Neural networks as complex systems

An educational activity to show the epistemological change of machine learning

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The era of Big Data and Machine Learning

Radical changes in the «era of Big Data and Machine Learning»

- Modify the impact of Science & Technology on society
  - applications have reached people's life and behaviour and generate strong emotional reactions, especially in the young generation (Rudin & Wagstaff, 2013)
- Challenge the epistemology of computer science
  - Investigation of the implications of new data-driven approaches
  - Authors have seen in these changes a "paradigm shift" (Hey, Tansley & Tolle, 2009; Kitchin, 2014)

A “paradigm shift”? Open debate

A new mode of science is being created, one in which the *modus operandi* is purely inductive in nature (Prensky, 2009; Clark, 2013): the data can speak for themselves free of theory

Objection →

Systems are designed to capture certain kinds of data (Berry, 2011; Leonelli, 2012) and the results are not free from theory, neither can they simply speak for themselves free of human bias (Gould, 1981)

DATA-DRIVEN SCIENCE: a hybrid combination of abductive, inductive and deductive approaches (Kitchin, 2014)

Open questions beyond the “shift or not-shift”

- Big Data and new data analytics – such as Machine Learning techniques – are disruptive innovations which are reconfiguring in many instances how research is conducted
- These rapid changes in science practice are rarely accompanied by an educational and cultural critical reflection on the implications of this unfolding revolution
  - Students are taught according to an idea of science that does not mirror the authenticity of the *modus operandi*

Open questions beyond the “shift or not-shift”

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A **knowledge gap** that deserves to be investigated and addressed

Aim of the study

Contribute to characterize the epistemological novelty of Machine Learning with respect to other approaches to Artificial Intelligence (imperative/procedural and logical/declarative)

- Issue addressed from the perspective of **educational research in STEM** (Science, Technology, Engineering and Mathematics)
- Result of a work conducted by the research group in STEM education at the Department of Physics and Astronomy of the University of Bologna
  (prof. Olivia Levrini, prof. Paola Fantini, dott. Laura Branchetti, Giovanni Ravaioli and Michael Lodi)

Research Question

Which discourses can be introduced to upper secondary-school students (16-19 y.o.) to make them aware of the «paradigm shift» introduced by Machine Learning?

- An **activity about Neural Networks** designed for a module on Artificial Intelligence within the I SEE project
- The analysis of the activity, centred around the interpretation of neural networks as complex systems, will allow us to highlight the epistemological aspects that can contribute to characterize the paradigm shift

The I SEE project

Inclusive STEM Education to Enhance the capacity to aspire and imagine future careers

(September 2016 - August 2019)

www.**iseeproject.eu**
iseeproject.eu@gmail.com

The I SEE project

Goal

design innovative approaches and teaching **modules on STEM advanced topics**, to foster students' capacities to imagine the future **(future-scaffolding skills)** and aspire to STEM careers

Intellectual Outputs

- **Teaching-learning modules** on STEM future-oriented topics
- **Guidelines** for teachers
- **Research reports** on the impacts of the modules on students' learning
- **Policy recommendations** to innovate science teaching

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Start-up module

- Topic: **climate change**
- Tested in a Summer School at Bologna, June2017
- 24 students and 8 teachers (from, Finland Iceland, Italy) + 8 researchers
- About 30 hours

Further modules

- Finland: **quantum computing** (about 20 hours)
- Iceland: **carbon sequestration** (about 20 hours)
- Italy: **artificial intelligence** (about 20 hours; 120 students involved in implementations in Italy and Finland)

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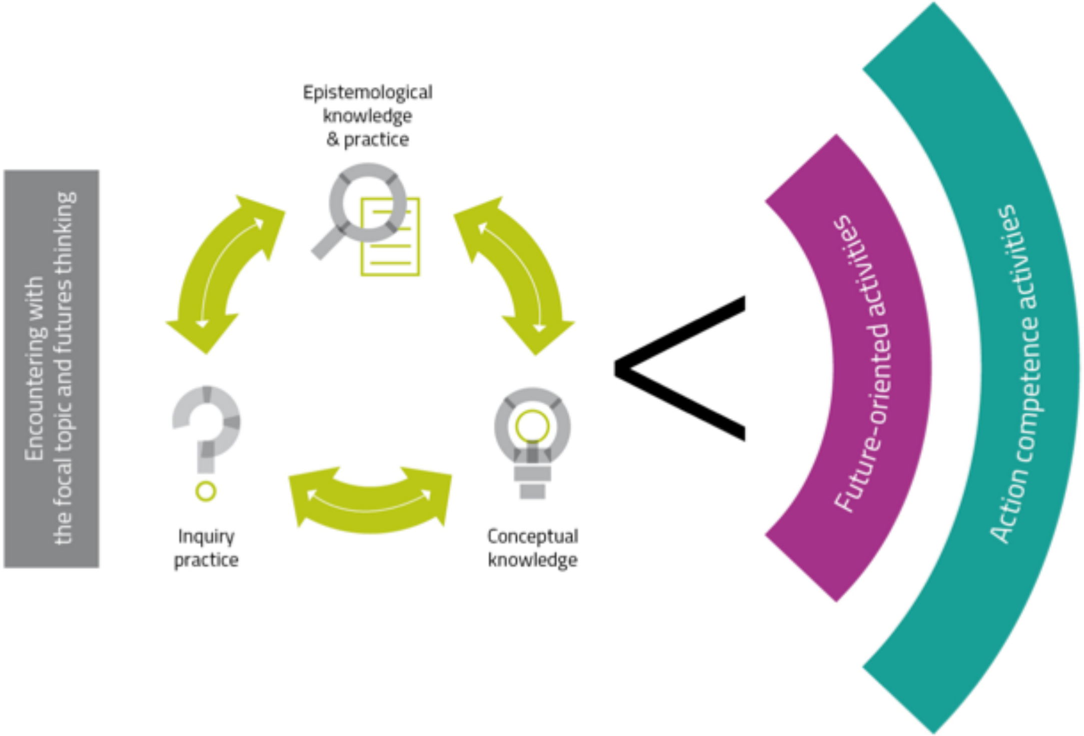
I SEE Module structure



