Andreas Holzinger
340.300 Principles of Interaction
Summer Term 2017

Selected Topics of interactive Machine Learning (iML): Interaction with Agents
Part 2: Multiagent & the Human in the Loop

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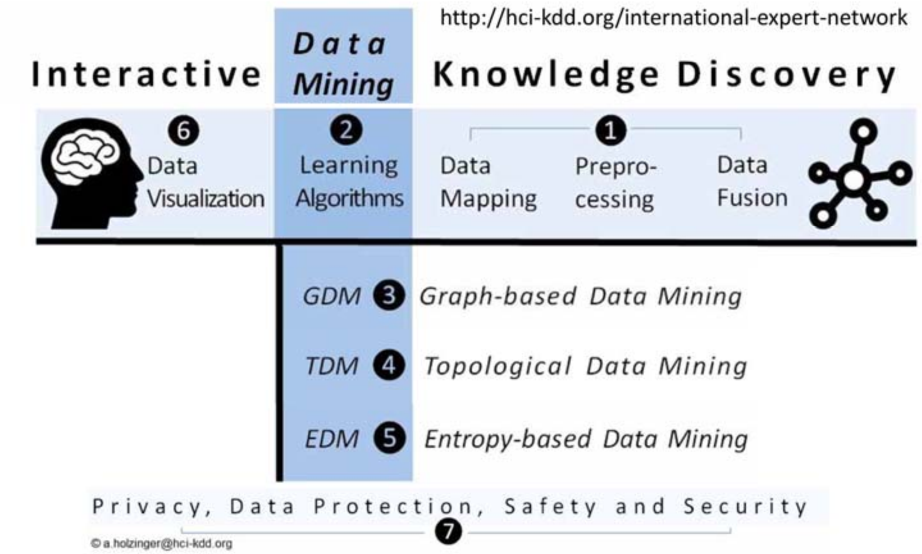
http://hci-kdd.org/interactive-machine-learning

Crazy Ideas > Science > Engineering > Business

Science **is to test crazy ideas –**
Engineering is to put these ideas into Business
Lucky Students ☺

ML needs a concerted effort fostering integrated research



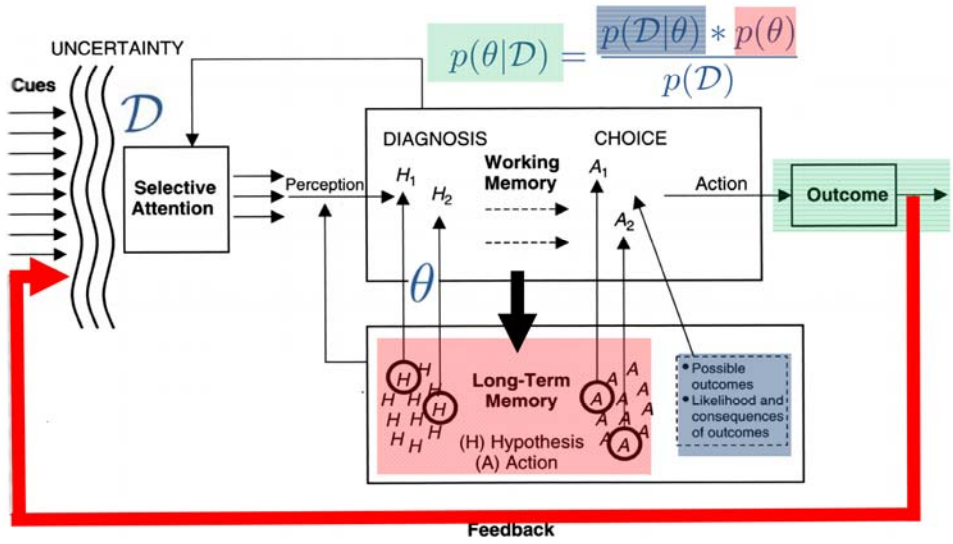
Holzinger, A. 2014. Trends in Interactive Knowledge Discovery for Personalized Medicine: **Cognitive Science meets Machine Learning.** IEEE Intelligent Informatics Bulletin, 15, (1), 6-14.

Red thread through this lecture

- **00 Reflection**
- **01 Intelligent Agents**
- **02 Multi-Agent (Hybrid) Systems**
- **03 Applications in Health**
- **04 Decision Making as a Search Problem**
- **05 iML Gamification**
- **06 Collective Intelligence**

00 Reflection

How do humans interact with the world?



Wickens, C. D. (1984) *Engineering psychology and human performance. Columbus (OH), Charles Merrill, Altered by Holzinger, A. (2017)*

01 Intelligent Agents

Define (1/3): Computational intelligence (CI) :=

- Study of the design of **intelligent agents**
- Set of *nature-inspired* methodologies to solve complex real-world problems, when traditional methods might be useless, because:
- 1) the processes might be too **complex** for mathematical reasoning within the given time,
- 2) the problem contains a lot of **uncertainties**
- 3) the problem/process is **stochastic** in nature

Kruse, R., Borgelt, C., Klawonn, F., Moewes, C., Steinbrecher, M. & Held, P. 2013. Computational Intelligence: A Methodological Introduction, Heidelberg, New York, Springer.
Online in both German and English: http://www.computational-intelligence.eu/

IFIP WG 12.9 http://www.ifip.org/bulletin/bulltcs/memtc12.htm

JKU

Define (2/3): Evolutionary Computing (EC) :=

HCI-KDD

- Subfield of CI which studies evolutionary algorithms [1] based on **evolutionary principles** (e.g. Darwin, Baldwin, Lamarck, Mendel [2]),
- **Trial-and-error problem solvers**, considered as
- **Global optimization** methods with metaheuristic or stochastic optimization character – mostly applied for black-box problems (with exception of interactive machine learning approaches, where the black box is opened to a glass box [3])

[1] Eiben, A. E. & Smith, J. E. 2015. *Introduction to evolutionary computing. Second Edition,* Berlin, Springer. Online: http://www.evolutionarycomputation.org/
[2] Holzinger, K., Palade, V., Rabadan, R. & Holzinger, A. 2014. Darwin or Lamarck? Future Challenges in Evolutionary Algorithms for Knowledge Discovery and Data Mining. In: Lecture Notes in Computer Science LNCS 8401. Berlin: Springer, pp. 35-56, doi:10.1007/978-3-662-43968-5_3.
[3] Holzinger, A. 2016. Interactive Machine Learning for Health Informatics: When do we need the human-in-the-loop? Brain Informatics, 3, (2), 119-131, doi:10.1007/s40708-016-0042-6.

JKU

Define (3/3): Genetic Algorithms (GA) :=

HCI-KDD

- search heuristic mimicking the process of **natural selection** used to generate useful solutions to optimization and search problems [1];
- particularly making use of techniques inspired by natural evolution (competing for resources), such as inheritance, reproduction, recombination, mutation, selection, inversion and crossover, according to a
- **fitness function (evaluation function)** [2].

[1] Mitchell, Melanie (1996). An Introduction to Genetic Algorithms. Cambridge, MA: MIT Press
[2] Kallel, L., Naudts, B. & Reeves, C. 2001. Properties of fitness functions and search landscapes. In: Kallel, L. (ed.) Theoretical Aspects of Evolutionary Computing. Heidelberg: Springer, pp. 175-206.

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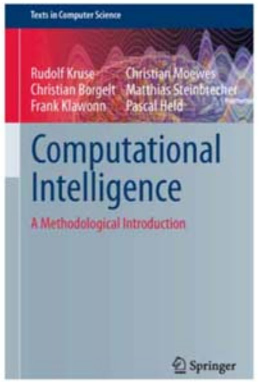
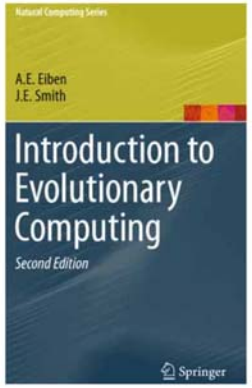
Recommended Books

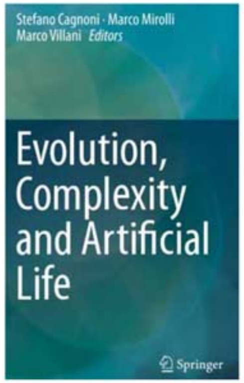
HCI-KDD



Kruse, R., Borgelt, C., Klawonn, F., Moewes, C., Steinbrecher, M. & Held, P. 2013. Computational Intelligence: A methodological Introduction, Heidelberg, New York, Springer.



Eiben, A. E. & Smith, J. E. 2010. Introduction to evolutionary computing, Springer Berlin.



Cagnoni, S., Mirolli, M. & Villani, M. 2014. *Evolution, Complexity and Artificial Life*, Springer.

