Plan of the lecture

0. This Overview
1. Learning and Representation
2. Deep Learning
3. Combining Learners
4. Reinforcement Learning
5. Shaping Exploration: Active Learning
6. Theory Frameworks

What makes learning useful (for us and for robots!)?

Learning is **the answer to a number of important questions:**

- how to **enhance limited knowledge** and **skills?**
- how to **improve performance** on a task?
- how to **avoid prestructuring everything** by hand?
- how to cope with **novelty and change?**
- how to get around in a world that can only **partially be known?**

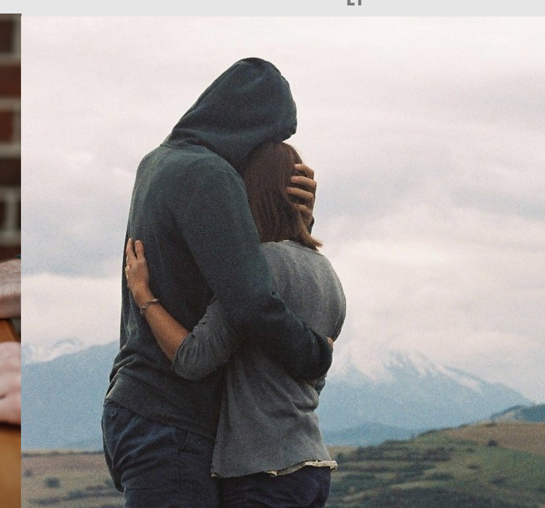
⇒ "Learning" is a single word,
but involves very many aspects!

Learning in the real world

- keeping a changing body calibrated
- acquiring new skills
- becoming familiar with
  - objects
  - places
  - people
  - ideas
- acting in social situations
- communication and language
- ...

Travis D. Eisele [public domain]

publicdomainarchive.com



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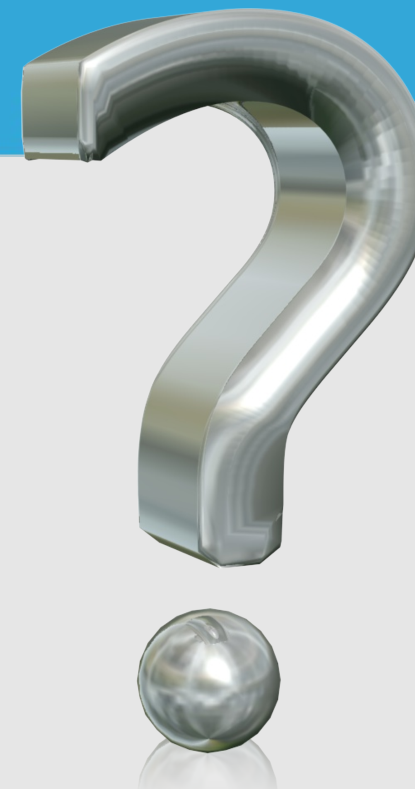
Some Questions to start with

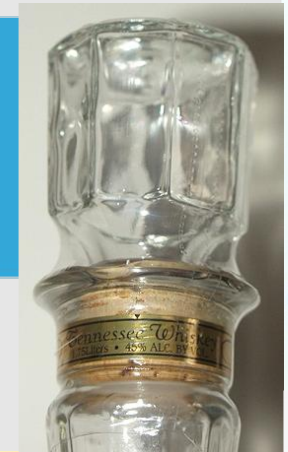


- how can we create systems that learn?
- are there fundamentally different kinds of learning?
- how do we (or animals) learn?
- can we replicate/surpass these capabilities?
- does machine learning resemble human learning in any way?
- ...

A closer look

Example: getting **liquid out of a bottle:**

- **reaching** and **grasping**
- proper **contact**
- **mechanism recognition**
- **selection** of opening movement
- **alignment** with target container
- pouring **control**
- ...



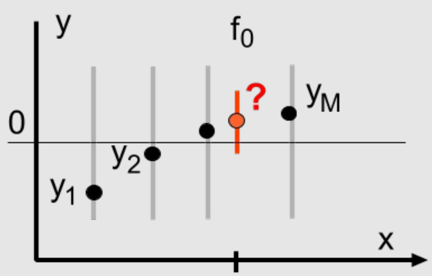
Universität Bielefeld

Neuroinformatics Group

Methods for formalization

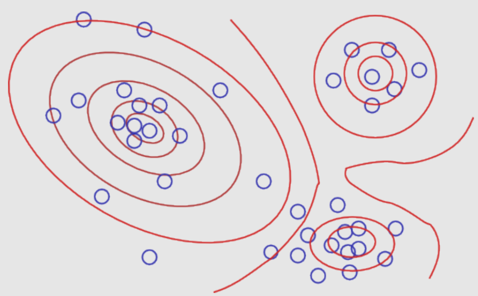
Mappings	Dynamics	Structures

Mappings



Gaussian processes

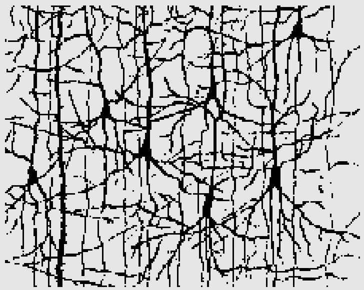
$$y(x) = \sum_{ij} k_i(x) K^{-1}_{ij} y_j$$



Kernel machines

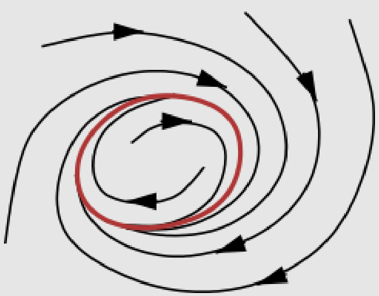
$$y(x) = c + \sum_i w_i K(x_i, x)$$

Dynamics



Recurrent networks

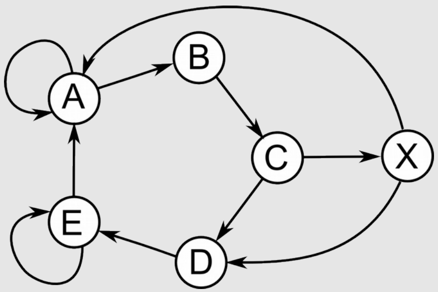
$$x_i(t+1) = \sigma\Big(\sum_j W_{ij} x_j(t)\Big)$$



Dynamical motion primitives

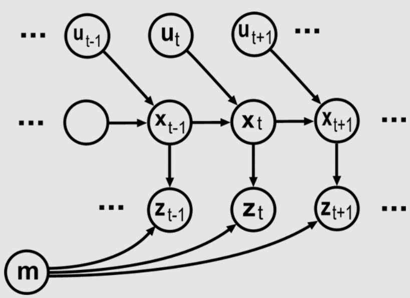
$$\ddot{x} = -a\dot{x} - bx + A(t) \sum_i w_i \cdot \psi_i(t)$$

Structures



FSA, grammars..

$$x_i(t+1) = \sum_j \boldsymbol{T}^a_{ij} x_j(t)$$



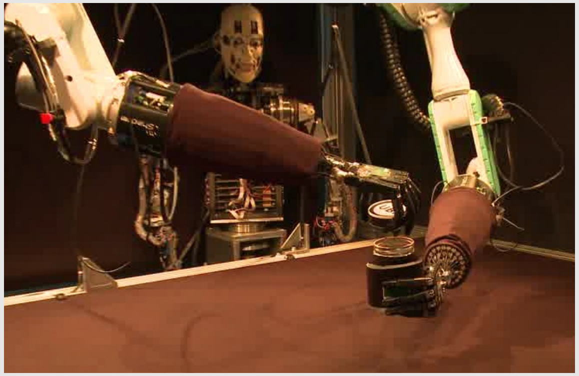
Graphical models

$$P(\boldsymbol{x}) = \prod_i P(x_i | U_i)$$

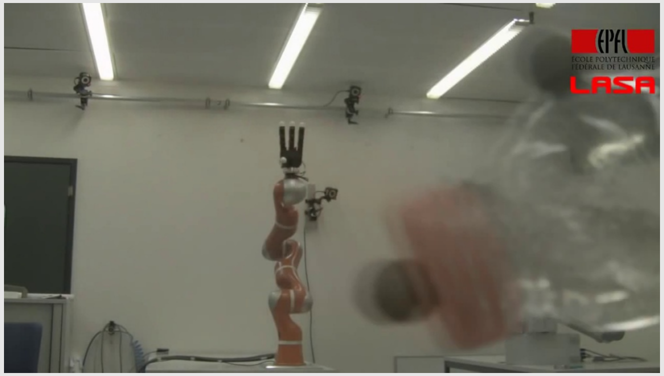
What robot learning can deliver today

Already *seemingly simple tasks combine lots of difficult challenges!* Thus

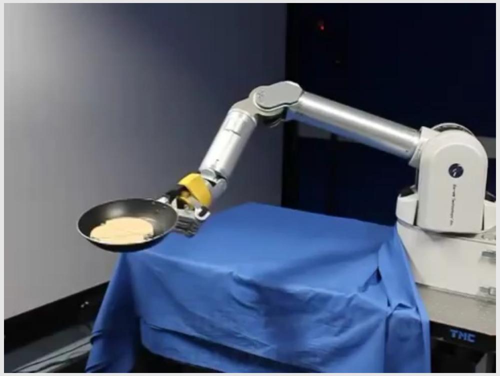
- simplified/specialized scenarios
- parametrized model to "format task"
- often focus on selected "action part" only
- usually learning on a single level
- still impressive examples through careful real-world embedding



