

Deep Learning Introduction and Application

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A Glossary of Artificial-Intelligence Terms

ARTIFICIAL INTELLIGENCE

AI is the broadest term, applying to any technique that enables computers to mimic human intelligence, using logic, if-then rules, decision trees, and machine learning (including deep learning).

MACHINE LEARNING

The subset of AI that includes abstruse statistical techniques that enable machines to improve at tasks with experience. The category includes deep learning.

DEEP LEARNING

The subset of machine learning composed of algorithms that permit software to train itself to perform tasks, like speech and image recognition, by exposing **multilayered neural networks to vast** amounts of data.

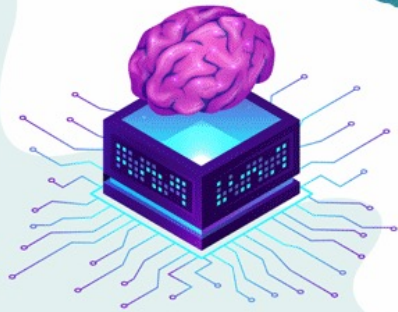
GLOBAL DEEP LEARNING MARKET

North America

Largest Market
By Region (2019)

APAC

Fastest-Growing Market
By Region (2020-2030)



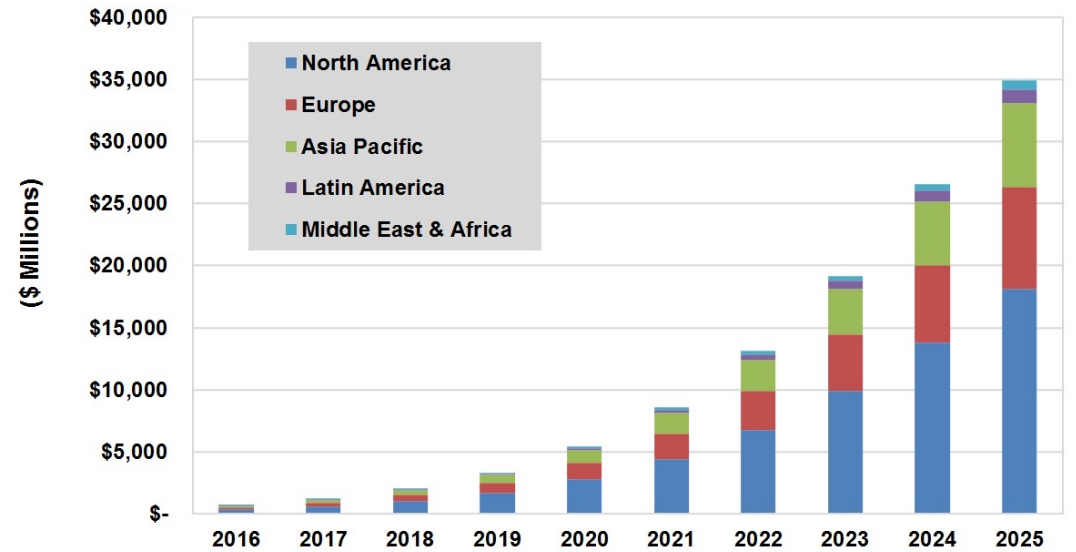
2019
Market Size
\$3.7
billion

2030
Market Size
\$102.4
billion

Market
Growth Rate
(2020-2030)
35.2%



Deep Learning Software Revenue by Region, World Markets: 2016-2025

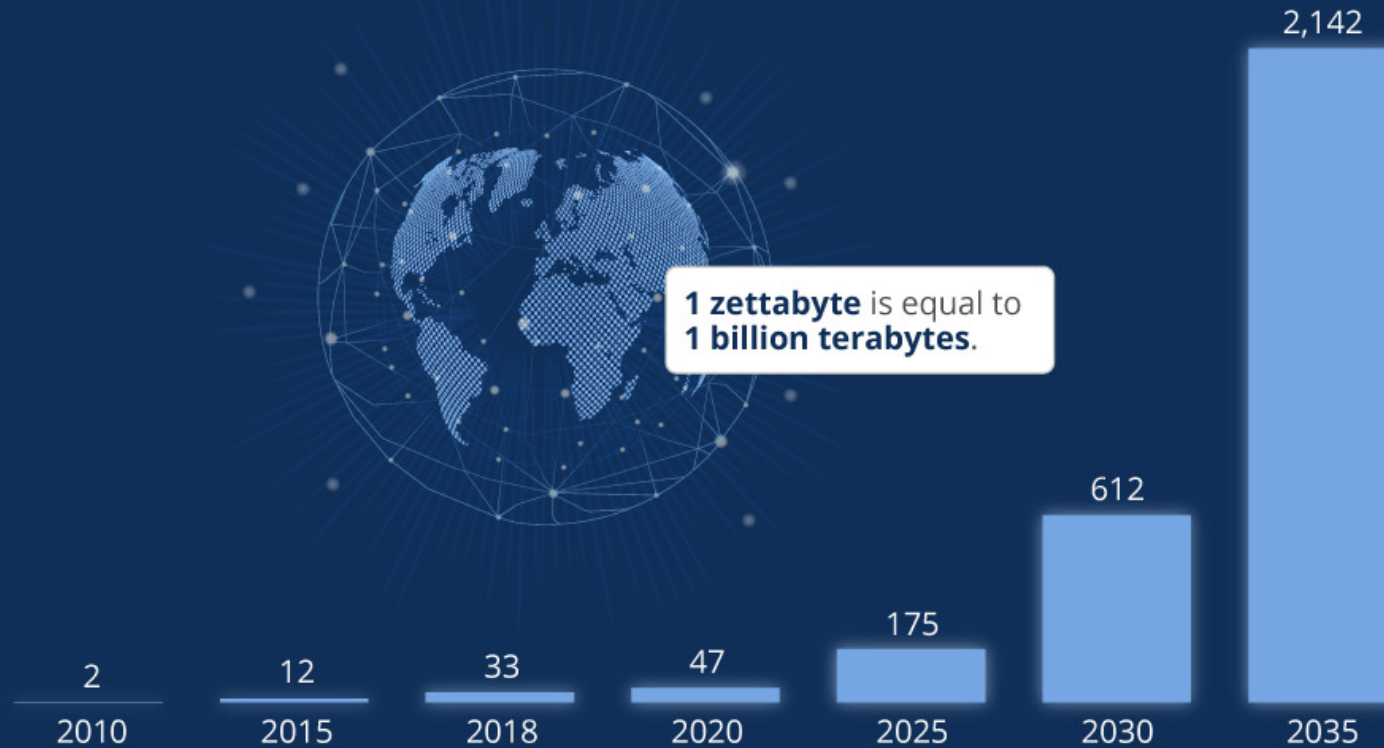


Source: Tractica

Motivation-> Data is changing

Global Data Creation is About to Explode

Actual and forecast amount of data created worldwide 2010-2035 (in zettabytes)



@StatistaCharts

Source: Statista Digital Economy Compass 2019

statista

A DAY IN DATA

The exponential growth of data is undisputed, but the numbers behind this explosion - fuelled by internet of things and the use of connected devcies - are hard to comprehend, particularly when looked at in the context of one day

500m

tweets are sent every day

Twitter



4PB

of data created by Facebook, including

350m photos

100m hours of video watch time

Facebook Research

DEMYSIFYING DATA UNITS

From the more familiar 'bit' or 'megabyte', larger units of measurement are more frequently being used to explain the masses of data

| Unit | Value | Size |
|---------------------|--------------------------|---|
| b bit | 0 or 1 | 1/8 of a byte |
| B byte | 8 bits | 1 byte |
| KB kilobyte | 1,000 bytes | 1,000 bytes |
| MB megabyte | 1,000 ² bytes | 1,000,000 bytes |
| GB gigabyte | 1,000 ³ bytes | 1,000,000,000 bytes |
| TB terabyte | 1,000 ⁴ bytes | 1,000,000,000,000 bytes |
| PB petabyte | 1,000 ⁵ bytes | 1,000,000,000,000,000 bytes |
| EB exabyte | 1,000 ⁶ bytes | 1,000,000,000,000,000,000 bytes |
| ZB zettabyte | 1,000 ⁷ bytes | 1,000,000,000,000,000,000,000 bytes |
| YB yottabyte | 1,000 ⁸ bytes | 1,000,000,000,000,000,000,000,000 bytes |

*A lowercase "b" is used as an abbreviation for bits, while an uppercase "B" represents bytes.

463EB

of data will be created every day by 2025

etc



95m

photos and videos are shared on Instagram

Instagram Business

294bn

billion emails are sent

Radicati Group

320bn

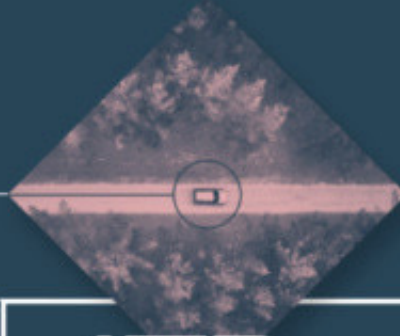
emails to be sent each day by 2021

306bn

emails to be sent each day by 2020

3.9bn

people use emails



4TB

of data produced by a connected car

Intel

65bn

messages sent over WhatsApp and two billion minutes of voice and video calls made

Facebook



Data is growing

28PB

to be generated from wearable devices by 2020

Statista



ACCUMULATED DIGITAL UNIVERSE OF DATA

4.4ZB

44ZB

Searches made a day

5bn

Searches made a day from Google

3.5bn











Smart Insights



Investments in the Deep Learning Trend

The Most Common Use Cases of AI

Estimated % of AI spending by use case in 2025

| Use Case | % of Spending | |
|---|---------------|---|
| Algorithmic financial trading | 17% |  |
| Image recognition and tagging | 16% |  |
| Patient data processing | 15% |  |
| Predictive maintenance | 10% |  |
| Content distribution on social media | 8% |  |
| Text query of images | 8% |  |
| Automated geophysical feature detection | 7% |  |
| Object identification and tracking | 7% |  |
| Object detection / classification | 6% |  |
| Contract analysis | 6% |  |

Source: Tractica Research's spending estimates for Top 10 AI use cases in 2025



From the Past to the future

- 2008-2013 Years of theoretical studies and hardware production
- 2016->..... **Time to bring out the application**
 - “Google and Movidius who have teamed up to increase adoption (of deep learning technology) within mobile devices.”
 - Google changed the «Page Rank» algorithm with «Rank Brain» Deep learning based
 - Facebook «face recognition» is deep learning based
 - Google and Apple cars use DL to drive autonomous vehicles
 - Toyota is spending \$1 billion on AI in Silicon Valley for autonomous cars
 - GPT3 is the current standard de-facto for text analysis

What is learning and a learning machine

Types of Learning



Supervised (inductive) learning

Training data includes desired outputs



Unsupervised learning

Training data does not include desired outputs



Semi-supervised learning

Training data includes a few desired outputs



Reinforcement learning

Rewards from sequence of actions

Supervised vs. unsupervised Learning



Supervised learning: classification is seen as supervised learning from examples.

Supervision: The data (observations, measurements, etc.) are labeled with pre-defined classes. It is like that a “teacher” gives the classes (supervision).

Test data are classified into these classes too.



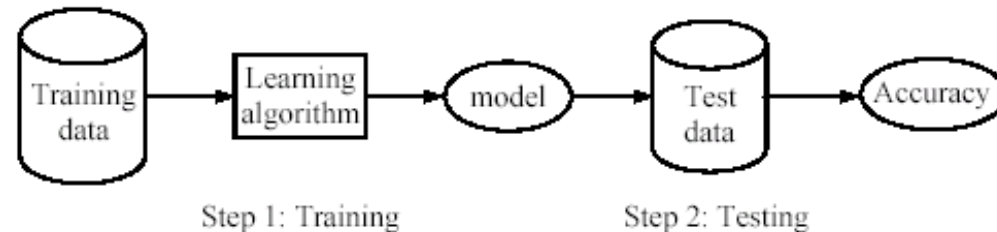
Unsupervised learning (clustering)

Class labels of the data are unknown

Given a set of data, the task is to establish the existence of classes or clusters in the data

Supervised learning process: two steps

- **Learning (training)**: Learn a model using the training data
- **Testing**: Test the model using **unseen test data** to assess the model accuracy



$$Accuracy = \frac{\text{Number of correct classifications}}{\text{Total number of test cases}},$$

Classification measures

- Accuracy is **only one measure** (error = 1-accuracy).
- Accuracy is **not suitable** in some applications.
- In text mining, we may only be interested in the documents of a particular topic, which are only a small portion of a big document collection.
- In classification involving skewed or highly imbalanced data, e.g., network intrusion and financial fraud detections, we are interested only in the minority class.
 - High accuracy does not mean any intrusion is detected.
 - E.g., 1% intrusion. Achieve 99% accuracy by doing nothing.
- The class of interest is commonly called the positive class, and the rest negative classes.