JKU

HCI-KDD

02 Multi-Agent (Hybrid*) Systems

*) not in the sense as we use it in "interactive ML", i.e.
The classical meaning of "hybrid" is the attempt to combine classical symbolic AI approaches (from the 1950ies) with newer approaches as e.g. the subsumption architecture (from the 1990ies)

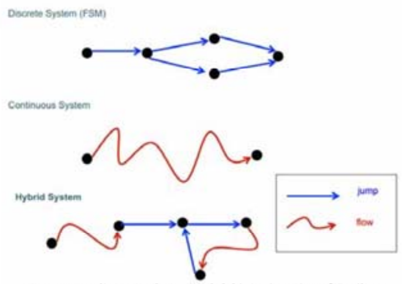


Image credit to Andreas Podelski, University of Freiburg

Recommendation: Michael Wooldridge

Michael Wooldridge

University of Oxford

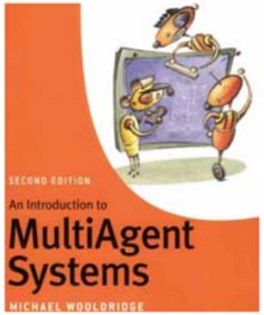
multi-agent systems, multiagent systems, knowledge representation, artificial intelligence, computer science

Verified email at cs.ox.ac.uk - Homepage

Follow

Citation indices	All	Since 2011
Citations	52571	16571
h-index	81	46
i10-index	260	170

Title 1–20	Cited by	Year
Intelligent agents: Theory and practice M Wooldridge, NR Jennings Knowledge engineering review 10 (2), 115-152	9433	1995
An introduction to multiagent systems M Wooldridge John Wiley & Sons	8083	2009
A roadmap of agent research and development NR Jennings, K Sycara, M Wooldridge Autonomous agents and multi-agent systems 1 (1), 7-38	2909	1998



Wooldridge, M. 2009. An introduction to multiagent systems, John Wiley & Sons

http://www.cs.ox.ac.uk/people/michael.wooldridge/pubs/imas/IMAS2e.html

http://www.cs.ox.ac.uk/people/michael.wooldridge/pubs/imas/videos/part1/

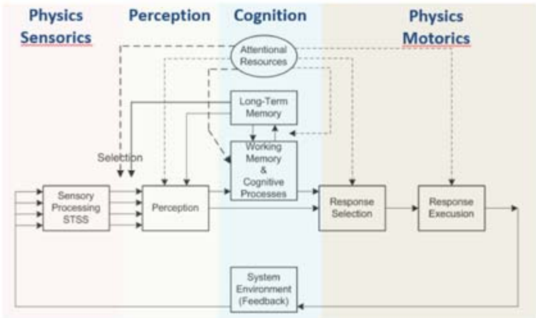
Retrospect: Five trends in the history of computing

http://micro.seas.harvard.edu/research.html

- Connection → computing as interaction of things
- Ubiquity → embedded computing at low cost
- Delegation → fully autonomous vehicles
- Intelligence → human problem solving
- Human-oriented abstractions → human learning

Again: It is all about decision making

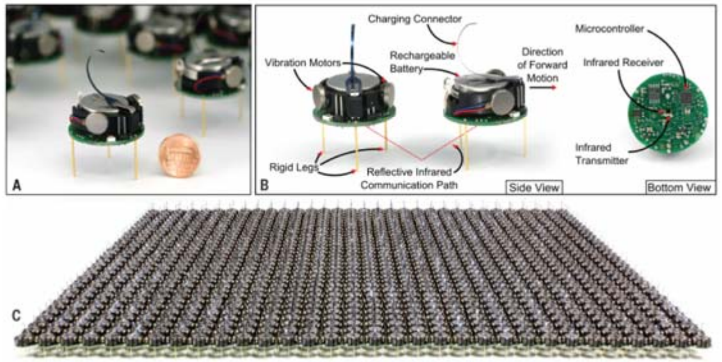
Perception > Decision > Action



- Agent:= computer system which is able to perform autonomous **interactions** in a certain environment to meet delegated goals
  - The agent has to decide WHAT action to perform
  - The agent has to decide WHEN to perform it

Our real-world is a multi-agent environment

Social ability in agents is interacting with other agents via cooperation, coordination, negotiation



Rubenstein, M., Cornejo, A. & Nagpal, R. 2014. Programmable self-assembly in a thousand-robot swarm. Science, 345, (6198), 795-799, doi:10.1126/science.1254295

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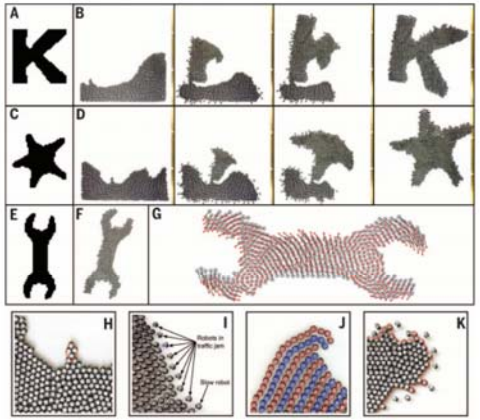
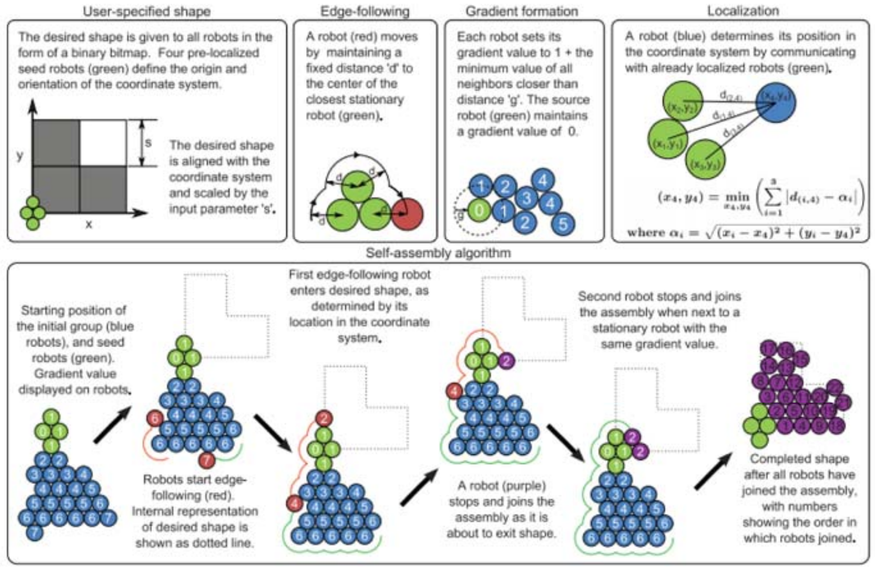
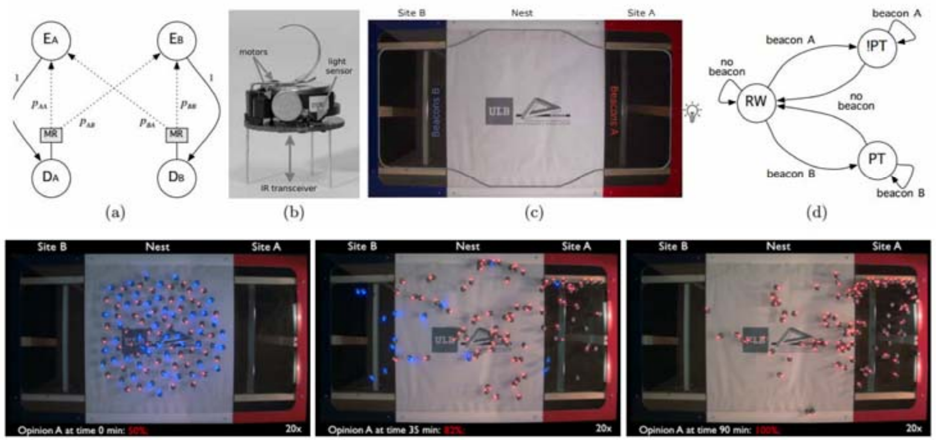


Rubenstein, M., Cornejo, A. & Nagpal, R. 2014. Programmable self-assembly in a thousand-robot swarm. Science, 345, (6198), 795-799, doi:10.1126/science.1254295



Rubenstein, M., Cornejo, A. & Nagpal, R. 2014. Programmable self-assembly in a thousand-robot swarm. Science, 345, (6198), 795-799, doi:10.1126/science.1254295



Valentini, G., Hamann, H. & Dorigo, M. Efficient decision-making in a self-organizing robot swarm: On the speed versus accuracy trade-off. Proceedings of the 2015 International Conference on Autonomous Agents and Multiagent Systems, 2015. International Foundation for Autonomous Agents and Multiagent Systems, 1305-1314.

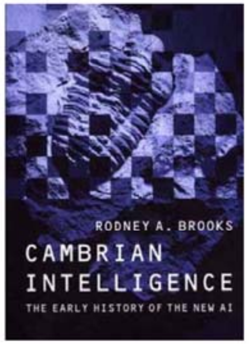
COMPARTMENTALIZATION	CORRUPTION	COMPLEXITY
PRIVACY Barriers erected to protect patient confidentiality are antagonistic to the open data movement	ERRONEOUS DATA Data contains artifacts due to many endogenous and exogenous noise sources	PREDICTION Estimates of future risk and events given present data
INTEGRATION Information relating to a single patient is stored in distinct, disconnected data archives	MISSING DATA Data collection comes at a cost to the patient and the provider	STATE ESTIMATION Inferences based upon a latent model of patient health or physiology
HARMONY Clinical concepts are not consistently defined across databases	IMPRECISE DATA Data is collected for a purpose other than retrospective data analysis	MULTIMODAL DATA Incorporation of a wide range of data sources, including free text and genomic data

Johnson, A. E., Ghassemi, M. M., Nemati, S., Niehaus, K. E., Clifton, D. A. & Clifford, G. D. 2016. Machine learning and decision support in critical care. Proceedings of the IEEE, 104, (2), 444-466, doi:10.1109/JPROC.2015.2501978.

