Towards Cloud Based Computational Intelligence

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CIT

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AGENTÚRA
NA PODPORU
VÝSKUMU A VÝVOJA

Structure of the talk :

1. **Introduction - Cloud Computing and AI**
2. **Intelligence as a Service**
3. **Consequences for domains – Virtualisation - What is a Robot ?**
4. **AI bricks – Cloud Based AI - exp. of AI brick for Fuzzy Classification**
5. **Culmulative Fuzzy Class Membership Criterion for Classification**
6. **Cloud Based HRI for Robotics**
7. **Conclusion**

Where we are located at ?

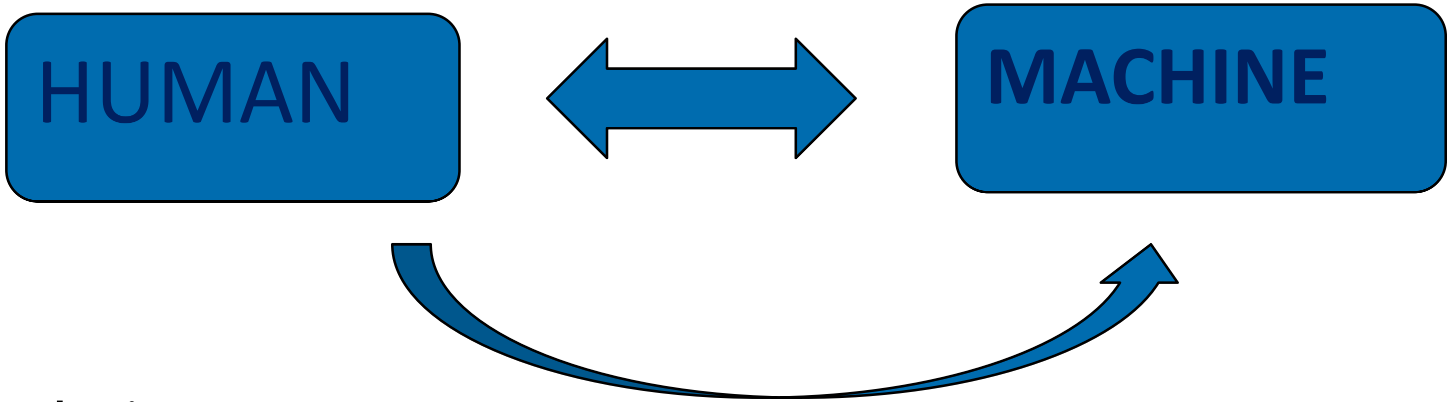
Staff & equipment

- One professor
- 4 assistent professor
- 8 PhD students
- 20 MSc. Students
- 20 BSc. Students

17 NAO Robots, 2 Stereo-heads, 2 AIBO Robots …

What is Artificial Intelligence ???

Many definitions …

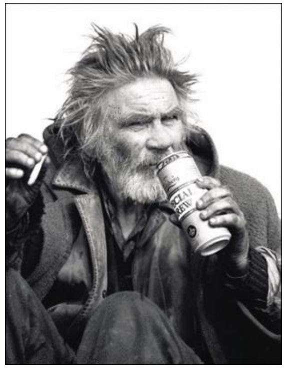


Simplified view to AI :

AI – takes labor from HUMAN and gives it to Machine

From Simple to very complex

- Remote control
- ..
- ABS, Rain Detector in the car ....
- ..
- Autonomous Systems



What is Knowledge ?

It is a big problem to make a definition
It is a mathematical function
approximation – so knowledge is

“IF – Then”
Relation

BIG DATA

Intelligence Machine
Machine IQ – theory

MIQ is IQ is in correlation of the „amount"

of Labor taken from Human and given to Machine during particular TASK (T) .

We do assume **GIQ-T is constant 1**

GIQ-T = HIQ-T + MIQ-T

HIQ-T and MIQ-T are from interval <0,1>

Bad news ...

How to define/compute HIQ for a TASK ????

How to define/compute MIQ for a particular TASK ?????

Can be determined in the selected domain –

CAR – Interaction CAR – DRIVER

IEEE Standard committee

WCCI 2010, 2014 – discussion

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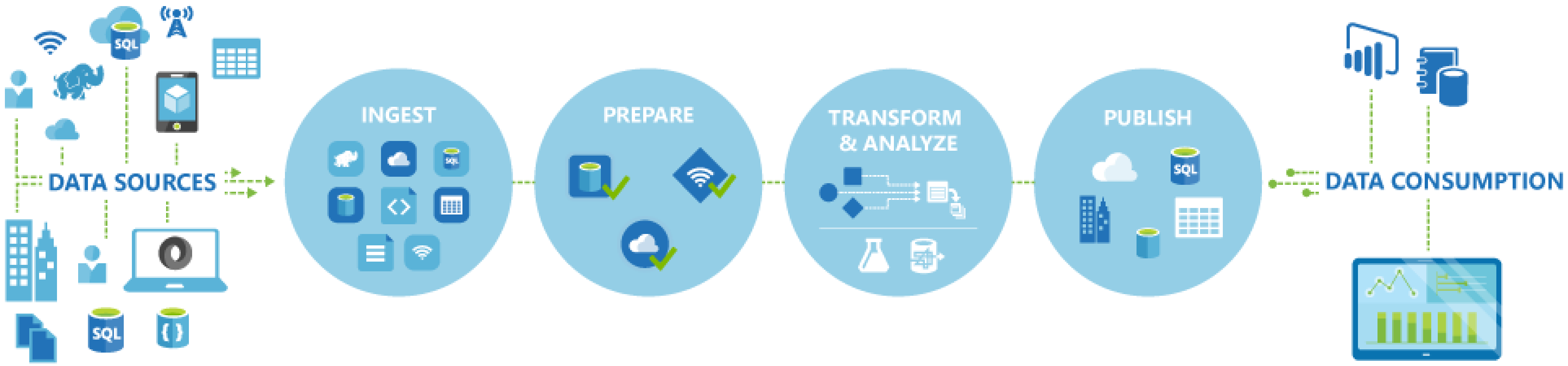
What is Cloud … ???

Example …. Office 365 …. From Microsoft

Cloud Computing – Data Factory

- Cloud-based data integration service that orchestrates and automates the movement and the transformation of data.
- Datasets, Pipelines and Actions, Scheduling and execution, Compute linked services.



Cloud Computing … some …

Cloud Computing approach

THINK BIG – START SMALL !!!!

Pls realize that

Cloud is NOT ONLY a remote DISK SPACE

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Major Question :

Does Cloud Computing Effects Computational Intelligence and core research thinking?

Will Cloud Computing change AI ??

- Will it change AI ? Machine Learning ???
- Will computer speed, storage and fast wi-fi change AI ??
- Do we need a thinking machine ?????
- to ask – means to think or find an answer ???
- AI bricks – granularity of AI problem solving

Fuzzy System on the Cloud – envision

response

Request

Inference Engine changing
In time based on changing
Rules from experts…

Rule set # 2

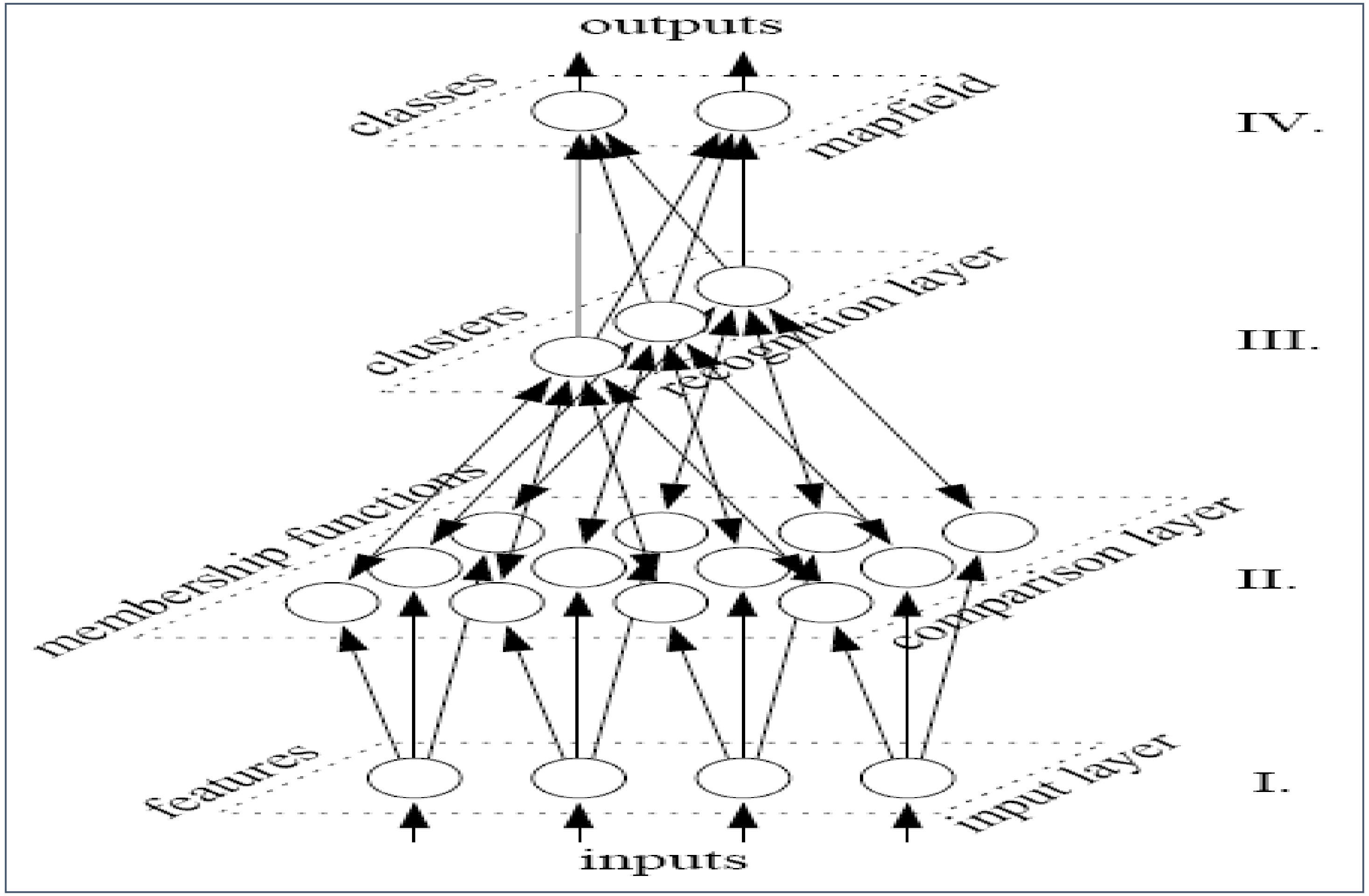
Rule set # 1

Rule set # 4

Rule set n-rules
(IF … Then …)

Rule set # 3

MFARTMAP implementation on the CLOUD...



Contribution from the CLOUD to AI Towards Collective Domain Knowledge

Intelligence as a service – we already have

General Cloud Based AI

- Tensor Flow Playground
- Microsoft Azure Machine Learning Cognitive Services
- Watson
- Alexa, Cortana, Google Now and etc..

What are AI bricks ?