CITEC



EPFL/LASA

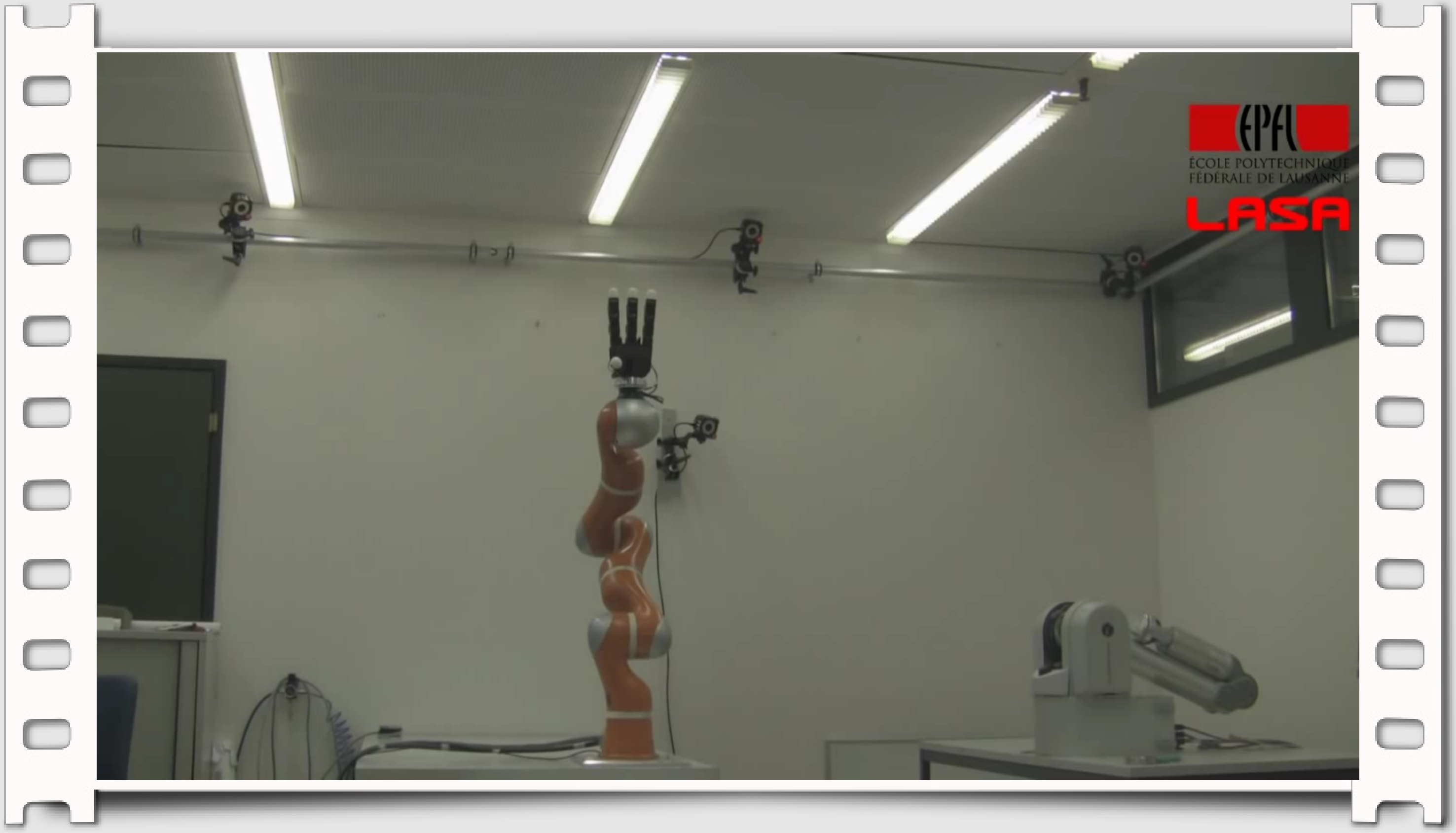


IIT

Examples (I)
Opening a jar

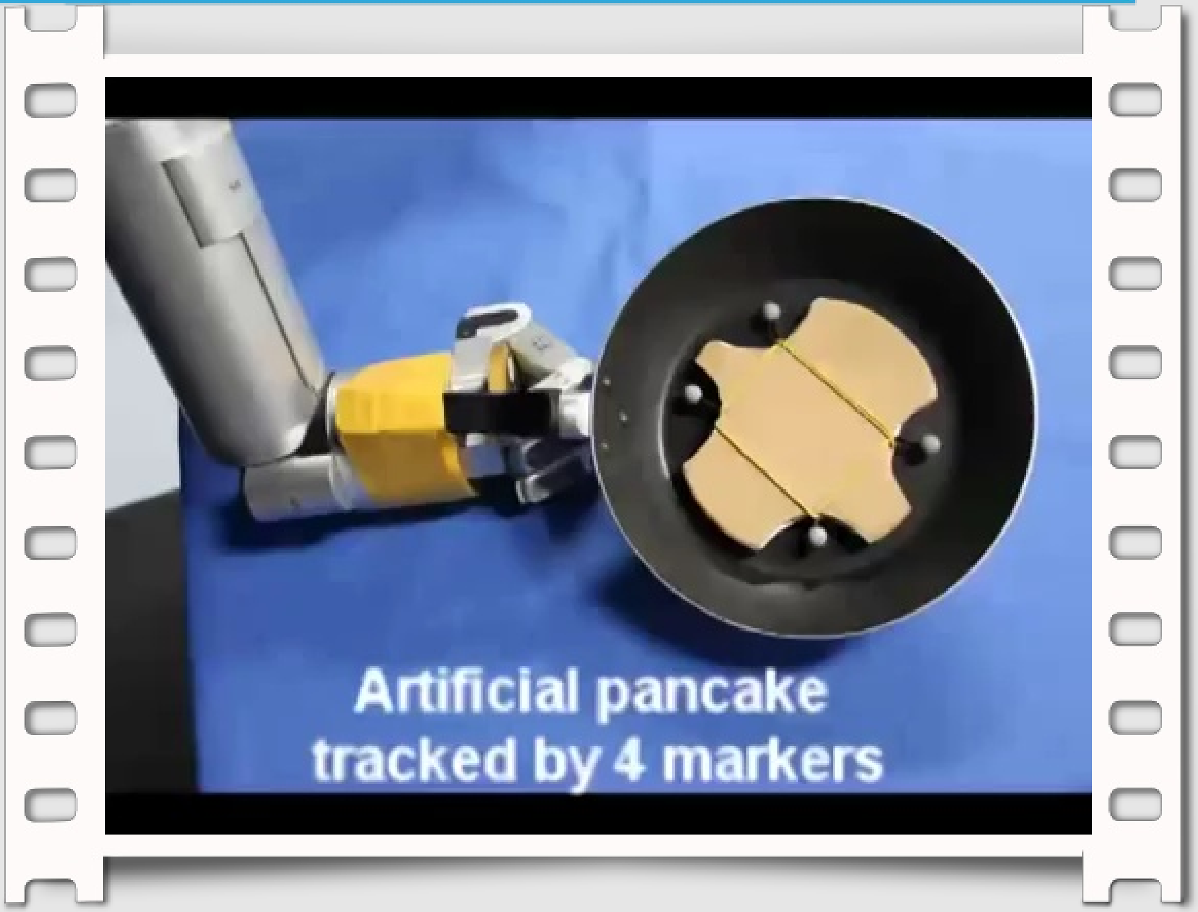
J. Steffen, C. Elbrechter, R. Haschke & H. Ritter (2010) IEEE Humanoids

Examples (II)
Catching a bottle



S. Kim, A. Shukla, A. Billard (2014) IEEE Trans. on Robotics

Examples (III)
Turning a pancake



P. Kormushev, S. Calinon, D. Caldwell (2010) IEEE IROS 2010

Learning in Humans

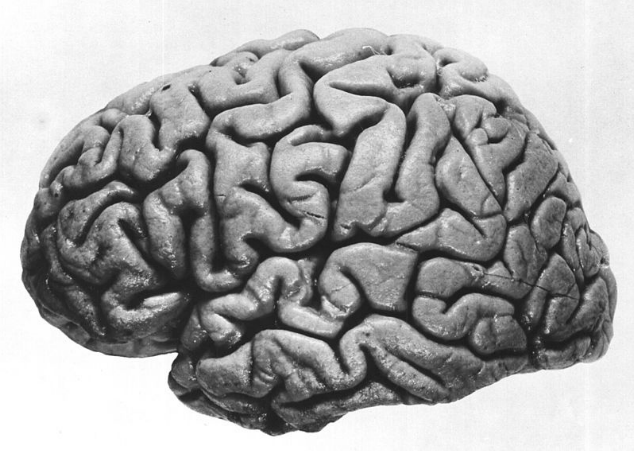
source YouTube

animals

source YouTube

Learning and Memory

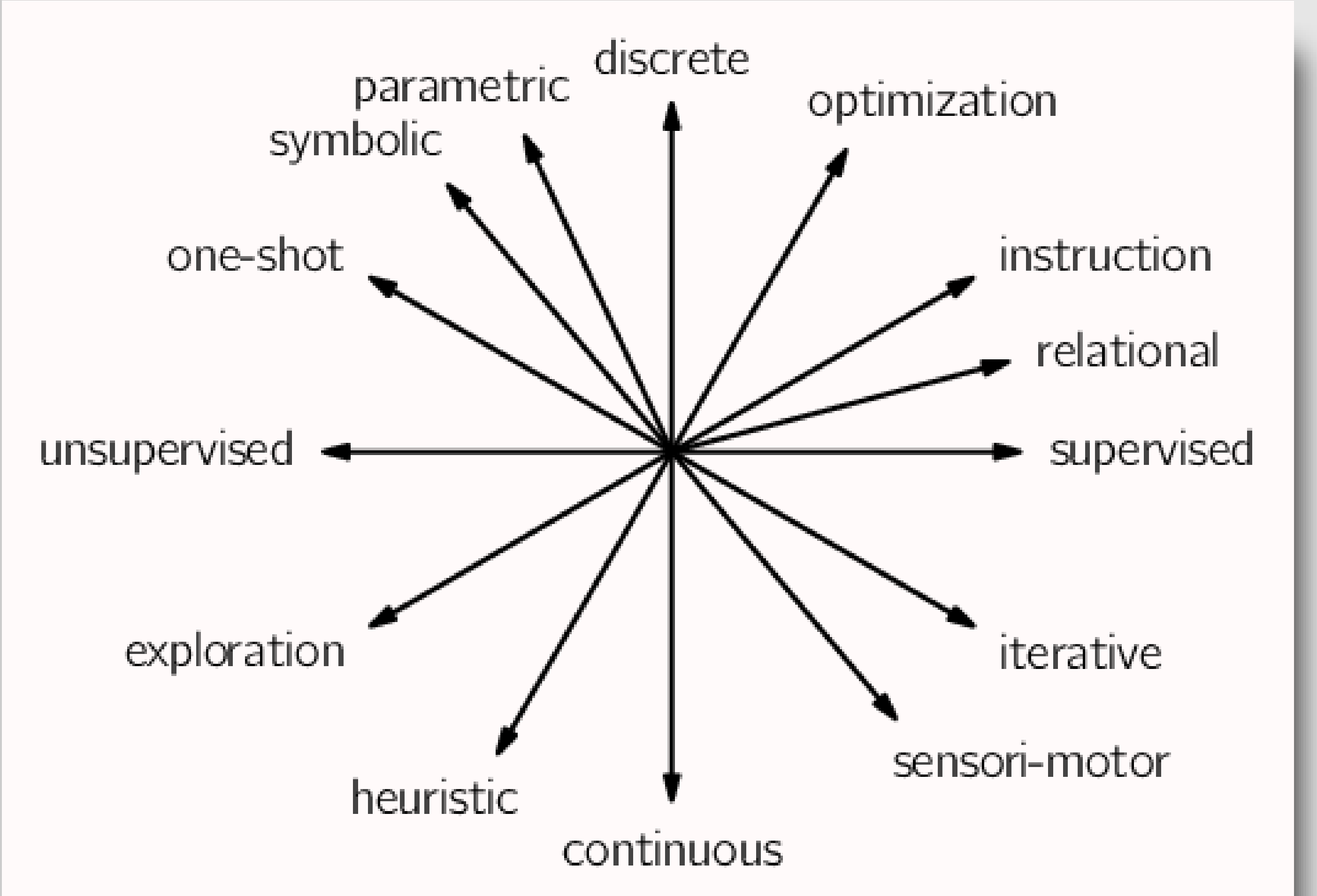
The variety of forms of learning is consistent with the existence of a number of distinguishable memory systems in the brain:



- **priming/association memory:** storing connections between activations (for learning of novel associations)
- **perceptual memory:** how do objects look, sound, feel? (enabling perceptual learning)
- **procedural memory:** how to perform a certain action, such as cycling or speaking a word? (enabling skill learning)
- **semantic memory:** holding general knowledge about objects and events: "milk is a drinkable white liquid", "Paris is the capital of France"! (enabling fact learning)
- **episodic memory:** storage of events in which one has participated (enabling remembering of episodes)

To fill these memories, a **12-year old child** had less than **5 million minutes of wake-time** at its disposal.