Scientific Value of Multi-Agents Research

- **Agent design:** How do we build agents that are capable of independent, autonomous action in order to successfully carry out the tasks that we delegate to them?
- **Society Design:** How do we build agents that are capable of interacting (cooperating, coordinating, negotiating) with other agents – and humans - in order to successfully carry out the tasks that we delegate to them, particularly when the other agents cannot be assumed to share the same interests/goals?
- **Agents as a paradigm** for software engineering: Software engineers have derived a progressively better understanding of the characteristics of complexity in software. It is now widely recognised that interaction is probably the most important single characteristic of complex software
- **Agents as a tool** for understanding human societies: Multiagent systems provide a novel new tool for simulating societies, which may help shed some light on various kinds of social processes.
- **Agents are the achievable bit of the AI project:** The aim of Artificial Intelligence as a field is to produce general human-level intelligence. This requires a very high level of performance in lots of areas: Vision, Natural language understanding/generation, Reasoning
- Building an agent that can perform well on a narrowly defined task in a specific environment is much easier (though not easy)

Rodney Brooks: "Cambrian Intelligence"



- 1. Intelligent behaviour can be generated without explicit representations of the kind that symbolic AI proposes.
- 2. Intelligent behaviour can be generated without explicit abstract reasoning of the kind that symbolic AI proposes.
- 3. Intelligence is an emergent property of certain complex systems.
- 1. Situatedness and embodiment: 'Real' intelligence is situated in the world, not in disembodied systems such as theorem provers or expert systems.
- 2. Intelligence and emergence: 'Intelligent' behaviour arises as a result of an agent's interaction with its environment. Also, intelligence is 'in the eye of the beholder'; it is not an innate, isolated property.

i-Robot company

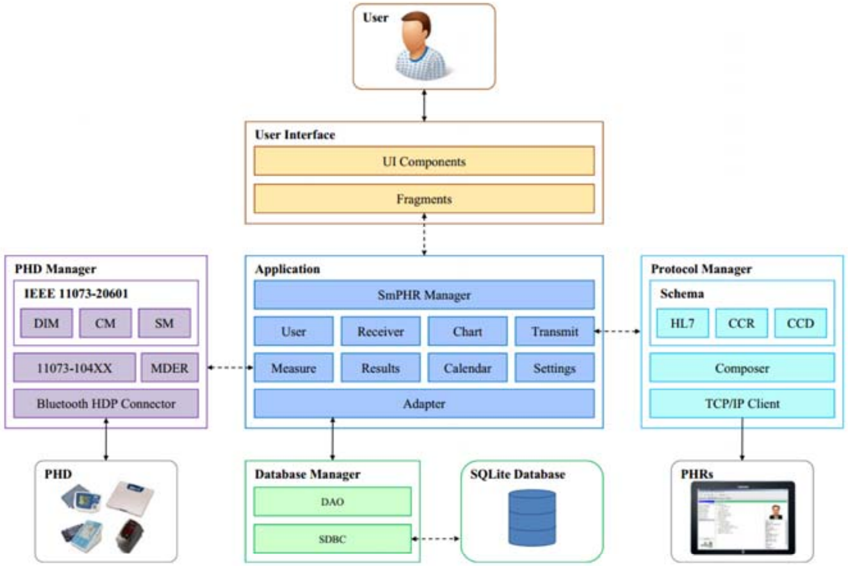
Subsumption architecture

- A subsumption architecture is a hierarchy of task-accomplishing behaviours.
  - Each behaviour is a simple rule-like structure.
  - Each behaviour 'competes' with others to exercise control over the agent.
- Lower layers represent more primitive kinds of behaviour, (such as avoiding obstacles), and have precedence over layers further up the hierarchy.
- The resulting systems are, in terms of the amount of computation they do, extremely simple.
- Some of the robots do tasks that would be impressive if they were accomplished by symbolic AI systems

Maes, P. 1993. Modeling adaptive autonomous agents. Artificial life, 1, (1_2), 135-162.

03 Applications of Multi-Agent Systems in Health Informatics

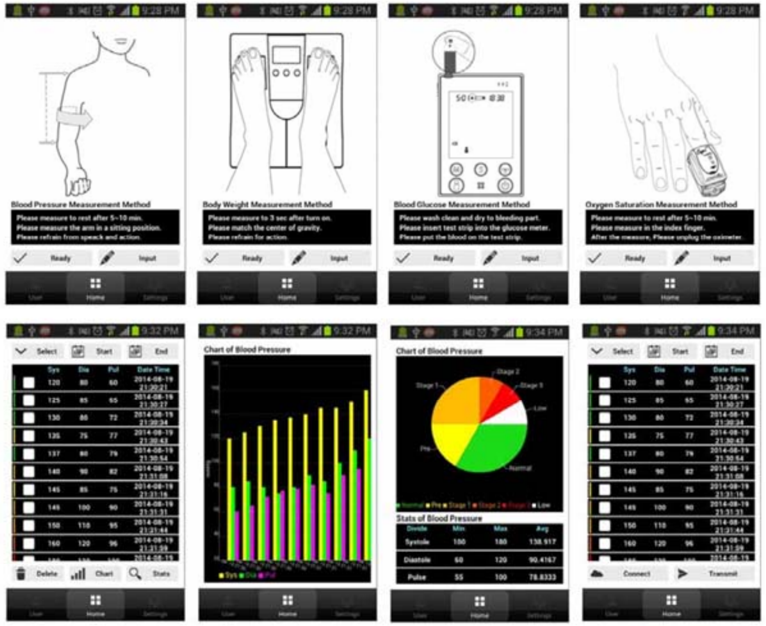
Multi-Agent m-Health Application: System Architecture



Park, H. S., Cho, H. & Kim, H. S. 2015. Development of a Multi-Agent m-Health Application Based on Various Protocols for Chronic Disease Self-Management. Journal of Medical Systems, 40, 1, 1-14, doi:10.1007/s10916-015-0401-5.

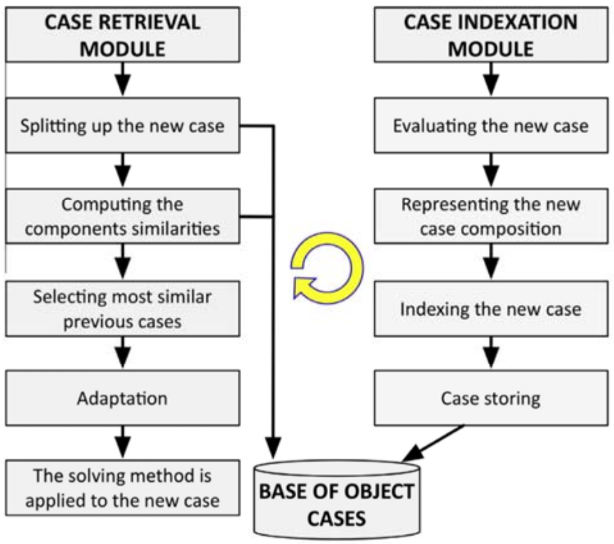
Multi-Agent m-Health Application: Vital Sign Measures

Park, H. S., Cho, H. & Kim, H. S. 2015. Development of a Multi-Agent m-Health Application Based on Various Protocols for Chronic Disease Self-Management. Journal of Medical Systems, 40, 1, 1-14, doi:10.1007/s10916-015-0401-5.

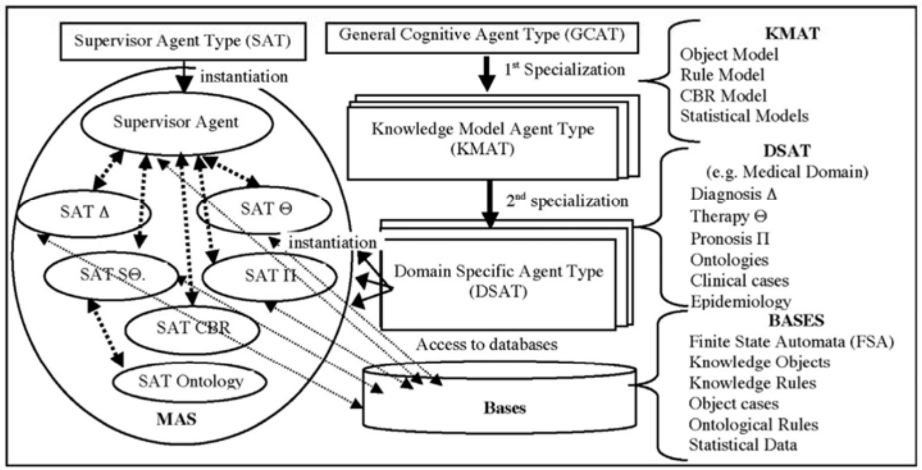


Case-Based Reasoning for clinical decision making MAS

Shen, Y., Colloc, J., Jacquet-Andrieu, A. & Lei, K. 2015. Emerging medical informatics with case-based reasoning for aiding clinical decision in multi-agent system. Journal of biomedical informatics, 56, 307-317, doi:10.1016/j.jbi.2015.06.012.