Examples of thousands (milions?) of "*AI bricks*" very intelligent in their specialization and very silly in all other tasks:

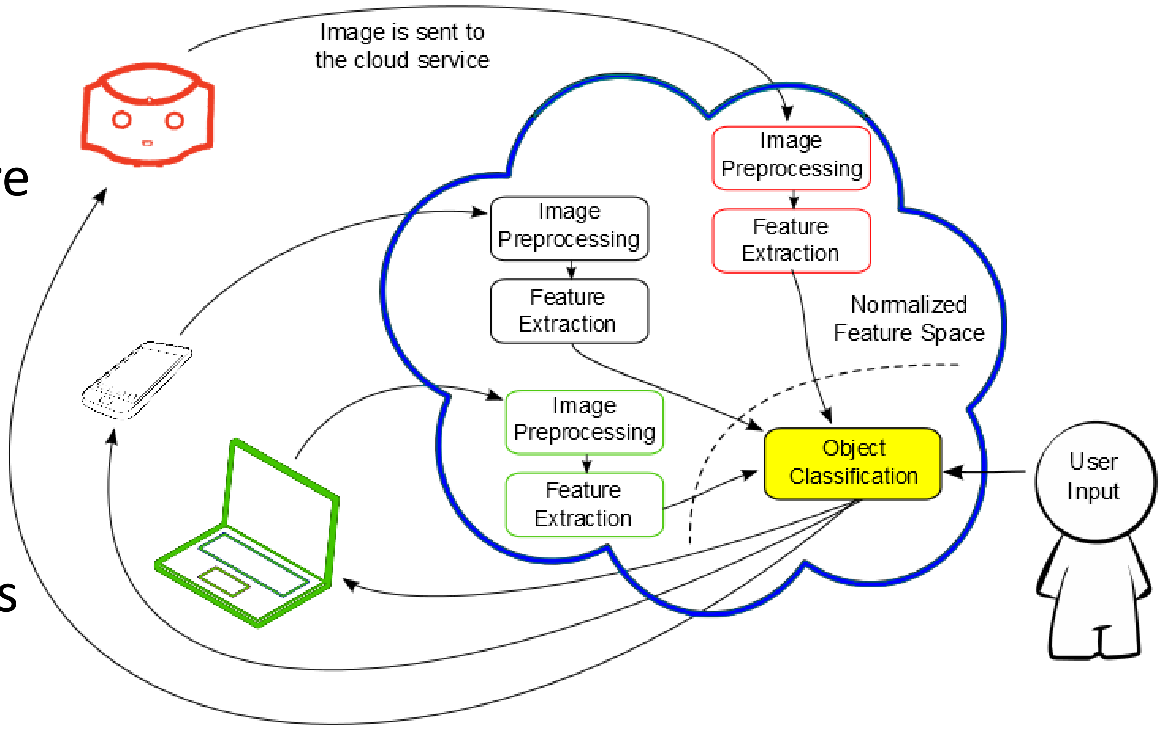
- RTS (Robot Tools Server) for redirecting each cloud-robot (machine in real live) to the optimal specialized tool (like DNS in WWW) for complete a mission.**(*AI Bricks* registered in RTS will survive by natural selection** on depending of **feedback** from all worldwide millions of cloud-robots or it's human owners, scoring successes or fails of robot ordered missions and tasks, scoring each *AI Brick* for deciding which cloud-tool better scored ***AI Brick*** use next time in similar circumstances.**)**
- Expert tools: chess (Deep Blue machine won the human world champion Kasparov on 1997), psichology, emotional intelligence, lawyer, languages, empathy, medical, history, mycology, weather, philosophy, feelings, etc...
- Prediction tools – prediction tools consider as modeling tool for simulation like processing

AI brinks ...2

- High process technic tools: Artificial vision for pattern recognition of thousands of objects with millions of patterns hosted in the Cloud. Voice recognition, Face recognition, etc. High Storage space for billions of patterns of reality, as our brain stores.
- Storage tools: Personalized experience of each robot. Memory of robots live.
- Downloading specialized programs and firmware "*on demand*" for robots. MATRIX movie - program for pilot helicopters?)
- Learning tools: the robots can learn from their own past experience depending on if a past mission failed or not, memory, knowhow, etc. A human from his born is always learning from it's own experience and delays 18 years in get a bit of maturity, and more than 30 years in working professionally with experience... lets give the same time to strong and generalist AI cloud-robots to learn! Learn by Doing!

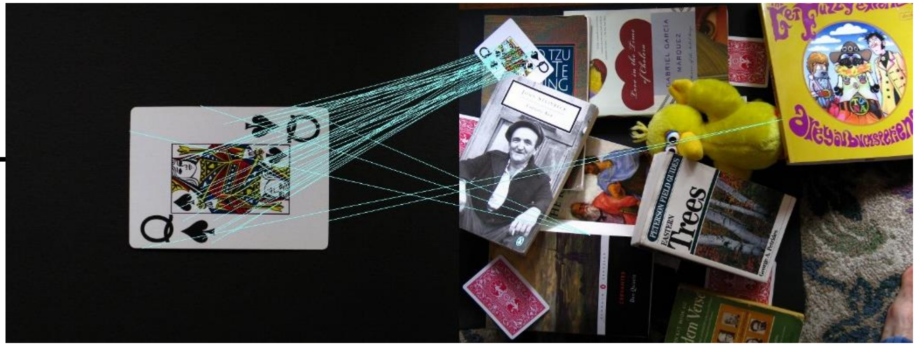
Cloud-based Object Recognition

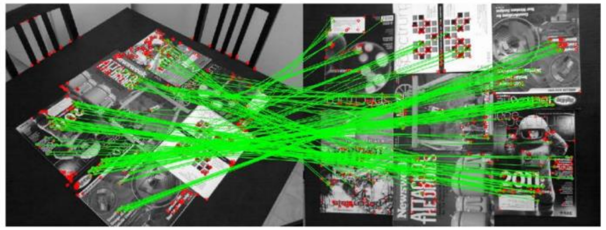
- Object recognition as a cloud service
- Methods used
  - SIFT, SURF for feature extraction
  - MF ArtMap and Gaussian for classification
- Planned as an “AI-brick”
  - To be used in various systems
  - Internet connection required

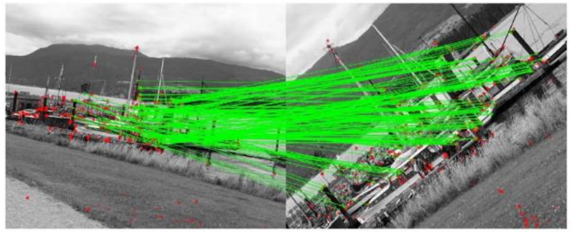


Cloud-based Feature Extraction (CBFE)

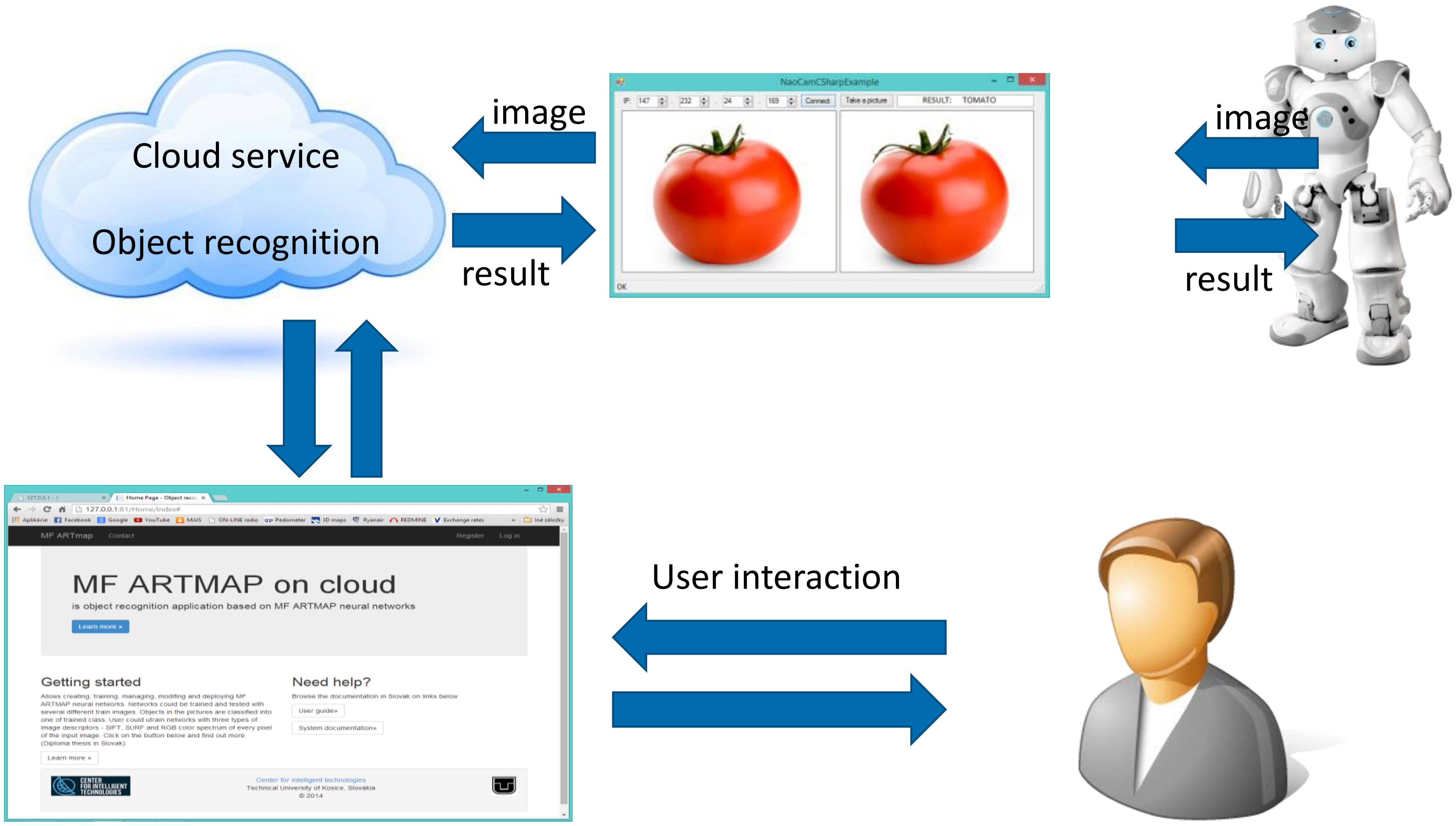
- We are using secondary features
  - Scale Invariant Feature Transform (SIFT
    - Invariant to scale, angle, translation
    - Uses key points – edges, corners
  - Speeded-Up Robust Feature (SURF)
    - Similar to SIFT, but faster
    - Different technique for scale invariance







Proof of concept - System scheme



Our Scope of Interest

- Microsoft Azure as a cloud platform
- Using basic methods of AI, implemented as cloud services (AI-bricks)
- Interconnecting these small building blocks
- We try to use the advantages of the cloud platform to the fullest
  - Fast NoSQL databases for storing relations
  - Cloud storage for data
  - Cloud services created from several small virtual machines dedicated to one task

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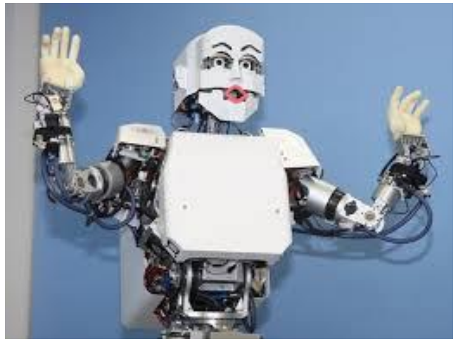
Can we develop collective Intelligence for Robots ??

WILKI

WORLD Incremental Learning

Knowledge Integrator



What is a Robot ??

Classical Robot Concept

This is a Robot !!!!