How to characterize learning



Delving back into the Plan of the lecture

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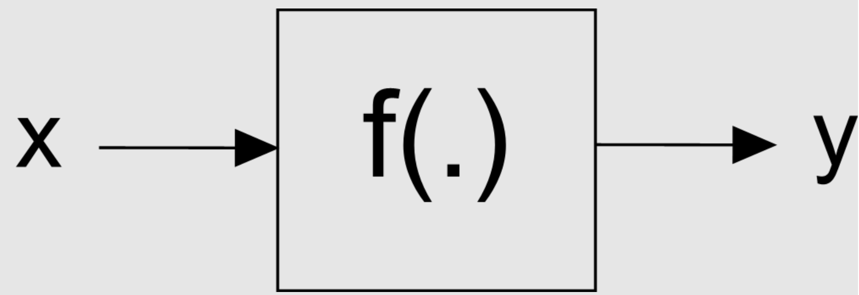
Function learning as a starting point

Most widely used approach:

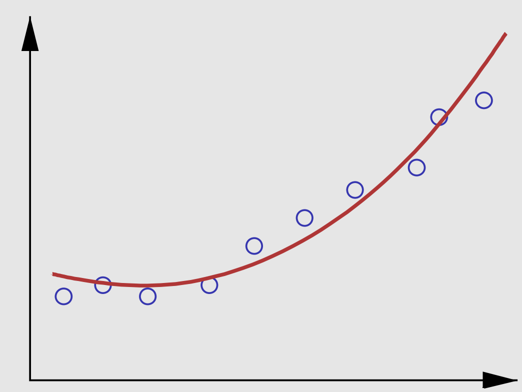
$$y = f(x;\theta)$$

$$\theta = \arg\min_{\theta} \sum_i ||y_i - f(x_i;\theta)||$$

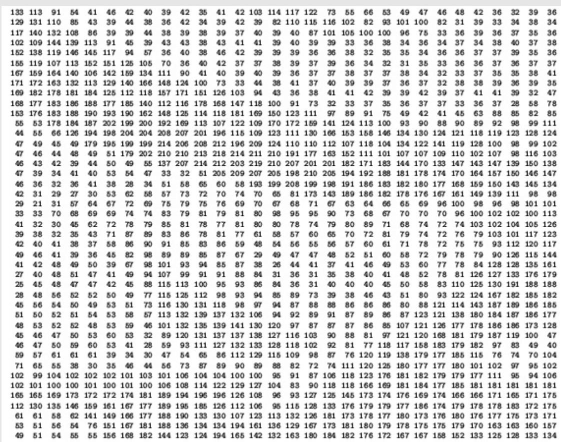


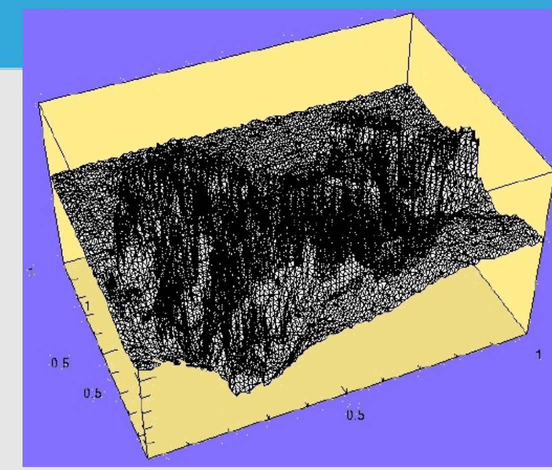
Many implementations for *f(.)*:

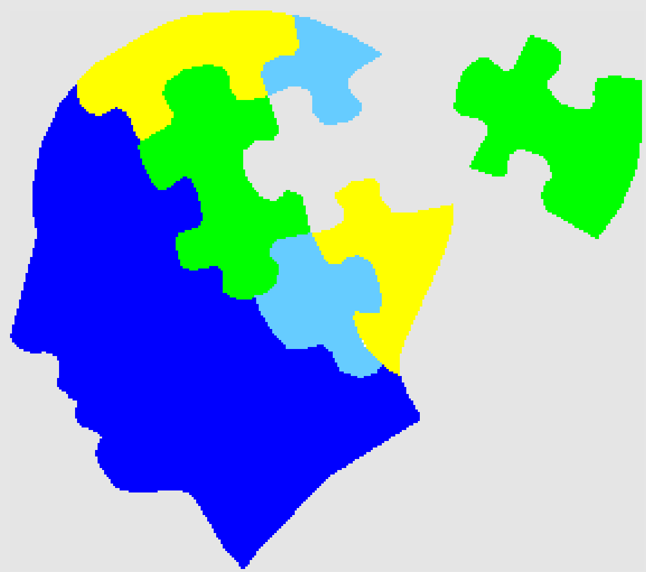
- linear mapping
- superposition of kernels: SVM
- layered neural network
- deep convolution nets
- polynomials
- ...