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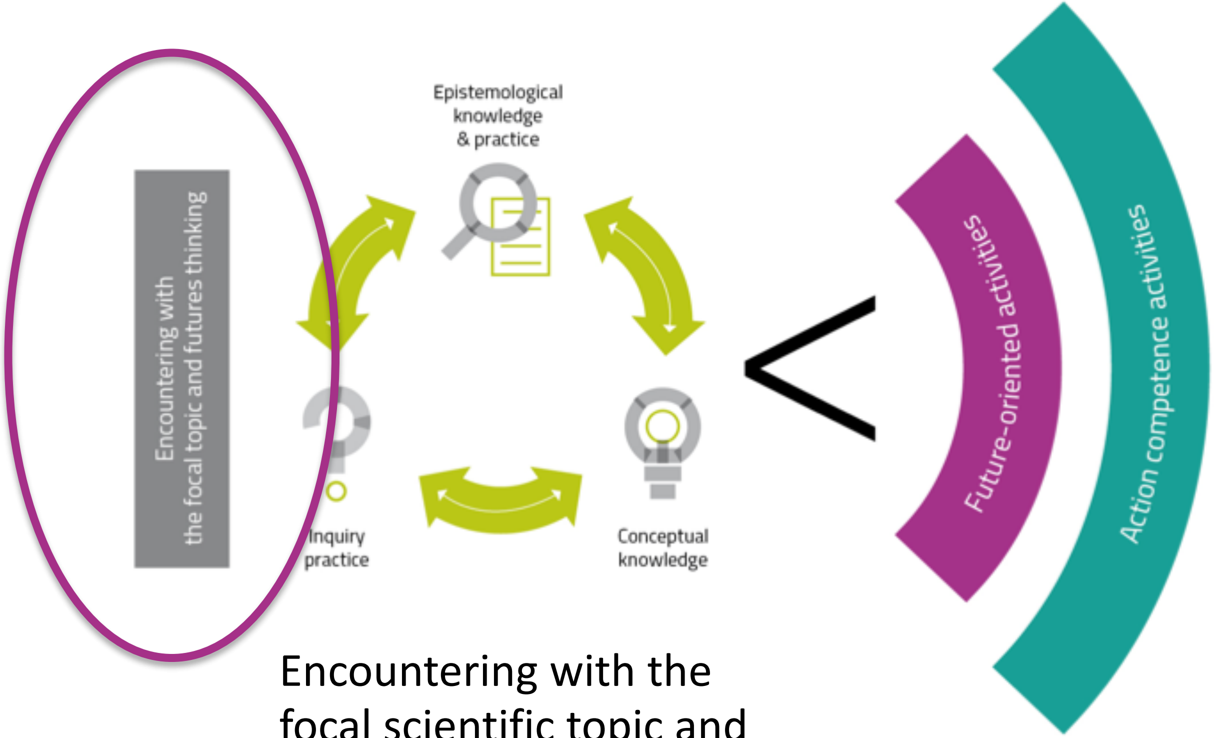
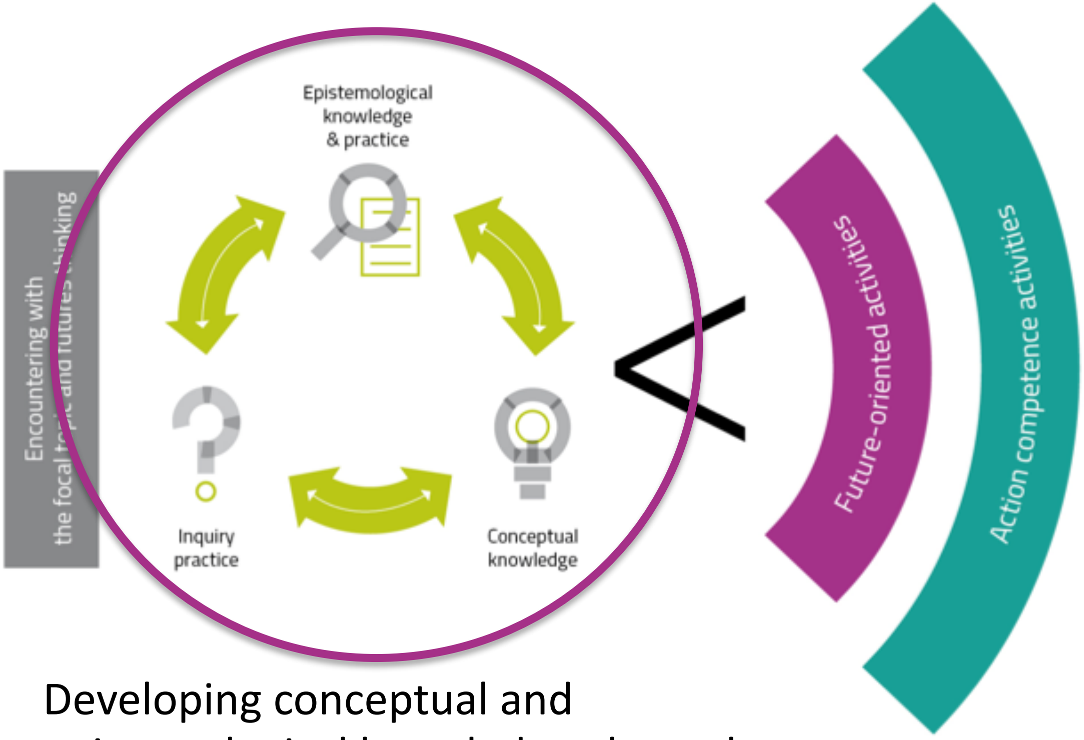