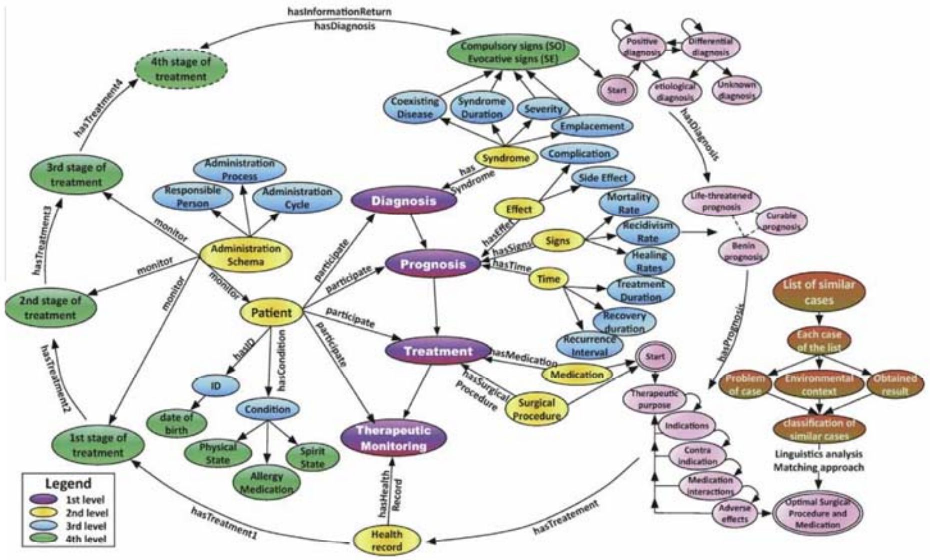


Specialization of agents in the Multi-agent System



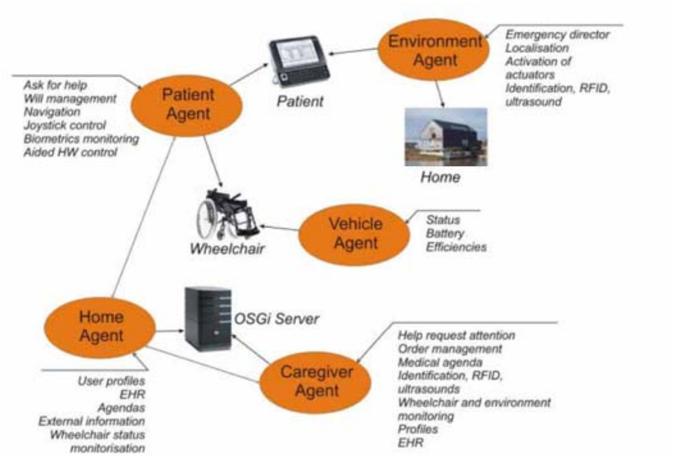
Shen, Y., Colloc, J., Jacquet-Andrieu, A. & Lei, K. 2015. Emerging medical informatics with case-based reasoning for aiding clinical decision in multi-agent system. Journal of biomedical informatics, 56, 307-317, doi:10.1016/j.jbi.2015.06.012.

Ontology used for prognosis of gastric cancer



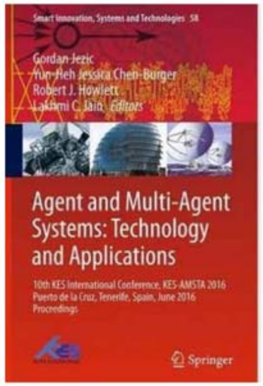
Shen, Y., Colloc, J., Jacquet-Andrieu, A. & Lei, K. 2015. Emerging medical informatics with case-based reasoning for aiding clinical decision in multi-agent system. Journal of biomedical informatics, 56, 307-317, doi:10.1016/j.jbi.2015.06.012.

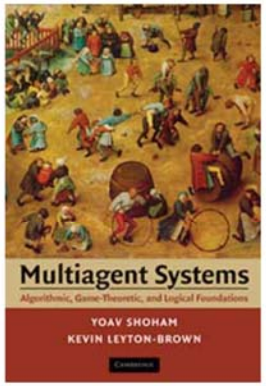
Last practical example …



Isern, D., Sánchez, D. & Moreno, A. 2010. Agents applied in health care: A review. International Journal of Medical Informatics, 79, (3), 145-166, doi:10.1016/j.ijmedinf.2010.01.003.

… and more theory



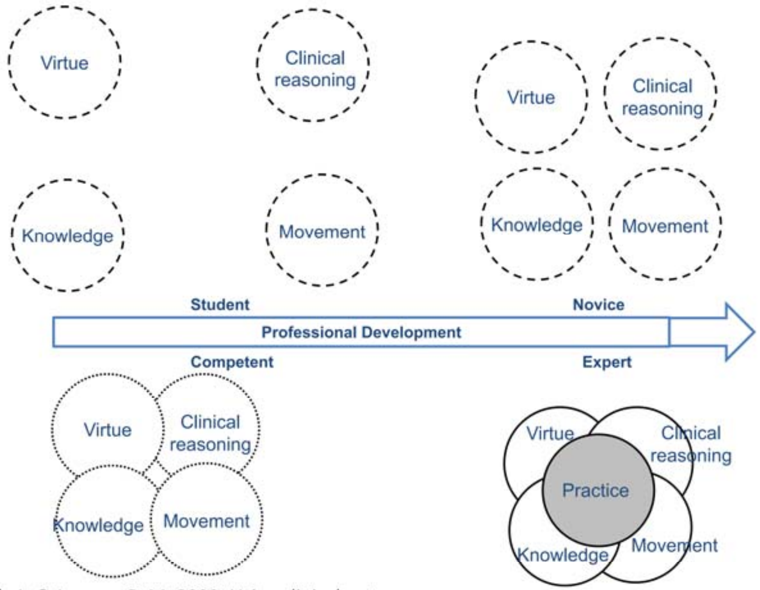


Schwartz, H. M. 2014. Multi-agent machine learning: A reinforcement approach, John Wiley & Sons.

04 Medical Decision Making as a Search Problem

Search in an arbitrarily high-dimensional space < 5 min. !

Medical Action is constantly reasoning/decision making



Resnik, L. & Jensen, G. M. 2003. Using clinical outcomes to explore the theory of expert practice in physical therapy. Physical Therapy, 83, (12), 1090-1106.

Remember: two types of Decision Making

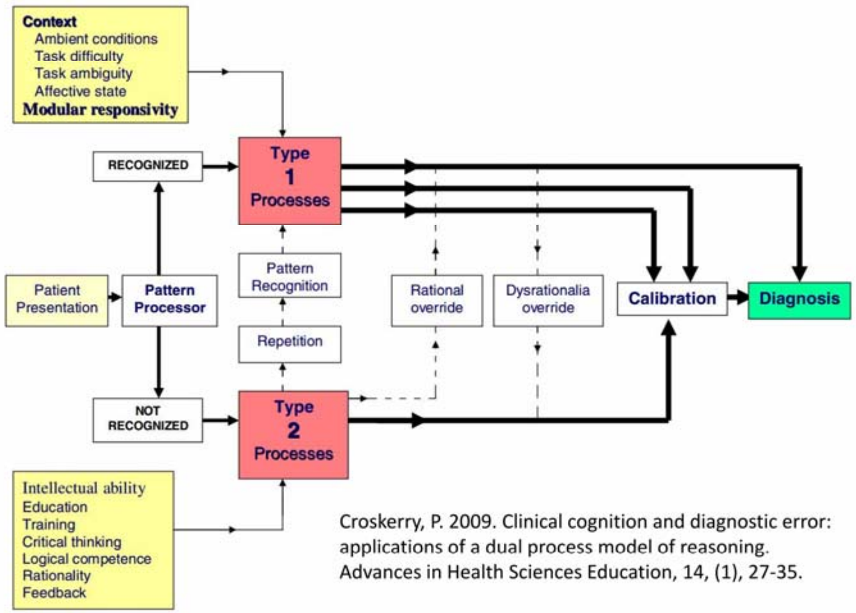
Characteristic	Type 1 Heuristic Intuitive	Type 2 Systematic Analytic
Cognitive Style	Heuristic associative (experience-based) Inductive reasoning	Bounded rationality (Hypothetico-deductive) Normative reasoning
Cost (high/low)	Low	
Automaticity(high/low)		Low
Rate (fast/slow)		Low
Reliability (high/low)	Low	
Errors (high/low)		Low
Effort (high/low)	Low	
Predictive Power (high/low)	Low	
Emotional Component		Low
Scientific Rigor (high/low)	Low	
Context (high/low)		Low
Cognitive Awareness	Low	

Remember: 2 types of Decision Making Croskerry 2009

Characteristic	Type 1 Heuristic Intuitive	Type 2 Systematic Analytic
Cognitive Style	Heuristic associative (experience-based) Inductive reasoning	Bounded rationality (Hypothetico-deductive) Normative reasoning
Cost	Low	High
Automaticity	High	Low
Rate	Fast	Slow
Reliability	Low	High
Errors	High	Low
Effort	Low	High
Predictive Power	Low	High
Emotional Component	High	Low
Scientific Rigor	Low	High
Context	High	Low
Cognitive Awareness	Low	High

Croskerry, P. 2009. Clinical cognition and diagnostic error: applications of a dual process model of reasoning. Advances in Health Sciences Education, 14, (1), 27-35.