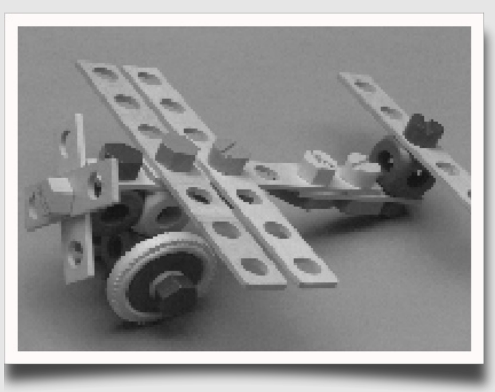


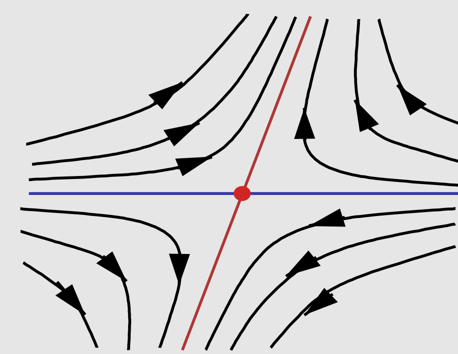
1. Representing Knowledge





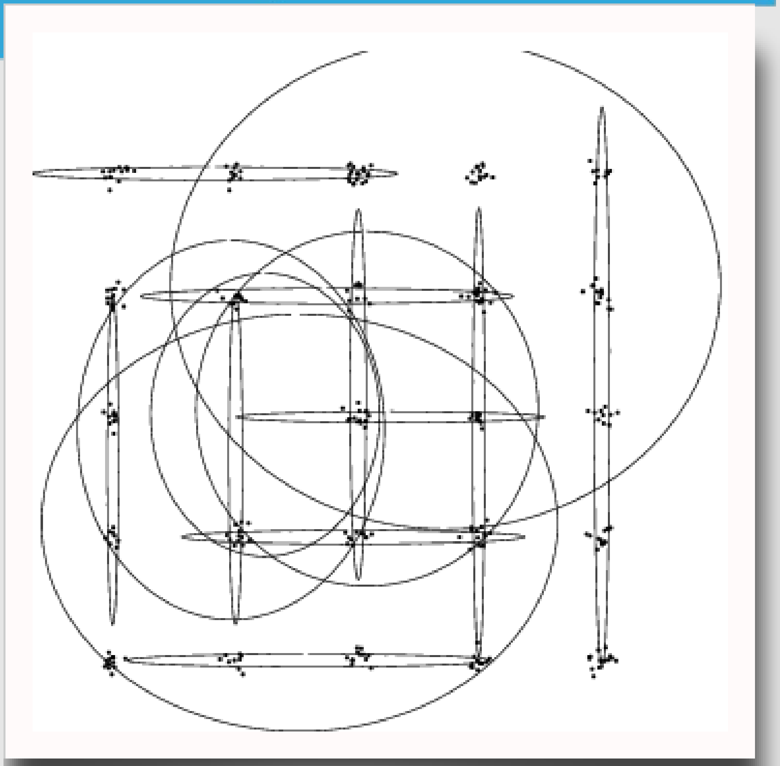


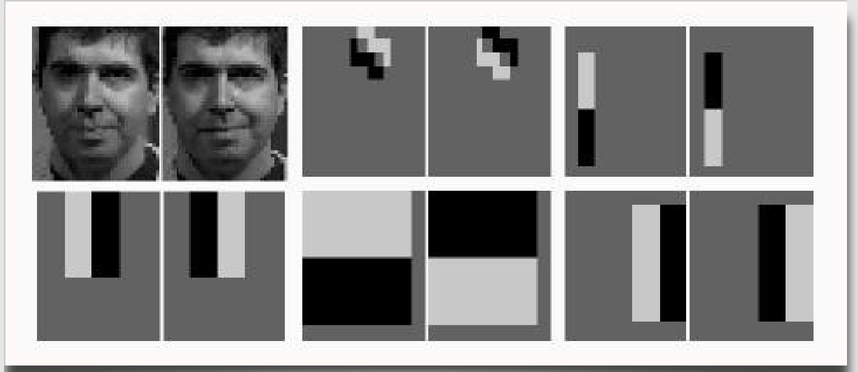




Elements of Representation

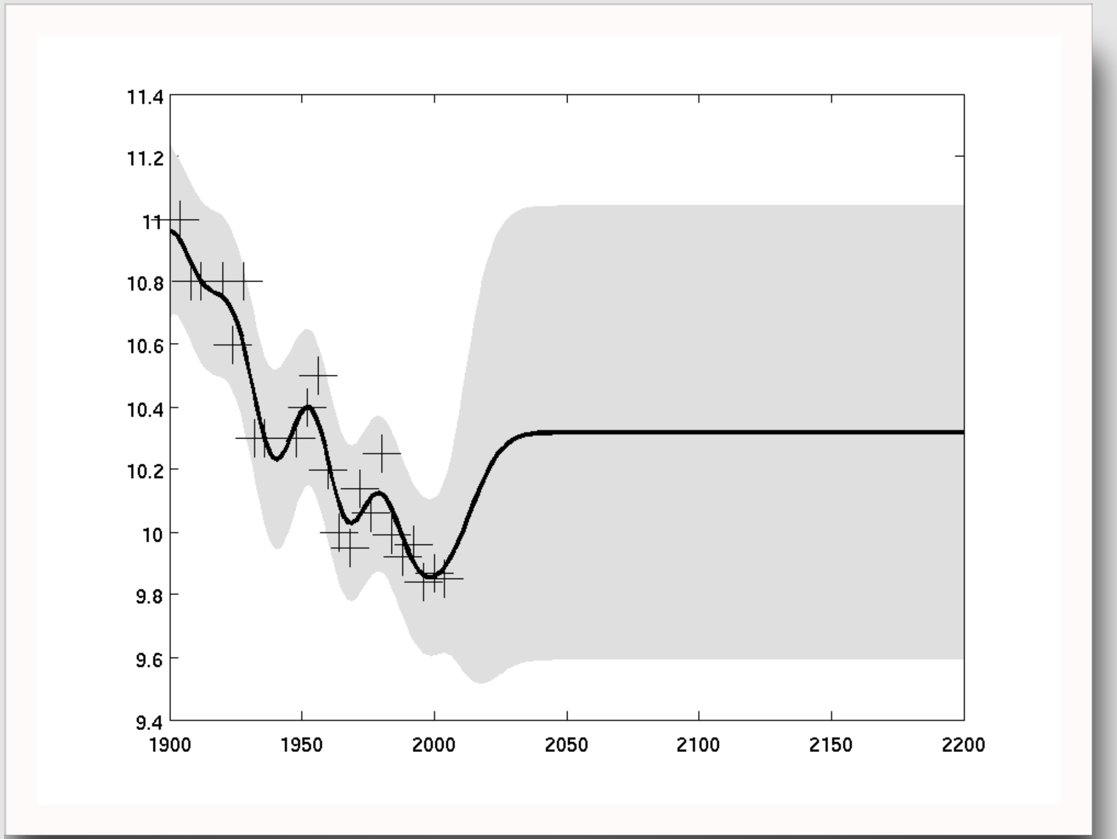
- parameters
- mappings
- dynamical systems
- deterministic vs. stochastic
- probabilities





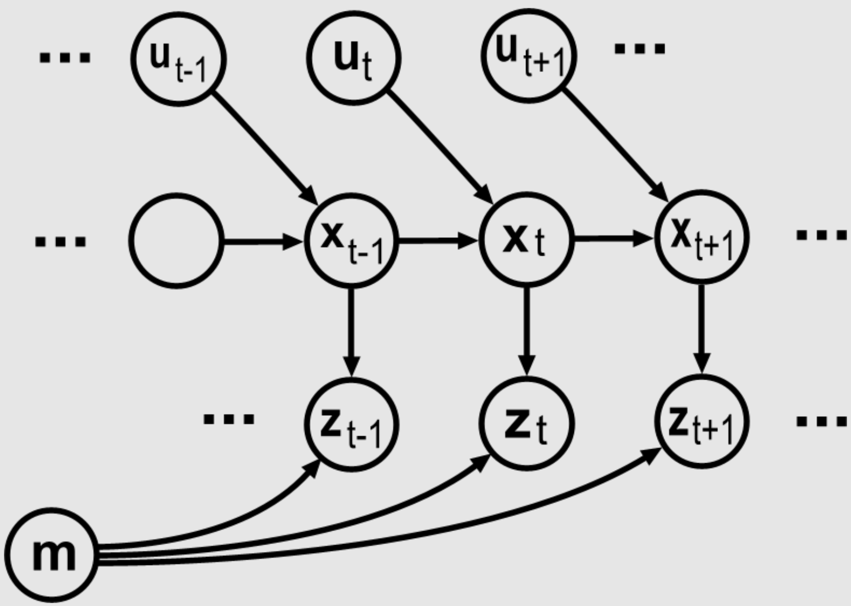
Gaussian Processes

- generalizing normal distributions
- principled priors for regression
- modeling dependencies between variables



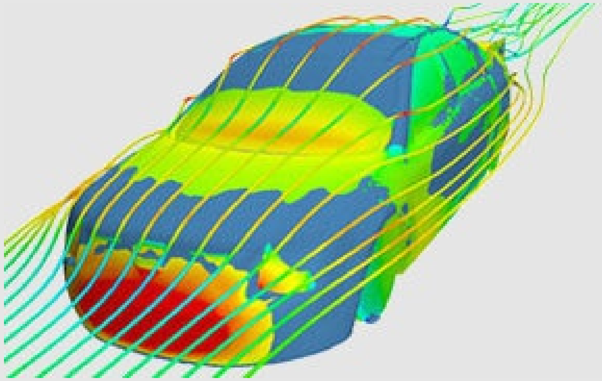
Graphical Models

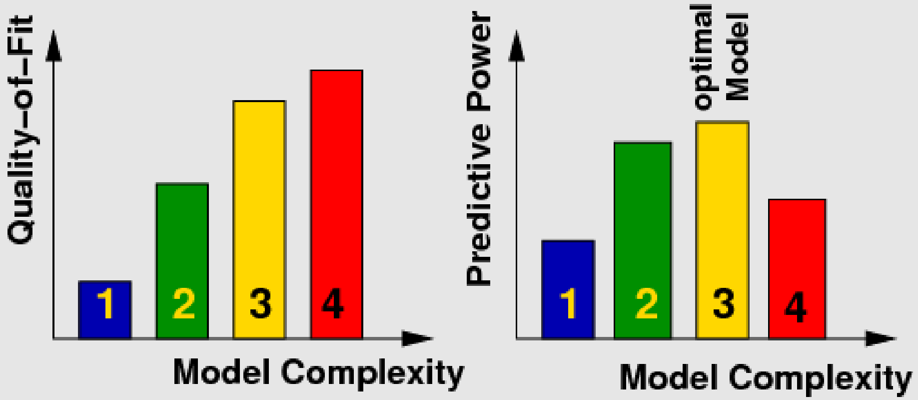
- decomposing probability densities
- expressing causal relationships
- structuring error propagation
- special cases: Boltzman machines



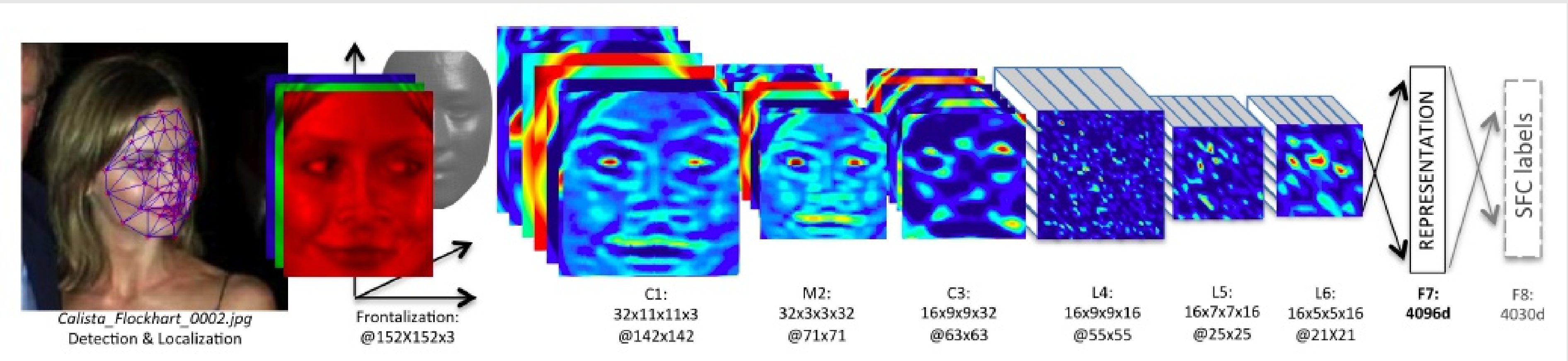
Further Aspects

- the "right" embodiment
- computation vs. physics
- complexity and architecture
- ...





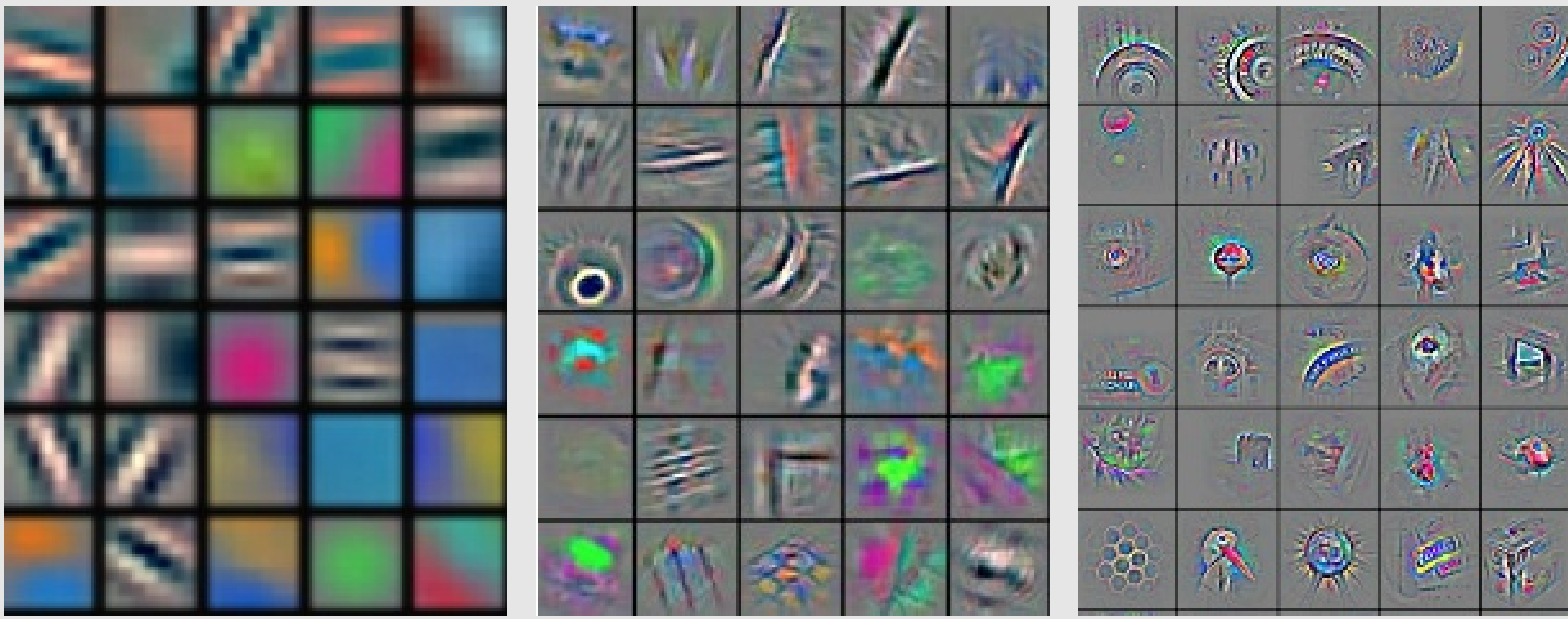
2. Deep Learning



Quelle: DeepFace/Facebook AI Research

- pixel intensities activate artificial neurones
- trainable connections effect in each layer transformation step
- training specialize neurons to increasingly abstract features
- output is classifier result