What do we mean by learning?

- **Given**

- a data set D ,
- a task T , and
- a performance measure M ,

a computer system is said to **learn** from D to perform the task T if after learning the system's performance on T improves as measured by M .

- In other words, the learned model helps the system to perform T better as **compared to no learning**.

Fundamental assumption of learning

Assumption: The distribution of training examples is identical to the distribution of test examples (including future unseen examples).

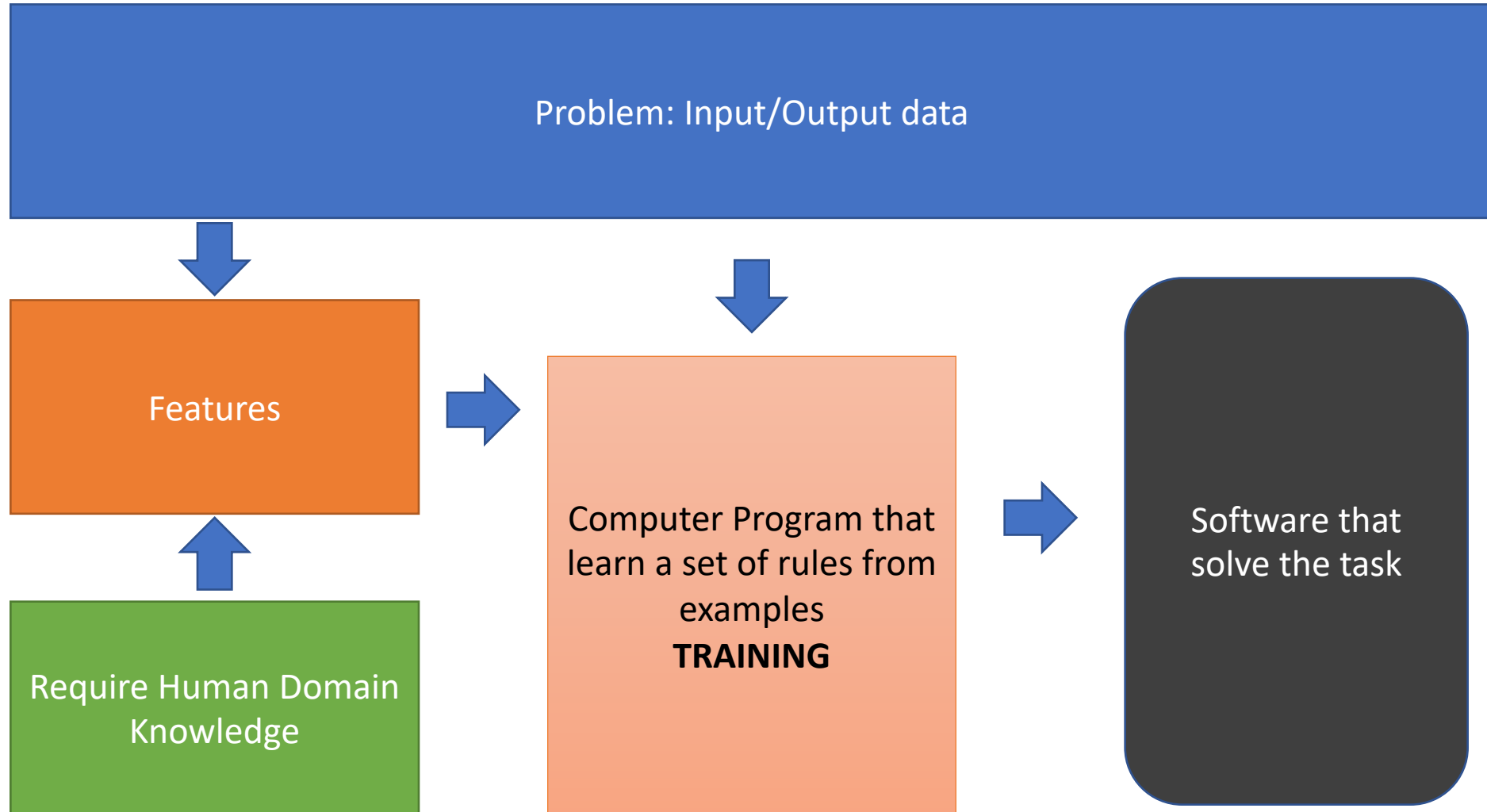
In practice, this assumption is often violated to certain degree.

Strong violations will clearly result in poor classification accuracy.

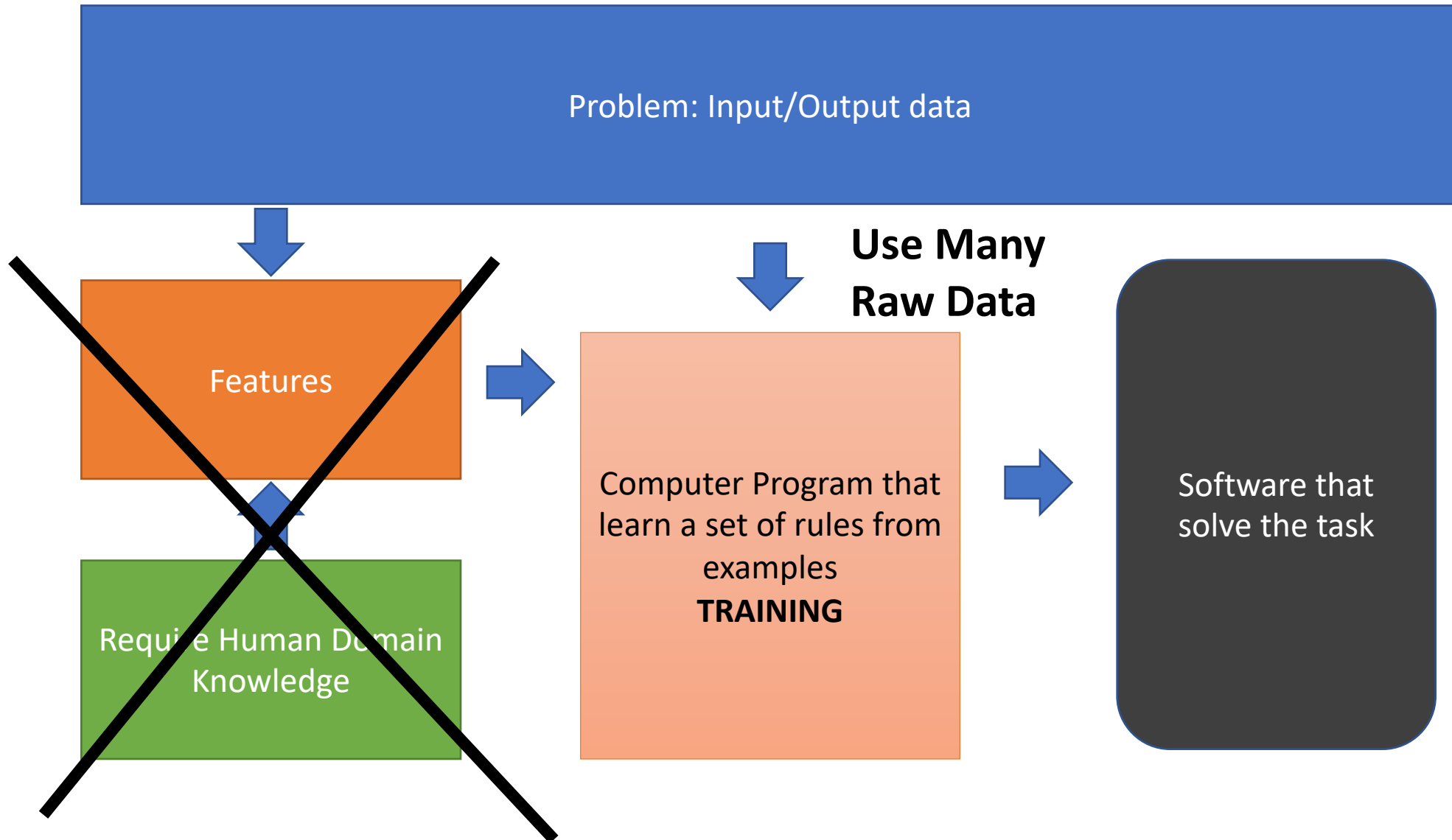
To achieve good accuracy on the test data, training examples must be sufficiently representative of the test data.

General structure of a learning model

Learning Pipeline



Innovation of Deep Learning



Much more Data are needed: OCR Example

Tesseract Google OCR

- 800 Chars needed for Training
- Avg Trainig Time 10 minutes
- Core i7 PC NO GPU



DEMO code @

<http://christopher5106.github.io/computer/vision/2015/09/14/comparing-tesseract-and-deep-learning-for-ocr-optical-character-recognition.html>

Deep Neural Network

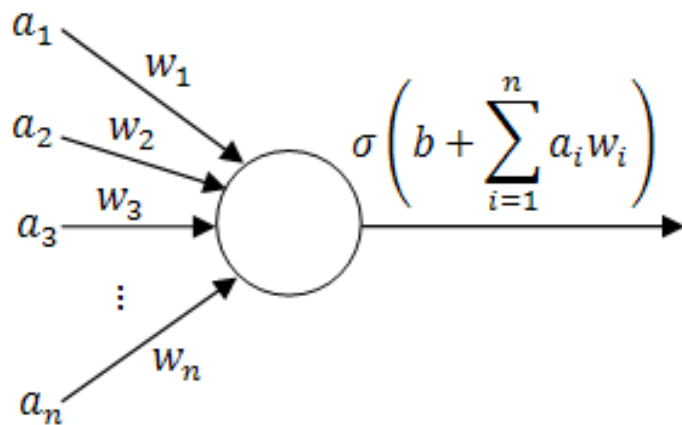
- 5000 chars needed for Training
- Avg Training time 30 minutes
- Core i7 PC + NVIDIA GPU CARD

| Technology | Accuracy |
|--------------------------------|------------|
| Tesseract eng language | 40% |
| Tesseract trained language | 60% |
| DEEP neural network(NN) | 98% |

From the Perceptron to

- Perceptron is the analogous of a neuron
- Computational model -> perform linear classification

