Programmation: l'ère des spécifications, l'ère de l'apprentissage, l'ère du feedback

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TAO

AFIA – AFIHM, 2015

Revisiting the art of programming

1970s Specifications — Languages & thm proving

1990s Programming by Examples — Pattern recognition & ML

2010s Interactive Learning and Optimization

- Optimizing coffee taste — Herdy, 96
- Visual rendering — Brochu et al., 10
- Choice query — Viappiani et al., 10
- Information retrieval — Joachims et al., 12
- Robotics

  Akrour et al., 12; Wilson et al., 12; Knox et al. 13; Saxena et al 13

Programming with the Human in the Loop

Interaction, Learning, Optimization

Centennial + 3

Turing 1950

Computing Machinery and Intelligence

... the problem is mainly one of programming.

brain estimates: 10^{10} *to* 10^{15} *bits*

Fruit Fly	10^5
Cockroach	10^6
Cat	10^9
Chimpanzee	$7\ 10^9$
Elephant	$23\ 10^9$
Human	$89\ 10^9$

I can produce about a thousand digits of program lines a day

[Therefore] *more expenditious method seems desirable.*

$\Rightarrow$ Machine Learning

Overview

Preamble

Machine Learning: All you need is...

- ...logic
- ...data
- ...optimization

All you need is expert's feedback

- Reinforcement learning
- Programming by Feedback

Programming, An AI Frontier

ML: All you need is logic

Perception $\rightarrow$ Symbols $\rightarrow$ Reasoning $\rightarrow$ Symbols $\rightarrow$ Actions

Let's forget about perception and actions for a while...

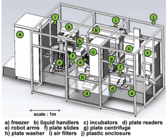
Symbols $\rightarrow$ Reasoning $\rightarrow$ Symbols

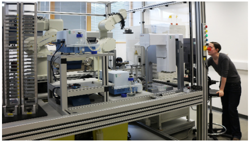
Requisite

- Strong representation
- Strong background knowledge
- Strong optimization tool

The Robot Scientist

King et al, 04, 11





Adam: generate hypotheses from background knowledge and experimental data, design experiments to confirm/infirm hypotheses
Eve: drug screening, hit conformation, and cycles of QSAR hypothesis learning and testing.

ML: The logic era

So efficient

- Search: Reuse constraint solving, graph pruning,..

Requirement / Limitations

- Initial conditions: critical mass of high-order knowledge
- ... and unified search space
- Symbol grounding, noise

Of primary value: intelligibility

- (A means: for debugging)
- An end: to keep the expert involved.

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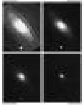
All you needed was data

Ast. series 

Pierre de Rosette 

World

Natural phenomenons

Human–related phenomenons

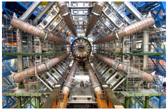
Data / Principles

Maths. Modelling

Common Sense

You are here

All you need is big data

Sc. data 

World

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Big data

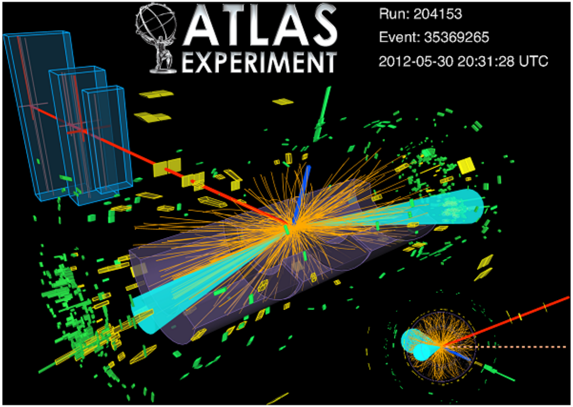
IBM Watson defeats human champions at the quiz game Jeopardy

i	1	2	3	4	5	6	7	8	
1000^i	kilo	mega	giga	tera	peta	exa	zetta	yotta	bytes

- Google: 24 petabytes/day
- Facebook: 10 terabytes/day; Twitter: 7 terabytes/day
- Large Hadron Collider: 40 terabytes/seconds