Example features

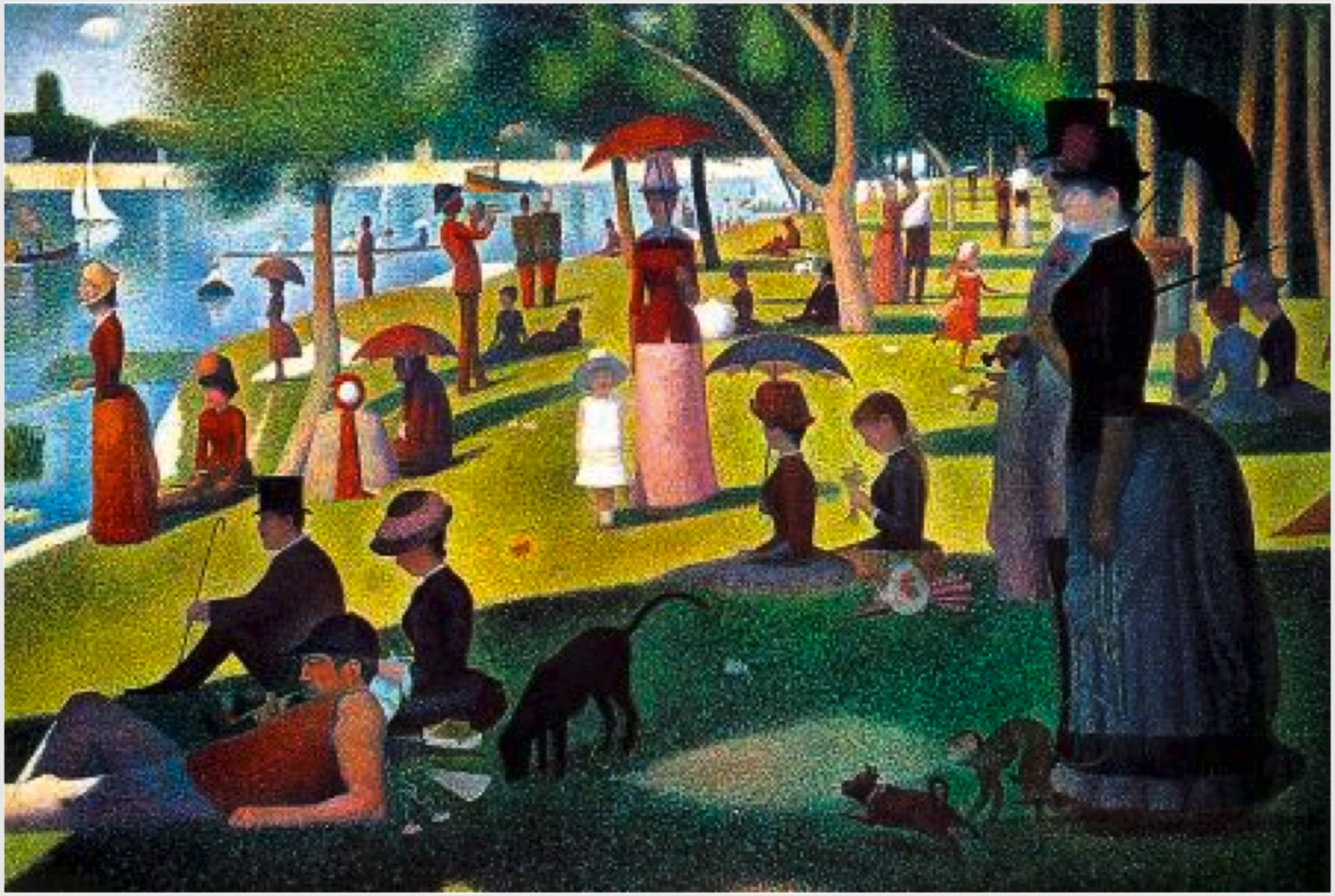


Quelle Y.LeCun/ICML2013

"Deep Network Art"

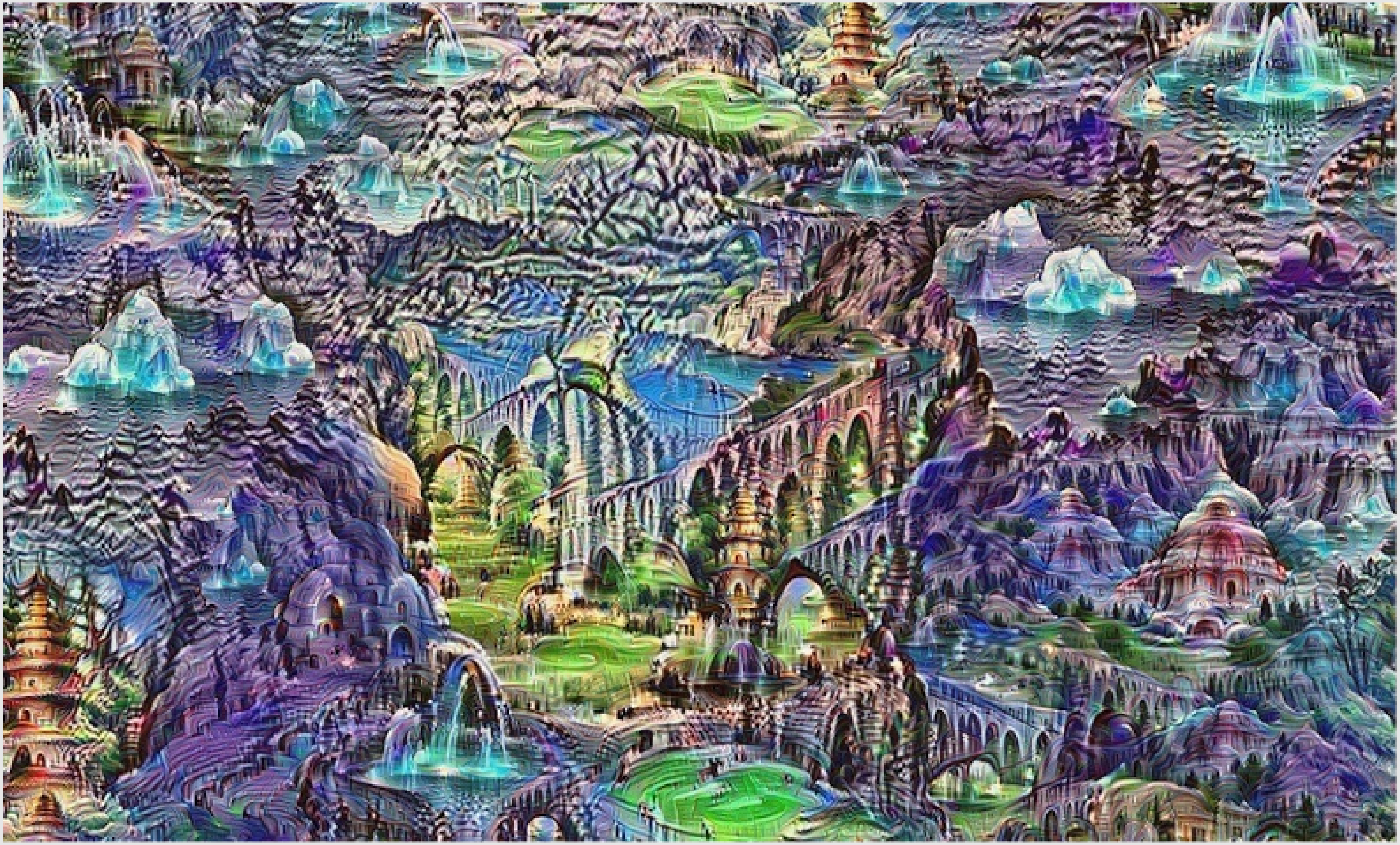
ANN processing by M. McNaughton

"Deep Network Art"



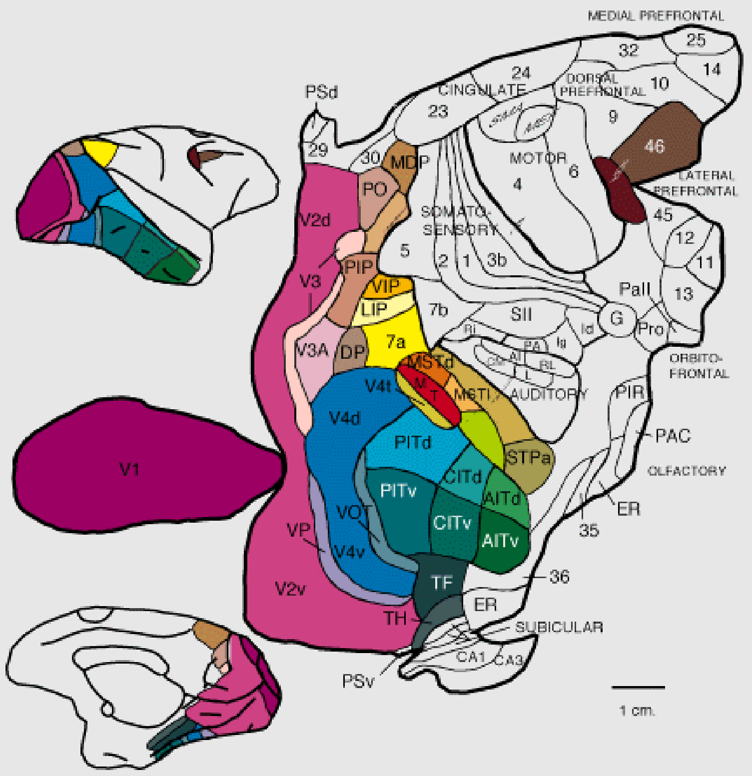
Seurat 1884: Etude pour Un dimanche a la Grande Jatte