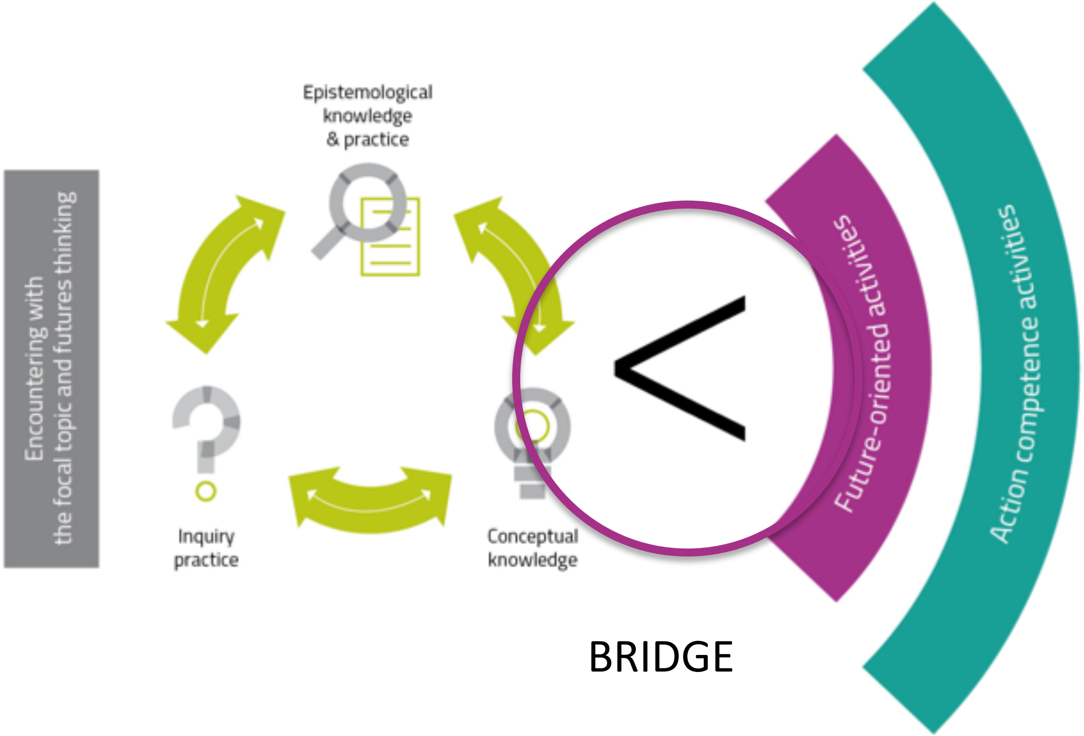
Encountering with the focal scientific topic and future thinking

I SEE Module structure



Developing conceptual and epistemological knowledge about the scientific topic (through active learning)

