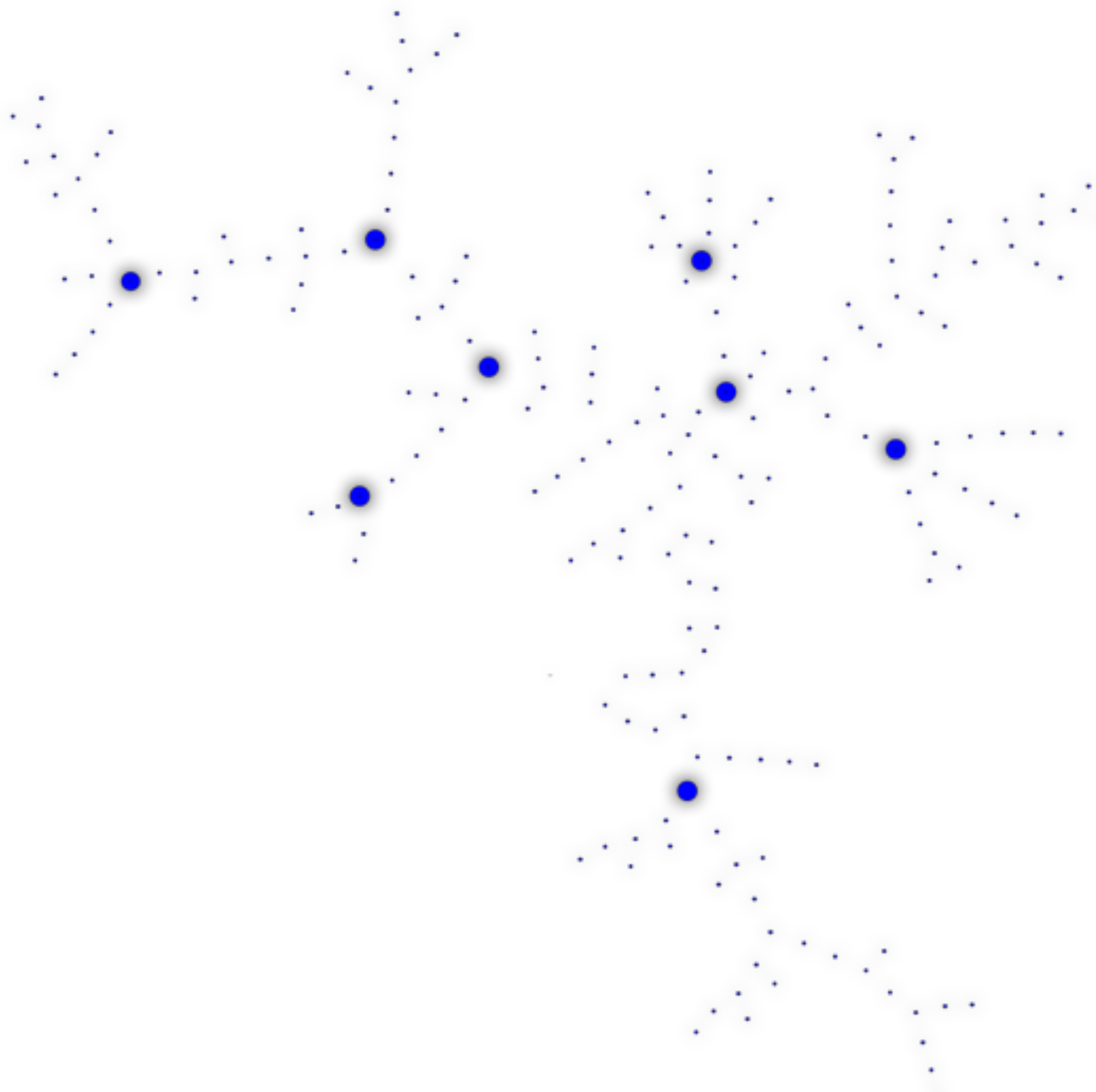
- coupling national markets
- maximizing total economical welfare
- optimizing network capacity utilization
- modeling complex economical constraints