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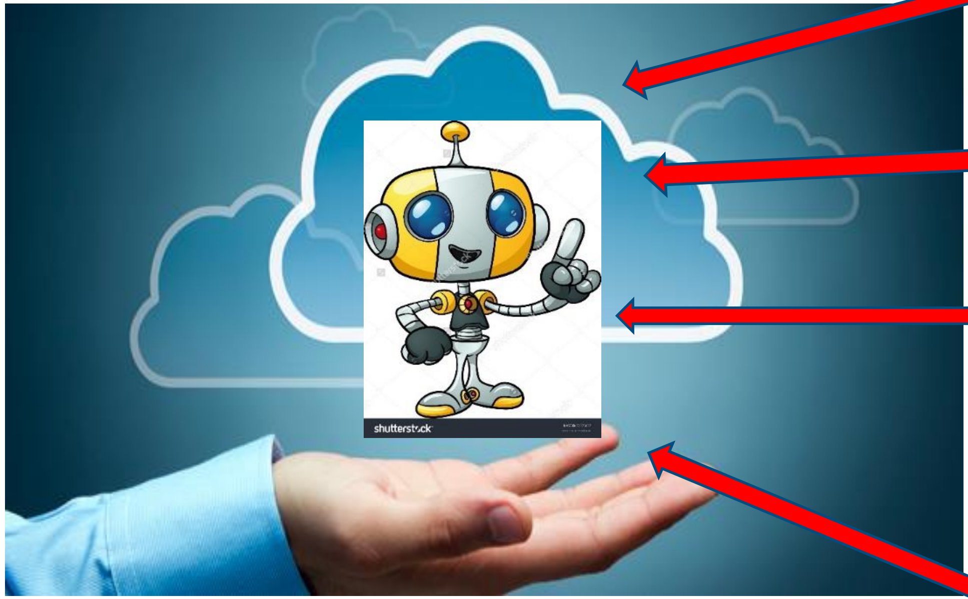
Virtual Robot Concept ???
This is a Robot



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Ubiquitous Robot Concept URC???

ubiquitous "turning up everywhere," 1837, from ubiquity + -ous. The earlier word was ubiquitary (1580s), from Mod.L. ubiquitarius, from ubique.

Synonym - **Omni present**

Virtual or Real Robo

Feature to network with VR or CR any sensor, any information from Inernet , Any of Human ……

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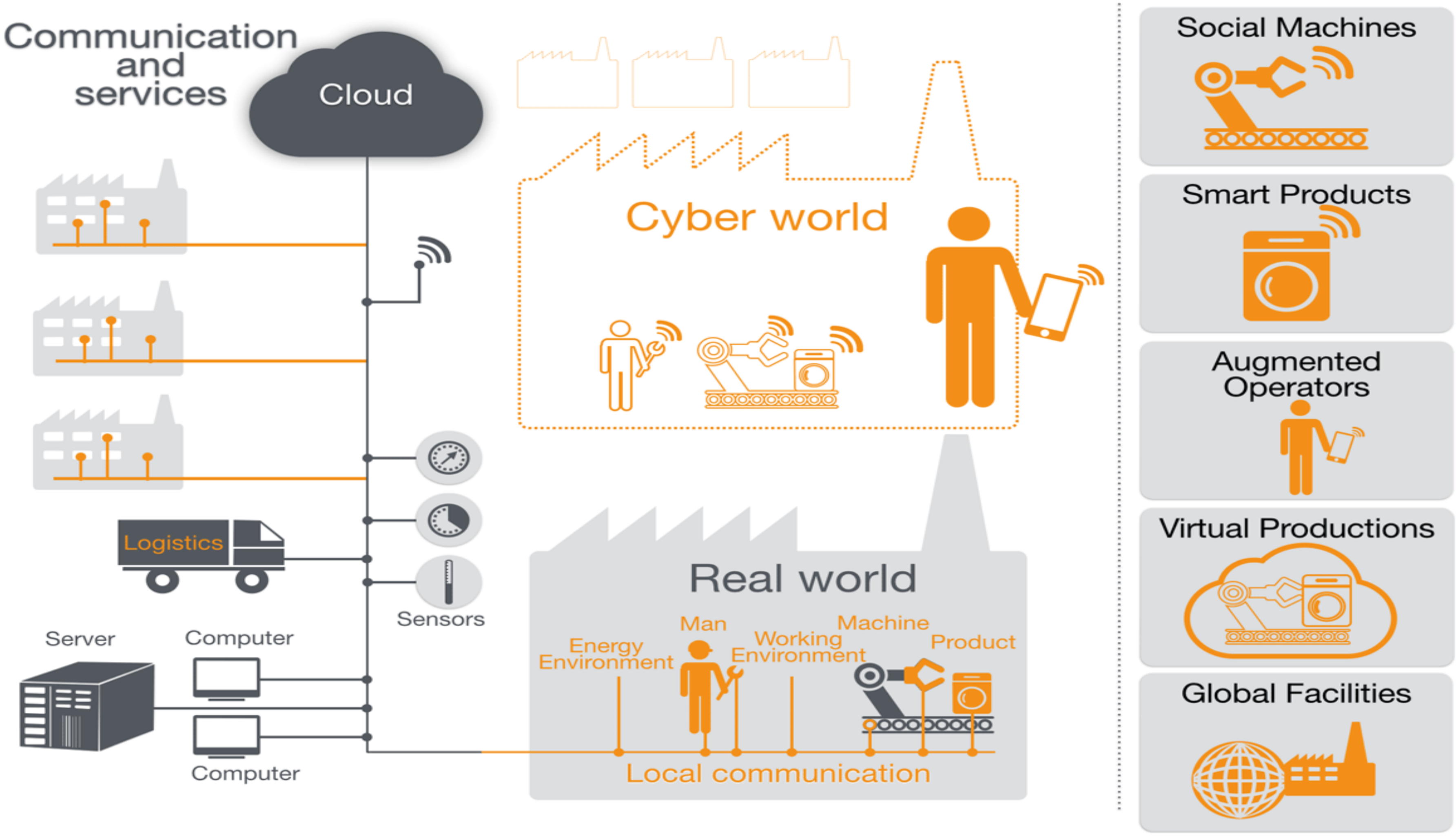
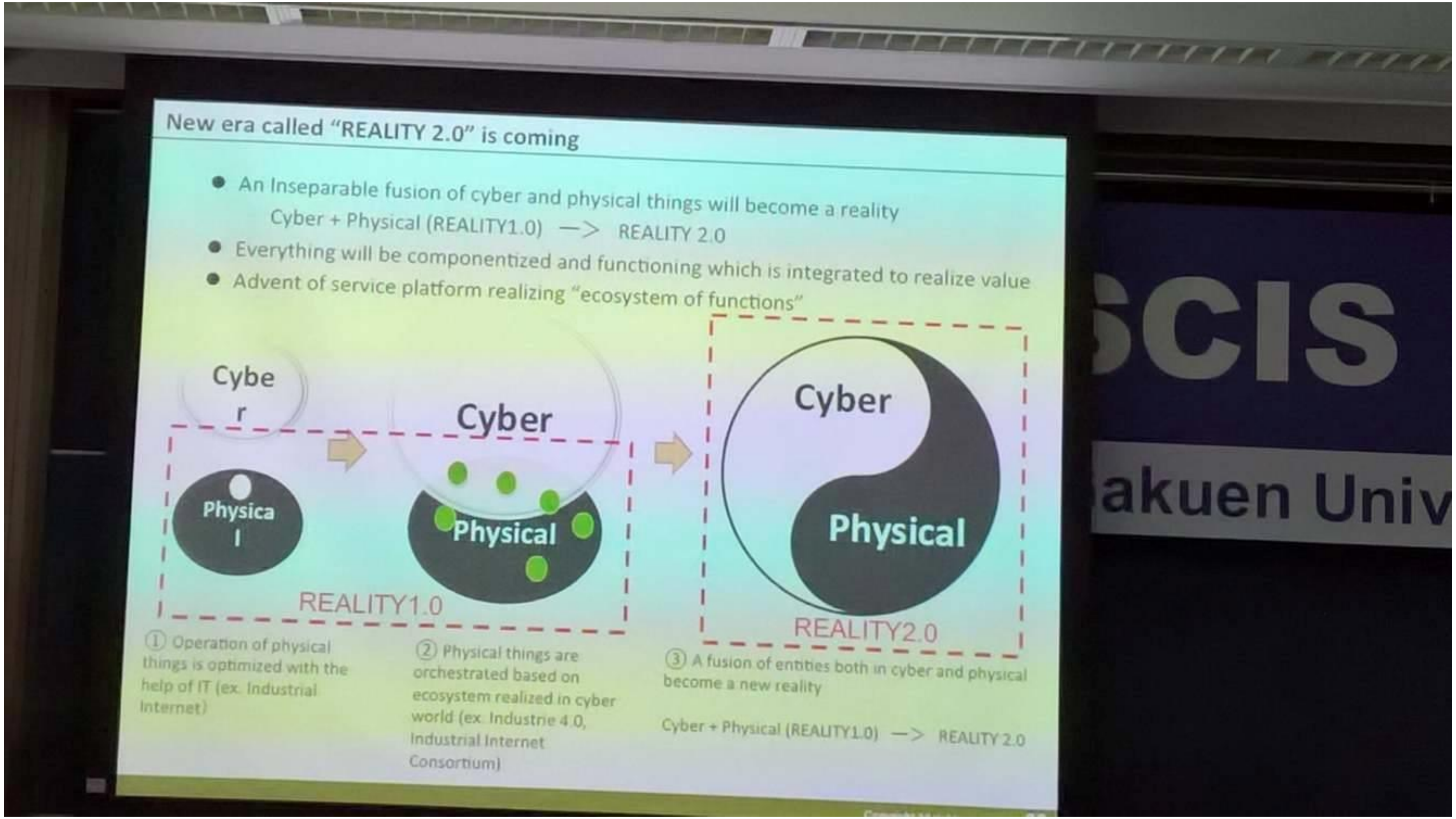
Industry 4.0 – impact to factories of future



In Japan - Dr. Iwano from JST



What is Cloud Robotics ?

- Cloud Computing + Robotics = Cloud Robotics
- Intelligent system on Cloud
  - Methods of artificial intelligence implemented on the cloud
  - So-called **“AI-bricks”**
- New technologies can influence the methods of AI
  - Faster databases
  - Available processing power on demand
  - Storage on demand
  - …

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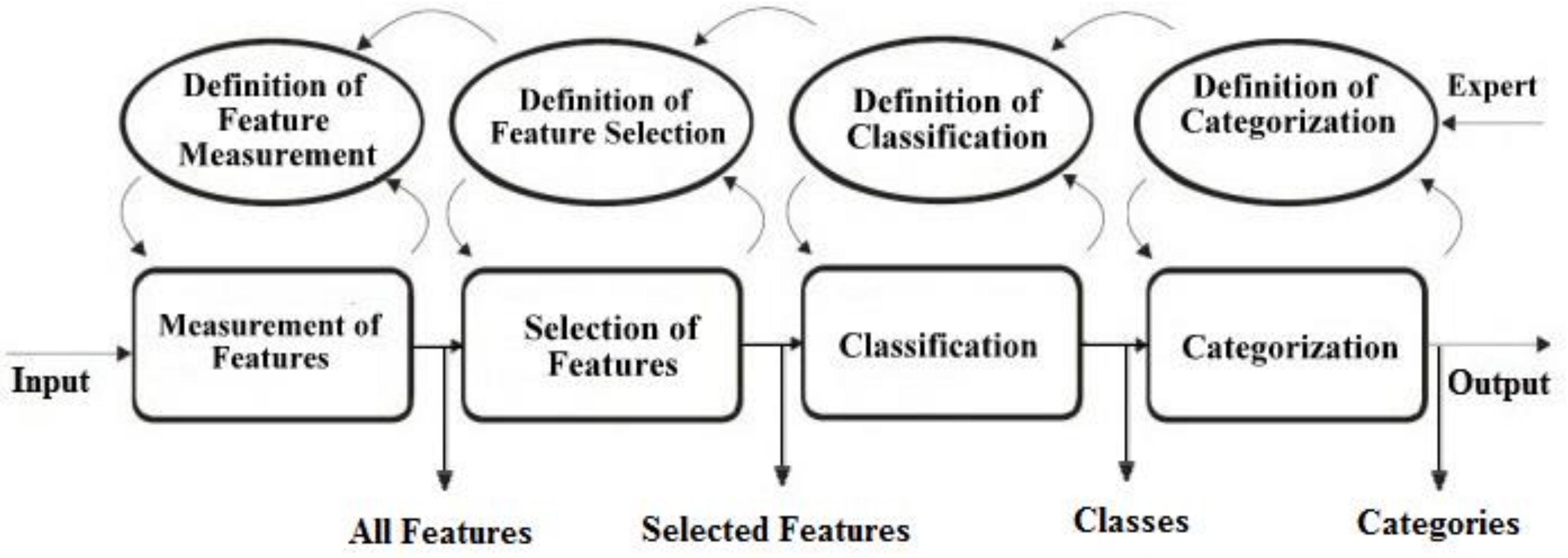
1. Cloud Based HRI for Robotics
2. Conclusion