I SEE Module structure



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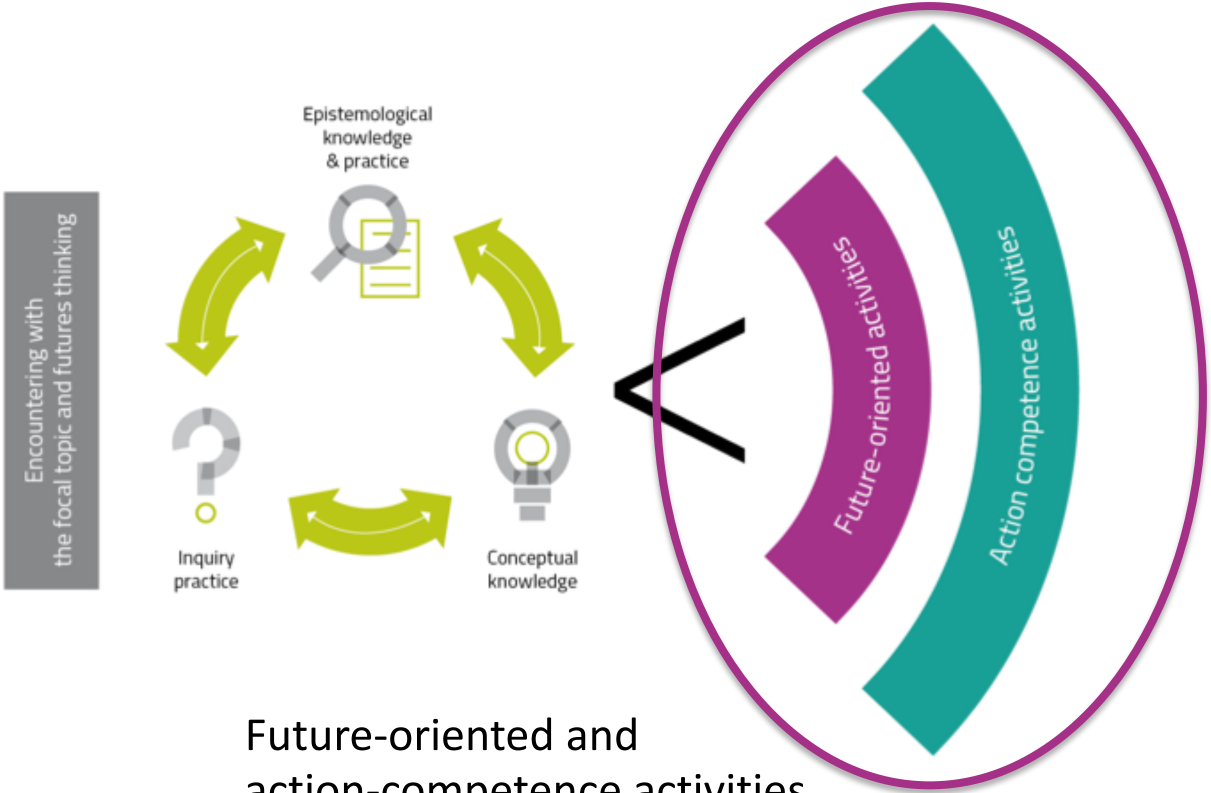
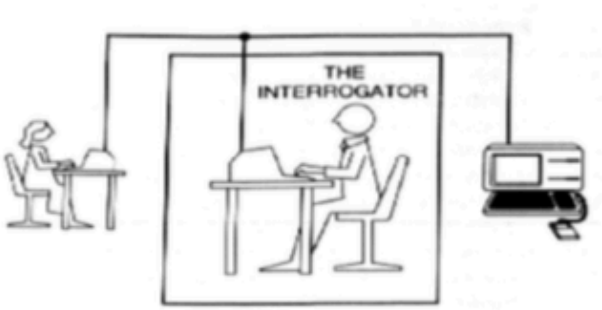


Future-oriented and
action-competence activities

	Part 1 **Encountering the focal topic**	1. Overview lectures on AI and the perspective of complex systems	Lectures
		2. The words of complexity	Group activity
		3. AI applications?	Group activity
	Part 2 **Conceptual and epistemological knowledge**	4. AI - Imperative approach	Lecture + Class Activity
		5. AI - Logical approach	Lecture + Class activity
		6. AI – Machine Learning approach	Lecture + Class activity
Λ	**Bridge**	7. Complexity and future studies	Lecture
	Part 3 **Future-oriented activities**	8. The town of ADA 1: analysis of a complex citizenship context of urban planning	Group activity
		9. The town of ADA 2: possible future scenarios	Group activity
		10. The town of ADA 3: desirable future, back-casting and action planning	Group activity

I. OVERVIEW LECTURES

to introduce the conceptual and epistemological knowledge that will be developed and deepened throughout the teaching module



- **AI and culture**
  Prof. Gianni Zanarini, *Physician*
- **History of AI**
  Prof. Paola Mello, *Computer Engineer*