Model for diagnostic reasoning



Croskerry, P. 2009. Clinical cognition and diagnostic error: applications of a dual process model of reasoning. Advances in Health Sciences Education, 14, (1), 27-35.

Always Remember

Most (if not all) medical decisions can be formulated as a search in a huge search space [1]

Medical Decision Making is searching for an optimal ("good"*) solution within a search space

***) Attention in clinical practice:**
"Good intentions are the opposite of good"
in German: "Gut gemeint ist das Gegenteil von gut"

[1] Pena-Reyes, C. A. & Sipper, M. 2000. Evolutionary computation in medicine: an overview. Artificial Intelligence in Medicine, 19, (1), 1-23.

Why EC for health applications? Example 1

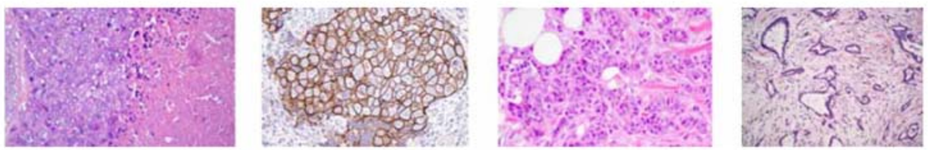
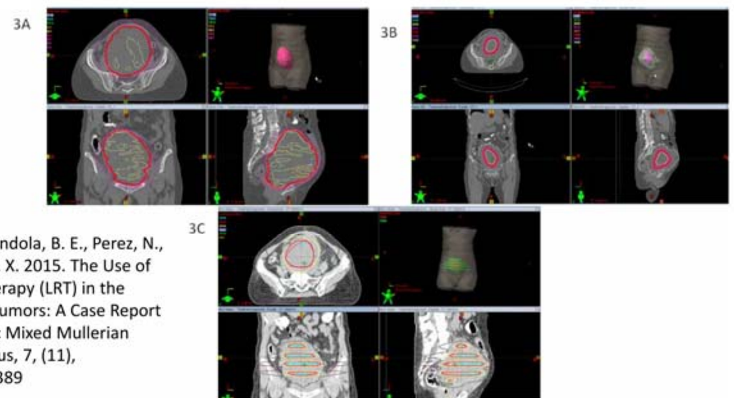


Image Source: https://blogforbreastcancer.wordpress.com/2015/06/30/biopsy-basics-prediction-prognistics-pathology/

- Example 1: a pathologist analyzing biopsies to decide whether they are malignant or not.
- The pathologist is searching in the space of all possible cell features for a set of features permitting to provide a clear diagnosis

Pena-Reyes, C. A. & Sipper, M. 1999. A fuzzy-genetic approach to breast cancer diagnosis. *Artificial intelligence in medicine*, 17, (2), 131-155.

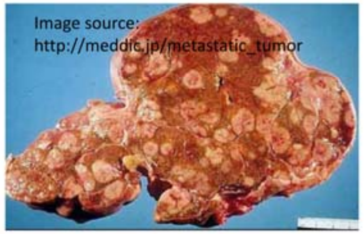
Why EC for health applications? Example 2



Suarez, J. M. B., Amendola, B. E., Perez, N., Amendola, M. & Wu, X. 2015. The Use of Lattice Radiation Therapy (LRT) in the Treatment of Bulky Tumors: A Case Report of a Large Metastatic Mixed Mullerian Ovarian Tumor. Cureus, 7, (11), doi:10.7759/cureus.389

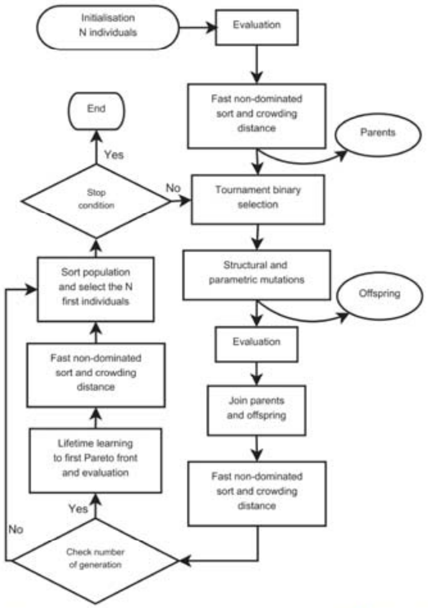
- Example 2: A radiologist planning a sequence of radiation doses is searching for the best treatment in the space of all possible treatments

Why EC for health applications? Example 3



The optimal allocation of organs in liver transplantation is a problem that can be resolved using machine-learning techniques. Classical methods of allocation included the assignment of an organ to the first patient on the waiting list without taking into account the characteristics of the donor and/or recipient.

Cruz-Ramírez, M., Hervás-Martínez, C., Fernandez, J. C., Briceno, J. & De La Mata, M. 2013. Predicting patient survival after liver transplantation using evolutionary multi-objective artificial neural networks. Artificial intelligence in medicine, 58, (1), 37-49, doi:doi:10.1016/j.artmed.2013.02.004.



05 Gamification for testing interactive Machine Learning

Science is to test crazy ideas – Engineering is to put these ideas into Business
A. Holzinger

Motivation for Research

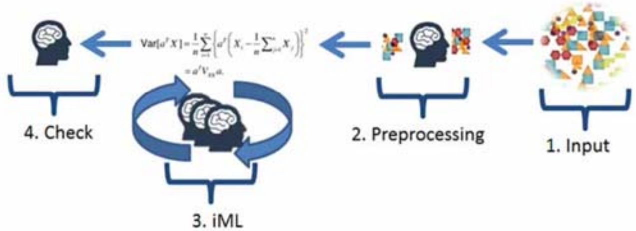
Central question: What if we could solve hard computational problems just by playing games?

Idea: increasing the performance of Machine Learning algorithms by human interaction in form of playing simple games

Advantages:

- Trivial - no need to understand technical background (the simpler the better)
- Reaching large number of people
- Enjoyable and control-able motivator
- Fits well to **federated learning** approach

Interactive Machine Learning: Human is seen as an agent involved in the actual learning phase, step-by-step influencing measures such as distance, cost functions …

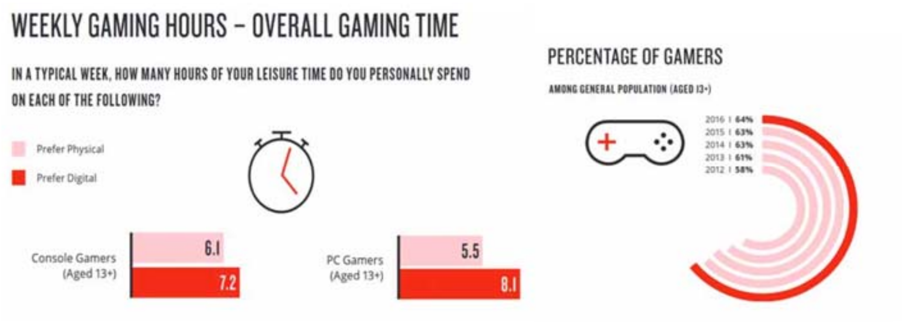


Holzinger, A. 2016. Interactive Machine Learning for Health Informatics: When do we need the human-in-the-loop? Brain Informatics, 3, (2), 119-131, doi:10.1007/s40708-016-0042-6.

Holzinger, A. 2016. Interactive Machine Learning (iML). Informatik Spektrum, 39, (1), 64-68, doi:10.1007/s00287-015-0941-6.

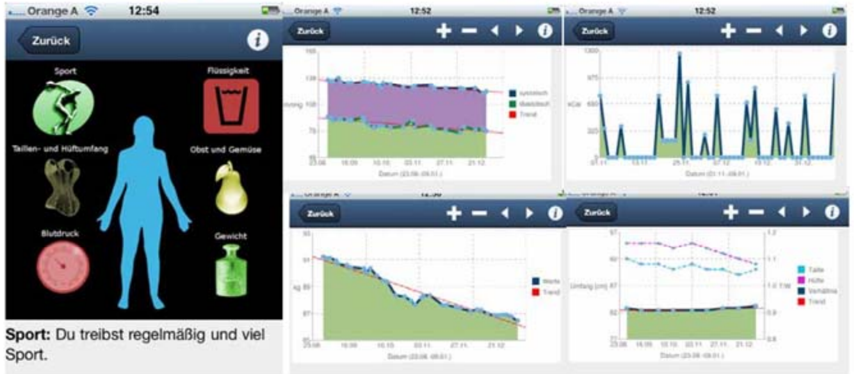
Holzinger, A., Plass, M. & Kickmeier-Rust, M. D. Interactive Machine Learning (iML): a challenge for Game-based approaches. In: Guyon, I., Viegas, E., Escalera, S., Hamner, B. & Kegl, B., eds. Challenges in Machine Learning: Gaming and Education, 2016 Barcelona. NIPS Workshops.