Distributed Image processing

The Fundamental approach to categorization
inspiration by prof. Bezdek and Pal



Cumulative Fuzzy Class Membership Criterion Decision-based Classifier

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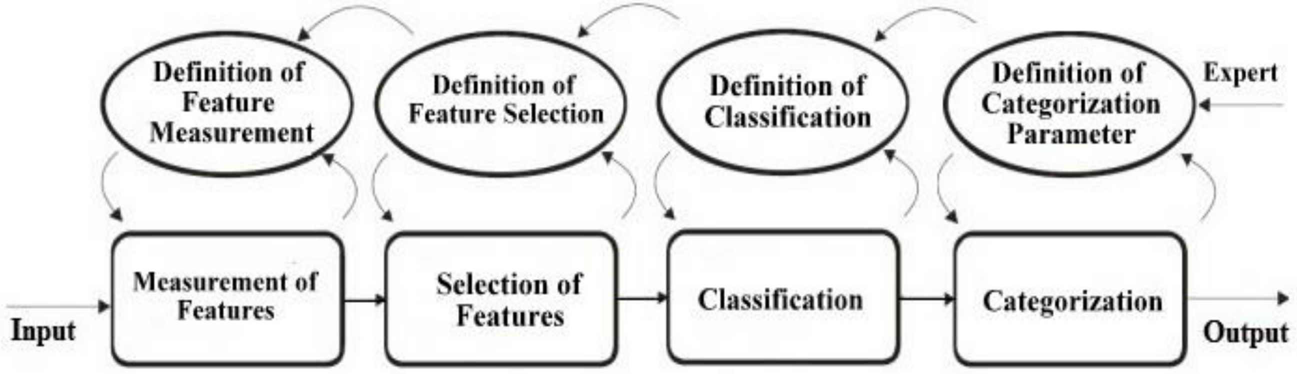
Introduction

Classification

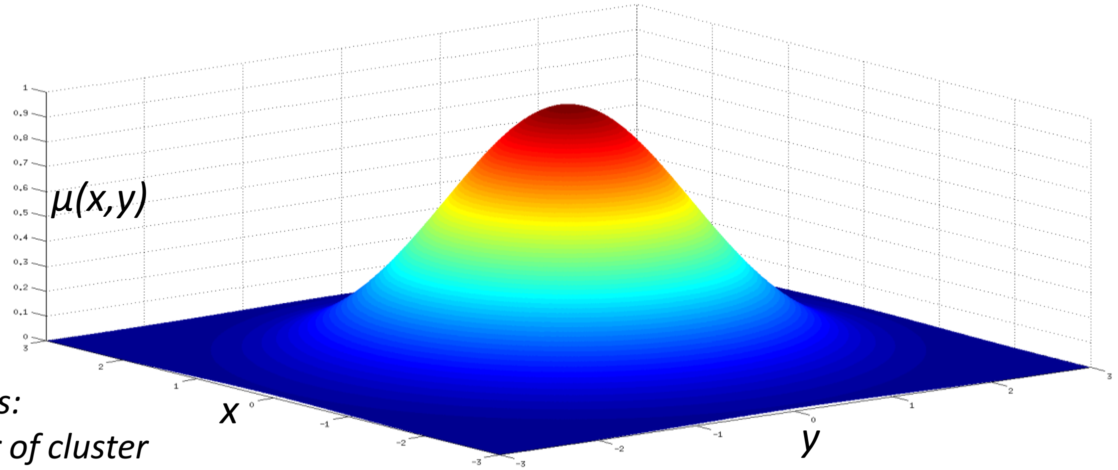
- Classification – one of the basic principles of pattern recognition
- Feature selection – determine feature space
- What is more useful to invest time for?
  - to select of good set of features OR
  - **to develop a general and robust classifier**



- Main motivation: create or use not “black-box” classifier
- For **extraction of semantic information** from data

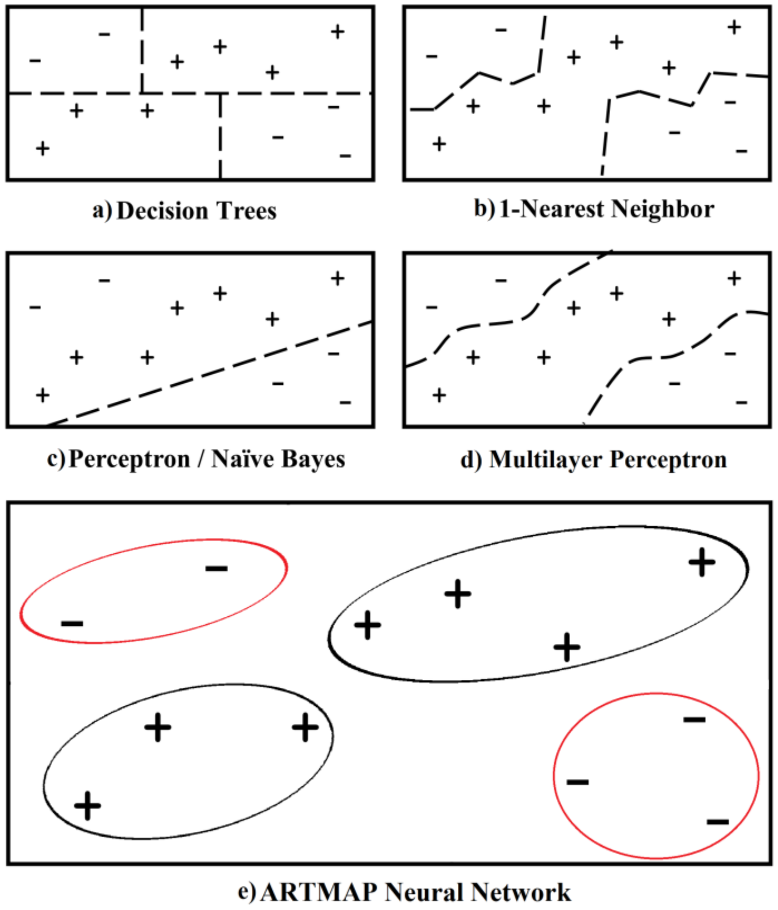
Not “black-box” classifier
MF ARTMAP neural network

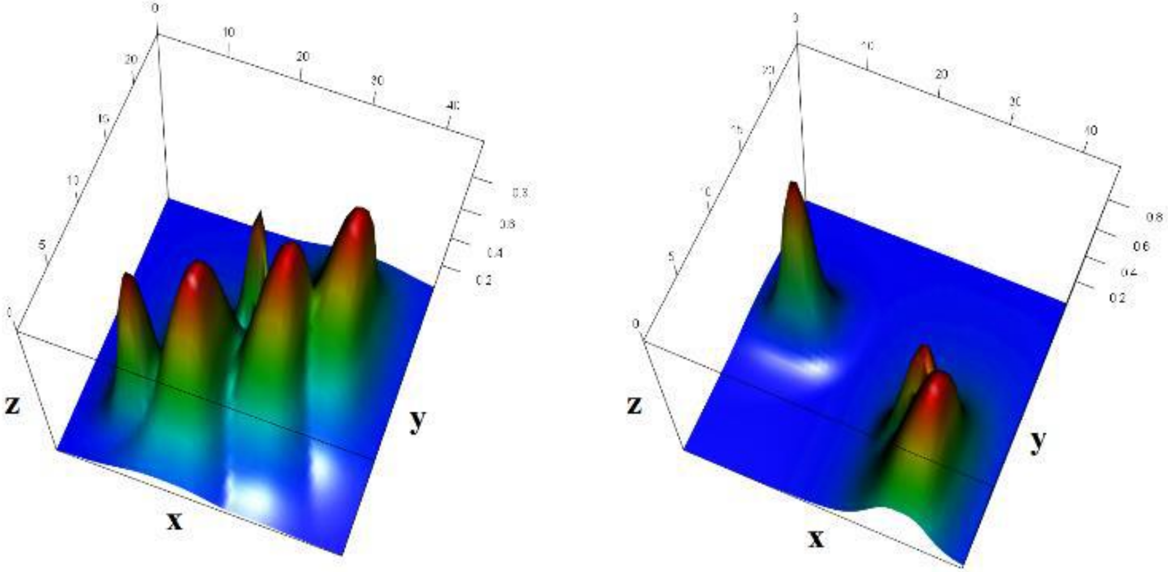
- **Membership Function ARTMAP →** symbiosis of **fuzzy sets theory** and **ART theory**
- MF ARTMAP clusters inputs in the feature space
- Create **Fuzzy clusters**
- Why not “black-box”?
  - compute **membership** of the input to the each cluster and class
  - create **decision surface over data**



Parameters:
Xs – center of cluster
E – variance
F – width of cluster’s core

Classifiers and feature space





Decision surface by MF ARTMAP

- how various classifiers affect the feature space
- create various hyper-planes or decision surfaces
- If n-dimensional feature space
  - Hyper-planes are (n-1) or n-dimensional
  - Decision surfaces create (n+1) dimension

MF ARTMAP

Mathematical description

- Data in feature space – organized in fuzzy clusters
- Fuzzy cluster:

$$A \in \left\{[\overline{x}_{1,}\mu_A(\overline{x}_1)], \dots, \left[\overline{x}_{n_p,}\mu_A\left(\overline{x}_{n_p}\right)\right]\right\}$$

- Point $\overline{x} = [x_1, \dots, x_n]^T$
- Fuzzy class:
  $C_i = \left\{\bigcup_{j=1}^{m_i} A_j^i\right\},\ i = 1 \dots n_c$
- Relation between class and cluster:
  $\mu_{C_i}(\overline{x}) = \max_j\left(\mu_{A_j^i}(\overline{x})\right)$

- Membership function: $\mu_A(\overline{x}) = \dfrac{1}{1+\sum_{i=1}^{n}\left|\frac{x_i - xs_i}{E_i}\right|^{F_i}}$
- Output: vector of memberships $\overline{\mu}_C$
- Decision rule for winner class:
  $CL(\overline{x}) = C_{\underset{i}{\operatorname{argmax}}\left(\mu_{C_i}(\overline{x})\right)}$
- Create decision surface based on **Membership Function**

New decision surface – CFCMC
Cumulative **F**uzzy **C**lass **M**embership **C**riterion