http://energy.n-side.com/day-ahead/

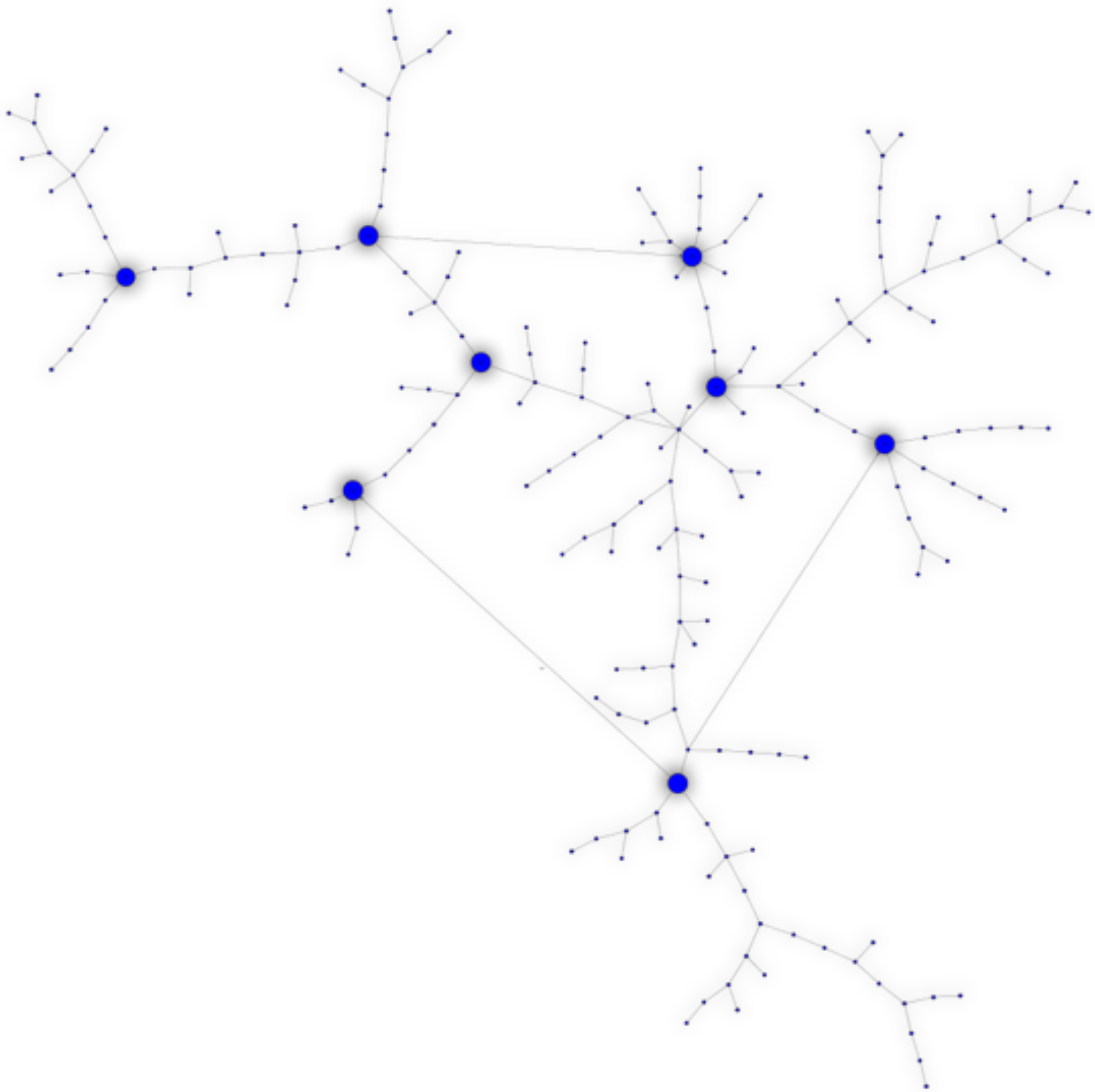
Evolution of the energy system



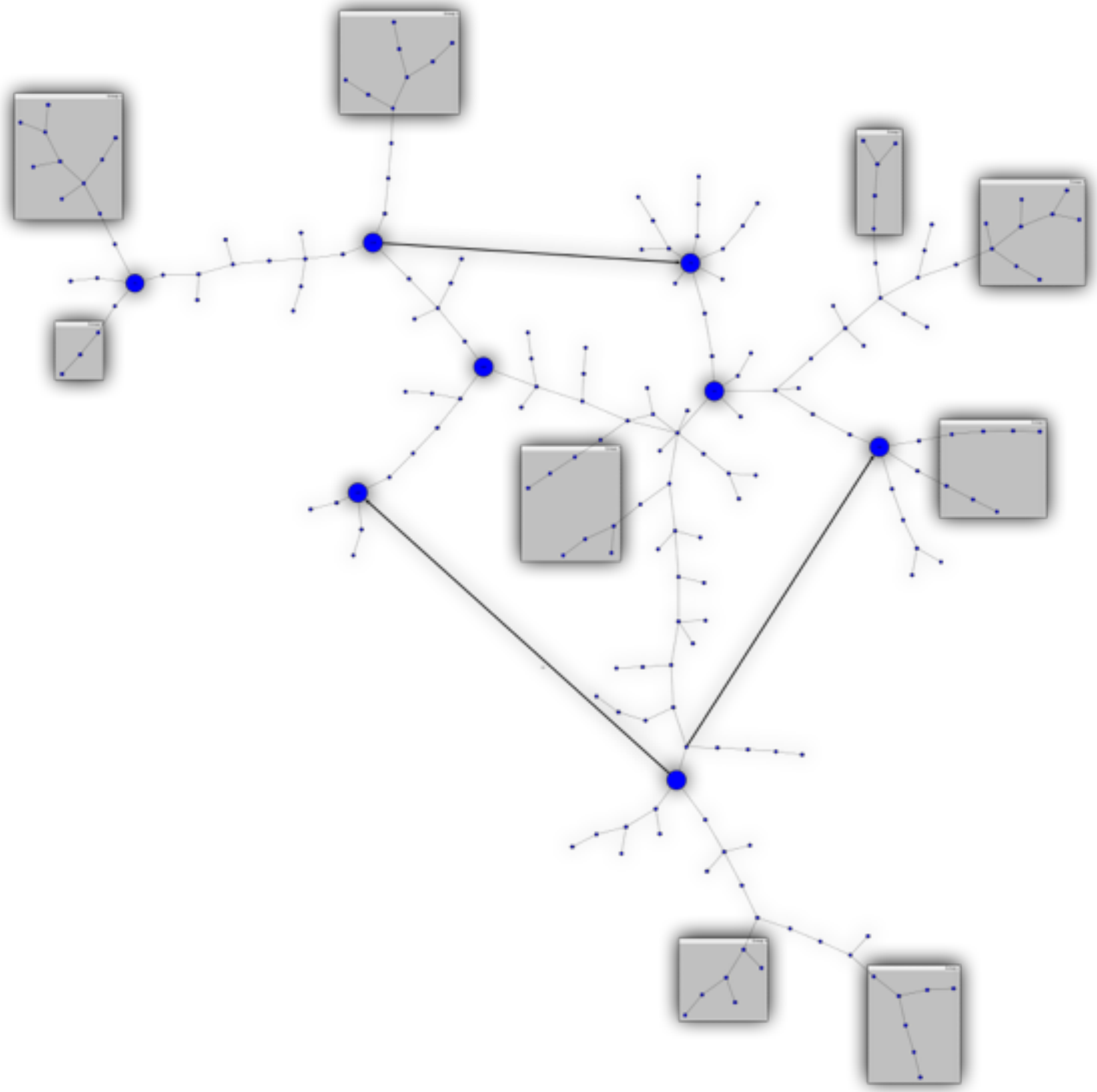
From decentralization…



From decentralization to centralization



From decentralization to centralization, and back



Why are we now talking about AI, and not just about optimization?

We are now trying to optimize more and more locally, because renewable energy sources are distributed, data is ubiquitous and computation power as well.

However, the ratio “gain / (time to spend for gathering the data and solving the problem)” is way smaller than for large centralized projects.

AI offers the possibility to automate the data gathering, modeling and optimization stages. For instance, learn from the habits of users of a house, propose some car pooling options, correlate all this with calendar events.

Rethinking the operation of distribution systems

Active network management.
Smart modulation of generation sources, loads and storages so as to operate safely the electrical network without having to rely on significant investments in infrastructure.

GREDOR project.
Redesigning in an integrated way the whole decision chain used for managing distribution networks in order to perform active network management optimally (i.e., maximisation of social welfare).

www.gredor.be

Empowering consumers and distributed generation

Microgrids are modern, localized, small-scale grids, contrary to the traditional, centralized electricity grid (macrogrid).