Games: trend is still increasing



Source: US Games 360 Report: 2017 - Nielsen - http://www.nielsen.com/us/en/insights/reports/2017/us-games-360-report-2017.html

Mobile Wellness Assistant …



Holzinger, A., Dorner, S., Födinger, M., Valdez, A. C. & Ziefle, M. (2010) Chances of Increasing Youth Health Awareness through Mobile Wellness Applications. In: *Lecture Notes in Computer Science LNCS 6389. Berlin, Heidelberg, Springer, 71-81.*

Gamification works

- adding video game elements in a non gaming context …
- has been used in health, education, solving of computational problems, etc.
- e.g.: Mira rehab games - motivating people to get better

Brauner, P., Holzinger, A. & Ziefle, M. 2015. Ubiquitous computing at its best: Serious exercise games for older adults in ambient assisted living environments European Alliance on Innvoation (EAI) Endorsed Transactions: Pervasive Games, 1, (4), 1-12, doi:http://dx.doi.org/10.4108/sg.1.4.e3.

Human interaction is required

- Reduce dimensions of complex structures, to find an input format for the ML algorithm
- example: mapping a protein to points in 2D
- more important example: Protein Folding process to Traveling Salesman Problem (TSP)

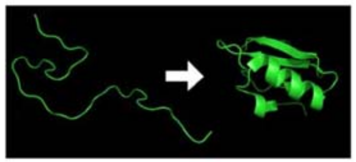
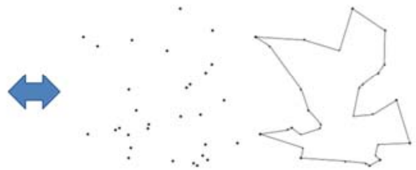


Illustration of the process of protein folding. Chymotrypsin inhibitor 2 from pdb file 1LW6

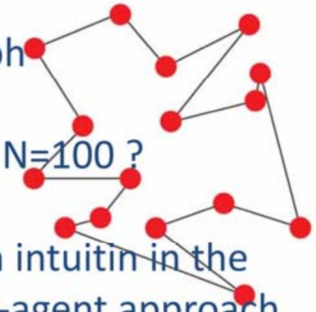


TSP from http://mathworld.wolfram.com/TravelingSalesmanProblem.html 29.05.2017

Proteins are the building blocks of life

- Proteins -> chain of amino acids
- basis of "how biology gets things done"
- Protein folding – extremely important for health
- proteins fold into special shapes to carry out particular functions
- misfolding: diseases, … cancer, Alzheimer's, etc.
- Understanding protein folding = understanding diseases = helping develop new drugs = meaningful input for our iML algorithm

Theoretical background - PP - TSP



- Find the shortest tour in a graph
- NP hard problem
- How many different routes for N=100 ?
- 10^{155}
- We need heuristics and human intuitin in the loop of a nature-inspired multi-agent approach

Sim, K. M. & Sun, W. H. 2003. Ant colony optimization for routing and load-balancing: Survey and new directions. IEEE Transactions on Systems Man and Cybernetics Part a-Systems and Humans, 33, (5), 560-572, doi:10.1109/tsmca.2003.817391.

Macgregor, J. N. & Ormerod, T. 1996. Human performance on the traveling salesman problem. Perception & Psychophysics, 58, (4), 527-539, doi:10.3758/bf03213088.

06 Ant's and Collective Intelligence Human-in-the-loop

Three of the more important swarm based approaches

- Particle Swarm Optimization (PSO)
  - based on social behaviour of bird flocks used as method for continuous optimization problems
- Artificial Bee Colonies (ABC)
  - Algorithms based on foraging of honey bee swarms used for continuous optimization problems
- **Ant Colony Optimization (ACO)**
  - Algorithms based on social behaviour of ants, used as metaheuristic for (hard) combinatorial optimization problems (e.g. for TSP-like problems)

Martens, D., Baesens, B. & Fawcett, T. 2011. Editorial survey: swarm intelligence for data mining. Machine Learning, 82, (1), 1-42, doi:10.1007/s10994-010-5216-5.

Ants are search machines

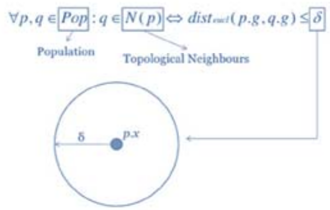
- Ants wander randomly and search for food
- If an ant finds food it returns home laying down a **pheromone trail** on its way back
- Other ants stumble upon the trail and start following this pheromone trail - **reinforcing**
- Other ants also return home and also deposit pheromones on their way back (**reinforcing** the trail) – when a path is blocked they explore alternative routes …

Colorni, A., Dorigo, M. & Maniezzo, V. 1991. Distributed optimization by ant colonies. Proceedings of the first European conference on artificial life ECAL 91, 134-142.

Theoretical background - iML - ACO basics

Algorithm 1 AS algorithm pseudocode

```
Initialize trail
while stopping criteria not satisfied do
    position each ant in starting position
    repeat
        for each ant do
            choose next node by state transition rule
        end for
    until every ant completed the tour
    perform global pheromone updating rule
end while
```



- A simple ant algorithm consists of:
  - **a state transition rule**
    this rule takes a distance and pheromone measure and decides the possibility to choose an edge in the graph
  - **a pheromone updating rule**
    this rule updates the pheromones according to the “traffic” on particular edges (usually after every iteration)

What is the probability for selecting a particular path?

$$p_{ij} = \frac{[\tau_{ij}]^\alpha \cdot [\eta_{ij}]^\beta}{\sum_{l \in J_i^k} [\tau(t)]^\alpha \cdot [\eta]^\beta}$$

- p_{ij} ... **probability** of ants that they, at a particular node i, select the route from node $i \rightarrow j$ (**“heuristic desirability”**)
- $\alpha > 0$ and $\beta > 0$ ... the **influence parameters** (α ... history coefficient, β ...heuristic coefficient) usually $\alpha \approx \beta \approx 2 < 5$
- τ_{ij} ... the **pheromone value** for the components, i.e. the amount of pheromone on edge (i,j)
- k ... the set of usable components
- J_i ... the set of nodes that ant k can reach from v_i (tabu list)
- $\eta_{ij} = \frac{1}{dij}$ ... attractiveness computed by a heuristic, indicating the “a-priori **desirability”** of the move

Theoretical background - iML - ACO interactive

- We made the algorithm interactive
  - There is a possibility to stop the algorithm during and after an iteration and change some values

The Human Kernel Experiment (1/3)

http://functionlearning.com

Demos of experiments for *The Human Kernel*

This page contains links to the experiments described in Section 4 of The Human Kernel [bibtex].

- **Part 1: Extrapolating from smooth functions.**
  In the first experiment, described in Section 4.2 of the paper, participants were asked to exptrapolate from several functions, where the true underlying relationships were draws from a Gaussian process with a rational quadratic kernel. [Link]
- **Part 2: Extrapolating from smooth functions.**
  In the second experiment, described in Section 4.3 of the paper, participants were asked to exptrapolate from functions that are difficult or impossible for conventional Gaussian process methods to capture. [Link]
- **Part 3: Preference for smoothness/simplicity.**
  In the third experiment, described in Section 4.4 of the paper, participants were asked to express their preferences over different kinds of explanations or underlying relationships, given a small number of data points. [Link]

Wilson, A. G., Dann, C., Lucas, C. & Xing, E. P. The Human Kernel. In: Cortes, C., Lawrence, N. D., Lee, D. D., Sugiyama, M. & Garnett, R., eds. Advances in Neural Information Processing Systems, NIPS 2015, 2015 Montreal. 2836-2844.

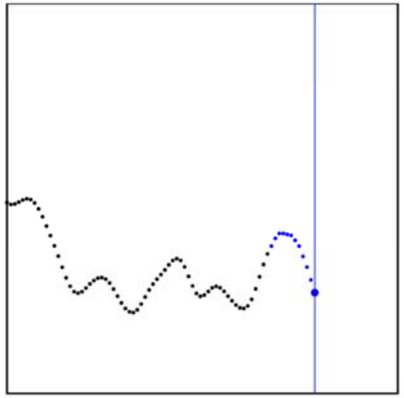
The Human Kernel Experiment (2/3)

Judgment 12 out of 33

This is the first function from the system. Please try to predict the new points as well as y

Please click along the blue line to say what you think the height of the point is for that lo

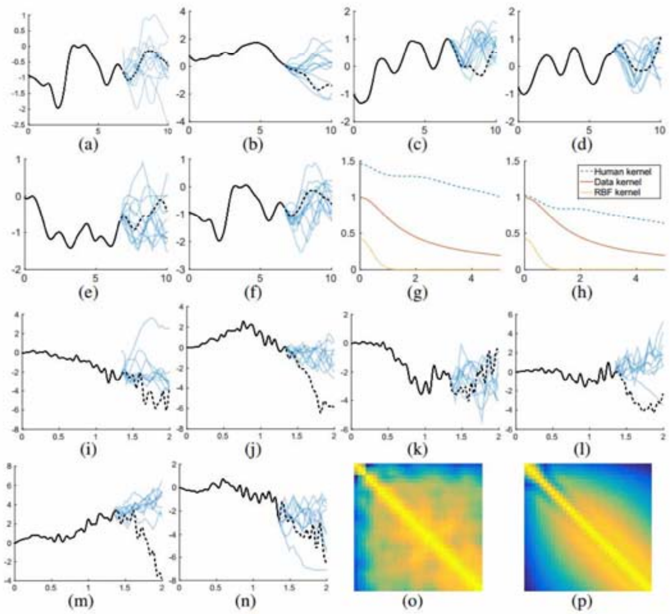
Once you have selected a position along the line, **hit the 's' key to submit the point**.