- **CFCMC → C**umulative **F**uzzy **C**lass **M**embership **C**riterion
- Based on MF ARTMAP neural network – **Fuzzy Membership Function**
- Cumulates Fuzzy Membership Function into **Membership Criterion**
- In comparison to Membership Function, CFCMC surface is
  - More complex
  - With better adaptability
  - With better flexibility

Cumulative Fuzzy Class Membership Criterion – new Decision Surface

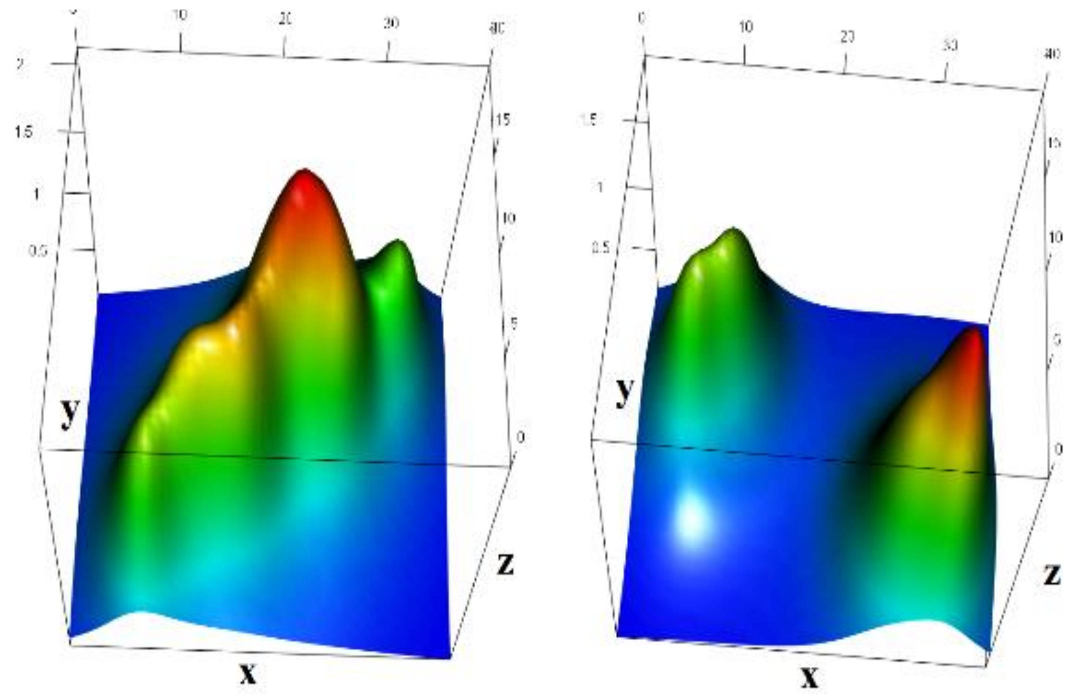
Mathematical description

- Assumption: data in feature space are split into n_c classes C_i where $i = 1 \ldots n_c$
- Class C_i - defined by training pattern $\tilde{p}_j^i$ where $j = 1 \ldots N_i$, N_i - number of training patterns of the i-th class
- Each training pattern defines a **fuzzy class membership criterion** $\kappa_{\tilde{p}}(\overline{x})$
$$\kappa_{\tilde{p}_j^i}(\overline{x}) = \frac{1}{1+\left(\frac{\left\|\overline{x}-\tilde{p}_j^i\right\|}{E_i}\right)^{F_i}}$$
- **Cumulative Fuzzy Class Membership Criterion** $\chi_{C_i}(\overline{x}) = \sum_{j=1}^{N_i} \kappa_{\tilde{p}_j^i}(\overline{x})$

Decision rule for winner class

- Output from CFCMC: vector $\overline{\chi}_C$ of values of membership criterions to each class
- Decision rule:
  - $\mathrm{CL}(\overline{\mathrm{x}}) = C_{\underset{i}{\operatorname{argmax}}\left(\chi_{C_i}(\overline{\mathrm{x}})\right)}$
- To choose a winner class – surfaces for each class are compared

Cumulative Fuzzy Class Membership Criterion surface



Class A Class B

Adaptation of CFCMC

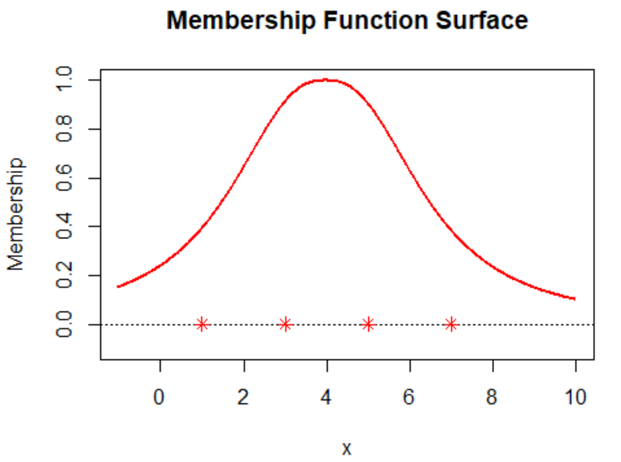
Algorithm description

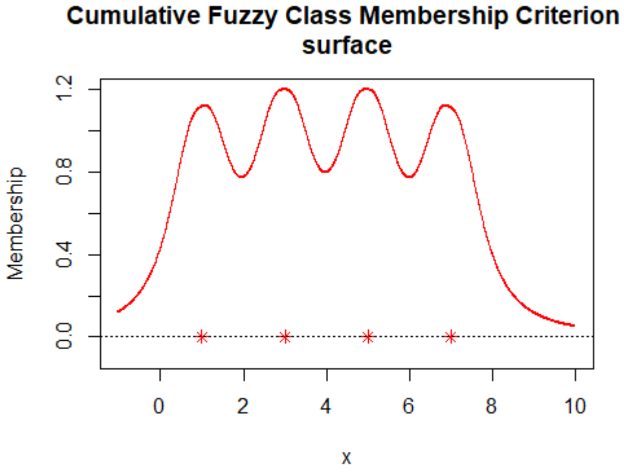
- **Initialization phase** – creating of the CFCMC surface
  1. Split data to three sets:
     1. Training
     2. Validation
     3. Test
  2. Initializing of values of parameters E and F and threshold for “not classified” patterns
- **Learning phase** – adaptation of the shape of the CFCMC surface
  1. Optimization of parameters E and F for each class C_i (by **Simulated Annealing**)

$$\bar{p} = \left[E_1, F_1; E_2, F_2; \dots; E_i, F_i; \dots; E_{n_c}, F_{n_c}\right], \text{ where } i = 1 \dots n_c$$

Comparison of Membership function and CFCMC surfaces

One dimensional problem



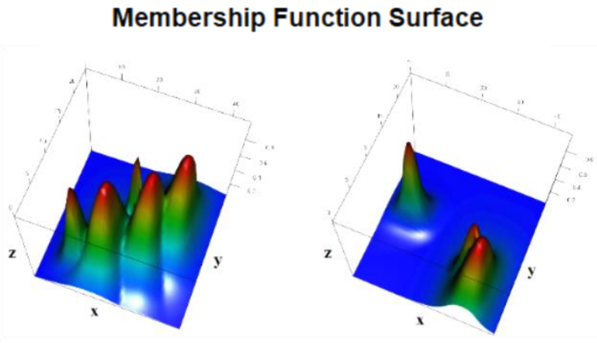


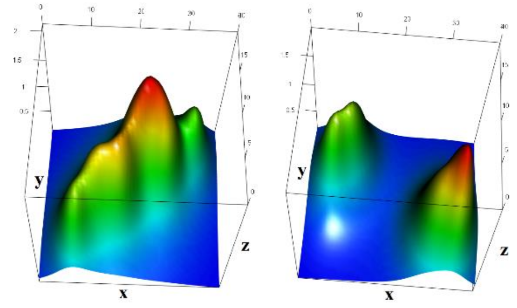
Equation for creating of surface

$$\mu_{C_i}(\overline{x}) = \max_j \left(\mu_{A_j^i}(\overline{x}) \right)$$

$$\chi_{C_i}(\overline{x}) = \sum_{j=1}^{N_i} \kappa_{\tilde{p}_j^i}(\overline{x})$$

Two dimensional problem

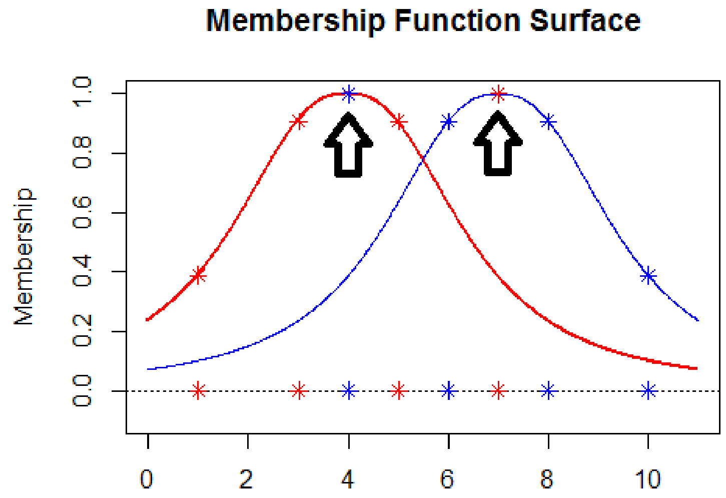


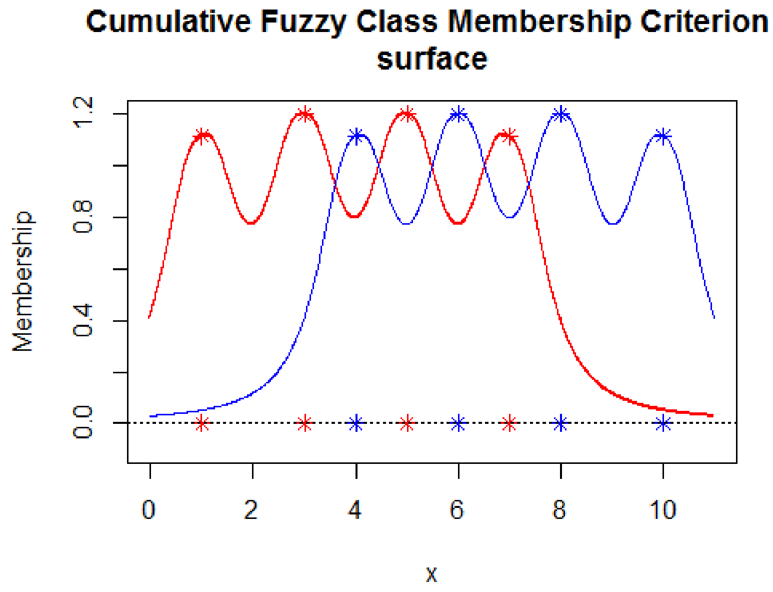


Comparison of MF ARTMAP and CFCMC

Differences between MF ARTMAP and CFCMC

- **Clusters:**
  - *MF ARTMAP*: dynamically created – may contain more patterns
  - *CFCMC*: created for every pattern
- **Membership of pattern to class**:
  - *MF ARTMAP*: maximum membership from each clusters of the same class
  - *CFCMC*: sum of memberships to each cluster of the same class
- **Interval of values of membership**:
  - *MF ARTMAP:* consist of clusters – membership function ∈ <0,1>
  - *CFCMC*: more complex – membership criterion ∈ <0,Inf)
- **Parameters**:
  - *MF ARTMAP:* each cluster – unique set of parameters E and F of Cauchy-like function
  - *CFCMC:* each pattern of same class – same set of parameters E and F