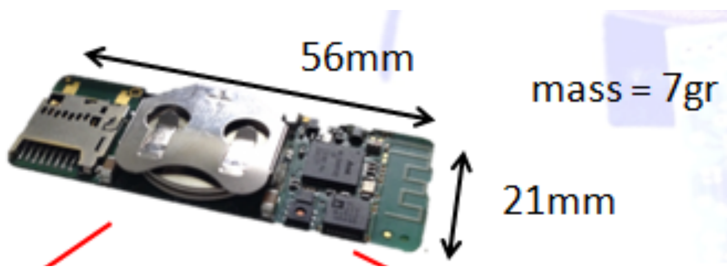
Some microgrids can operate disconnected from the centralized grid and operate autonomously, strengthen grid resilience and help mitigate grid disturbances.

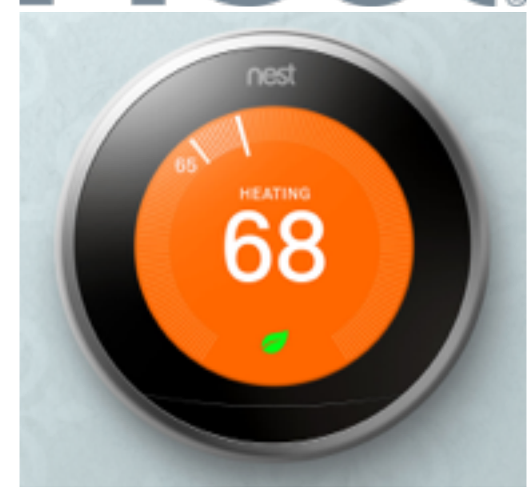
Optimizing the sizing and the operation of a microgrid requires both optimization and AI techniques.