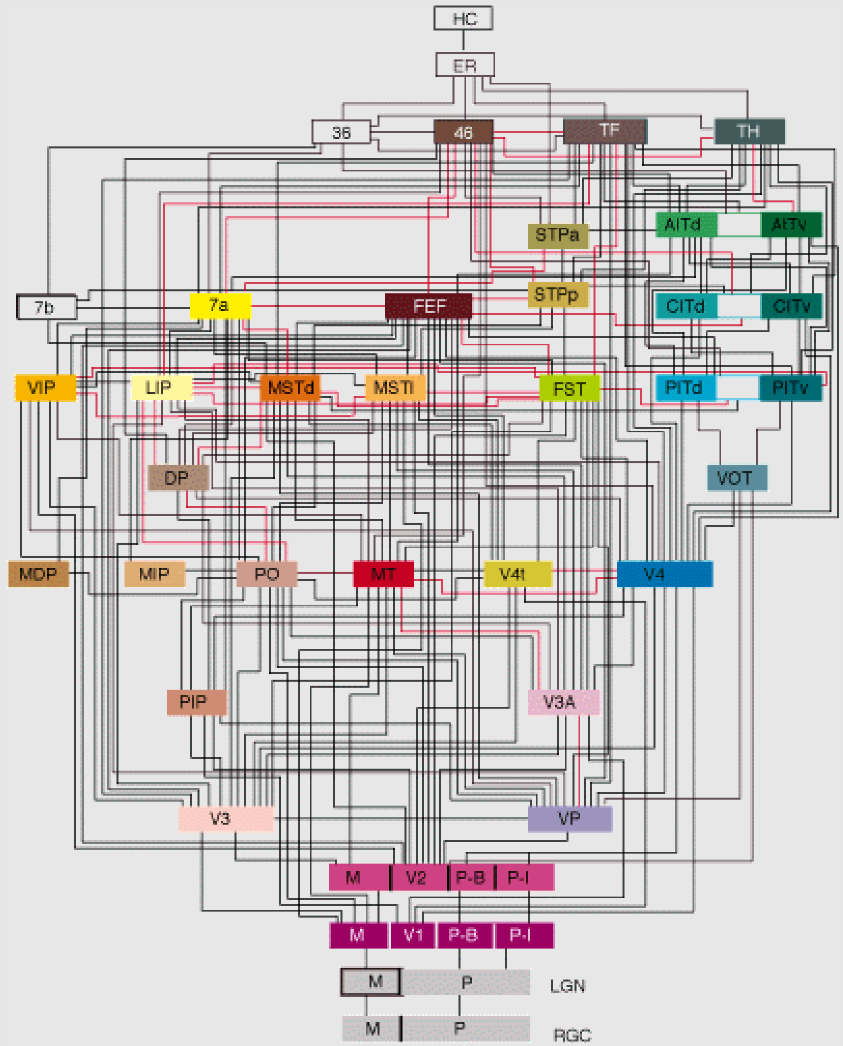
"Inceptionism"



Michael Tyka/inceptionsm gallery

Real world learning systems are even more complicated..





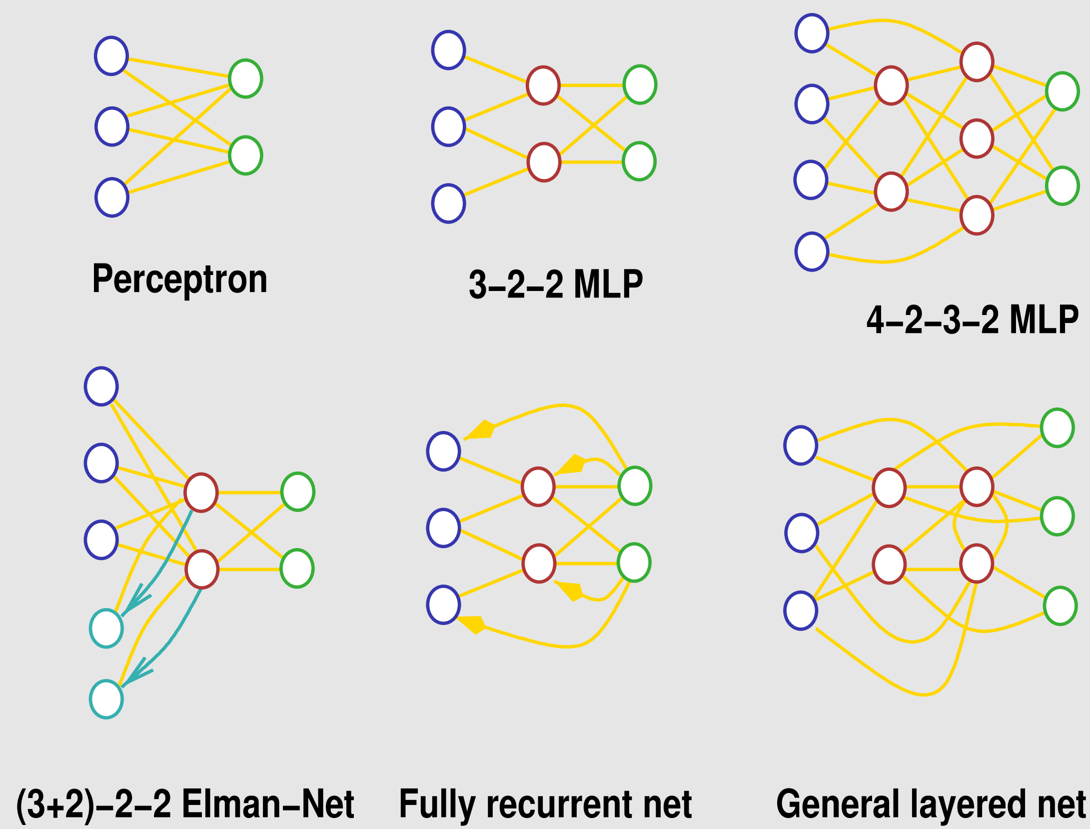
3. How to combine learners?

Different kinds of properties

- size, structure
- complexity of function (linear/nonlinear)
- weak/strong learner

Different kinds of "combination"

- superposition, product,
- competition
- hierarchy, graph

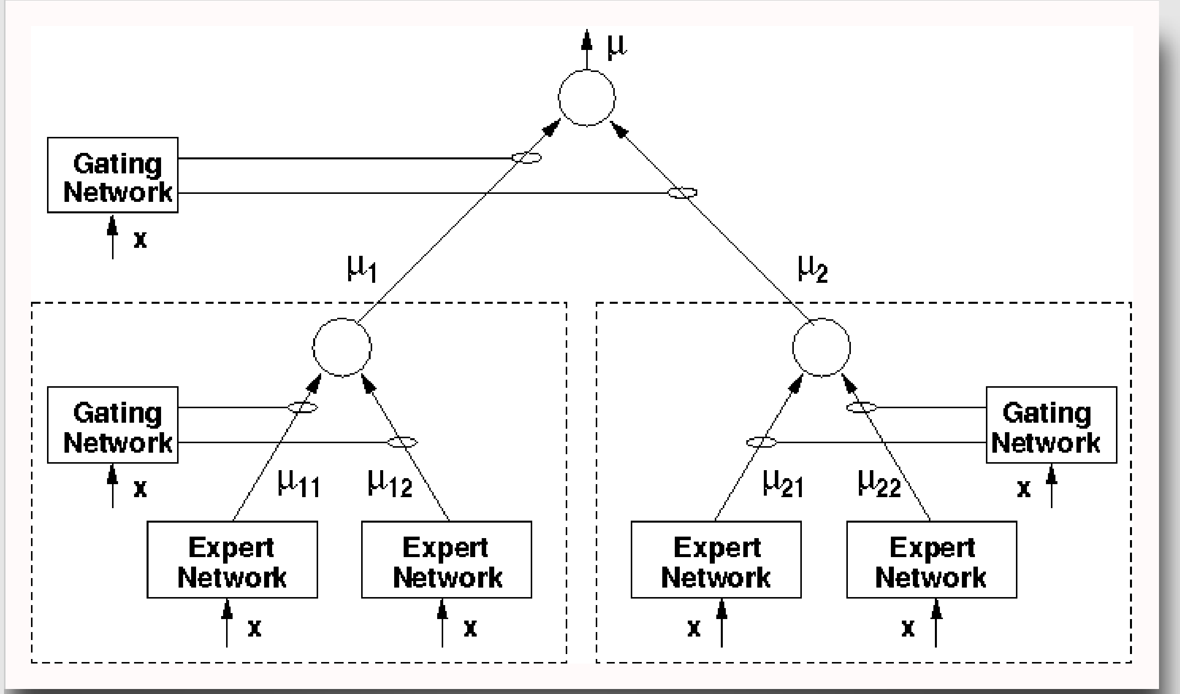


Experts Architecture

Creating flexibility by combining "experts"

$$y = \sum_i w_i(x, \boldsymbol{u}) f_i(x, \boldsymbol{v}_i)$$

$$y = \prod_i f_i(x, \theta_i)$$



AdaBoost

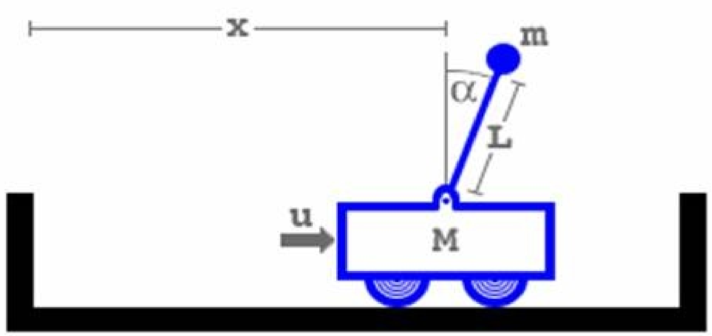
Making a **"strong" learner from many "weak learners"**

$$y = \sum_i w_i H_i(x, \theta_i)$$

Rough idea:

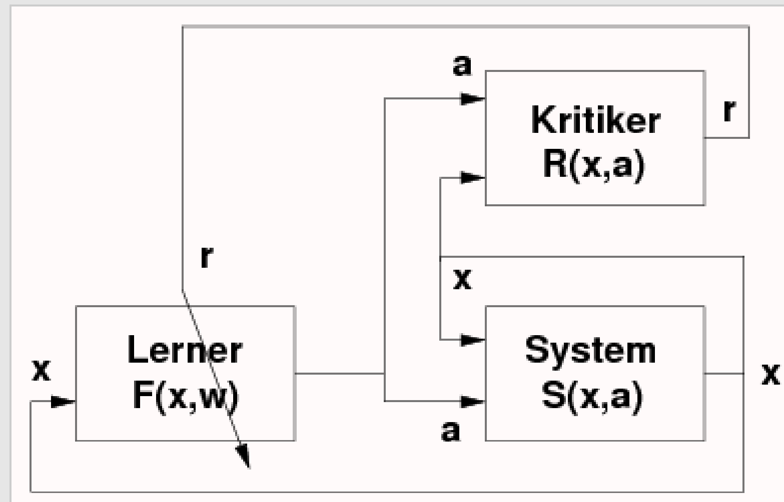
- train sequence of "weak" classifiers on "weighted" training examples
- adapt weights according to misclassifications
- combine many "weak" classifiers into one "strong classifier"

4. Reinforcement Learning



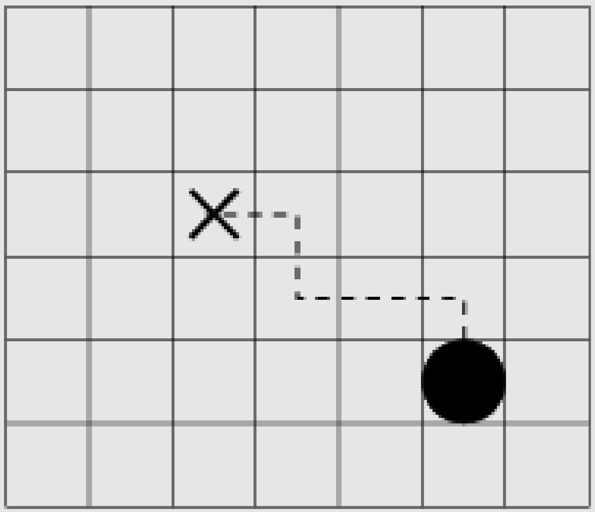
$$\ddot{x} = \frac{u + mL\dot{\alpha}^2\sin\alpha - mg\cos\alpha\sin\alpha}{M + m - m\cos^2\alpha}$$

$$\ddot{\alpha} = \frac{u\cos\alpha - (M+m)g\sin\alpha + mL\dot{\alpha}\cos\alpha\sin\alpha}{mL\cos^2\alpha - (M+m)L}$$



Example: "Learning Bugs"

Learning from Delayed Rewards



γ^4	γ^3	γ^2	γ^3	...		
γ^3	γ^2	γ	γ^2	γ^3	...	
γ^2	γ	**1**	γ	γ^2	γ^3	...
γ^3	γ^2	γ	γ^2	γ^3	γ^4	...
...	γ^3	γ^2	γ^3	γ^4	γ^5	...
	...	γ^3	γ^4	γ^5	...	

Key ideas:

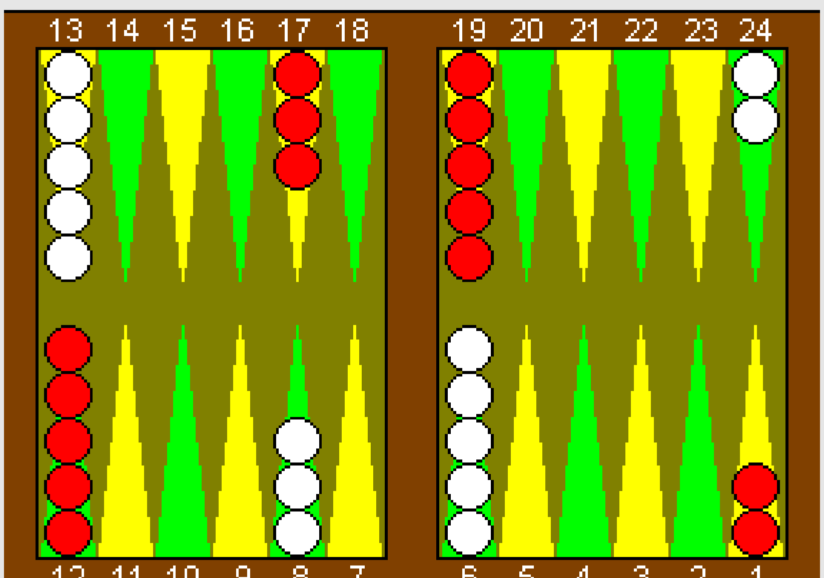
- discounted rewards
- value function

$$V = r_0 + \gamma r_1 + \gamma r_2 \ldots$$

- value propagation

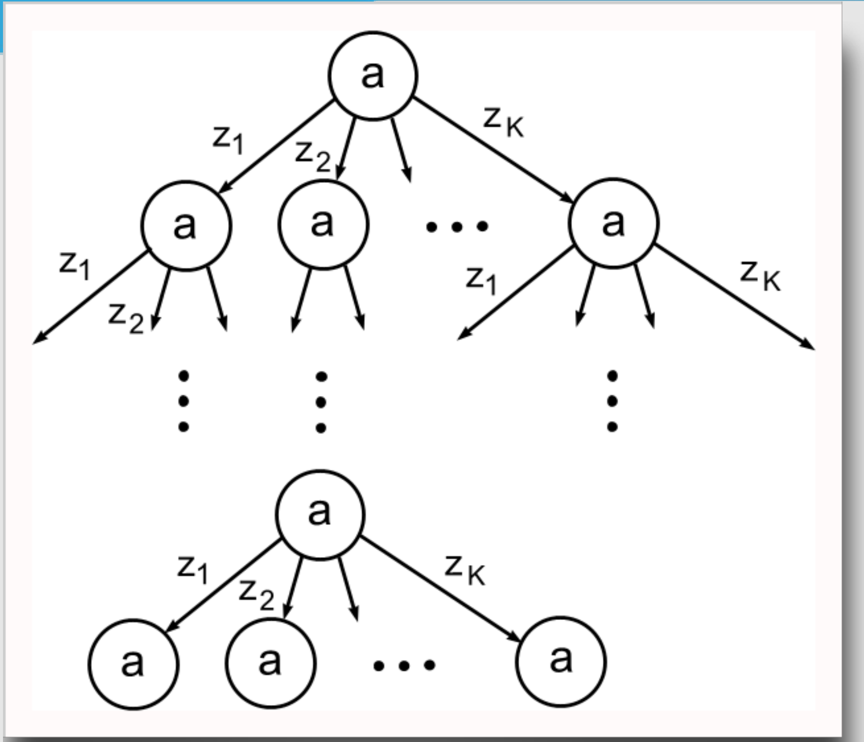
Algorithms

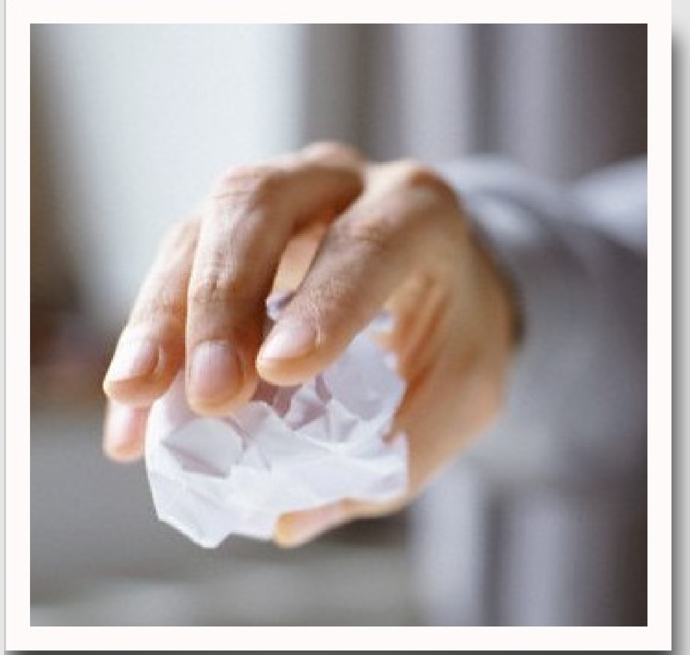
- Iteration approaches
- Q-Learning
- Linearized models
- Path methods



Partial Observability

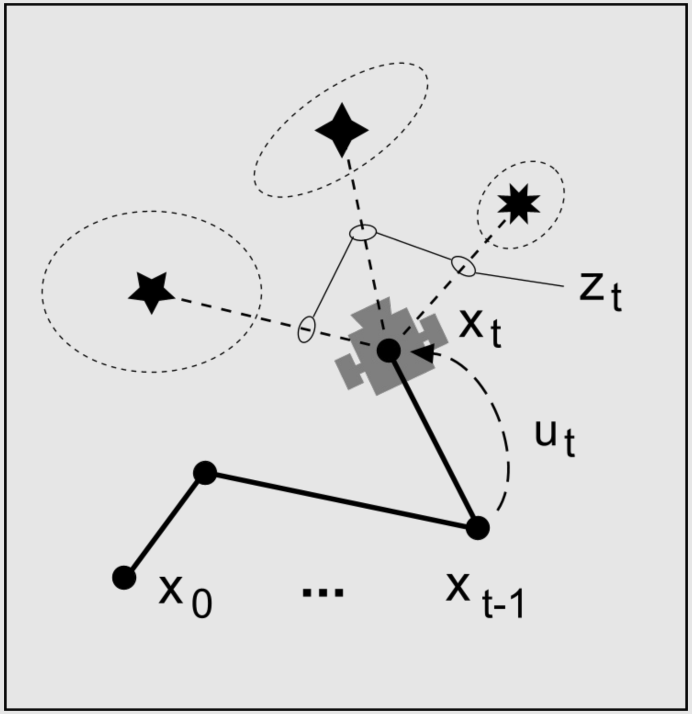
- inaccessible states
- robust control
- POMDP frameworks
- POMDP learning