Experiments

- Goal: MF ARTMAP vs. CFCMC in classification accuracy
- Benchmark data from UCI Machine Learning Repository
- Initialization phase:
  - 20% of data set – test set – same set for MF ARTMAP and CFCMC
  - CFCMC – 60% training set – 20% validation set
  - MF ARTMAP – 80% training set
- Learning phase – cost function:
  1. Classification accuracy – training and validation set – **maximize**
  2. Ratio of "not classified" - $\frac{\text{"not classified" patterns}}{all\ patterns}$ - **minimize**
  - Classification accuracy – Kappa coefficient from contingency table

Results

Dataset		MF ARTMAP	CFCMC
IRIS	*correct*	98%	**99%**
	incorrect	2%	1%
	not classified	0%	0%
BUPA	*correct*	52%	**64%**
	incorrect	32%	32%
	not classified	16%	4%
PIMA	*correct*	60%	**72%**
	incorrect	11%	27%
	not classified	29%	1%
CANCER	*correct*	36%	**94%**
	incorrect	2%	5%
	not classified	62%	1%
WINE	*correct*	44%	**82%**
	incorrect	8%	18%
	not classified	48%	0%

Final comparison

MF ARTMAP vs. CFCMC

#	Criterion	MF ARTMAP	CFCMC
1	**Incremental learning** MF ARTMAP is in its essence neural network with ability of incremental learning because of ability of dynamically creating clusters in feature space. That is not possible in CFCMC.	✓	✗
2	**Not a "black-box"** Both classifiers we can use for semantic extraction because of post-processing of known decision surfaces for each class in data.	✓	✓
3	**Higher classification accuracy** Based on result from our experiments, CFCMC achieved higher classification accuracy.	✗	✓

Semantic extraction from CFCMC or MF ARTMAP

- Computes memberships to each class
  - Create *IF-THEN* rule:
    - if the membership values of vector *x* to a class *A* and a class *B are* very similar
    - IF *x* THEN *A or B*
- Shape of decision surface is known for each class
  - Auxiliary output about clusters, classes, similarities and dissimilarities between classes
  - Information about one particular class – Intra-class knowledge
  - The relation among several classes – Inter-class knowledge
  - For instance: computation of coverage of decision surfaces of two classes

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1. **Cloud Based HRI for Robotics – Dr. Magyar**
2. Conclusion – Video

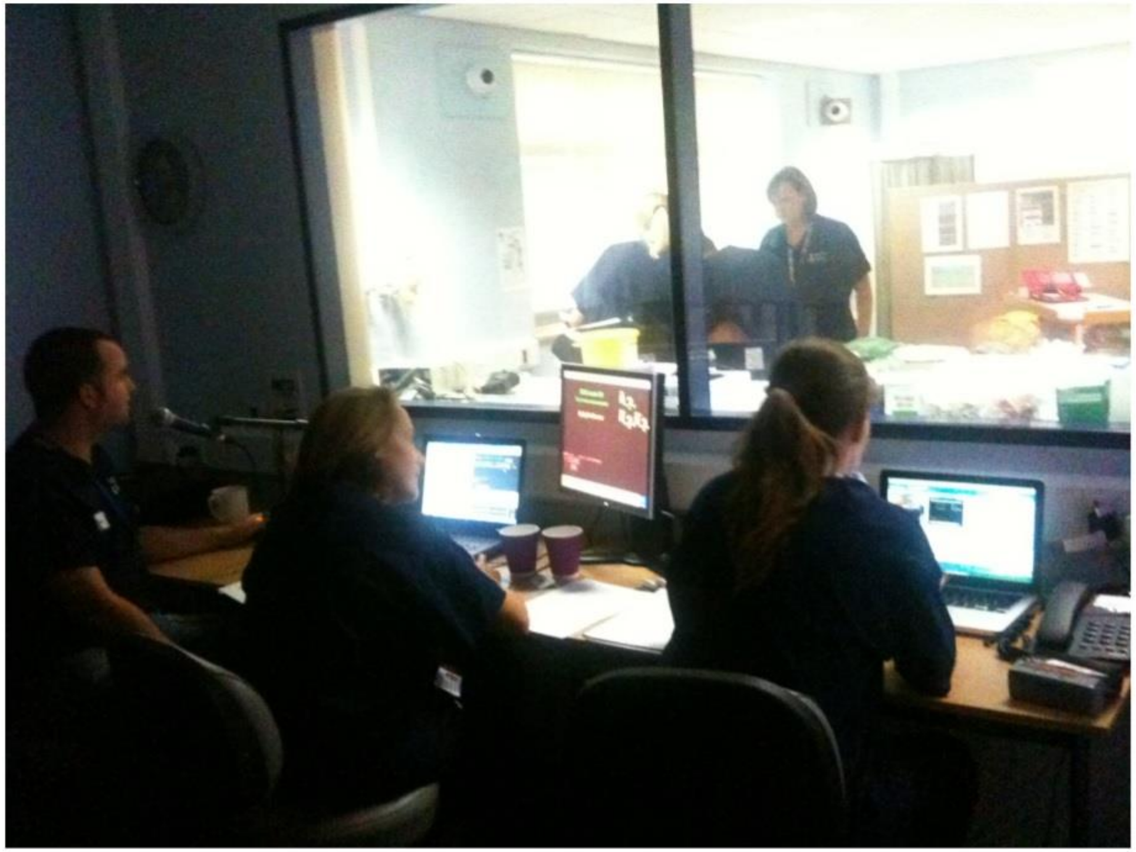
A robot as a coach for cognitive stimulation therapy

THE WIZARD OF OZ METHOD

"… is a research experiment in which subjects interact with a (computer) system that **subjects believe to be autonomous**, but which is actually being **operated or partially operated by an unseen (hidden) human being.**"

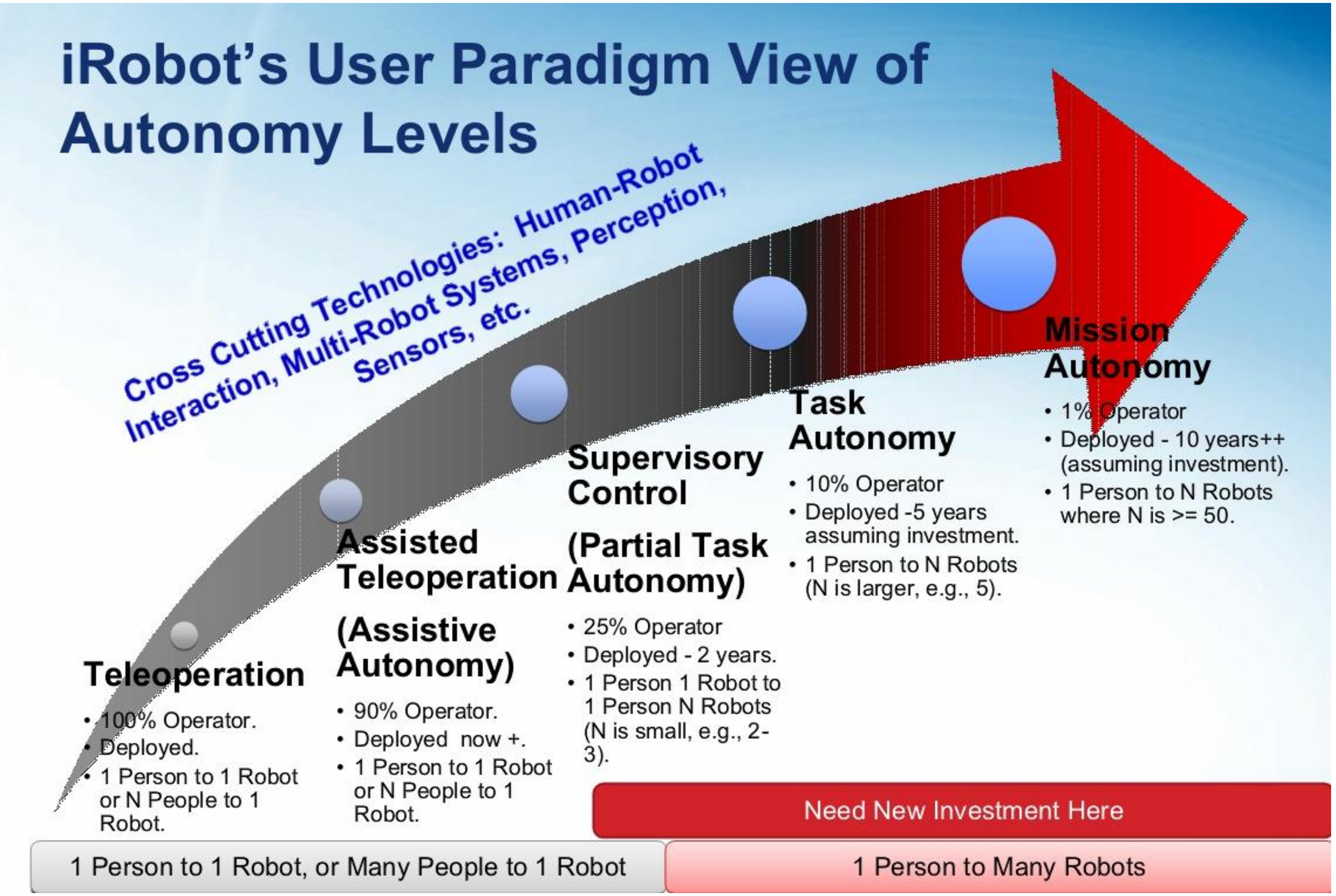
- Hannington & Bella, 2012

THE WIZARD OF OZ METHOD (2)



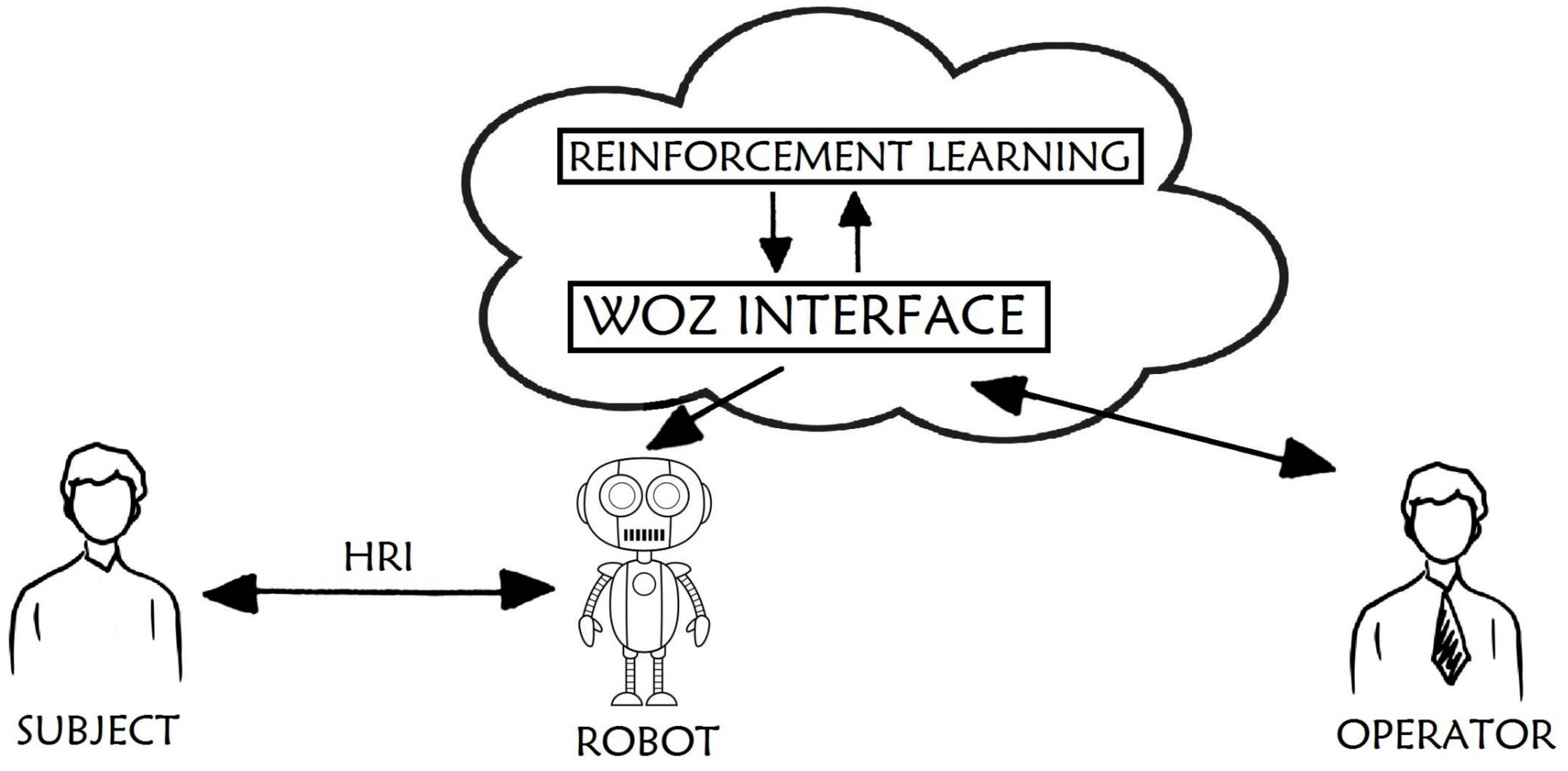
- Riek, 2012

THE WIZARD OF OZ METHOD (3)