Smart Cities

Smart homes

Smart sensors



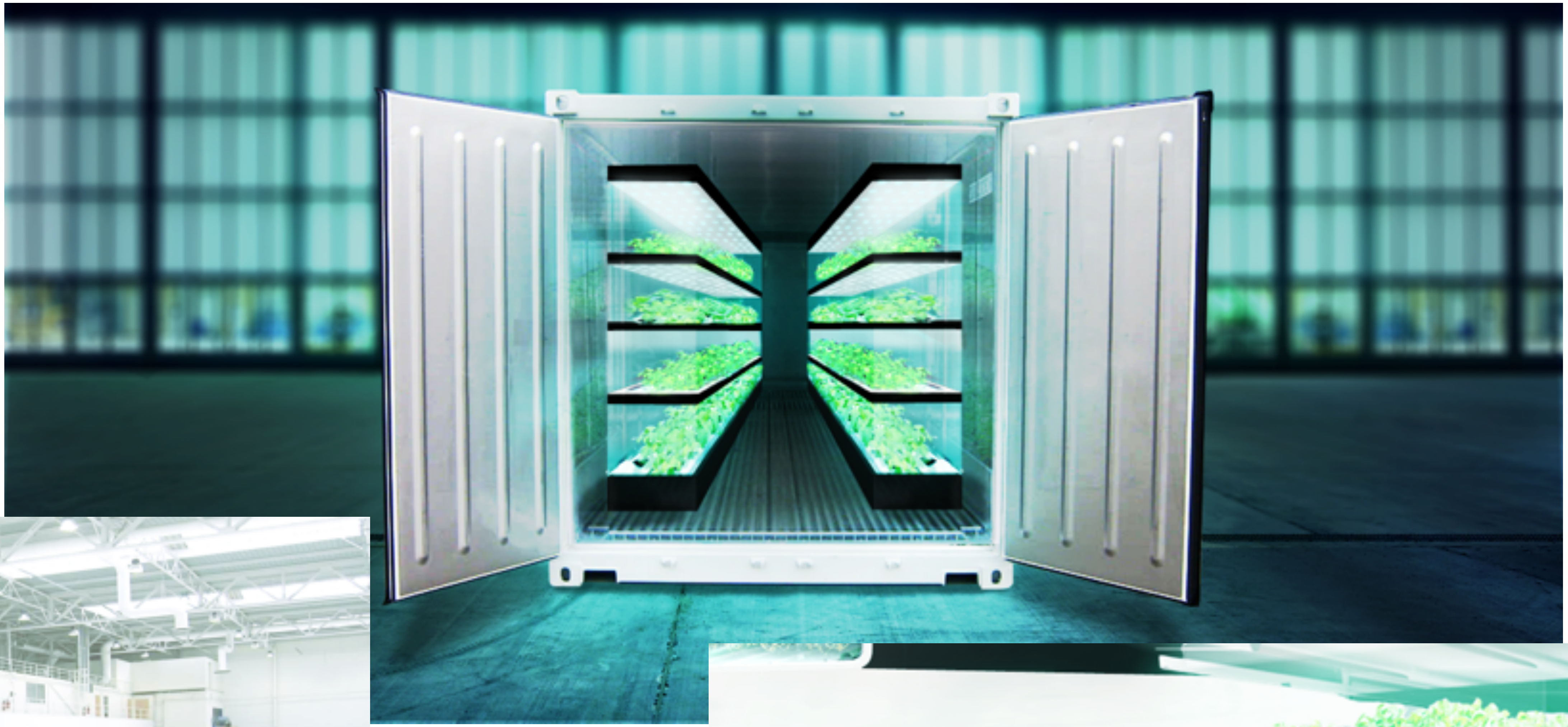


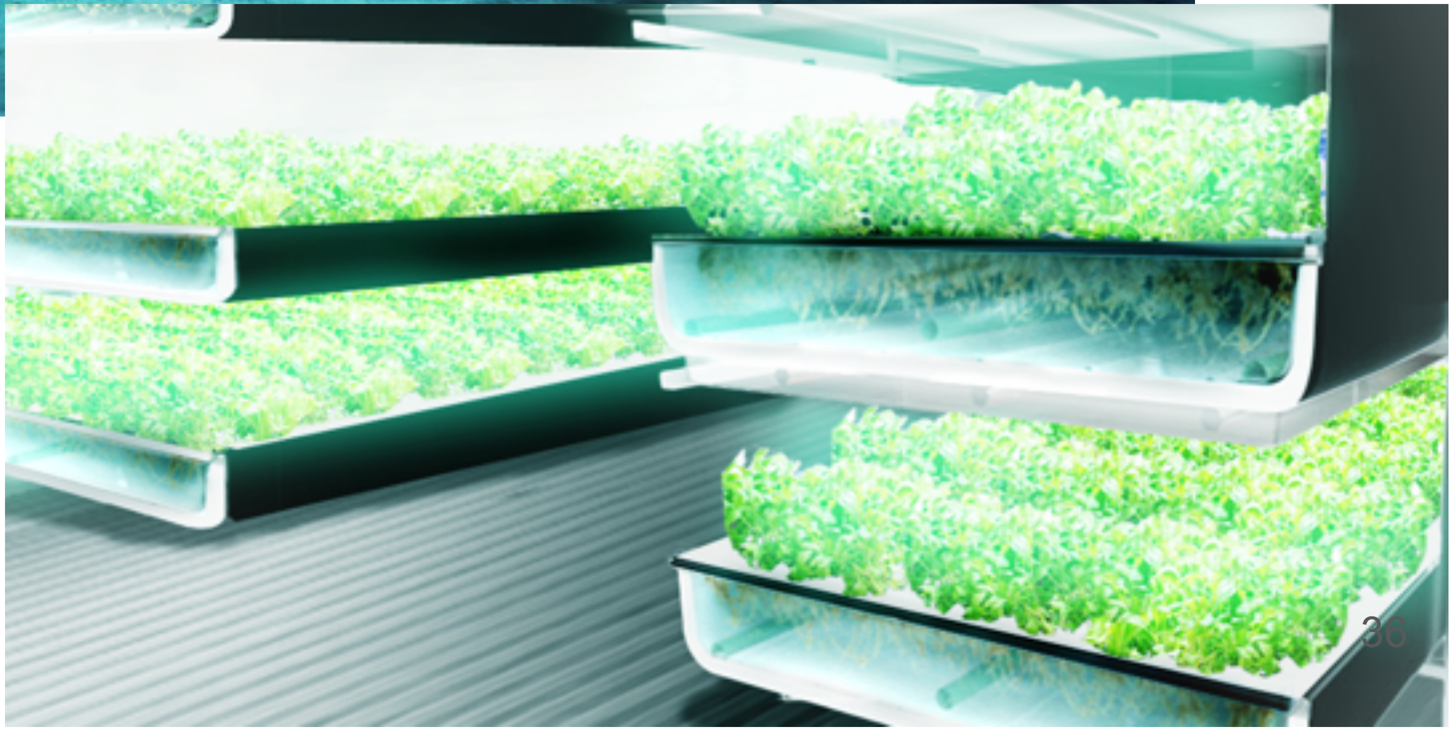
Wireless communication

Smart mobility

Smart lighting

Urban Agriculture





So, why using a PV panel as a goban?

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