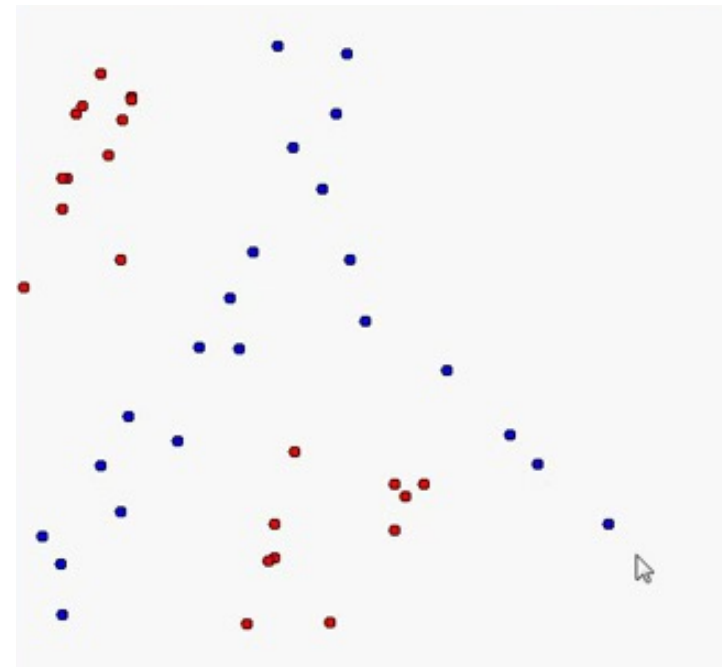
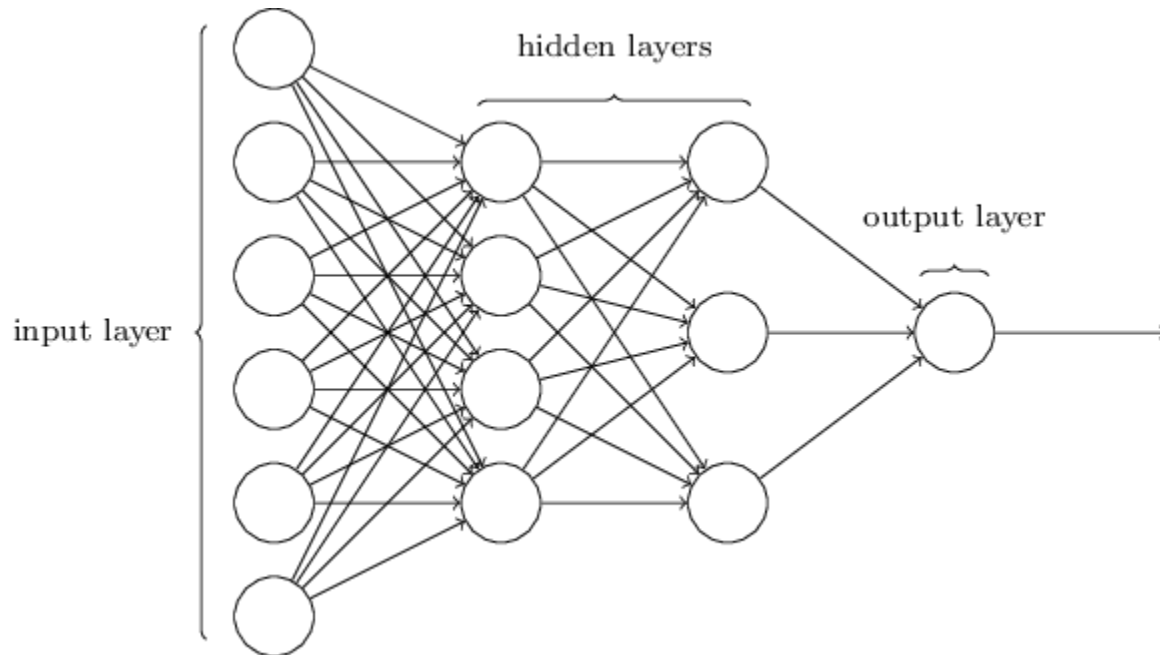
Perceptron is a linear Classifier



Multilayered Neural Network

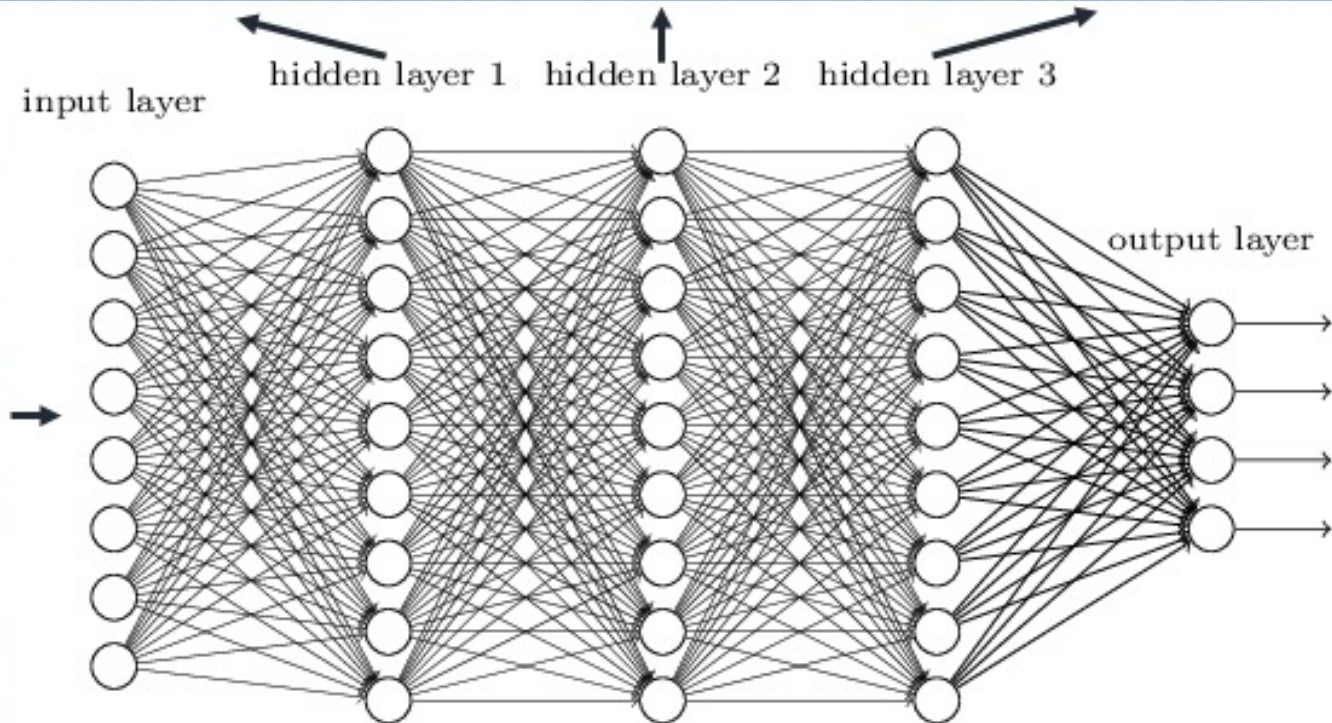
- Stacking perceptrons **vertically** we obtain a layer
- Stacking layers **horizontally** we obtain a network

Network With 3 layers is a non-linear classifier

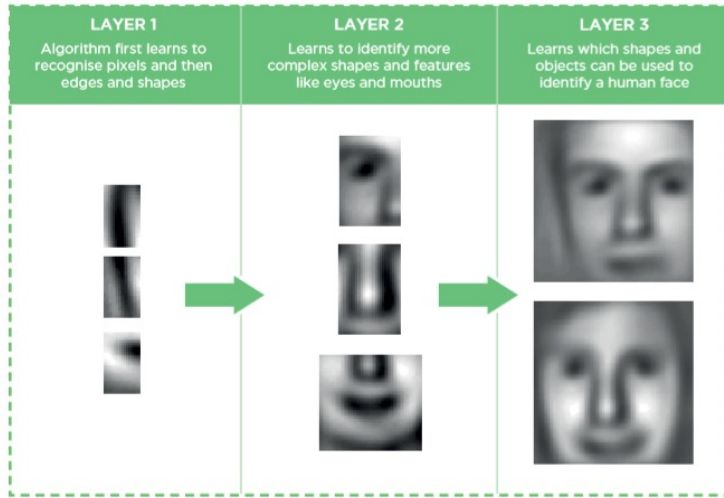


Going Deep

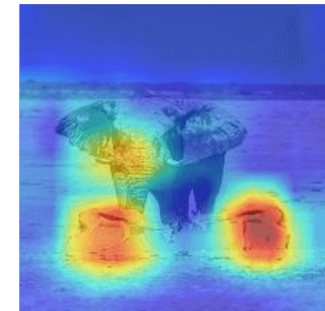
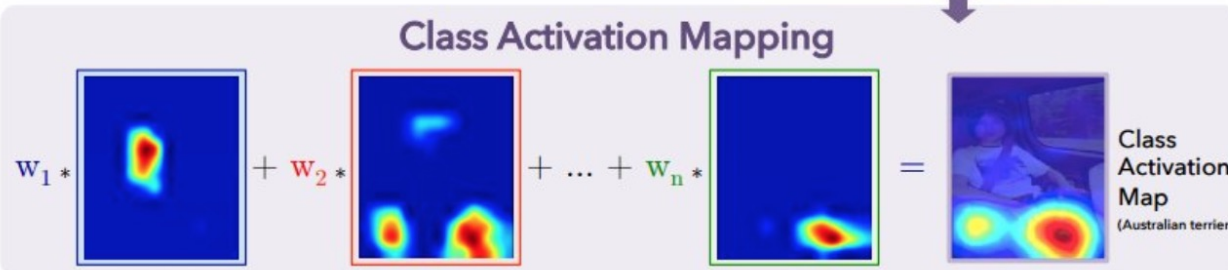
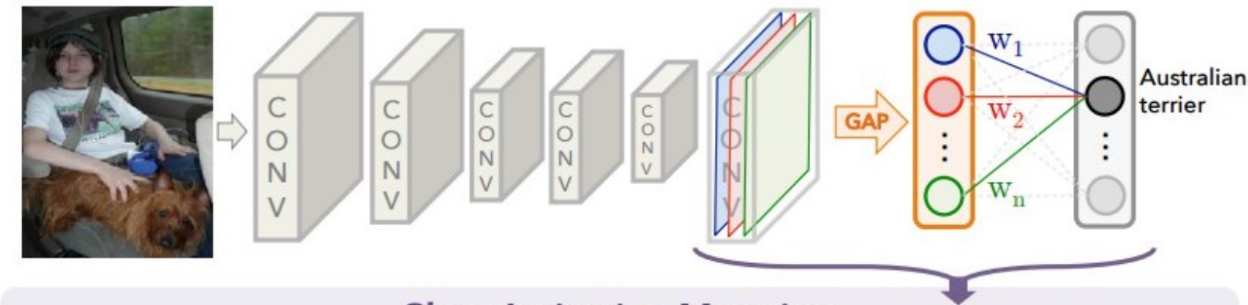
Deep neural networks learn hierarchical feature representations



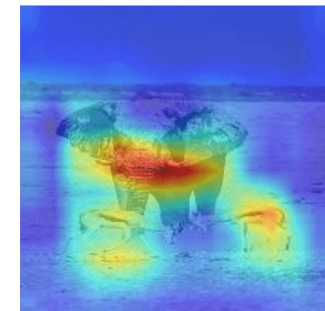
How the network learn the world



- Inner Representation is compositional
- Semantic representation must be inspected with additional techniques e.g. Class Activation Maps



gazelle



elephant

Deep Networks For:

Numerical Data -> Deep Neural Network

Applications: Production management, Prediction, Controls and Robotics

Multimedia Data-> Convolutional Network

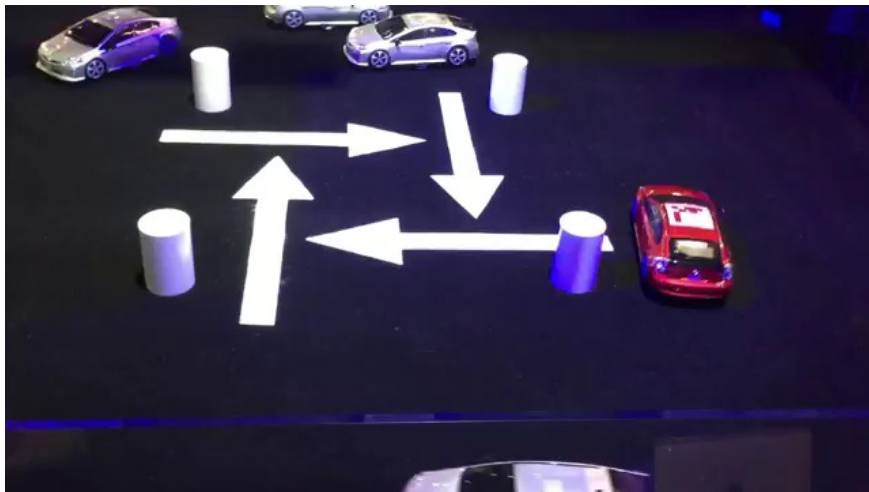
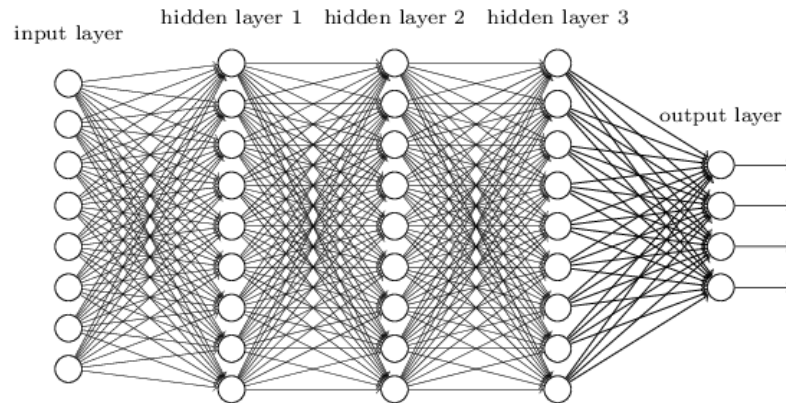
Applications: Image and Video classification, Face recognition, Licence Plate Detection, OCRs..