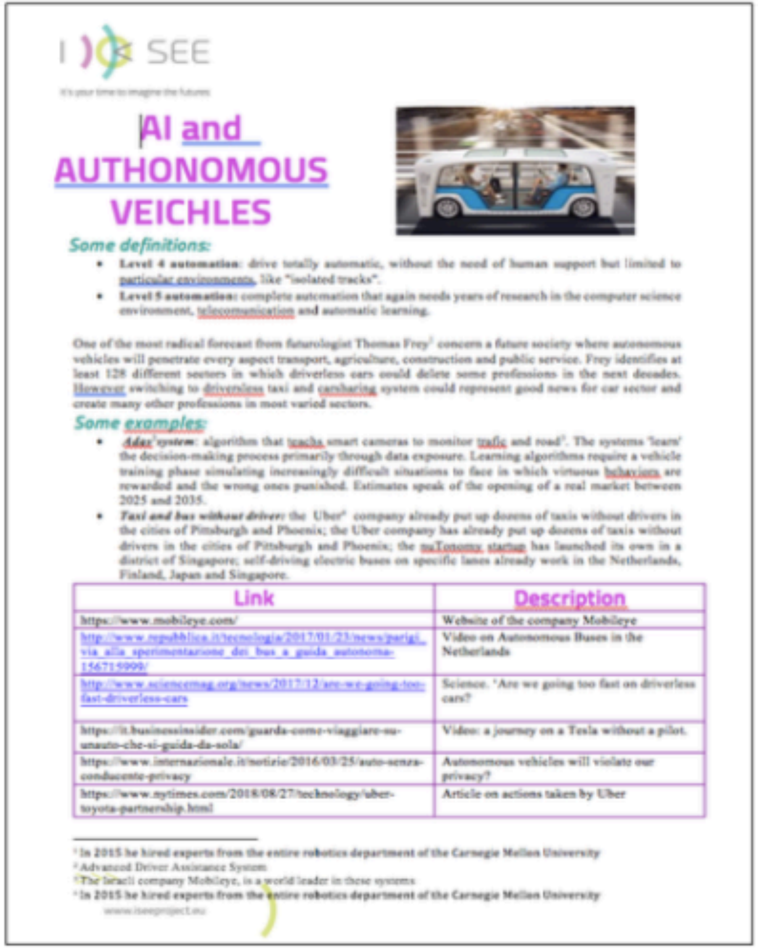
II. THE WORDS OF COMPLEXITY

to understand what it means to study a problem from the point of view of complexity

III. GROUP ACTIVITY - AI EVERYWHERE

to understand the new opportunities and perspectives that AI opens in the job market

- Autonomous vehicles
- Archeology
- Arts
- Services
- Scientific research
- Astronomical observations



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AI and AUTHONOMOUS VEICHLES

Some definitions:

- **Level 4 automation**: drive totally automatic, without the need of human support but limited to particular environments, like "isolated tracks".
- **Level 5 automation:** complete automation that again needs years of research in the computer science environment, telecomunication and automatic learning.

One of the most radical forecast from futurologist Thomas Frey[1] concern a future society where autonomous vehicles will penetrate every aspect transport, agriculture, construction and public service. Frey identifies at least 128 different sectors in which driverless cars could delete some professions in the next decades. However switching to driverless taxi and carsharing system could represent good news for car sector and create many other professions in most varied sectors.

Some examples:

- ***Adas[2] system***: algorithm that teachs smart cameras to monitor trafic and road[3]. The systems 'learn' the decision-making process primarily through data exposure. Learning algorithms require a vehicle training phase simulating increasingly difficult situations to face in which virtuous behaviors are rewarded and the wrong ones punished. Estimates speak of the opening of a real market between 2025 and 2035.
- ***Taxi and bus without driver***: the Uber[4] company already put up dozens of taxis without drivers in the cities of Pittsburgh and Phoenix; the Uber company has already put up dozens of taxis without drivers in the cities of Pittsburgh and Phoenix; the nuTonomy startup has launched its own in a district of Singapore; self-driving electric buses on specific lanes already work in the Netherlands, Finland, Japan and Singapore.

Link	Description
https://www.mobileye.com/	Website of the company Mobileye
http://www.repubblica.it/tecnologia/2017/01/23/news/parigi_via_alla_sperimentazione_dei_bus_a_guida_autonoma-156715999/	Video on Autonomous Buses in the Netherlands
http://www.sciencemag.org/news/2017/12/are-we-going-too-fast-driverless-cars	Science. 'Are we going too fast on driverless cars?
https://it.businessinsider.com/guarda-come-viaggiare-su-unauto-che-si-guida-da-sola/	Video: a journey on a Tesla without a pilot.
https://www.internazionale.it/notizie/2016/03/25/auto-senza-conducente-privacy	Autonomous vehicles will violate our privacy?
https://www.nytimes.com/2018/08/27/technology/uber-toyota-partnership.html	Article on actions taken by Uber

[1] In 2015 he hired experts from the entire robotics department of the Carnegie Mellon University
[2] Advanced Driver Assistance System
[3] The Israeli company Mobileye, is a world leader in these systems
[4] In 2015 he hired experts from the entire robotics department of the Carnegie Mellon University

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Approaches to AI

to point out criteria to navigate through the technical details and give them a broader meaning

IV. **Imperative approach**	Lecture + Class Activity
V. **Logical approach**	Lecture + Class activity
VI. **Machine Learning approach**	Lecture + Class activity

