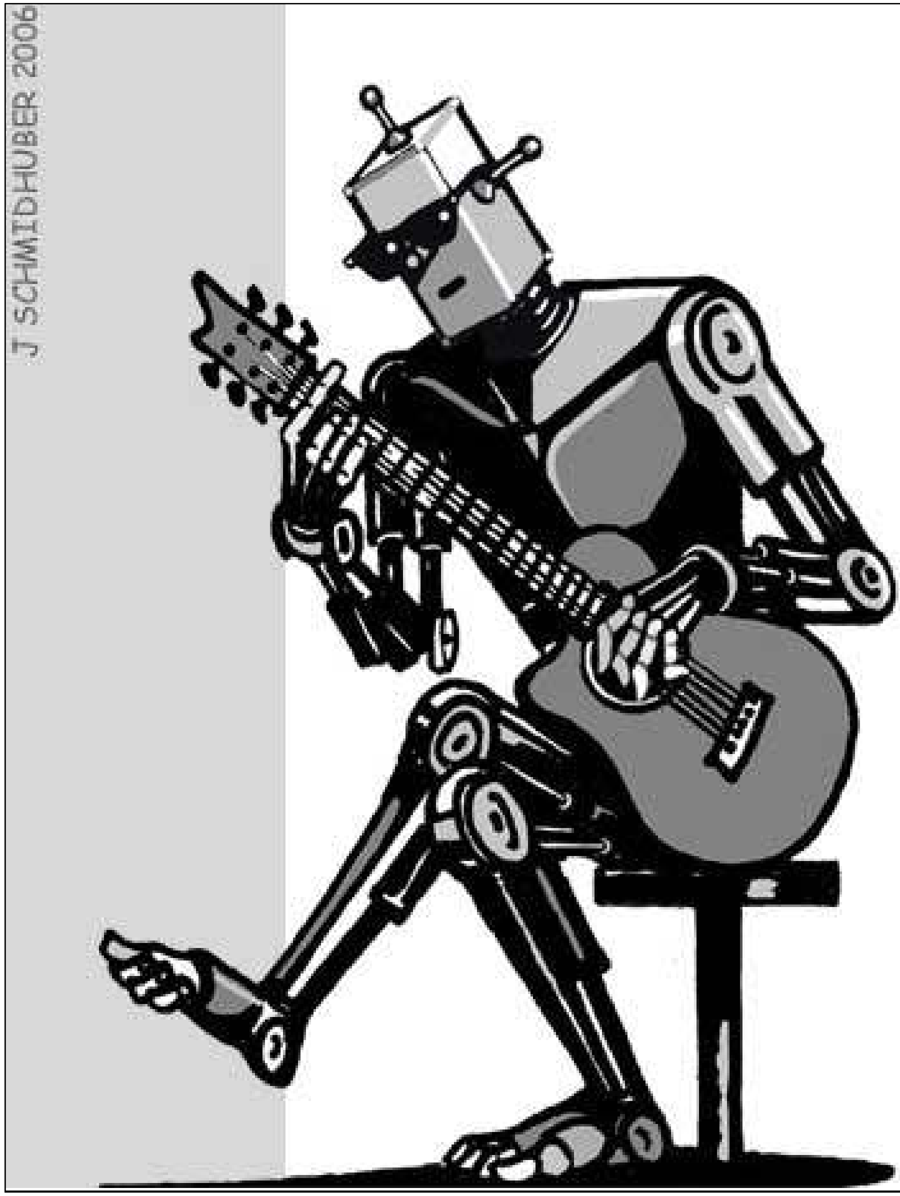


Learning how to Learn Learning Algorithms: Recursive Self-Improvement

Jürgen Schmidhuber
The Swiss AI Lab IDSIA
Univ. Lugano & SUPSI
http://www.idsia.ch/~juergen

NNAISENSE

Jürgen Schmidhuber
You_again Shmidhoobuh

“True” Learning to Learn (L2L) is not just transfer learning! Even a simple feedforward NN can transfer-learn to learn new images faster through pre-training on other image sets