Time series -> Recurrent Neural Network

Applications: Financial Analysis, Audio and Speech analysis, Text analysis and translation, Forecasting

Numerical Data -> Deep Neural Network

Deep neural network



From CES2016 Red car is human guided

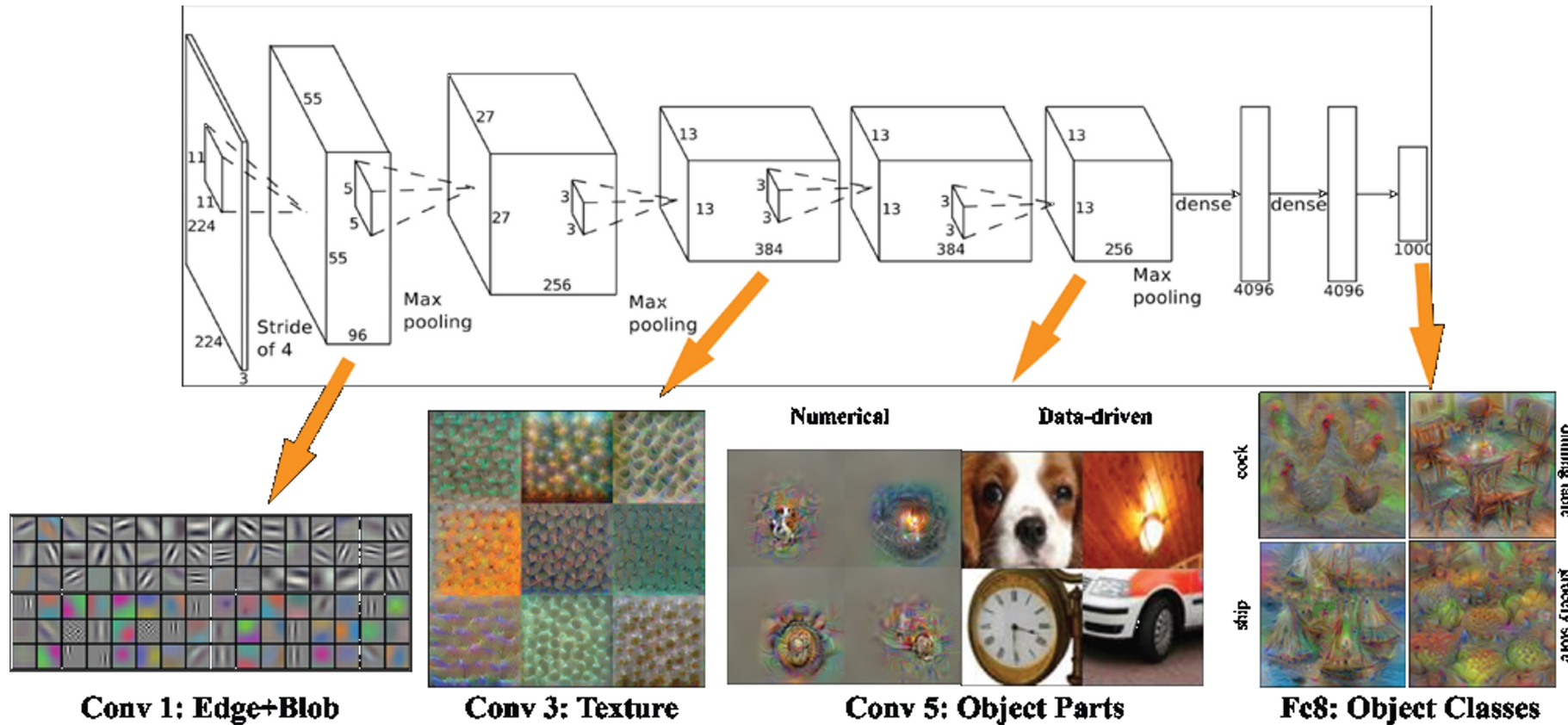
Pros:

- Use Digital Sensors data as input
- Theoretically can learn every classification function
- Can predict a flexible number of outcomes

Cons:

- Many parameters to be learned
- Many training data needed
- Input dimension must be kept small

Multimedia Data-> Convolutional Network



Pros:

- Use Image as Raw Data
- Can predict a flexible number of outcomes
- Use convolutions to reduce the number of parameters

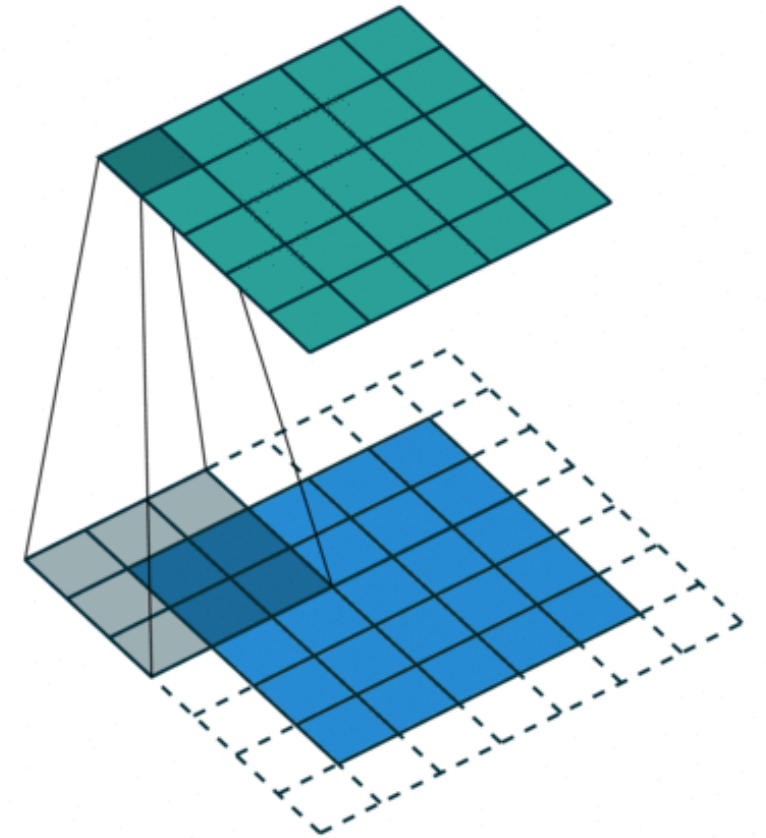
Cons:

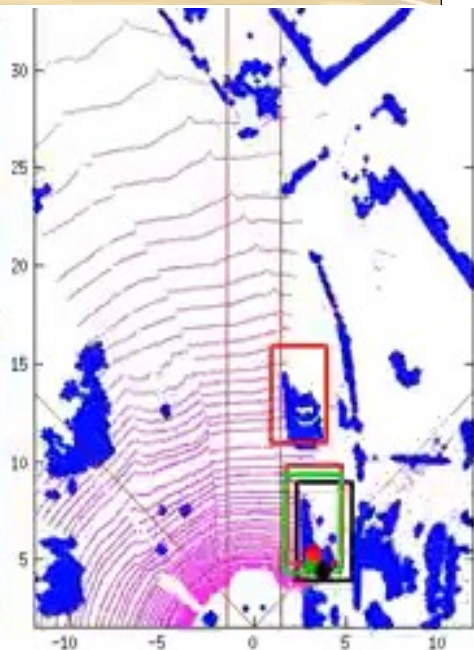
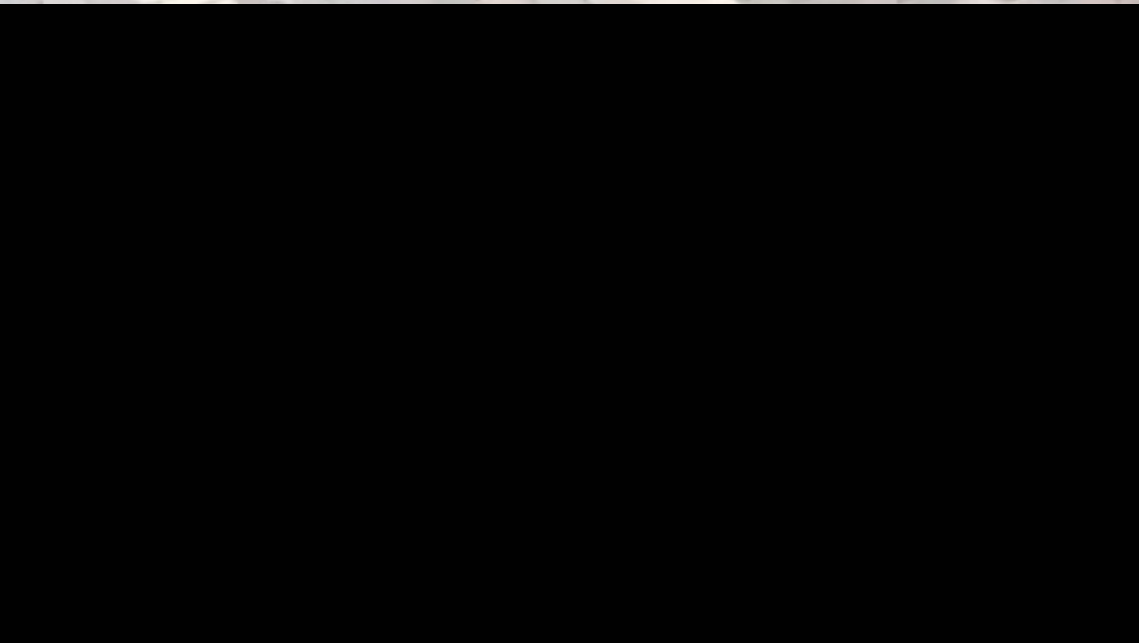
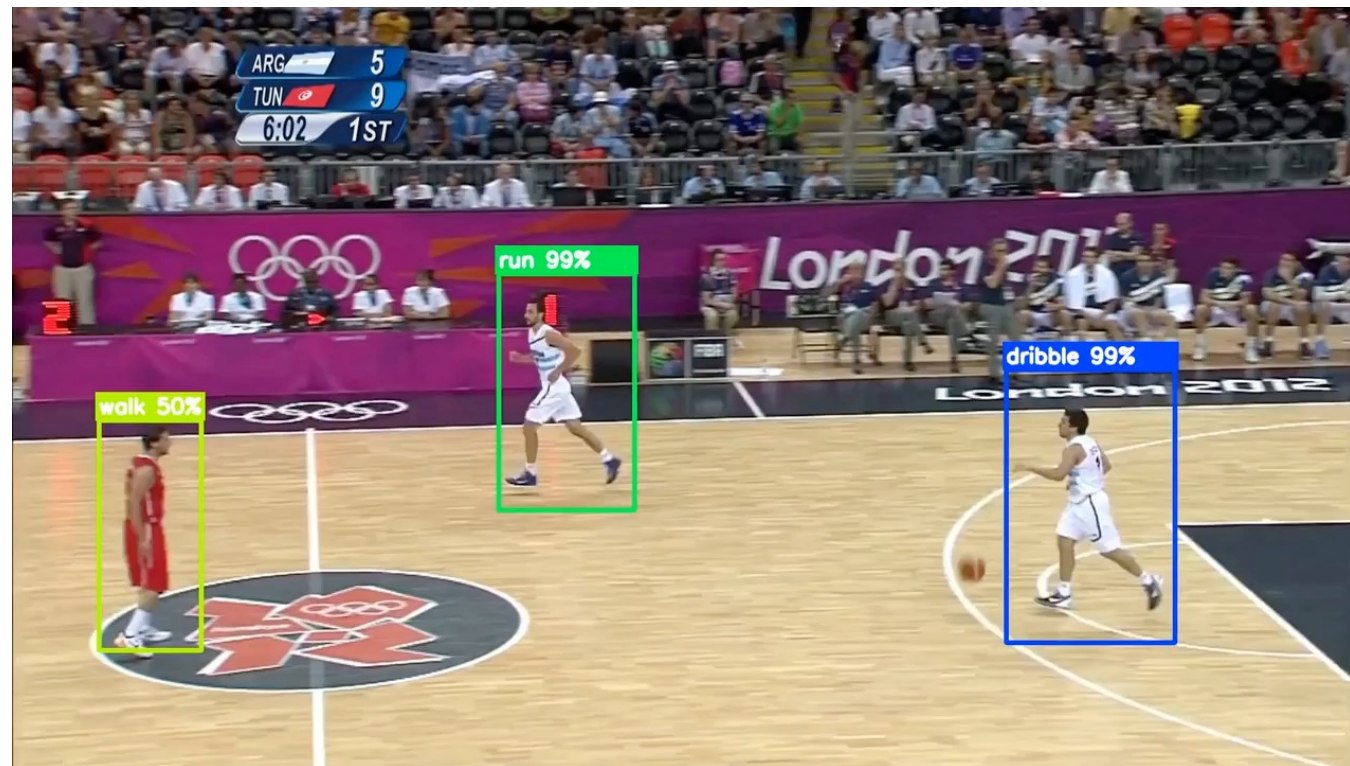
- Image Scaling must be handled
- Input has «mostly» fixed shape
- Annotating images costs