Wilson, A. G., Dann, C., Lucas, C. & Xing, E. P. The Human Kernel. In: Cortes, C., Lawrence, N. D., Lee, D. D., Sugiyama, M. & Garnett, R., eds. Advances in Neural Information Processing Systems, NIPS 2015, 2015 Montreal. 2836-2844.

The Human Kernel Experiment (3/3)

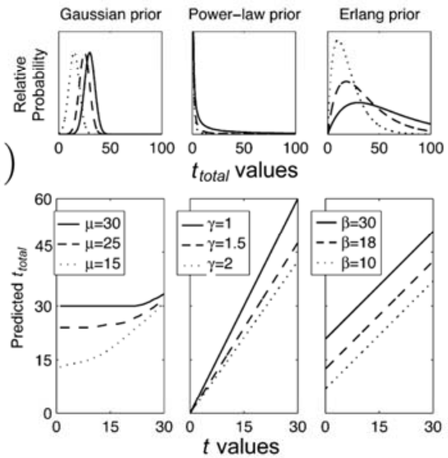
Wilson, A. G., Dann, C., Lucas, C. & Xing, E. P. The Human Kernel. In: Cortes, C., Lawrence, N. D., Lee, D. D., Sugiyama, M. & Garnett, R., eds. Advances in Neural Information Processing Systems, NIPS 2015, 2015 Montreal. 2836-2844.



Bayesian predictor computes a probability distribution

Life spans: Insurance agencies employ actuaries to make predictions about people's life spans—the age at which they will die—based upon demographic information. If you were assessing an insurance case for an 18-year-old man, what would you predict for his life span?

$$p(t_{\text{total}}|t) \propto p(t|t_{\text{total}})p(t_{\text{total}})$$



Griffiths, T. L. & Tenenbaum, J. B. 2006. Optimal predictions in everyday cognition. Psychological science, 17, (9), 767-773, doi:10.1111/j.1467-9280.2006.01780.x.

Remember: How do grow a mind

Tenenbaum, J. B., Kemp, C., Griffiths, T. L. & Goodman, N. D. 2011. How to grow a mind: Statistics, structure, and abstraction. Science, 331, (6022), 1279-1285, doi:10.1126/science.1192788.

Ants communicate via non-linear pheromones trails

Figure 2. Pharaoh's ants, *Monomorium pharaonis*, form branching networks of pheromone trails.
Here the network has been formed on a smoked glass surface to aid visualisation. (Image courtesy of Duncan Jackson.)

Sumpter, D. J. T. & Beekman, M. 2003. From nonlinearity to optimality: pheromone trail foraging by ants. Animal Behaviour, 66, (2), 273-280, doi:10.1006/anbe.2003.2224.

Problem Solving: Humans vs. Computers

When is the human *) better?

***) human intelligence/natural intelligence/human mind/human brain/human learning**

- **Natural Language Translation/Curation**
  Machine cannot understand the context of sentences [3]
- **Unstructured problem solving**
  Without a pre-set of rules, a machine has trouble solving the problem, because it lacks the creativity required for it [1]
- **NP-hard Problems**
  Processing times are exponential and makes it almost impossible to use machines for it, so human still stays better [4]

When is the computer **) better?

****) Computational intelligence, Artificial Intelligence/ Machine Learning algorithms**

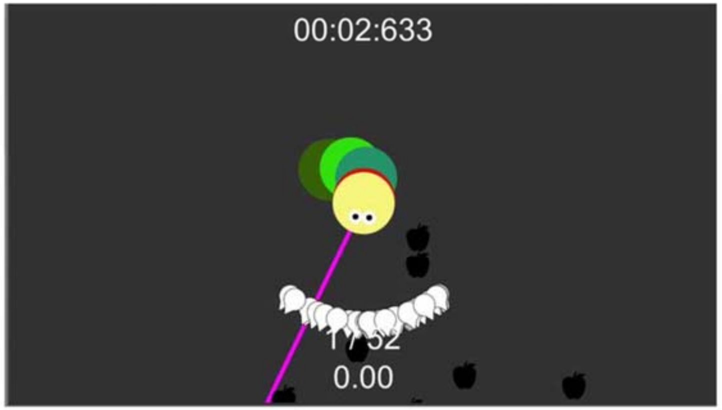
- **High-dimensional data processing**
  Humans are very good at dimensions less or equal than 3, but computers can process data in arbitrarily high dimensions
- **Rule-Based environments**
  Difficulties for humans in rule-based environments often come from not recognizing the correct goal in order to select the correct procedure or set of rules [2]
- **Image optimization**
  Machine can look at each pixel and apply changes without human personal biases, and with more speed [1]

[1] https://www.instartlogic.com/blog/man-vs-machine-learning-based-optimizations
[2] Cummings, Mary Missy. "Man versus machine or man+ machine?." *Intelligent Systems, IEEE* 29.5 (2014): 62-69.
[3] Pizlo, Zygmunt, Anupam Joshi, and Scott M. Graham. "Problem Solving in Human Beings and Computers (formerly: Heuristic Problem Solving)." (1994).
[4] Griffiths, Thomas L. "Connecting human and machine learning via probabilistic models of cognition." *INTERSPEECH*. 2009.

Game 1

- Goal: eat all apples as fast as possible
- distribution of apples = TSP
- In the background:
- suggestion to choose certain apples by ant algorithm (not necessary - human vs. machine)
- consideration of your choices

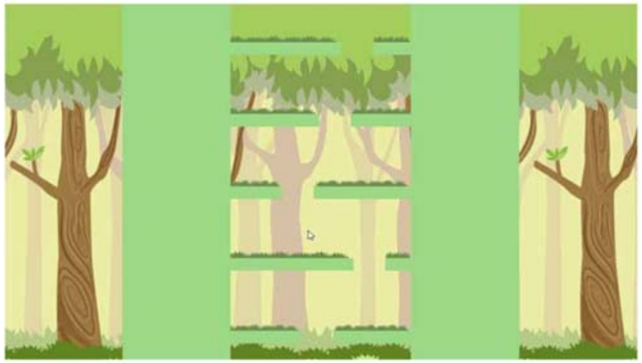
Game 1



Game 2

- Goal: Move as far down as possible
- you need to choose between 2 directions = 2 edges in the TSP

Game 2



Future Outlook

- possible extensions of games:
- High-scores (online and local) – extremely motivating [1]
- UI improvements
- competition elements including levels, achievements, multiplayer, …
- please check the Games (URLs on the Website)
- and send your comments via e-Mail

[1] Ebner, M. & Holzinger, A. 2007. Successful implementation of user-centered game based learning in higher education: An example from civil engineering. Computers and Education, 49, (3), 873-890, doi:10.1016/j.compedu.2005.11.026.

Conclusion

Necessity for a human-in-the-loop – thanks to Geoffrey

https://www.youtube.com/watch?v=2HMPRXstSvQ

- Standard (monkey work) –
  yes … let the algorithm do it ☺
- The gained time can be spent for increasing quality – focus to research and/or complex tasks
- Still there will be computational hard problems where a human expert can bring in experience, expertise knowledge, intuition
- **Most of all: Black box approaches can not explain WHY a decision has been made**

Thank you!

Questions

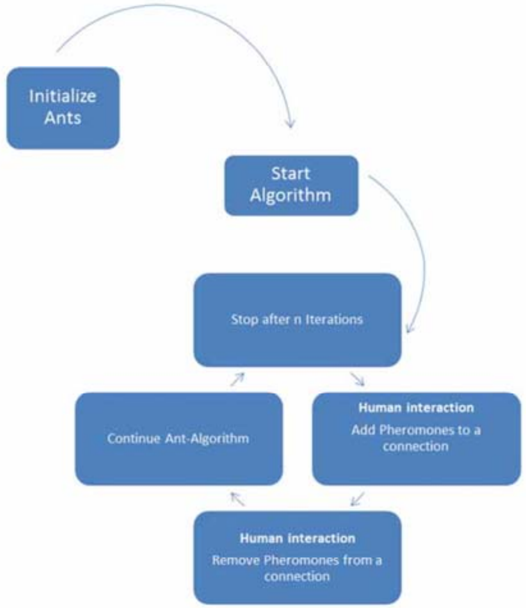
Sample Questions (1)

- What are the advantages of a computational agent ?
- How is an agent defined?
- What is social ability in agents?
- Why is Gamification so powerful?
- What is collective intelligence?
- Why are Ant Algorithms interesting?
- What is the human kernel?

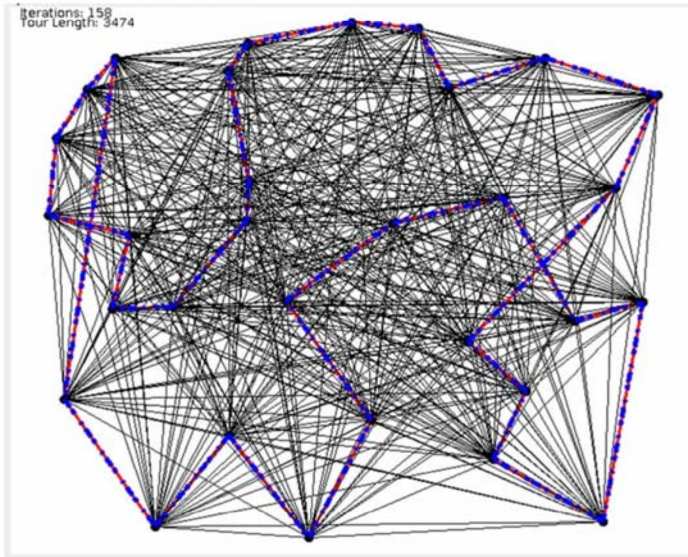
Sample Questions (2)

- Please explain the five mainstreams in ML!
- Why is it generally not easy to solve problems in health informatics?
- What is the model of a computational agent?
- Why is protein folding a hard problem?
- Explain why the study of human learning and machine learning can benefit from each other?
- What is a Pheromone and how does it work?
- In which areas are humans better than computers?
- What is the human kernel experiment?
- Why is simulated annealing interesting?
- Explain the Ant Colony Algorithm via pseudo code!
- Why should we study natural computing?