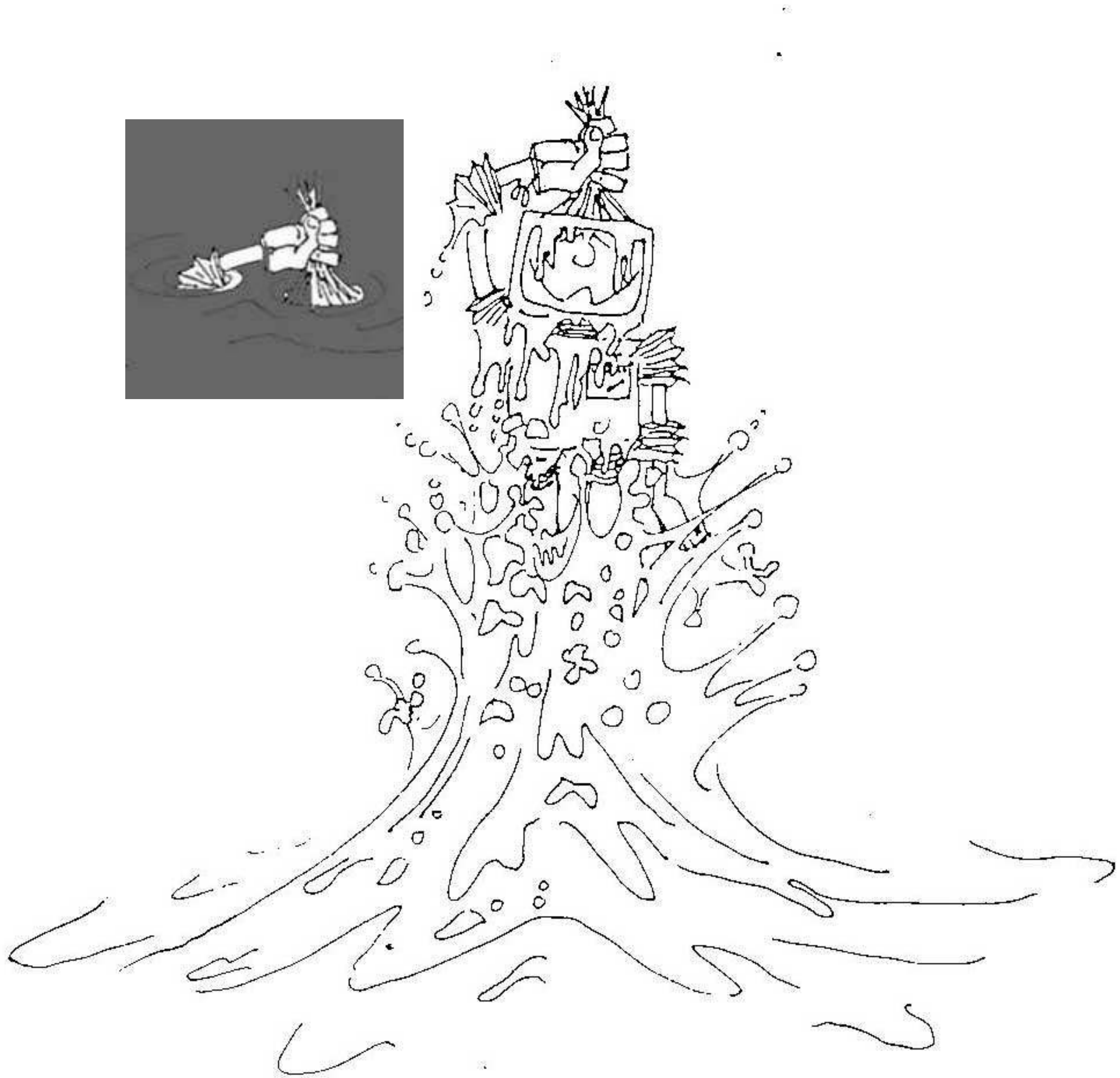
True L2L is not just about learning to adjust a few hyper-parameters such as mutation rates in evolution strategies (e.g., Rechenberg & Schwefel, 1960s)