Convolution

- Is a **spatial operation** with a learnable kernel
- Kernel shift spatially over data support
- Implies **translation invariance**

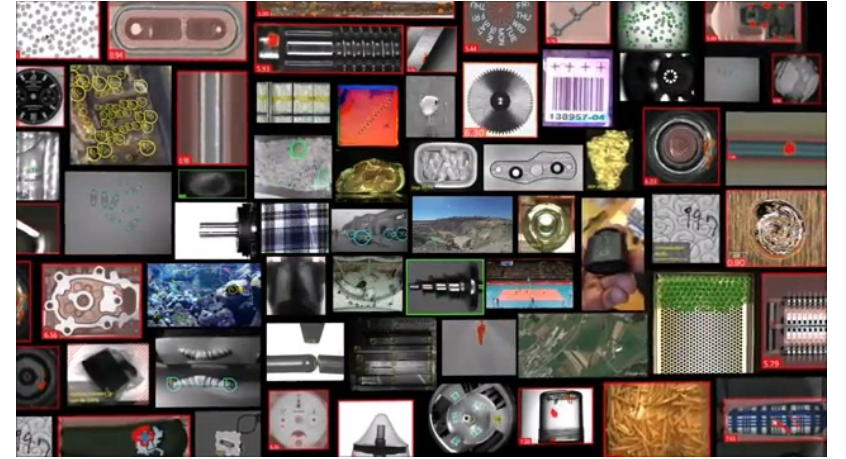
<https://medium.com/syncedreview/a-guide-to-receptive-field-arithmetic-for-convolutional-neural-networks-42f33d4378e0>







First, the robot arm tries to pick up iron cylinders at random positions

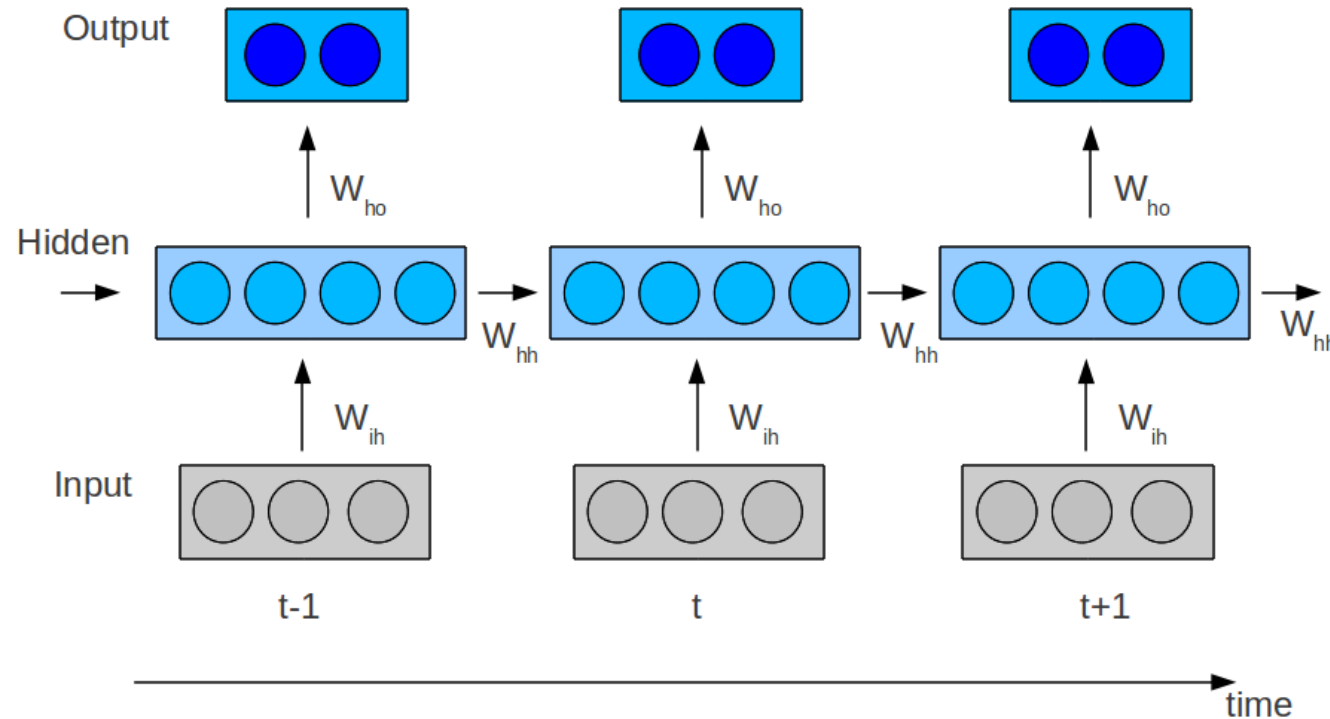


Inspection time



+/- 200 msec.

Time series -> Recurrent Neural Network



Pros:

- Use Temporal Data
- Has memory of the past
- Can predict future outcomes

Cons:

- Hard to train
- It forgets!
- Parameters grows as time grows

```
cybernaut@Cyberlion:~/neuralengine_3stream$ th demo2.lua
```

```
Loading data. Please wait...
```

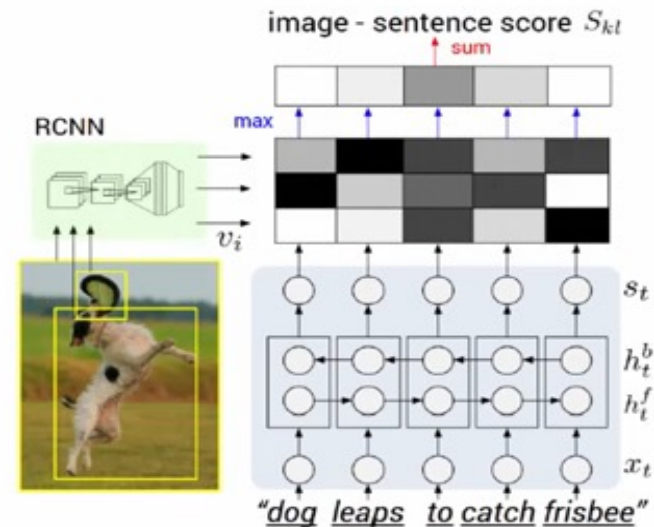
```
constructing clones inside the LanguageModel
```

```
|
```

Text and Music Writing

tyntd-iafhatawiaoihrdemot lytdws e ,tfti, astai f ogoh eoase rrranbyne 'nhthnee e
plia tklrtd t o idoe ns,smtt h ne etie h,hregtrs nigti,aoaenns lng

"Tmont thithey" fomesscerliund
Keushey. Thom here
sheulke, anmerenith ol sivh I lalterthend Bleipile shuvy fil on aseterlome
coaniogennc Phe lism thond hon at. MeiDimorotion in ther thize."



Robot Dynamics Control

Applications made in ER



<https://aimagelab.ing.unimore.it/>

- Study Deep Learning techniques for:

- People tracking
- People detection 2D and 3D
- Human Behavior understanding
- Anomaly Detection
- Vehicles-human interaction
- Geometric view synthesis