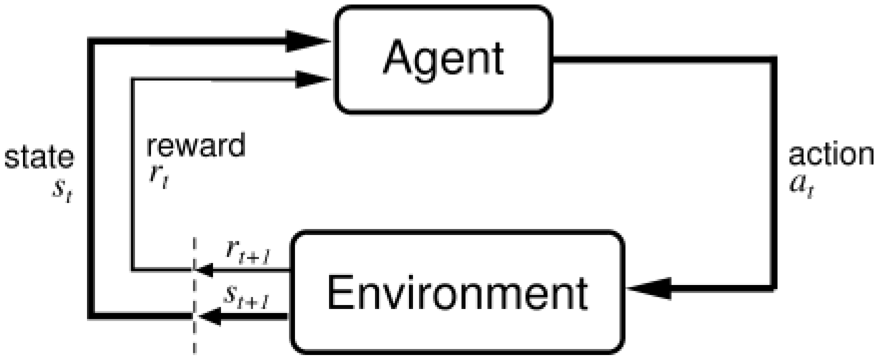
Video

THE OVERALL ARCHITECTURE



REINFORCEMENT LEARNING

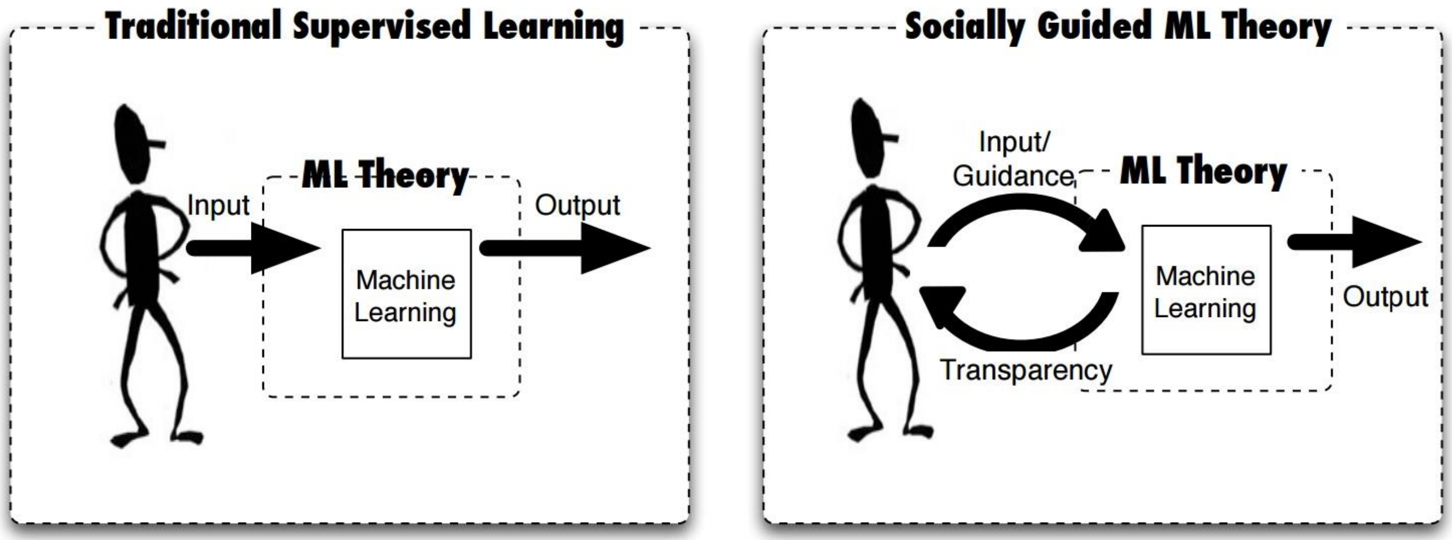
- determines how to map situations to actions
- states, actions, reward function
- Q-table



$$Q = \begin{array}{c c} & \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\ \begin{array}{c} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} & \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \end{array}$$

INTERACTIVE REINFORCEMENT LEARNING

- interactive reinforcement learning
- extension of the classic reinforcement learning technique
- the reward is given by a human, this is called **socially guided machine learning** (A. Thomaz, 2006)



CLOUD-BASED REINFORCEMENT LEARNING

- Publicly available algorithms without the need of installation
- Scalability
- Combine unique models into a general one
- Building a knowledge base by multiple users
- Sharing the knowledge between multiple robots
- Creating personalized robot behavior
- Accessible from the web or locally

COGNITIVE EXERCISES WITH ELDERLY

H1: Our modified interactive reinforcement learning algorithm is able to increase the robot's level of autonomy in a real-world social human-robot interaction scenario.

H2: The elderly will be able to accept and build a positive relationship with the robot even only after two interactions with it.

COGNITIVE EXERCISES WITH ELDERLY (2)

- The participants played two games called "Guess the fruit" and "Guess the animal"
- e.g. Please name a fruit which name starts with A
- The game lasted until the subject gave correct answers for all letters
- 10 subjects (2M/8F, average age 78.5, 68 to 94)

COGNITIVE EXERCISES WITH ELDERLY (3)

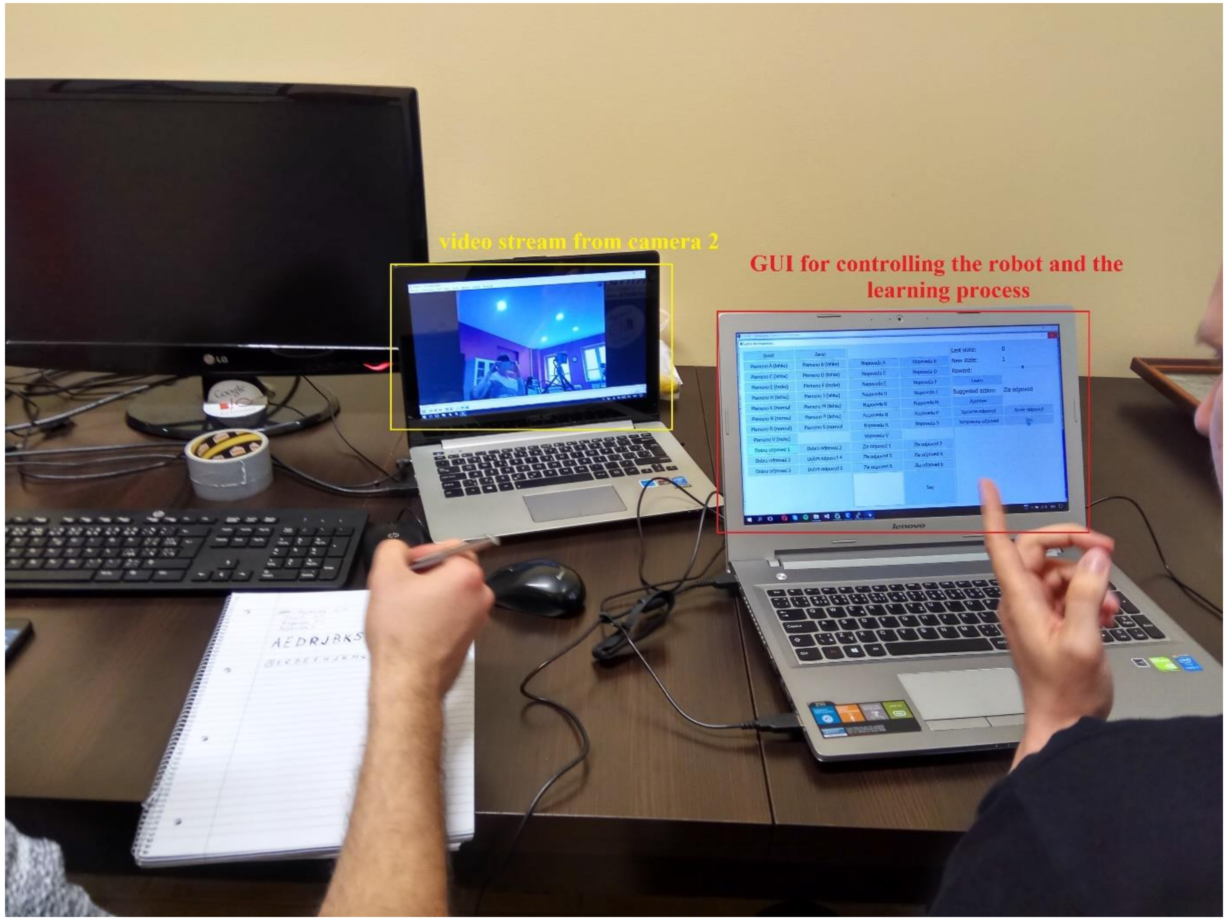
- 4 states: correct answer, incorrect answer, doesn't know, other
- 6 types of actions: easy question, question of medium difficulty, hard question, help, applause, sorrow
- the reward was defined by the teleoperator

COGNITIVE EXERCISES WITH ELDERLY (4)