The Higgs boson ML Challenge

Balazs Kégl, Cécile Germain et al.



https://www.kaggle.com/c/higgs-boson September 2014, 15th

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ML: All you need is optimization

Old times

- Find the best hypothesis
- Find the best optimization criterion
  - statistically sound
  - a well-posed optimization problem
  - tractable

SVMs and Deep Learning

Episode 1

- NNs are universal approximators,...
- ... but their training yields non-convex optimization problems
- ... and some cannot reproduce the results of some others...

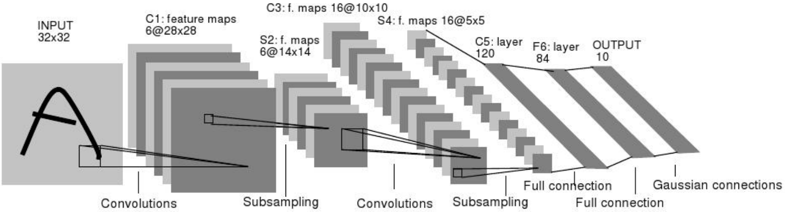


Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

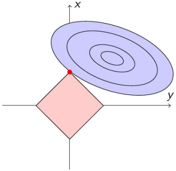
SVMs and Deep Learning

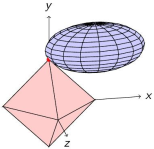
Episode 2

- At last, SVMs arrive ! Vapnik 92; Cortes &Vapnik 95
- Principle
  - Min $||h||^2$
  - subject to Constraint on $h(x)$

$$h(x_i).y_i > 1,\ |h(x_i) - y_i| < \epsilon,\ h(x_i) < h(x_i'),\ h(x_i) > 1...$$

- Convex optimization ! (well, except for hyper-parameters)
- More sophisticated optimization (alternate, upper bounds)...





Hastie 04; Bach 04; Srebro 11; ...

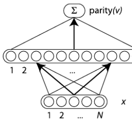
SVMs and Deep Learning

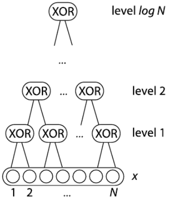
Episode 3

- Did you forget our AI goal ?
  (learning $\leftrightarrow$ learning representation)
- At last Deep learning arrives !

Principle

- We always knew that many-layered NNs offered compact representations Hasted 87





SVMs and Deep Learning

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SVMs and Deep Learning

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Principle

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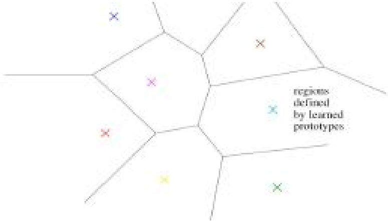
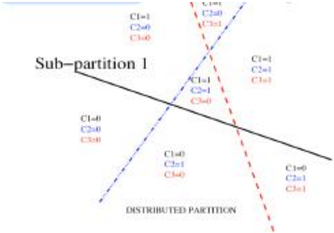
- But, so many local optima ! (poor optima)
- Breakthrough: unsupervised layer-wise learning
  Hinton 06; Bengio 06

SVMs and Deep Learning

From prototypes to features

- n prototypes $\rightarrow$ n regions
- n features $\rightarrow$ 2^n regions





SVMs and Deep Learning

Last Deep news

- Supervised training works, after all — Glorot Bengio 10
- Does not need to be deep, after all — Ciresan et al. 13, Caruana 13

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- Does not need to be deep, after all — Ciresan et al. 13, Caruana 13
  - Ciresan et al: use prior knowledge (non linear invariance operators) to generate new examples
  - Caruana: use deep NN to label hosts of examples; use them to train a shallow NN.

SVMs and Deep Learning

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Take home message

- It works
- But why ?
- Intelligibility ?