- **Conferences and Journals:**

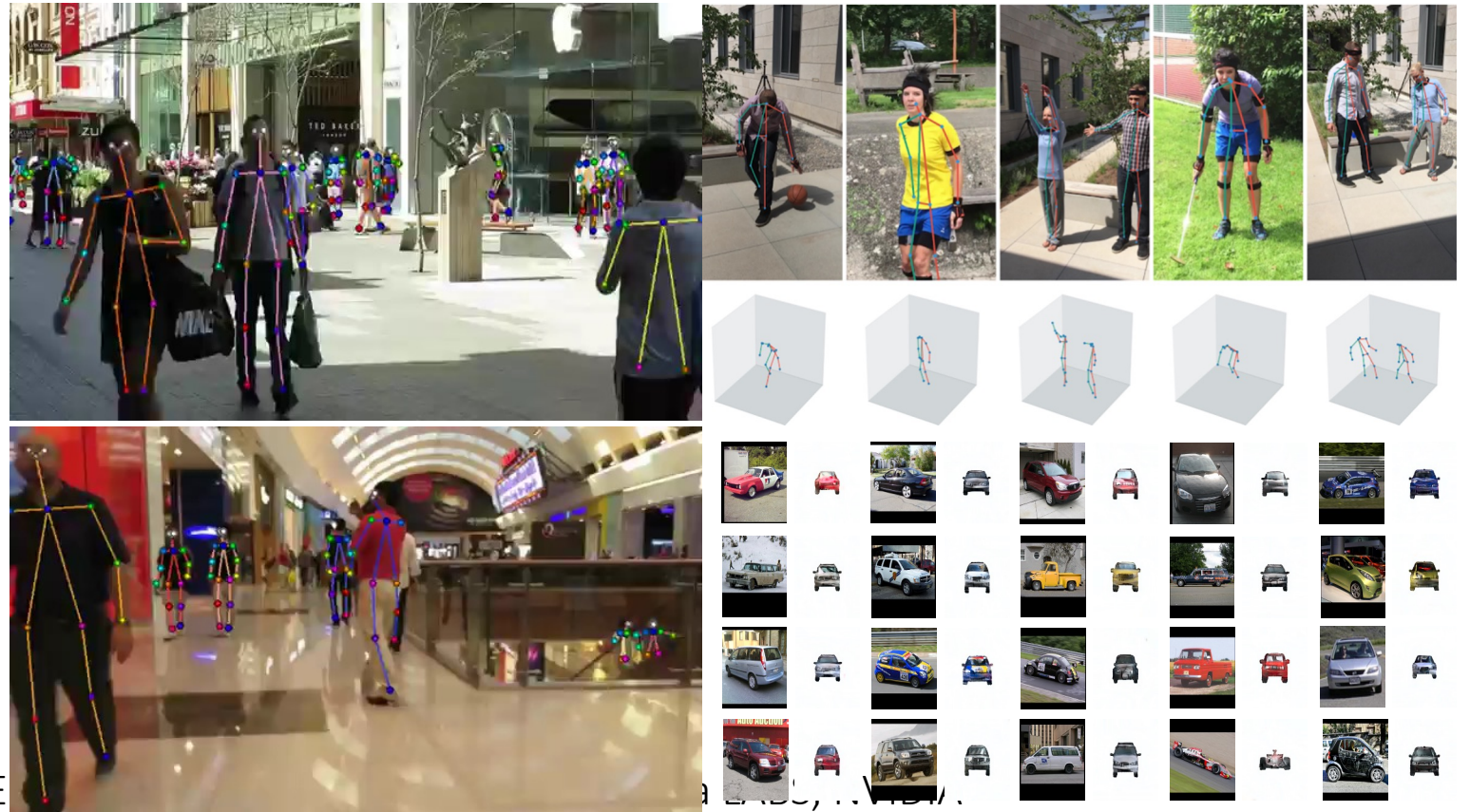
- CVPR, ICCV, TPAMI, TIP, TMM

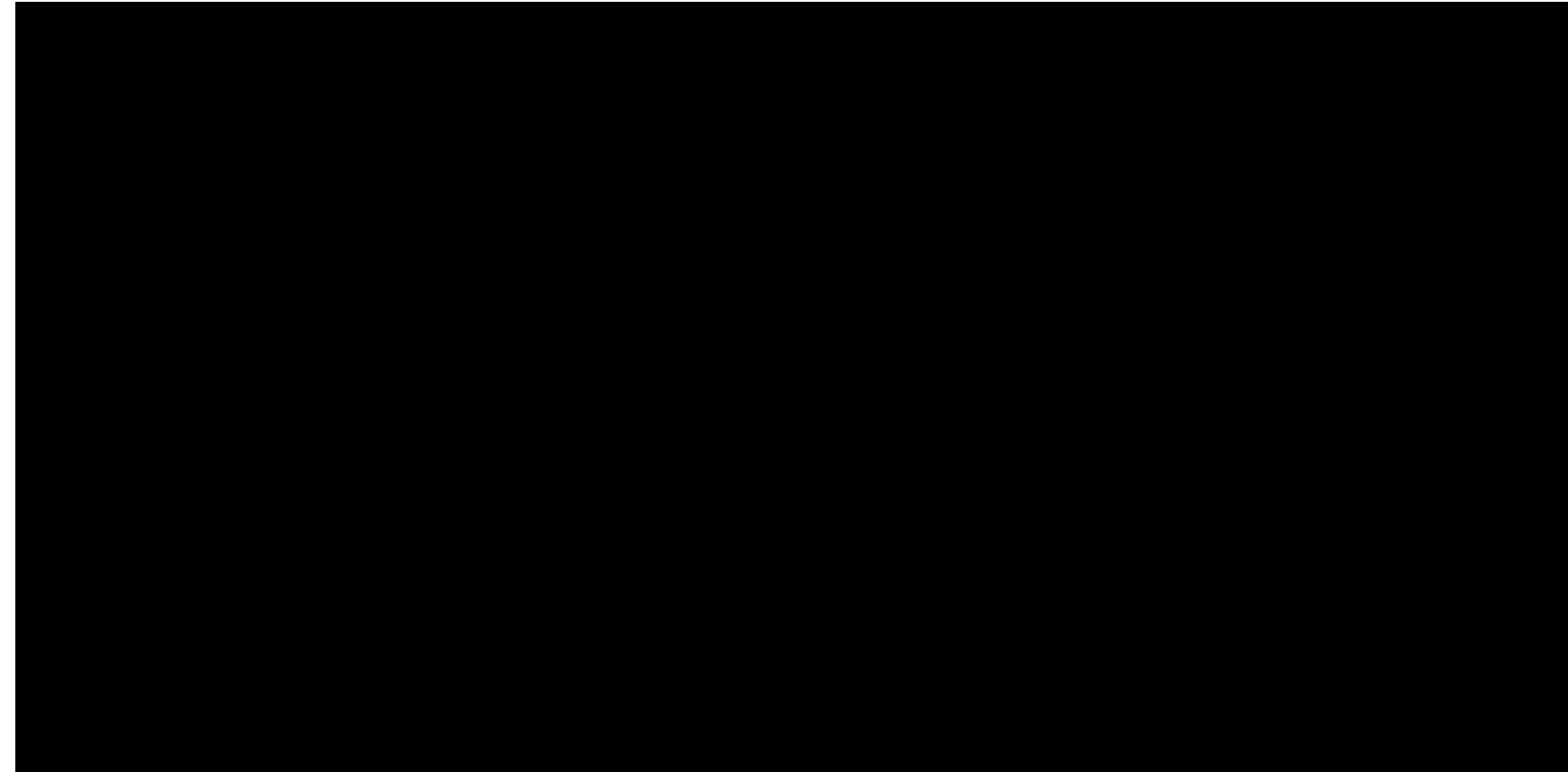
- **Projects and Collaborations:**

- PRIN COSMOS and PREVUE, EU PRYSTINE, E

- **AlmageLab Group:** Rita Cucchiara, Roberto Vezzani, Simone Calderara

- <http://aimagelab.ing.unimore.it>

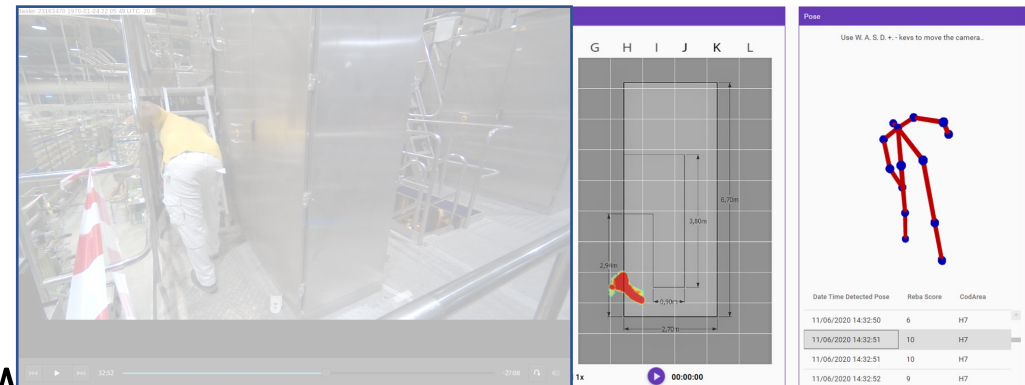
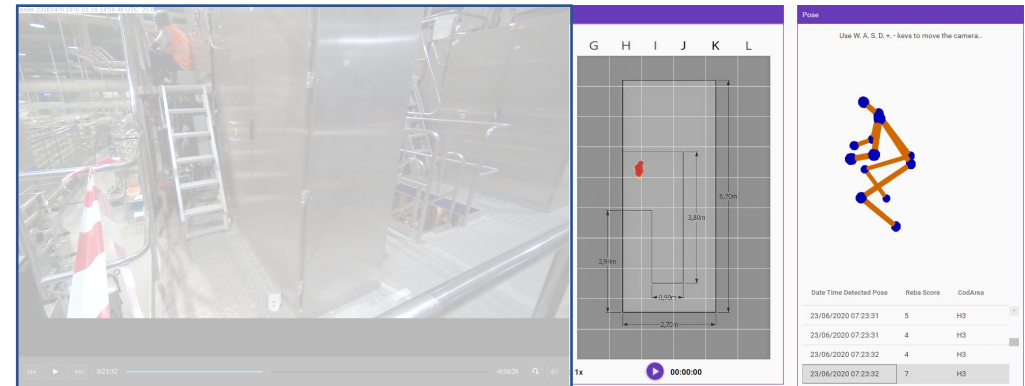
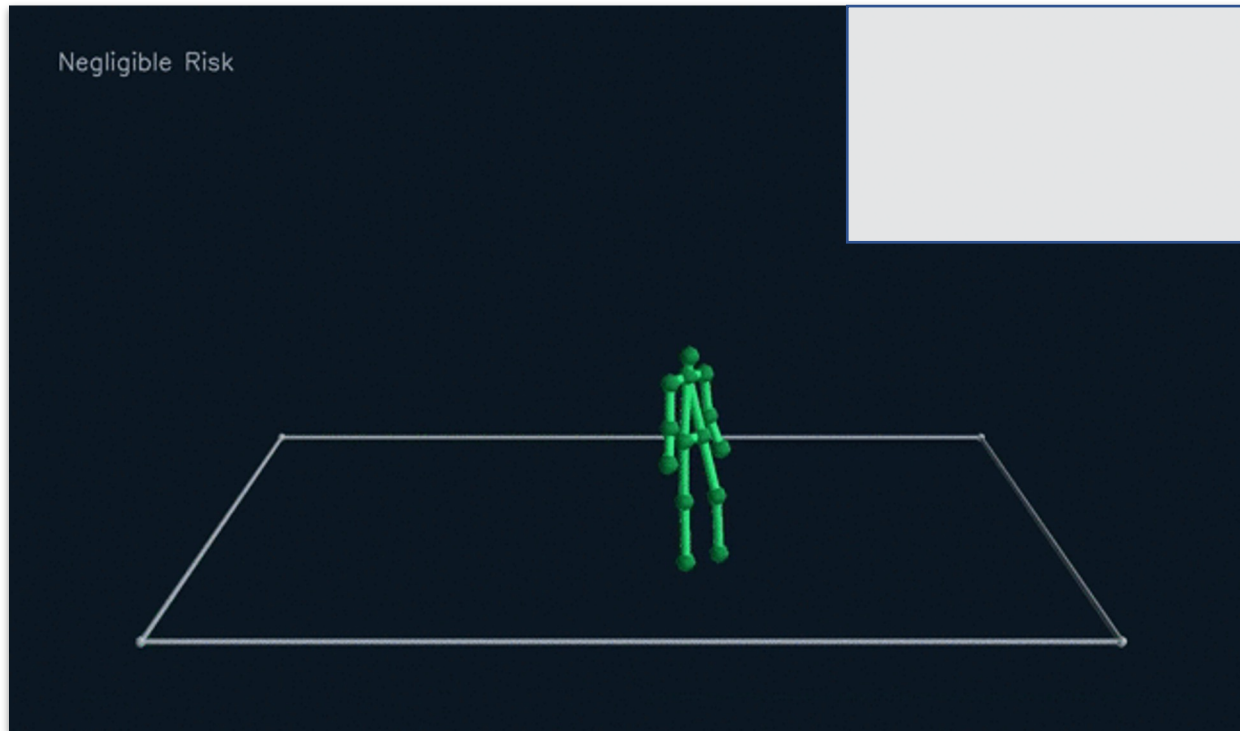






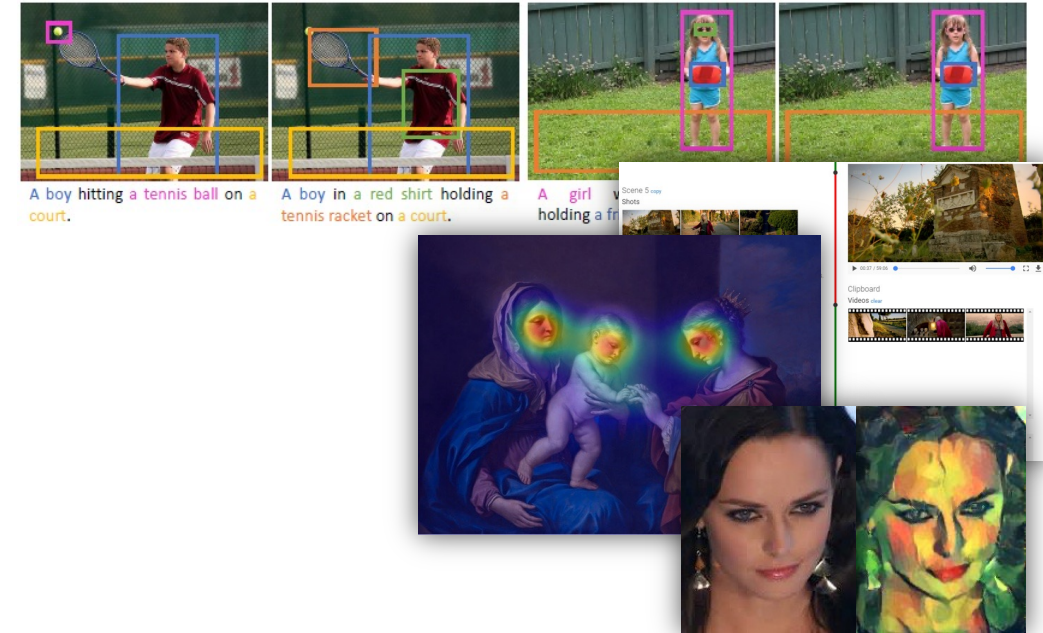
Can virtual data generalize to different environments?

Can we understand how people work and interact with machines?