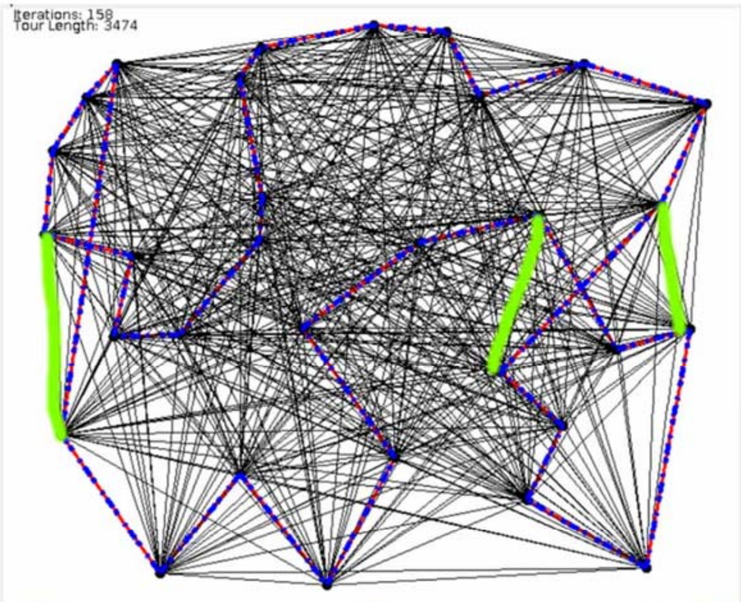
Appendix



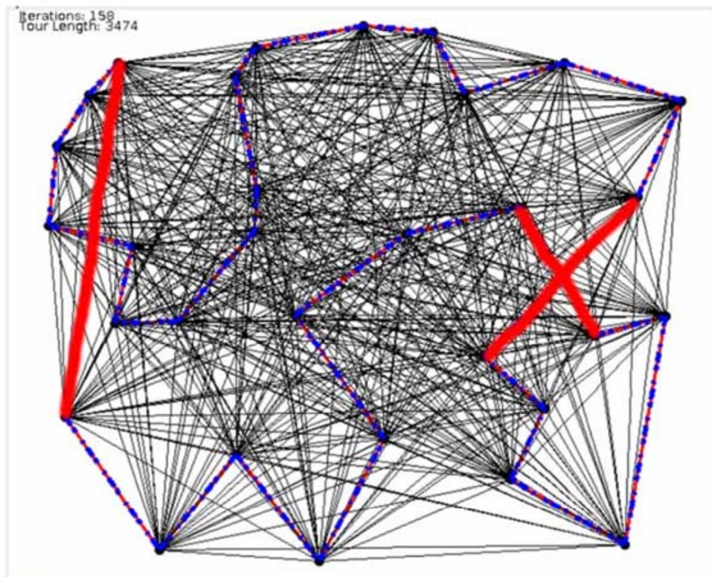
Bring in the Human



Add Pheromones

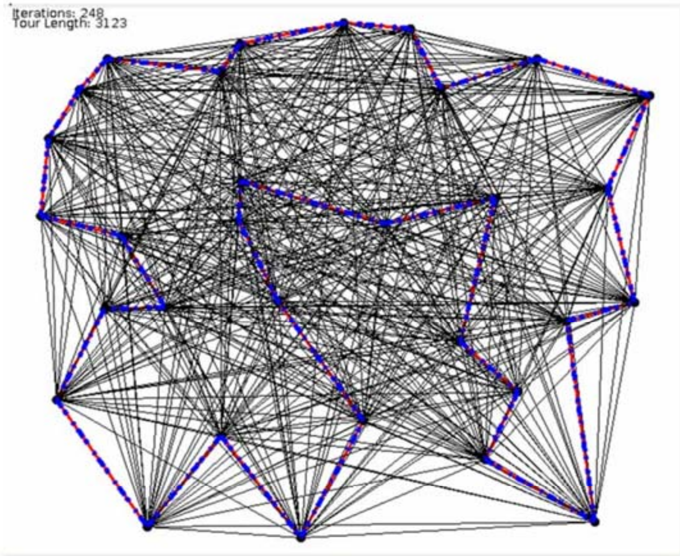


Remove Pheromones



Ant-Algorithm with iML

Result:

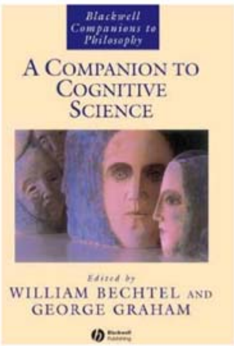


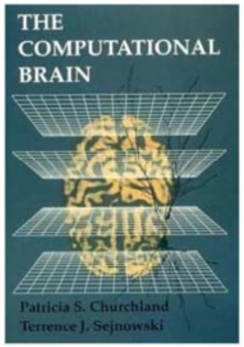
EVOLKNO: Future research in EAs [16]

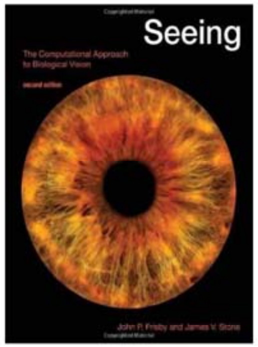
- Testing of novel Evolutionary algorithms:
  - Intelligent Water Drops
  - Bacteria Foraging Search
  - ...
- EVOLKNO crowdsourcing platform to implement and test new algorithms:
  - Open Source data for Researchers to test algorithms
  - Evaluate quality, reusability and efficiency of algorithms

[16] Holzinger, K., Palade, V., Rabadan, R., & Holzinger, A. (2014). Darwin or lamarck? future challenges in evolutionary algorithms for knowledge discovery and data mining. In Interactive Knowledge Discovery and Data Mining in Biomedical Informatics (pp. 35-56). Springer Berlin Heidelberg.

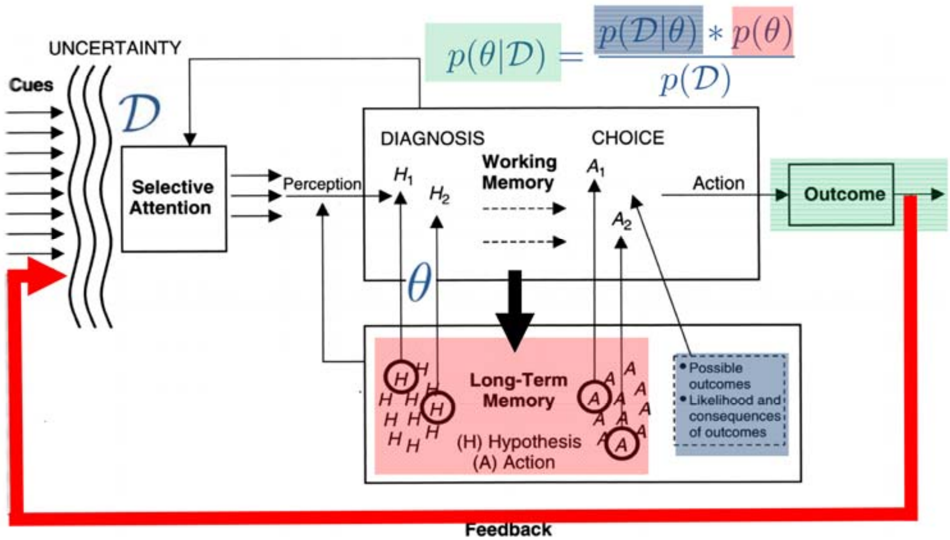
Recommendable reading for further studies







Human Decision Making: probabilistic reasoning



Wickens, C. D. (1984) *Engineering psychology and human performance. Columbus (OH), Charles Merrill, Altered by Holzinger, A. (2017)*

ML-Jungle Top Level View

Maths

Challenges

Cognition | Visualization | Data structure

Perception  Preprocessing

Decision | Interaction | Integration

Always with a focus/application in health informatics

CONCEPTS | THEORIES | PARADIGMS | MODELS | METHODS | TOOLS

- Curse of Dim
- DR
- NfL-Theorem
- Overfitting
- Non-Parametric
- Bayesian p(x)
- Complexity
- KL-Divergence
- Info Theory
- unsupervised
- supervised
- Semi-supv.
- online
- iML
- Gaussian P.
- Graphical M.
- NN
- DL
- SVM
- Linear Models
- RL
- PL
- AL
- Regularization
- Validation
- Aggregation
- Nature Inspired
- D. Trees
- Python
- Julia
- Etc.
- Azure
- Privacy ML

Exp. & Eval.