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Programming, An AI Frontier

Interactive optimization

Optimizing the coffee taste

Herdy et al., 96

Black box optimization:

$$\mathcal{F} : \Omega \rightarrow \mathbb{R} \qquad \text{Find arg max } \mathcal{F}$$

The user in the loop replaces $\mathcal{F}$

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Optimizing visual rendering — Brochu et al., 07

Optimal recommendation sets — Viappiani & Boutilier, 10

Information retrieval — Shivaswamy & Joachims, 12

Interactive optimization

Features

- Search space $X \subset \mathbb{R}^d$ (recipe x: 33% arabica, 25% robusta, etc)
- A non-computable objective
- Expert can (by tasting) emit preferences $x \prec x'$.

Scheme

1. Alg. generates candidates $x, x', x``, ..$
2. Expert emits preferences
3. goto 1.

Issues

- Asking as few questions as possible $\neq$ active ranking
- Modelling the expert's taste surrogate model
- Enforce the exploration vs exploitation trade-off

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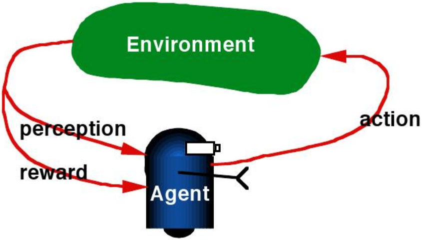
Reinforcement Learning



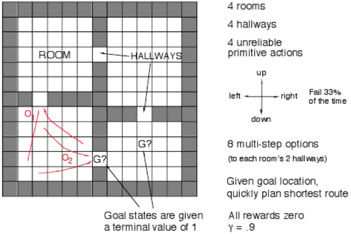
Generalities

- An agent, spatially and temporally situated
- Stochastic and uncertain environment
- Goal: select an action in each time step,
- ... in order maximize expected cumulative reward over a time horizon

What is learned ?

$$\text{A policy} = \text{strategy} = \{\ \text{state} \mapsto \text{action}\ \}$$

Reinforcement Learning, formal background



Notations

- State space $\mathcal{S}$
- Action space $\mathcal{A}$
- Transition $p(s, a, s') \mapsto [0, 1]$
- Reward $r(s)$
- Discount $0 < \gamma < 1$

Goal: a policy π mapping states onto actions

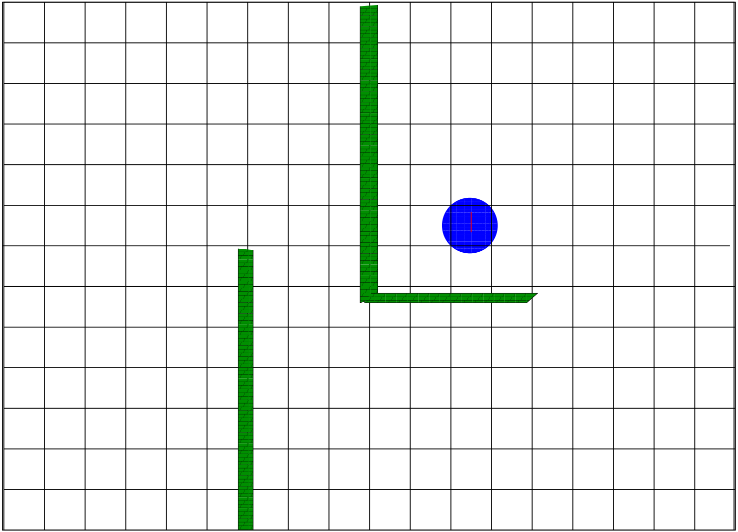
$$\pi : \mathcal{S} \mapsto \mathcal{A}$$

s.t.

$$\begin{aligned} \text{Maximize } E[\pi|s_0] &= \text{Expected discounted cumulative reward} \\ &= r(s_0) + \sum_t \gamma^{t+1}\; p(s_t, a = \pi(s_t), s_{t+1}) r(s_{t+1}) \end{aligned}$$