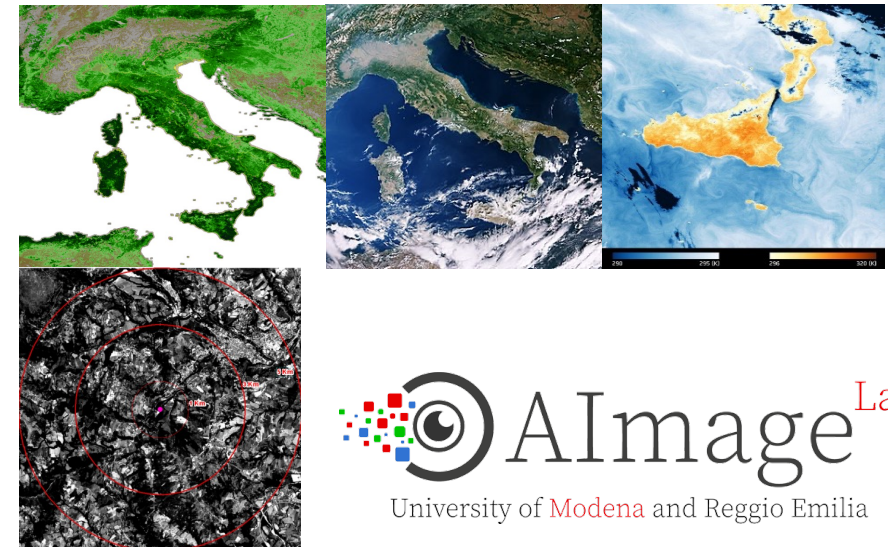
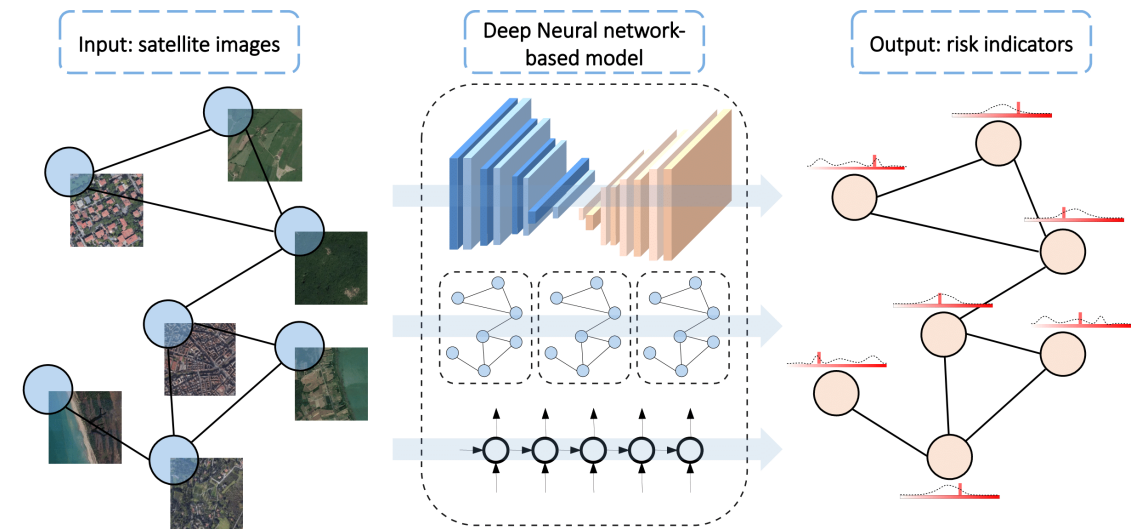
Machines of the future can reconfigure themselves with the consent of operators as a reward.

- **Embodied AI:** Integration between Vision, Language and Action
 - Automatic description of Images and Video
 - Natural Language and multi-modal retrieval
 - Vision and Language Navigation
 - Navigation of embodied agents in unseen environments
- Applications in Cultural Heritage and Digital Humanities
- **Conferences and Journals:**
- CVPR, ICCV, TPAMI, TIP, TMM
- **Projects and Collaborations:**
 - IDEHA, CULTMEDIA, AI4CH, AI4DH
 - Facebook AI Research, NVIDIA, University of Haifa (Israel)
- **AlmageLab Group:** Rita Cucchiara, Lorenzo Baraldi, Marcella Cornia
- <http://aimagelab.ing.unimore.it>

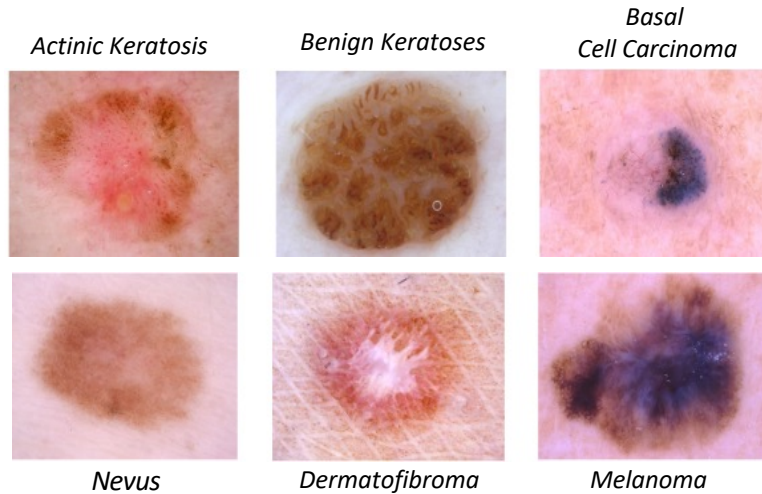


- Deep Learning and Graph based analysis for:
 - Satellite Images self-supervised feature extraction
 - Inference of physical phenomena from EO
 - Epidemic and vectors analysis using temporal EO
- **Projects and Collaborations:**
 - AI4VECT Italian Ministry of Health, AIDEO European Spatial Agency

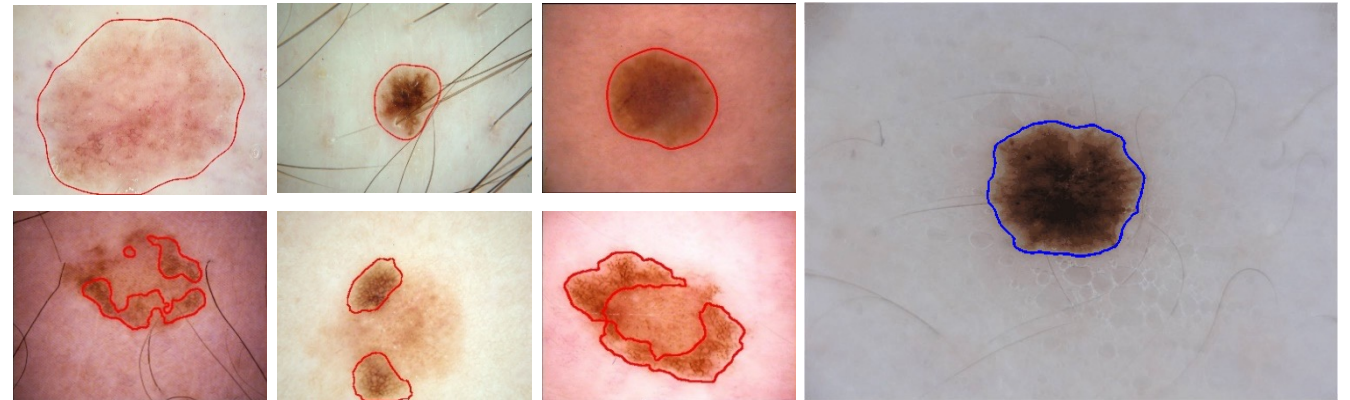
AlmageLab Group: Simone Calderara, Angelo Porrello
<http://aimagelab.ing.unimore.it>



Medical Imaging



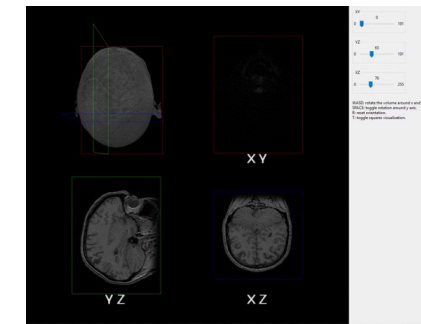
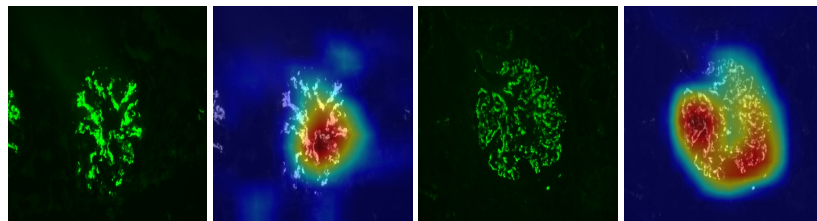
Lesion diagnosis



Lesion boundary segmentation and attribute detection

- **Third-place** (out of 64 research groups) at the 2019 international ISIC challenge (lesion diagnosis)

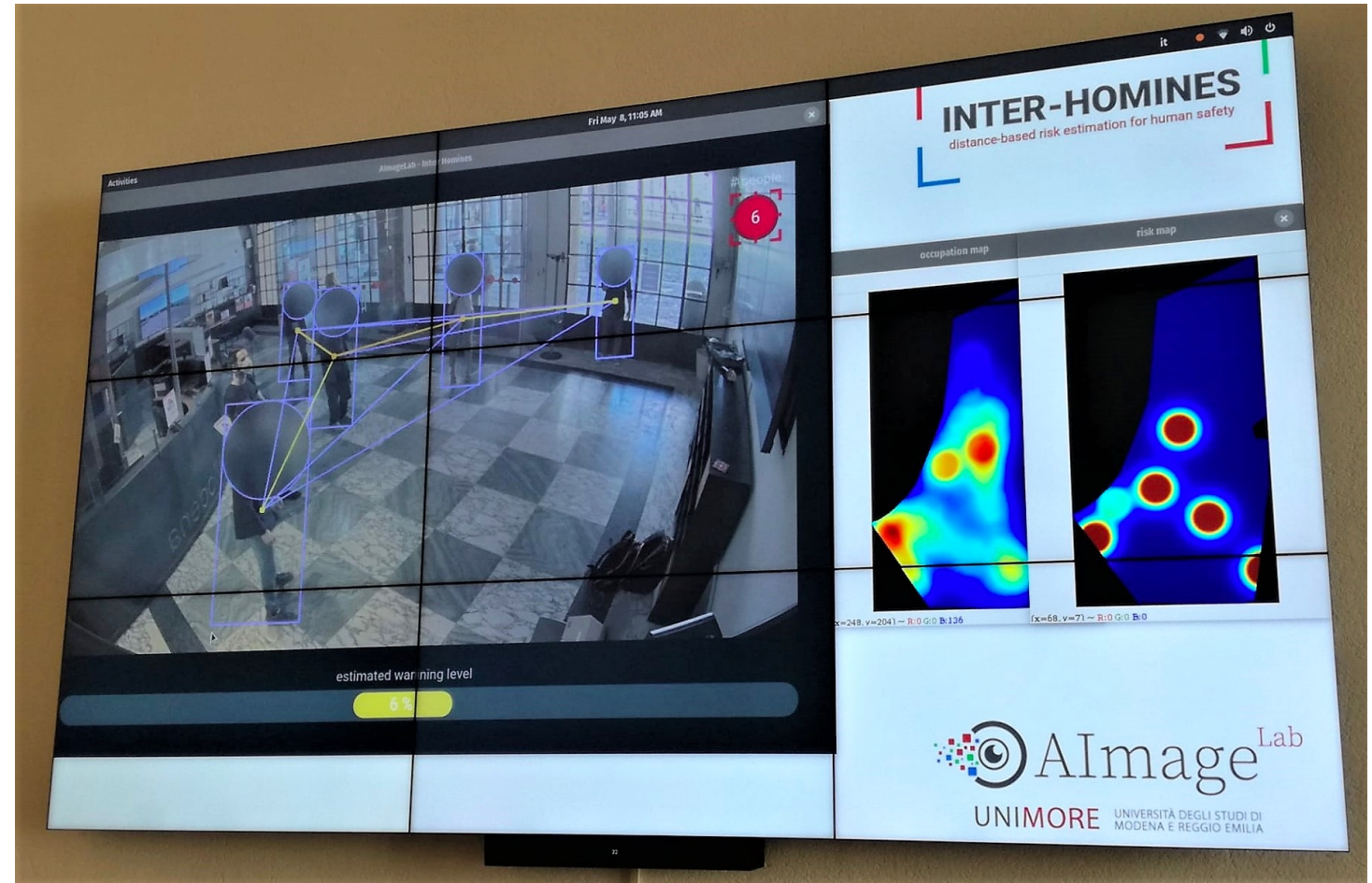
- DeepHealth (H2020): Deep-Learning and HPC to Boost Biomedical Applications for Health. **Period:** 2019 - 2021 **Budget:** 14.64 M€



- Intensity, patterns and locations of antibody deposits in immunofluorescence images from renal biopsies