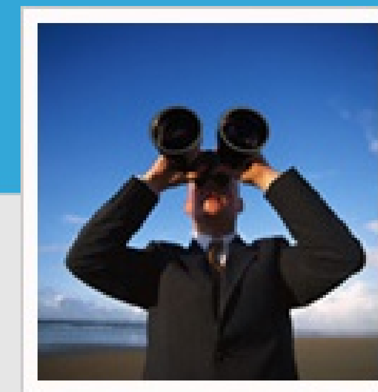


5. Shaping Exploration: Active Learning

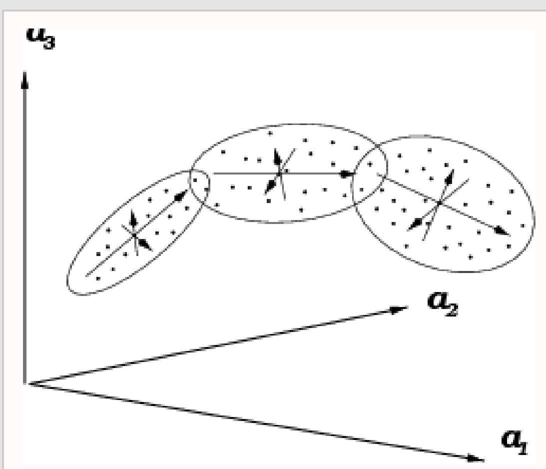
- real world learning depends on exploration
- selection of data points
- which data points are most useful?
- which data points are expensive?
- exploration of data points vs. exploration of actions
- mapping vs. control

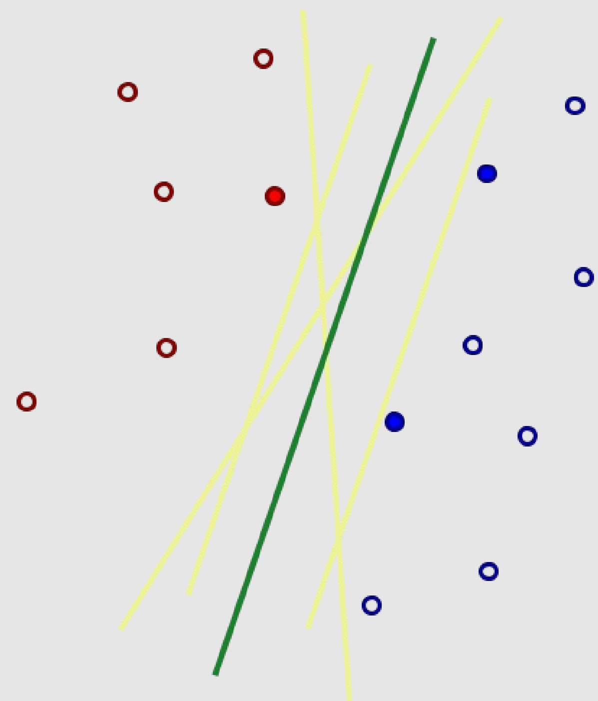


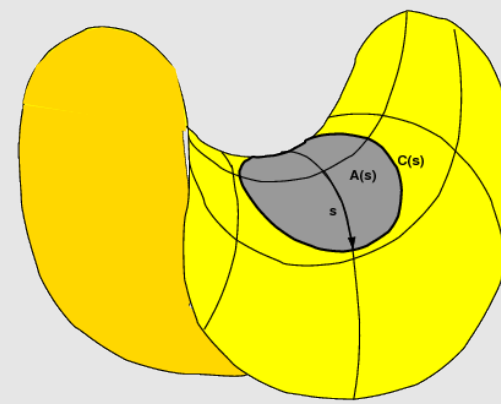
How to obtain data cheaply



- adding noise
- which variance to create?
- generating distortions
- label propagation





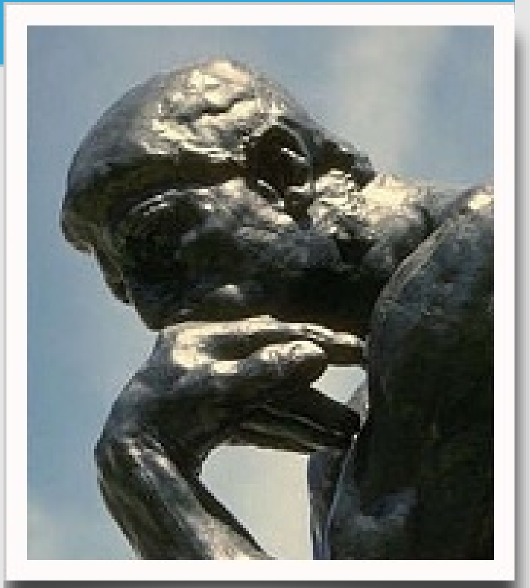


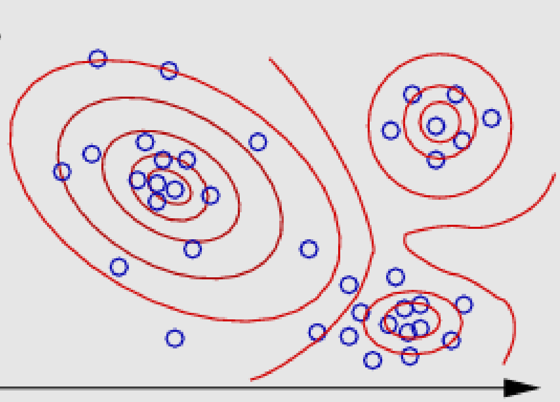
Information Maximization

- using information theory

$$S = -\sum_i P(x_i) log P(x_i)$$

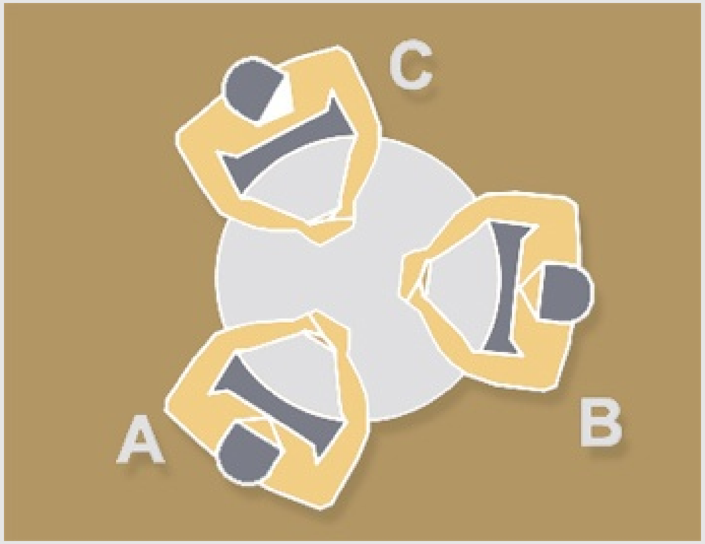
- sensitivity analysis
- using internal simulations
- model based sampling



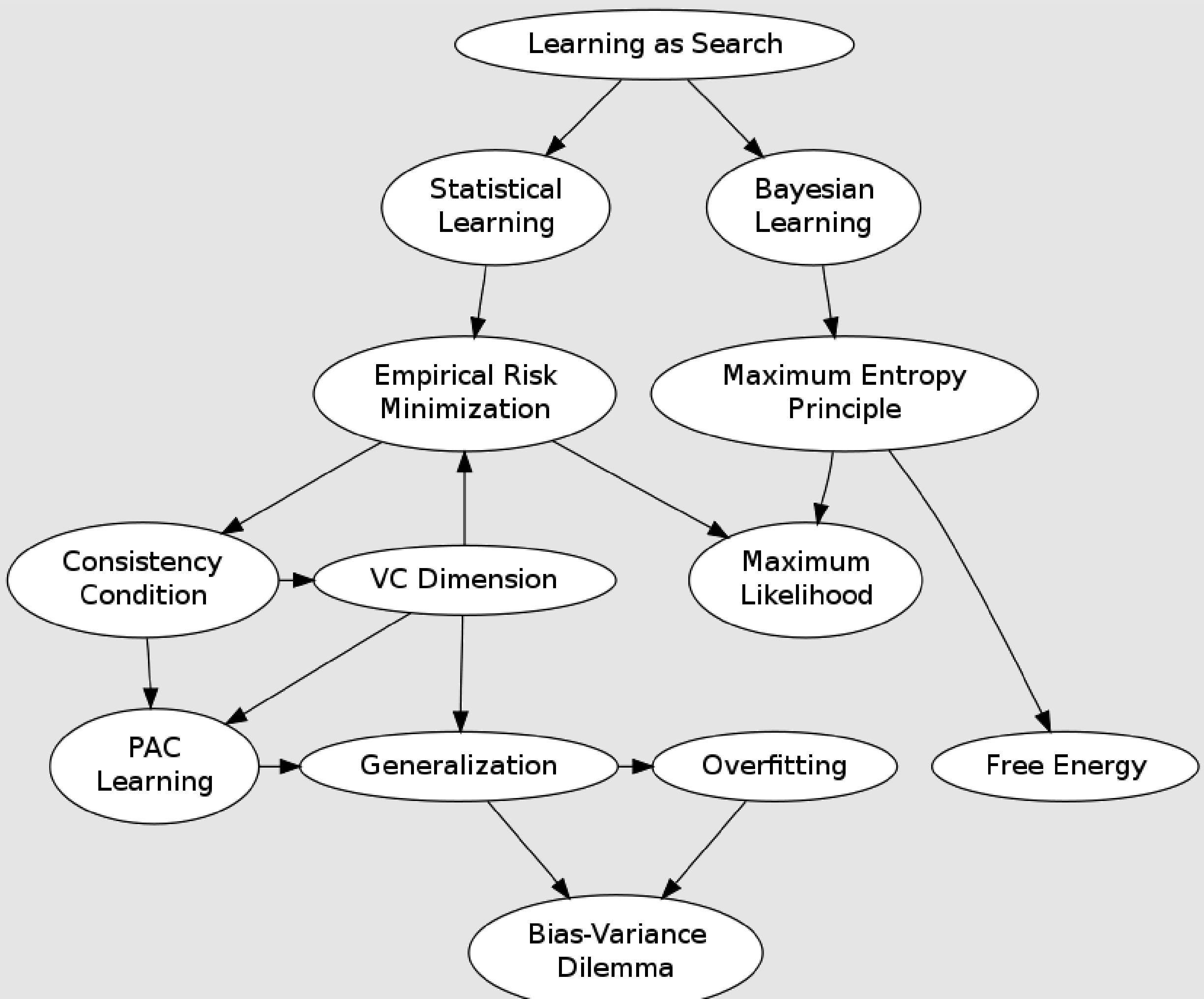


Query by Committee

- identifying "optimal questions"
- maximizing uncertainty
- keeping the committee "interesting"



6. Theory Frameworks



Major Perspective

How can we describe (statistical) learning?

$$E(\theta) = \sum_i E_i(\boldsymbol{z}_i, ; \theta)$$

$$E(\theta) = \int_x E_i(\boldsymbol{z}; \theta) P(\boldsymbol{z}) d\boldsymbol{z}$$

Learning as

- Parameter Identification
- as Likelihood Maximization
- as Risk Minimization
- as Bayesian Inference
- connected with physics principles