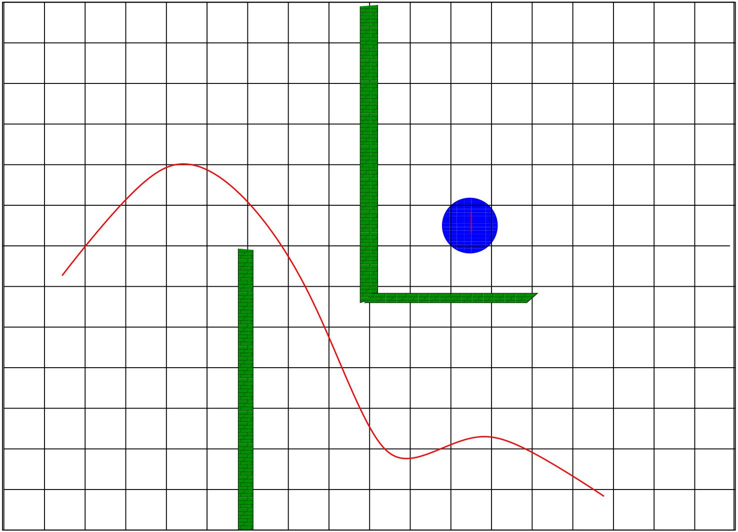
Find the treasure

Single reward: on the treasure.

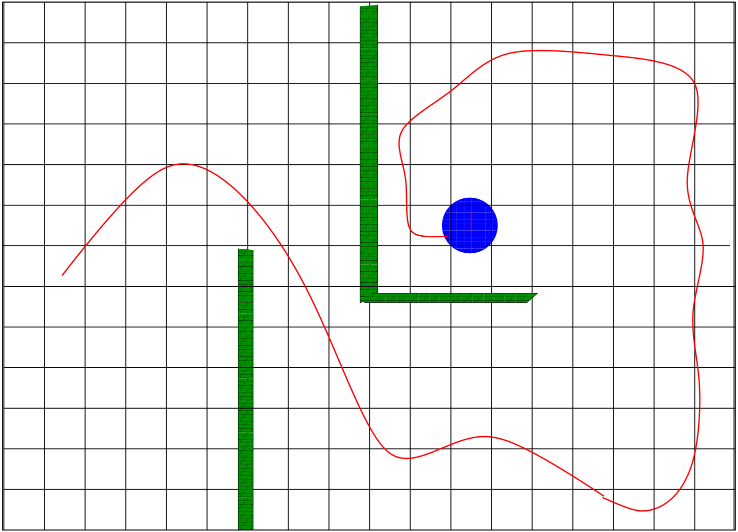


Wandering robot

Nothing happens...