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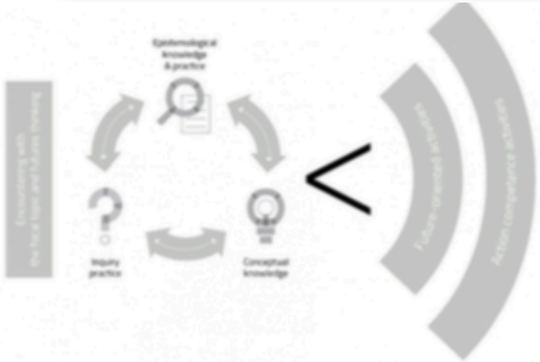
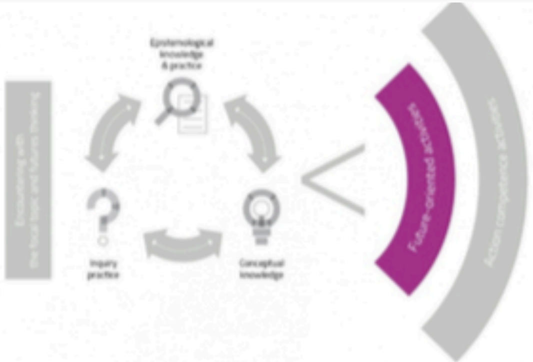
TIC-TAC-TOE





ANALYSIS OF A COMPLEX CONTEXT OF URBAN PLANNING

Which implications can a decision on AI have? Which stakeholders, values, scientific, technological and social issues are involved in a decision?

POSSIBLE FUTURE SCENARIOS

Which values, or scientific, technological, and social issues are involved in each of them?

DESIRABLE FUTURE, BACK-CASTING AND ACTION PLANNING

Which actions and action competence can contribute to achieving the desirable future?

The activity about AI approaches

	Imperative approach	Logical approach
The programmer	solves his/her task with an algorithm containing all the **steps**, in their order, the machine has to follow to produce the output	declares a set of **facts and logical rules** from which the machine itself infers the output *via* the inference engine

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Epistemological aspects embedded	• **Top-down** they need an expert to represent the problem and the solution is produced by deduction • **Symbolic**: the information the machine produces and the steps it follows consist in human-readable information	

The activity about Machine Learning

- Overview on general concepts of Machine Learning
  - Supervised vs unsupervised learning
  - Linear and logistic regression
- Focus on connectionist paradigm
  - Feed-forward Neural Networks and multilayer perceptron
  - The model of artificial neuron and architecture of the network
  - Training-validation-test phases
  - Forward- and error-back propagation algorithms
  - Accuracy of the network
- Parallelism between neural networks as complex systems

The science that gives computers the ability to learn without being explicitly programmed" (Samuel, 1959)

Neural networks as complex systems

HYPOTHESIS

The Machine Learning revolution shares some epistemological similarities with the revolution introduced by the science of complex systems

- Shift from classical determinism to probability
- Challenge the classical definition of explanation of phenomena
- Opacity of the models

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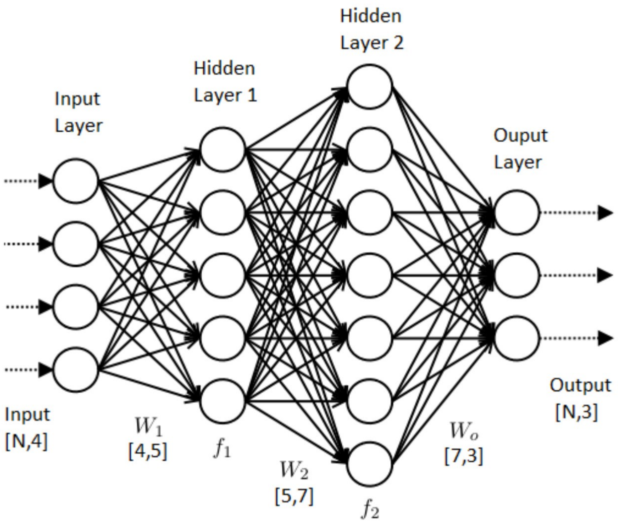
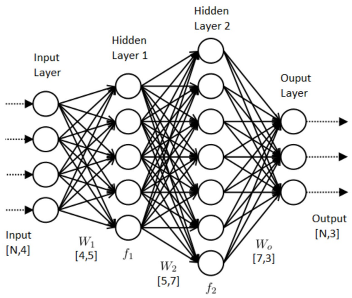
Make visible these similarities with a parallelism between neural networks and complex systems

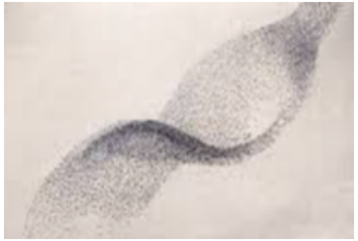
Neural networks as complex systems



Parallelism: Emergent property



- The “knowledge” of the network in not an *a priori* set competence
  - It is a property of the trained-tested net that emerges from simple local interactions among agents