Radical L2L is about encoding the initial learning algorithm in a universal language (e.g., on an RNN), with primitives that allow to modify the code itself in arbitrary computable fashion

Then surround this self-referential, self-modifying code by a recursive framework that ensures that only “useful” self-modifications are executed or survive (RSI)

J. Good (1965): informal remarks on an intelligence explosion through recursive self-improvement (RSI) for super-intelligences

My concrete algorithms for RSI: 1987, 93, 94, 2003

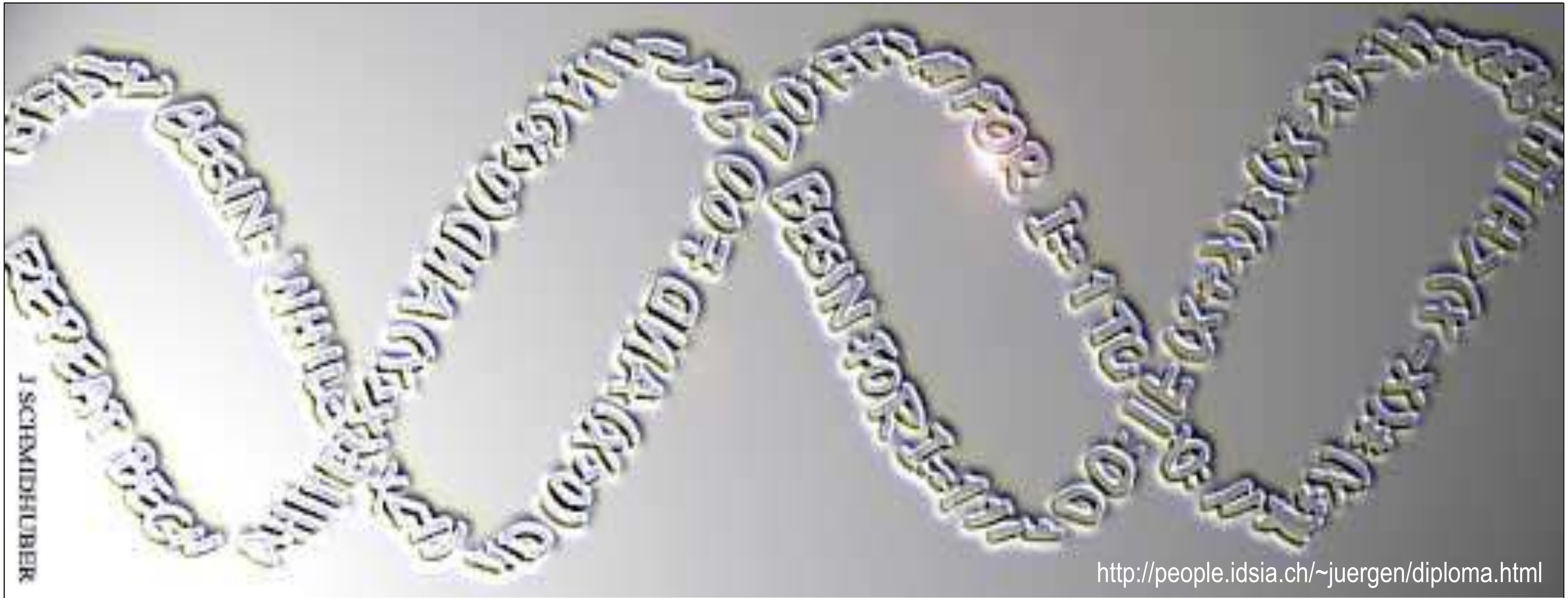


J. Schmidhuber, 1987

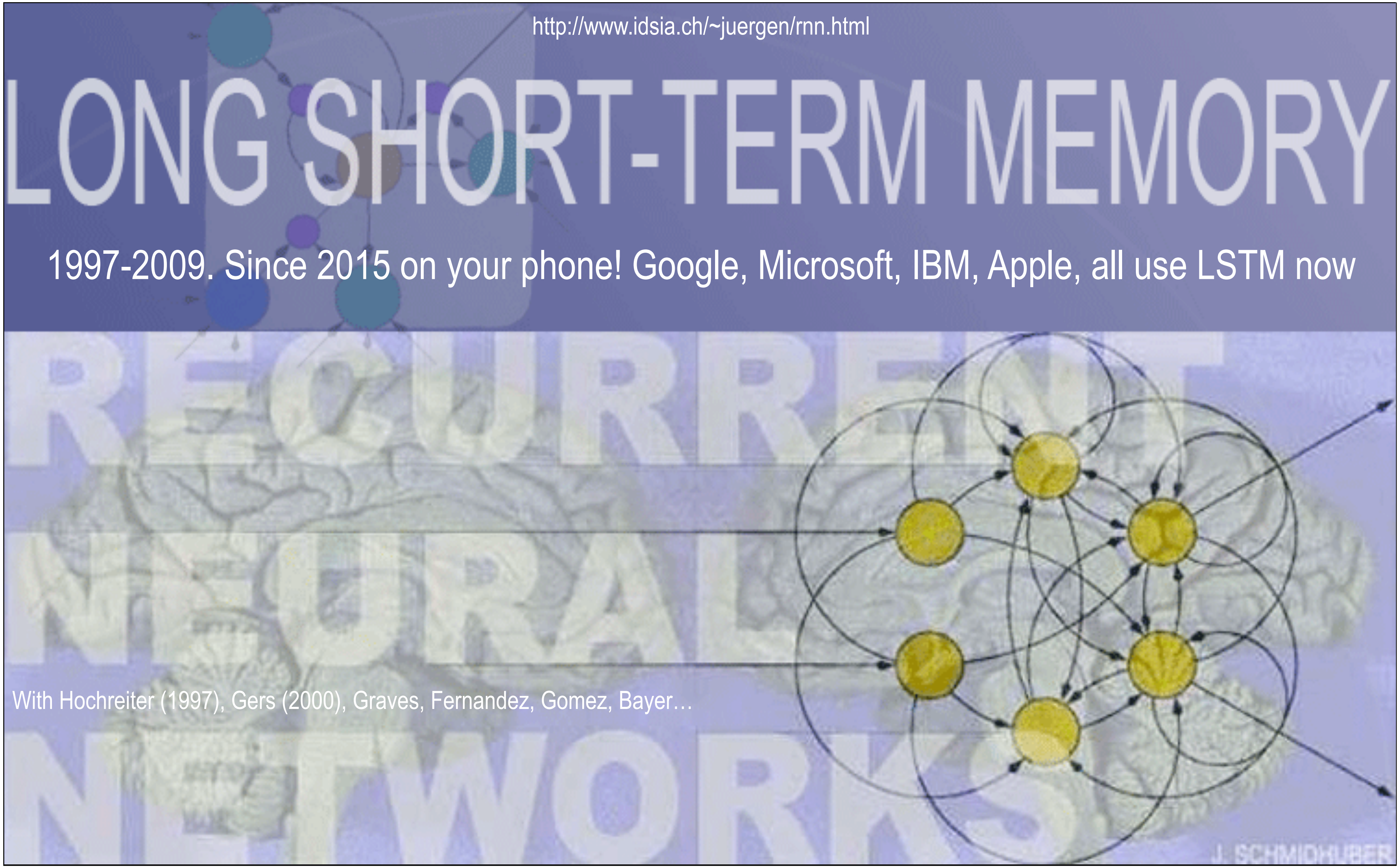
My diploma thesis (1987):
first concrete design of
recursively self-improving AI