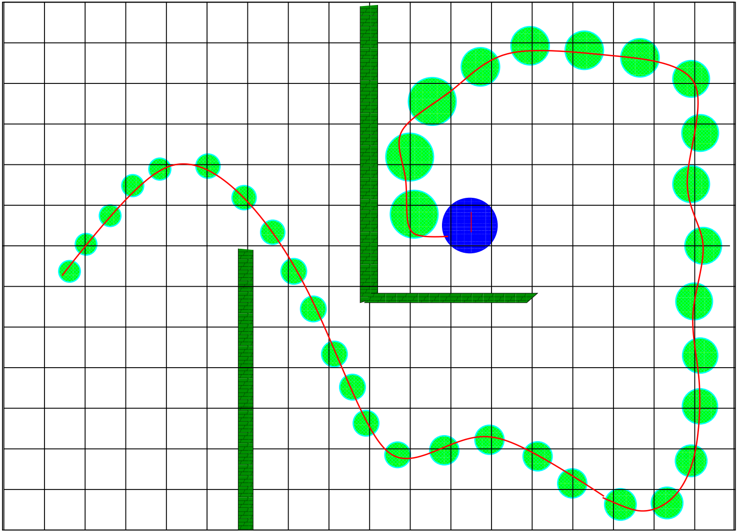


The robot finds it



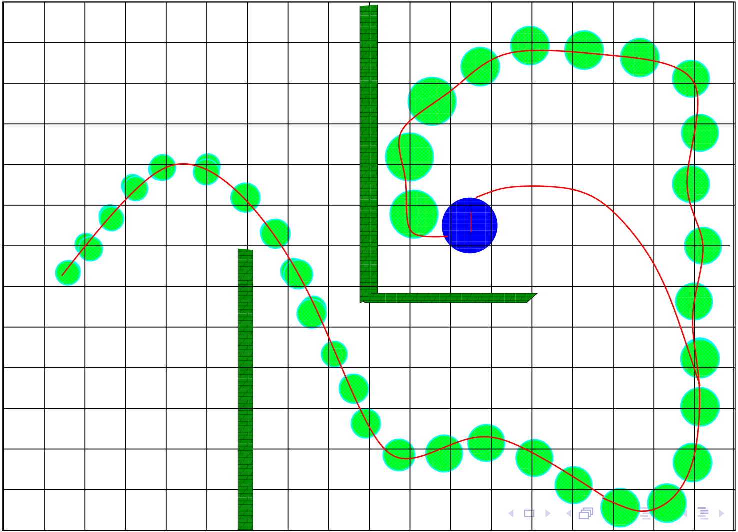
Robot updates its value function

$V(s,a) ==$ “distance“ to the treasure *on the trajectory*.



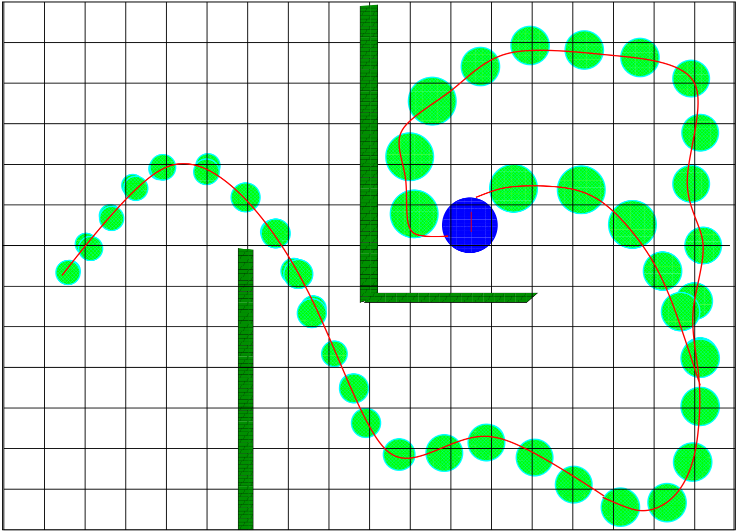
Reinforcement learning

* Robot most often selects $a = \arg\max V(s, a)$
* and sometimes explores (selects another action).
* Lucky exploration: finds the treasure again



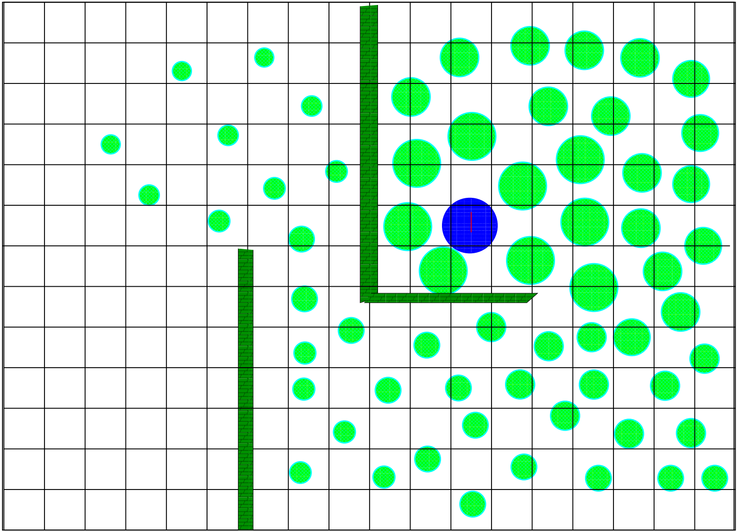
Updates the value function

* Value function tells how far you are from the treasure *given the known trajectories*.