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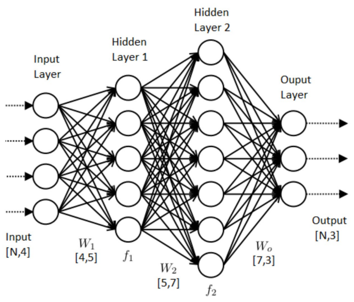

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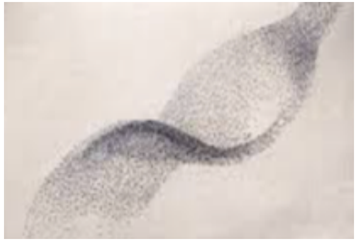
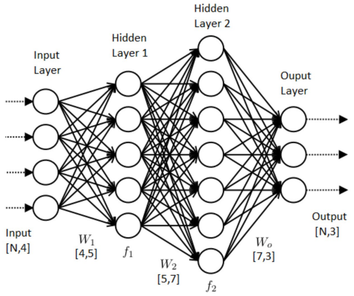


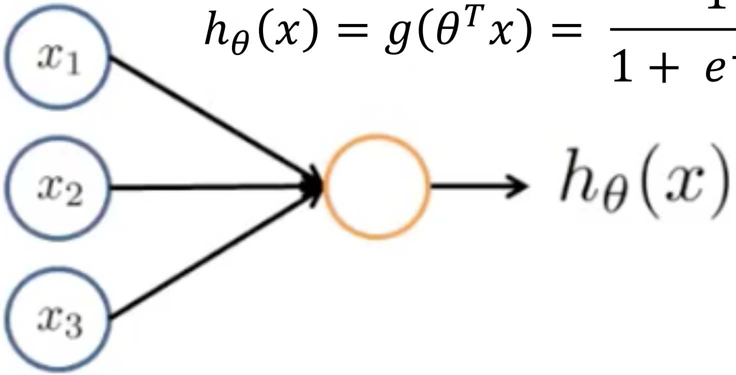
- The shape of the flock is not imposed to the single birds by a "chief"
  - It results from their self-organization

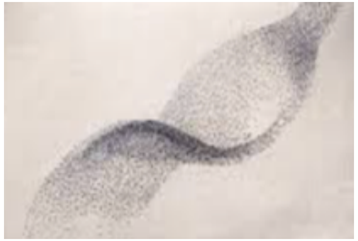
Parallelism: Rules for individual agents



- The rules every artificial neuron attends are simple, non-linear and involve only the states of the nearest neurons

$$h_\theta(x) = g(\theta^T x) = \frac{1}{1 + e^{-\theta^T x}}$$





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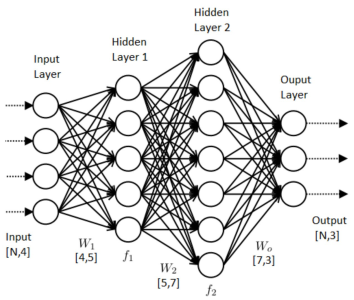

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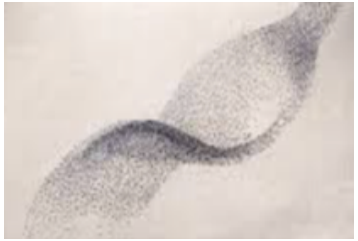
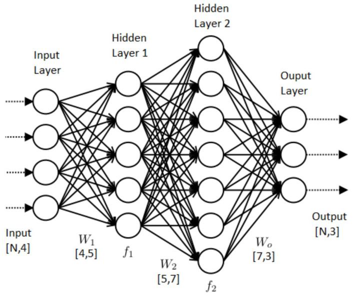
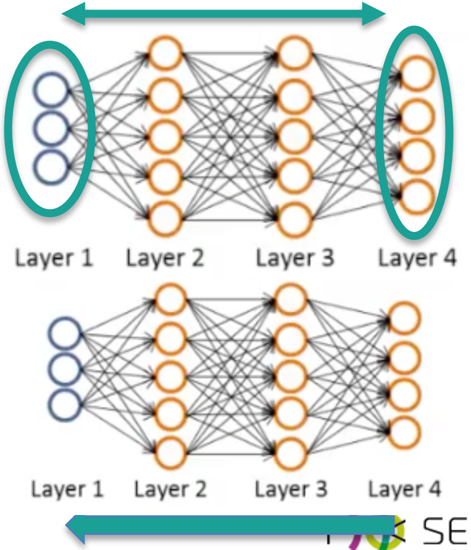


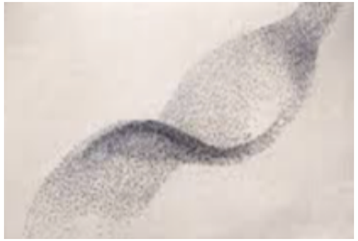
- Every bird moves according to simple rules based on distance, speed and density with respect to the nearest neighbours