Inter-Homines - Distance-based risk estimation for human safety

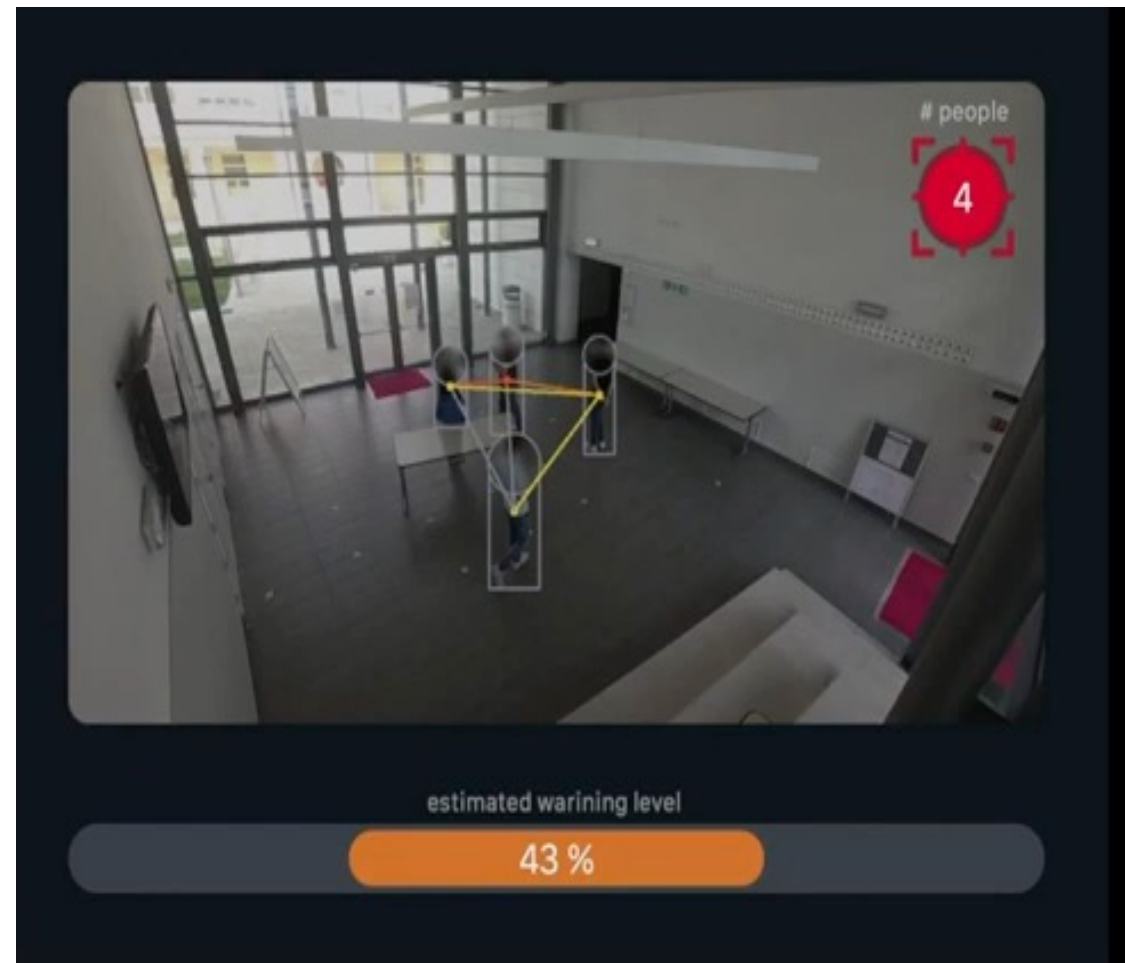
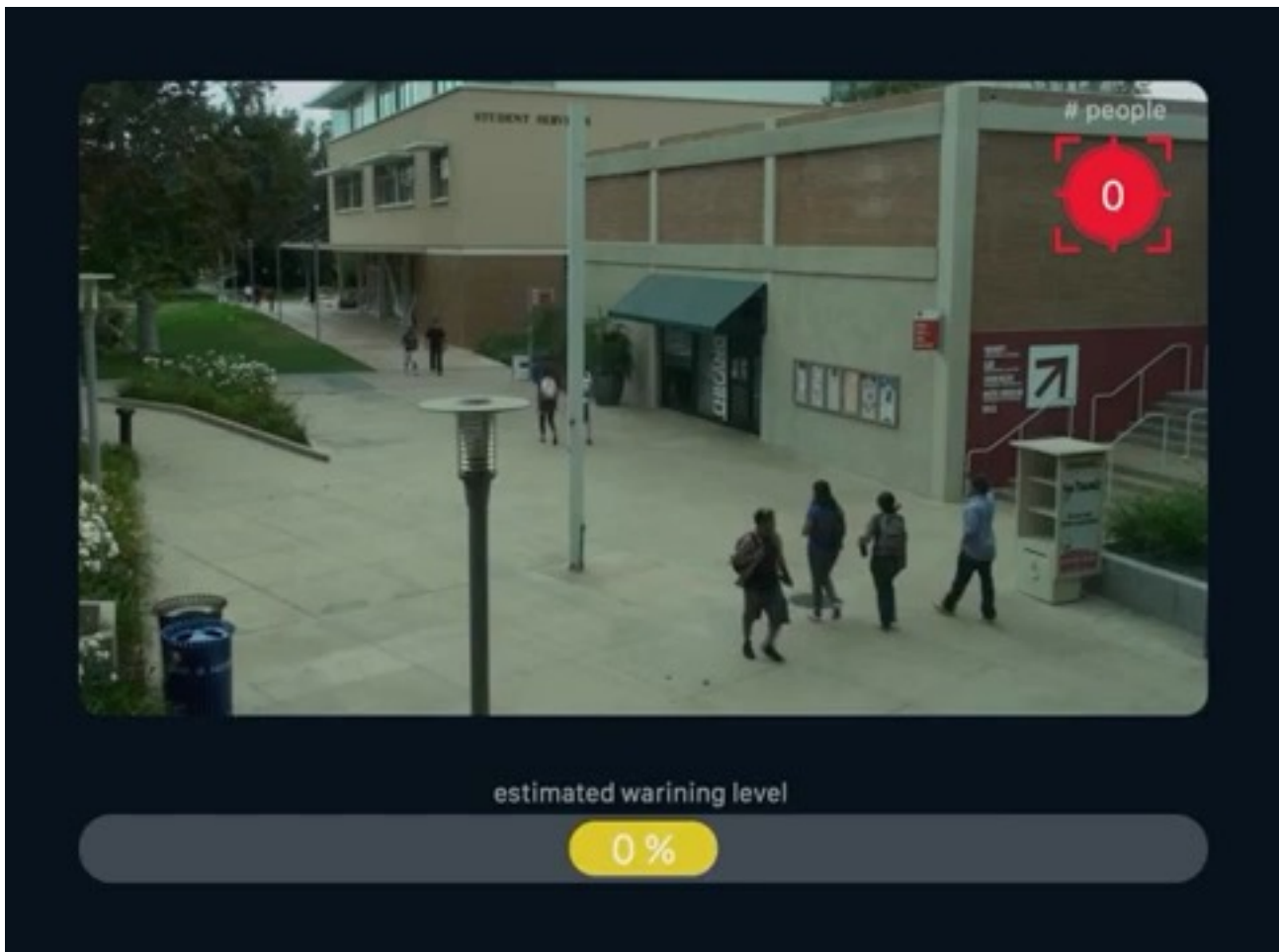
- Using cameras and AI to detect interpersonal distances
- Assess the risk of an area
- Sophisticated behavior analysis models for system robustness and risk evaluation



For more info <https://aimagelab.ing.unimore.it/imagelab/project.asp?idprogetto=82>

Prof. Rita Cucchiara rita.cucchiara@unimore.it Director of the Project

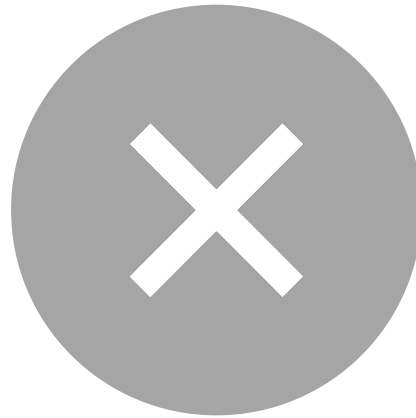
Dr. Matteo Fabbri matteo.fabbri@unimore.it



Future



WE ARE STILL MISSING
ABSTRACTION

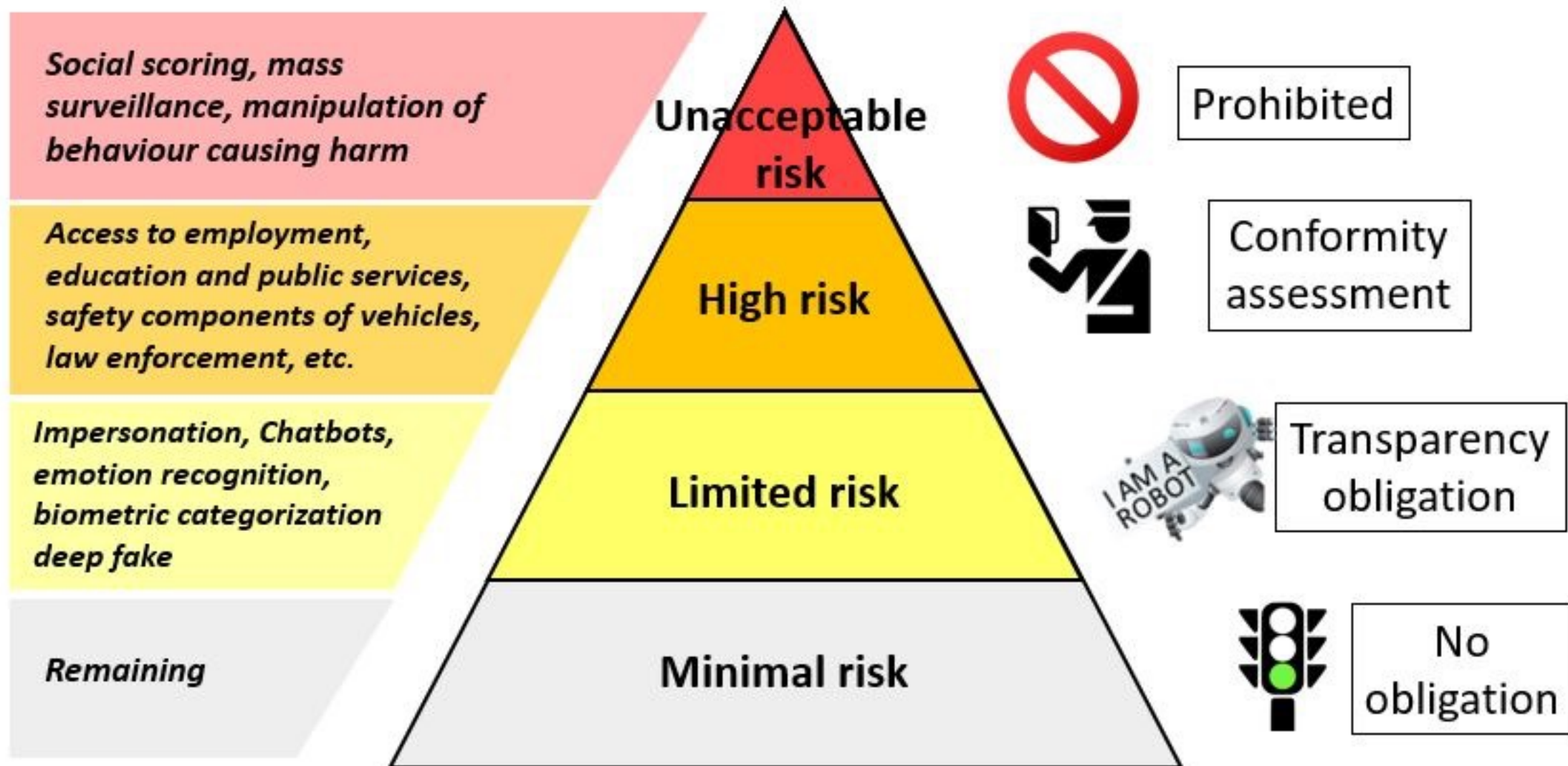


WE ARE MISSING
INTERPRETABILITY



WE ARE MISSING
AUTONOMY OF REASONING

EU Artificial Intelligence Act: Risk levels



Thank you for your attention

- More on us

- **Research:**

- AlmageLab Research Group: <http://aimagelab.unimore.it>
- Ellis Unit UNIMORE: <https://ellis.eu/units/modena-unimore>

- **Tech Transfer and Life Long Learning:**

- AIAcademy UNIMORE: <http://aiacademy.unimore.it/>



AI Academy