http://people.idsia.ch/~juergen/metalearner.html

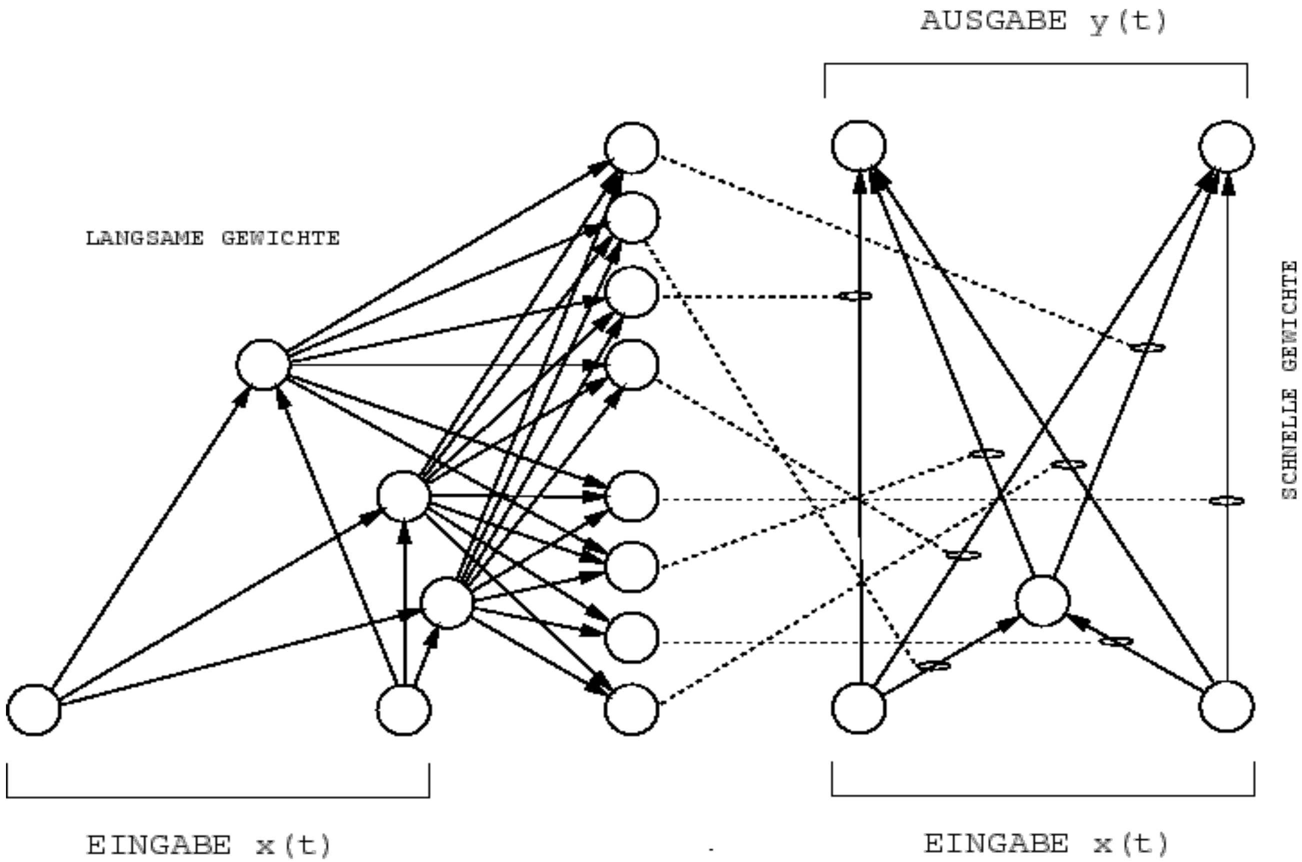
R-learn & improve learning
algorithm itself, and also the
meta-learning algorithm, etc…