Parallelism: Input-output circularity



- During the training phase, the weights of the network are assessed with a circular input-output process
  - The error-back propagation algorithm





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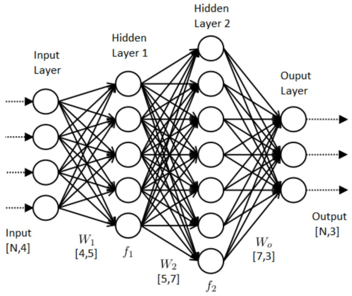

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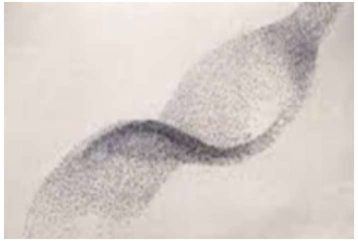
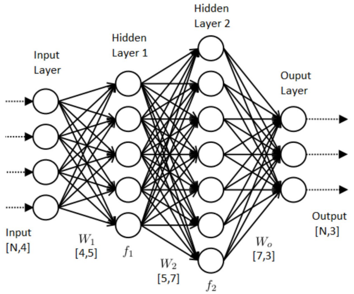
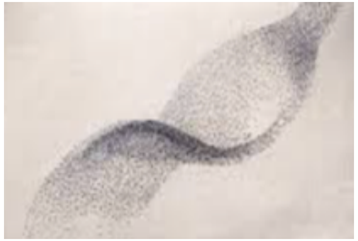


- The movement of the flock depends on the movement of the single birds but also the trajectories of the birds depend on the shape of the flock

Parallelism: Non-linear dependence





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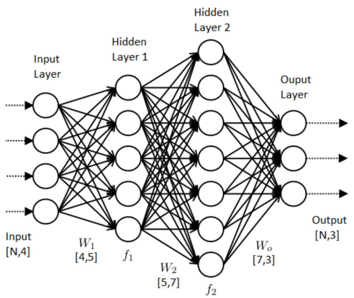

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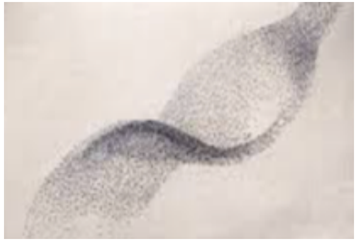

- The change of trajectory of a single bird may radically change the shape and trajectory of the flock

Neural networks as complex systems

Emergent property	The ANN's "knowledge" is not an *a priori* set competence, but is a property of the trained-tested net that emerges from simple local interactions among agents	The shape of the flock is not imposed to the single birds by a "chief", but results from their self-organization
Rules for individual agents	The rules every artificial neuron attends are simple, non-linear (they implement a logistic function) and involve only the states of the nearest neurons	Every bird moves according to simple rules based on distance, speed and density with respect to the nearest neighbours
Input-output circularity	During the training phase, the weights of the ANN are assessed with a circular input-output process (error back-propagation)	The movement of the flock depends on the movement of the single birds but also the trajectories of the birds depend on the shape of the flock
Input-output non-linear dependence	The outputs of the network are highly sensitive to the initial condition of the weights	The change of trajectory of a single bird may radically change the shape and trajectory of the flock

Epistemological highlights

- **Bottom-up** character of connectionist approach to Machine Learning

  We do not need any *a priori* expert knowledge about the task to perform

  The knowledge emerges from the examples with which the network is fed

- **Sub-symbolic** character

  Many individual agents and non-linear interactions create an opaqueness of the systems

  At the end of the process of learning, the steps the machine follows are not human-readable information but a matrix of connections' weights

<table>
<tr><th></th><th>Imperative approach</th><th>Logical approach</th><th>Machine Learning approach (focus on Connectionism)</th></tr>
<tr><td>The programmer</td><td>solves his/her task with an algorithm containing all the steps, in their order, the machine has to follow to produce the output</td><td>declares a set of facts and logical rules from which the machine itself infers the output via the inference engine</td><td>collects examples and sets the architecture of the network</td></tr>
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they need an expert to represent the problem and the solution is produced by deduction
• Symbolic:
the information the machine produces and the steps it follows consist in human-readable information</td><td>• Bottom-up
no need of a priori expert knowledge about the task
• Sub-symbolic
non human-readable information and opaqueness</td></tr>
</table>

Conclusions

- The establishment of the neural network/complex system comparison allowed to show to the students epistemological aspects that go beyond the connectionist paradigm in which the parallelism was constructed
- The parallelism allowed to illuminate important aspects of Machine Learning approach in general, giving space to deeper understanding of Samuel's definition
- This work is the starting point to address the knowledge gap between research and education in Machine Learning

Further steps

- New implementations (January-March 2020)
- Accurate data collection (pre- and post- interviews, questionnaires, focus groups)
- Qualitative data analysis to investigate students' reactions to the activity in terms of content understanding and emotional attitudes

If you want to provide any feedback or if you would like to work in the refinement of the activity and/or in the data analysis process, let's network in these days!

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Thank you
for your kind attention

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