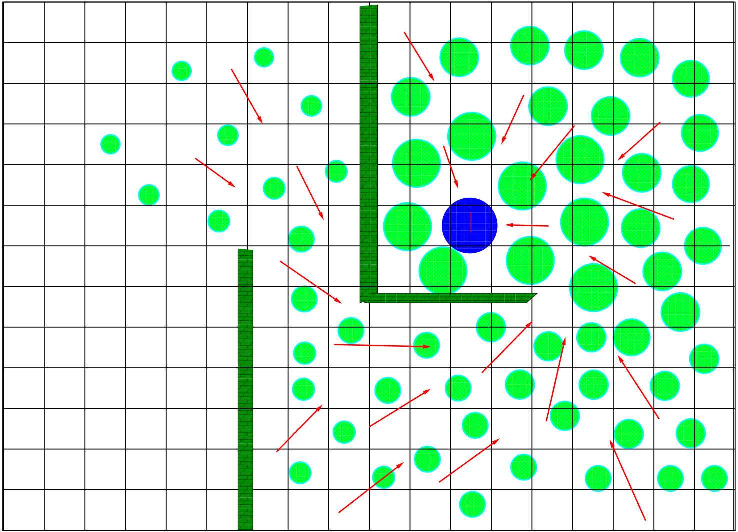
Finally

* Value function tells how far you are from the treasure



Finally

Let's be greedy: selects the action maximizing the value function



Reinforcement learning

Three tasks

- Learn values
- Learn transition model
- Explore

Issues

- Exploration / Exploitation dilemma
- Representation, approximation, scaling up
- REWARDS designer's duty

Relaxing Expertise Requirements


Relaxing Expertise Requirements in RL

Expert

▶ Associates a reward to each state	RL	Ex-per-tise ↘
▶ Demonstrates a (nearly) optimal behavior	Inverse RL	
▶ Compares and revises agent demonstrations	Co-active PL	
▶ Compares demonstrations	Preference PL, PF	

Agent

▶ Computes optimal policy based on rewards	RL	Au-ton-omy ↗
▶ Imitates verbatim expert's demonstration	IRL	
▶ Imitates and modifies	IRL	
▶ Learns the expert's utility	IRL, CPL	
▶ Learns, and selects demonstrations	CPL, PPL, PF	
▶ Accounts for the expert's mistakes	PF	

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Programming, An AI Frontier

Programming by feedback

Akrour &al. 14

Loop

1. Computer presents the expert with a pair of behaviors y_1, y_2
2. Expert emits preferences $y_1 \succ y_2$
3. Computer learns expert's utility function $\langle w, y \rangle$
4. Computer searches for behaviors with best utility

Critical issues

- Asks few questions
- Be robust wrt noise (expert makes mistakes & changes his mind)

Programming by Feedback

Ingredients

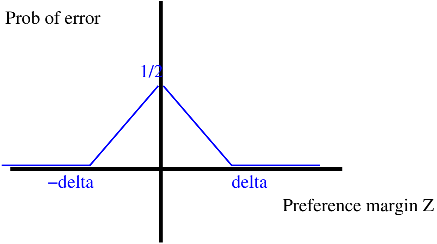
- Modelling the expert's competence
- Learning the expert's utility
- Selecting the next best behaviors
  - Which optimization criterion
  - How to optimize it