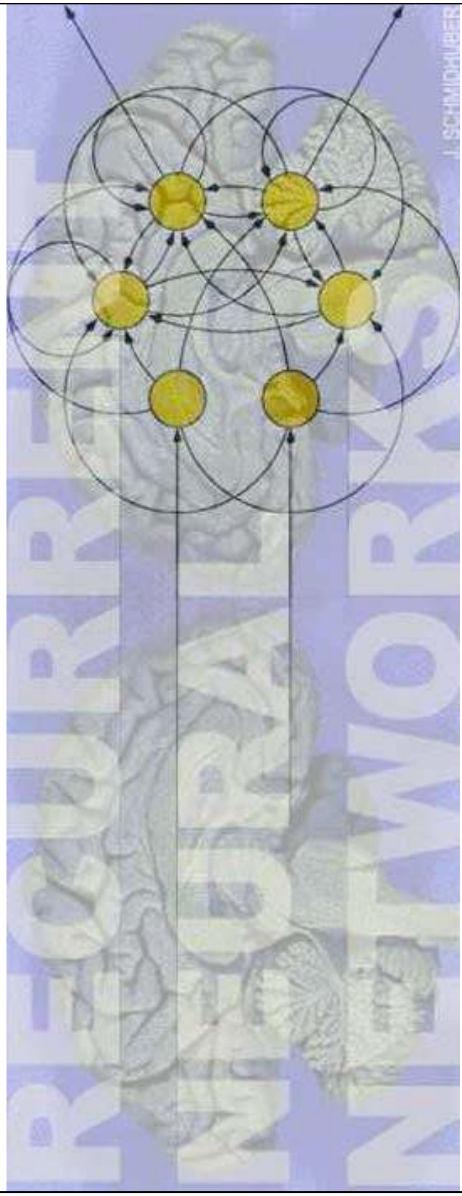
Genetic Programming recursively applied to itself, to obtain Meta-GP and Meta-Meta-GP etc: J. Schmidhuber (1987). Evolutionary principles in self-referential learning. On learning how to learn: The meta-meta-... hook. Diploma thesis, TU Munich


http://www.idsia.ch/~juergen/rnn.html
LONG SHORT-TERM MEMORY
1997-2009. Since 2015 on your phone! Google, Microsoft, IBM, Apple, all use LSTM now
RECURRENT
NEURAL
NETWORKS
With Hochreiter (1997), Gers (2000), Graves, Fernandez, Gomez, Bayer…
J. SCHMIDHUBER

Separation of Storage and Control for NNs: End-to-End Differentiable Fast Weights (Schmidhuber, 1992) extending v.d. Malsburg's non-differentiable dynamic links (1981)



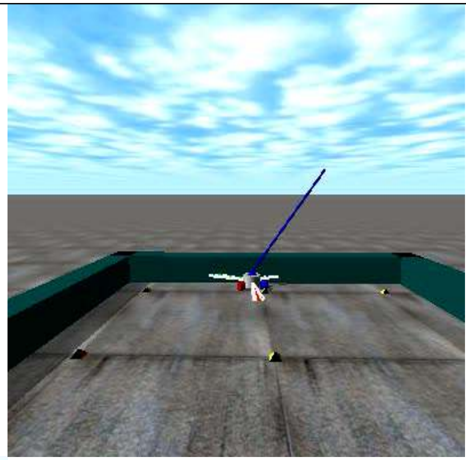
1993: More elegant Hebb-inspired addressing to go from (#hidden) to $(\#hidden)^2$ temporal variables: gradient-based RNN learns to control internal end-to-end differentiable spotlights of attention for fast differentiable memory rewrites – again fast weights