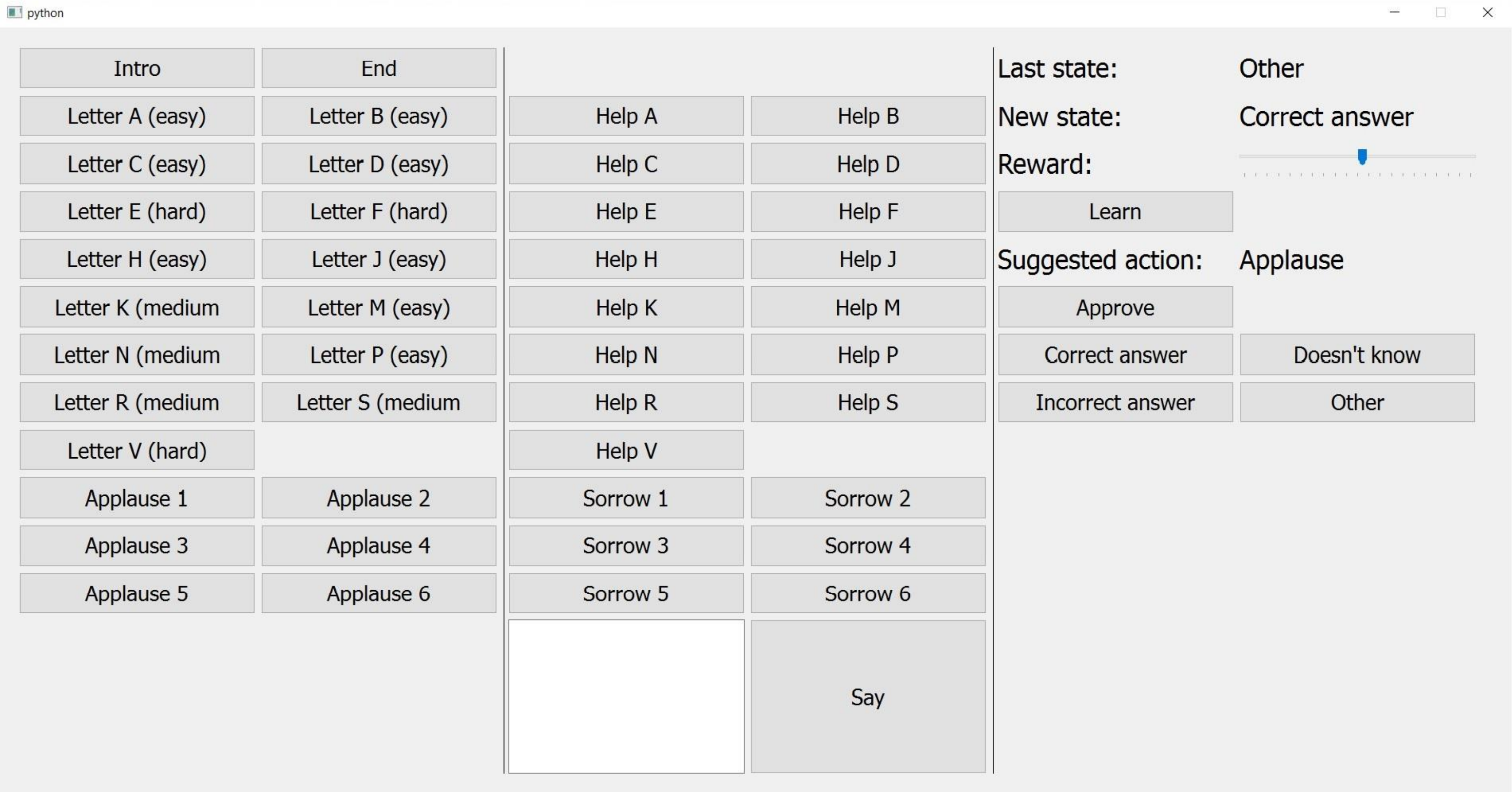
1. Meeting (group) – the participants were introduced to the goal of the experiments
2. Meeting (individual) – the subjects played the cognitive game “Guess the fruit”
3. Meeting (individual) – the subjects played the cognitive game “Guess the animal”
4. Meeting (individual) – the participants filled out a questionnaire about their experience from the sessions

COGNITIVE EXERCISES WITH ELDERLY (5)

COGNITIVE EXERCISES WITH ELDERLY (6)



COGNITIVE EXERCISES WITH ELDERLY (7)



COGNITIVE EXERCISES WITH ELDERLY (8)

s_t = last state, a = action, r = reward

WHILE NOT end of interaction:

    s_t = state of the subject labeled by the Wizard

    a = ε-greedy action selection

    IF Wizard accepts a THEN:

        execute a, label the new state (s_{t+1}) of the subject by the Wizard

    ELSE:

        a = action chosen by the Wizard

        execute a, label the new state (s_{t+1}) of the subject by the Wizard

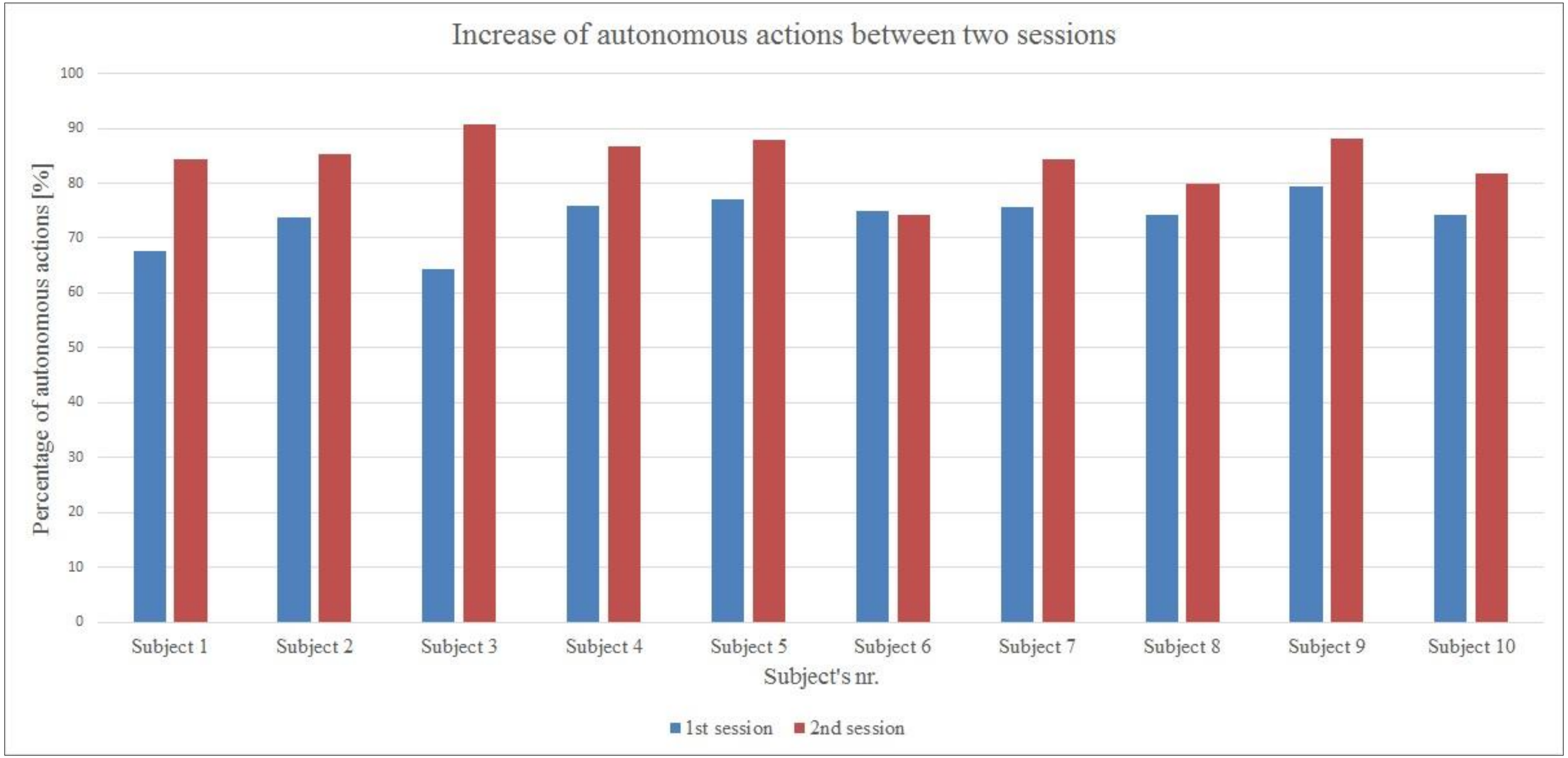
      r = reward given by the Wizard

      update Q-value

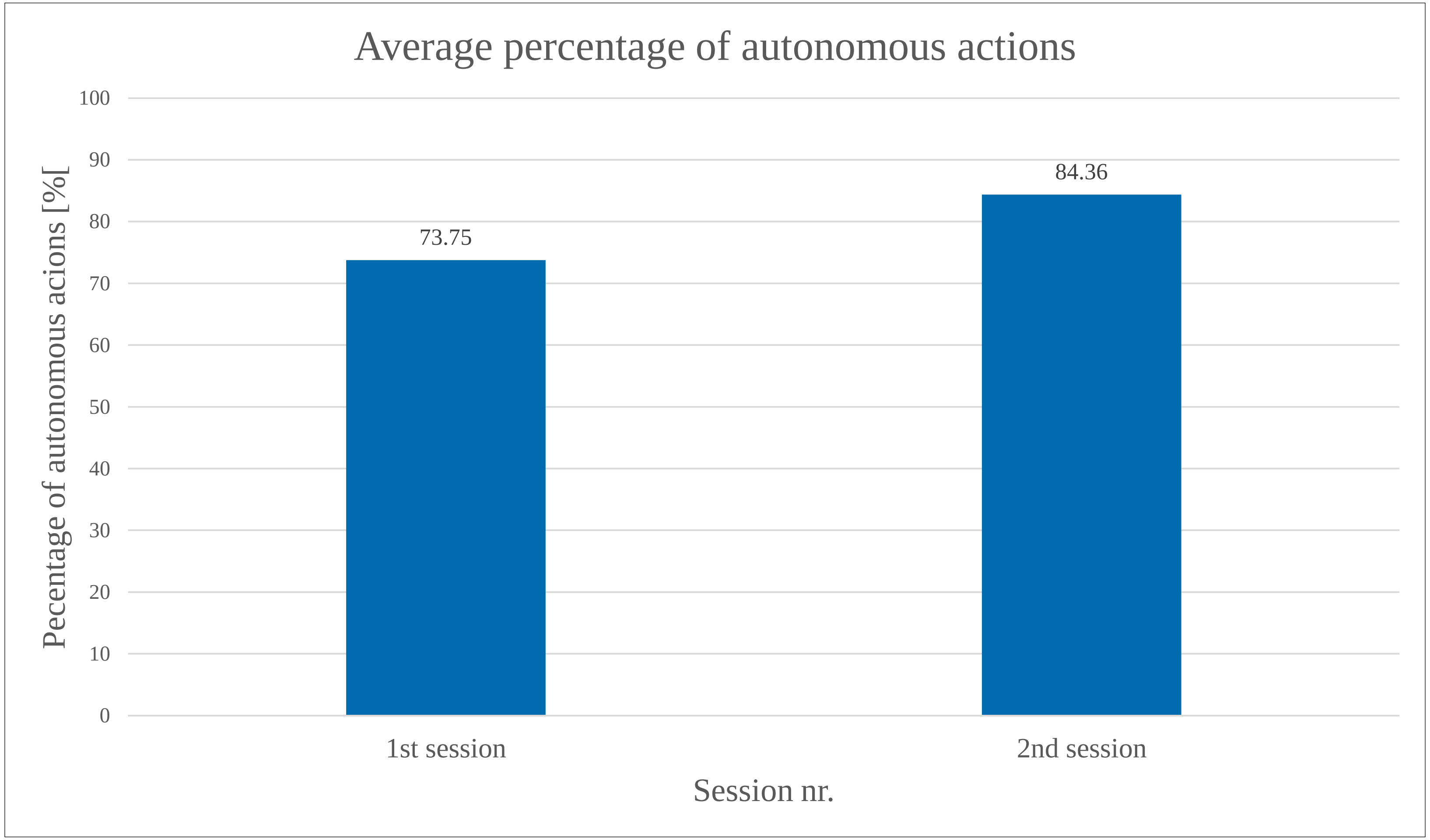
    $s_t = s_{t+1}$

ENDWHILE

COGNITIVE EXERCISES WITH ELDERLY (9)



COGNITIVE EXERCISES WITH ELDERLY (10)



Thank you for your attention

Any question, your comments

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