Modelling the expert's competence

Noise model $\delta \sim U[0, M]$

Given preference margin $z = \langle \mathbf{w}^*, \mathrm{y} - \mathrm{y}' \rangle$

$$P(\mathrm{y} \prec \mathrm{y}' \mid \mathbf{w}^*, \delta) = \begin{cases} 0 & \text{if } z < -\delta \\ 1 & \text{if } z > \delta \\ \frac{1+z}{2} & \text{otherwise} \end{cases}$$



Experimental validation

- Sensitivity to expert competence
  Simulated expert, grid world
- Continuous case, no generative model
  The cartpole
- Continuous case, generative model
  The bicycle
- Training in-situ
  The Nao robot

Sensitivity to (simulated) expert incompetence

Grid world: discrete case, no generative model

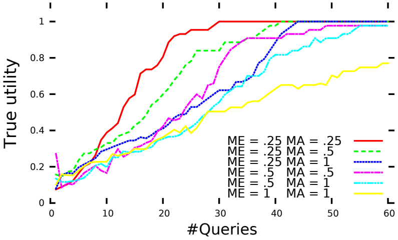
25 states, 5 actions, horizon 300, 50% transition noise

M_E	Expert incompetence
$M_A > M_E$	Computer estimate of expert's incompetence

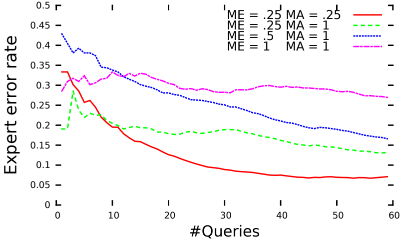
	$\cdots$	1/4	1/2	1
			1/4	1/2
1/64				1/4
1/128	1/64			$\vdots$
1/256	1/128	1/64		

True $\mathbf{w}^*$ on gridworld

Sensitivity to simulated expert incompetence, 2



True utility of $\mathbf{x}_t$



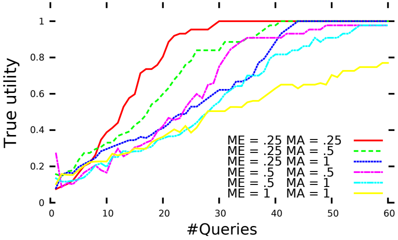
expert's mistakes

Two notions

- The true human's competence
- The learner's confidence in the human competence

What is best: trusting a (mildly) competent human, or (mildly) distrusting a competent human ?

Sensitivity to simulated expert incompetence, 3



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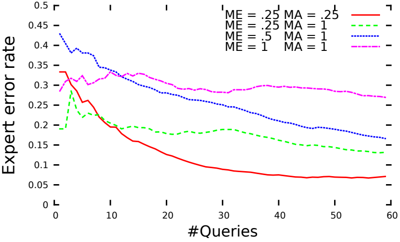

expert's mistakes

A cumulative (dis)advantage phenomenon:

The number of expert's mistakes *increases* as the computer underestimates the expert's competence.

For low M_A, the computer learns faster, submits more relevant demonstrations to the expert, thus priming a virtuous educational process.

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Conclusion

Feasibility of Programming by Feedback for simple tasks

Back on track:

One could carry through the organization of an intelligent machine with only two interfering inputs, one for pleasure or reward, and the other for pain or punishment.

Programming by Feedback

About interaction: as designer; as user

- No need to debug if you can just say: No !
  and the computer reacts (appropriately).

- I had a dream: a world where I don't need to read the fucking manual...

Future: Tackling the Under-Specified

Knowledge-constrained

Computation, memory-constrained

Acknowledgments

Riad Akrour
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Related

- Percy Liang, Michael I. Jordan, and Dan Klein, Learning programs: A hierarchical bayesian approach, in ICML 10.
- Sumit Gulwani, Automating string processing in spreadsheets using input-output examples, ACM SIGPLAN Notices 2011
- Dianhuan Lin& al., Bias reformulation for one-shot function induction, ECAI 2014.