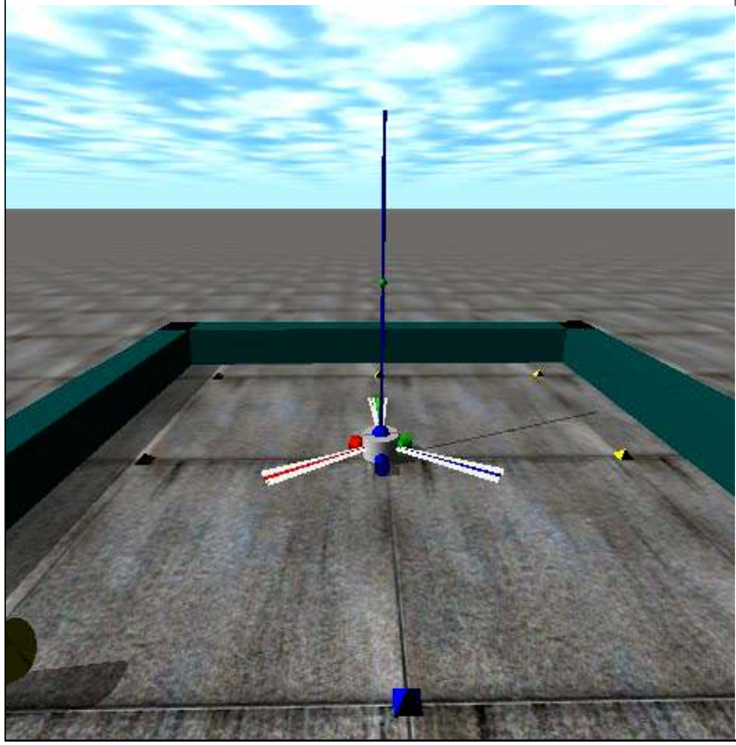


Schmidhuber, ICANN 1993: Reducing the ratio between learning complexity and number of time-varying variables in fully recurrent nets.

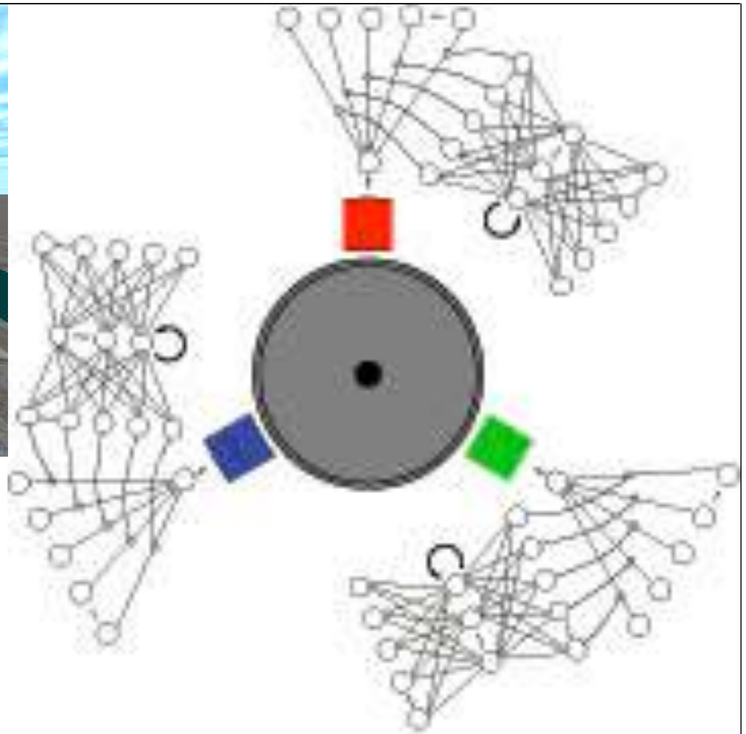
Similar to NIPS 2016 paper by Ba, Hinton, Mnih, Leibo, Ionesco

2005:
Reinforcement-
Learning or
Evolving RNNs
with Fast Weights



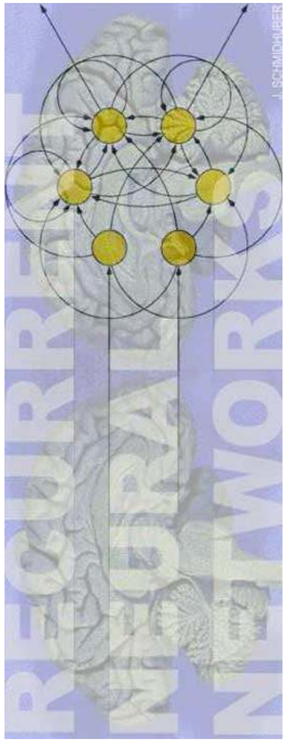


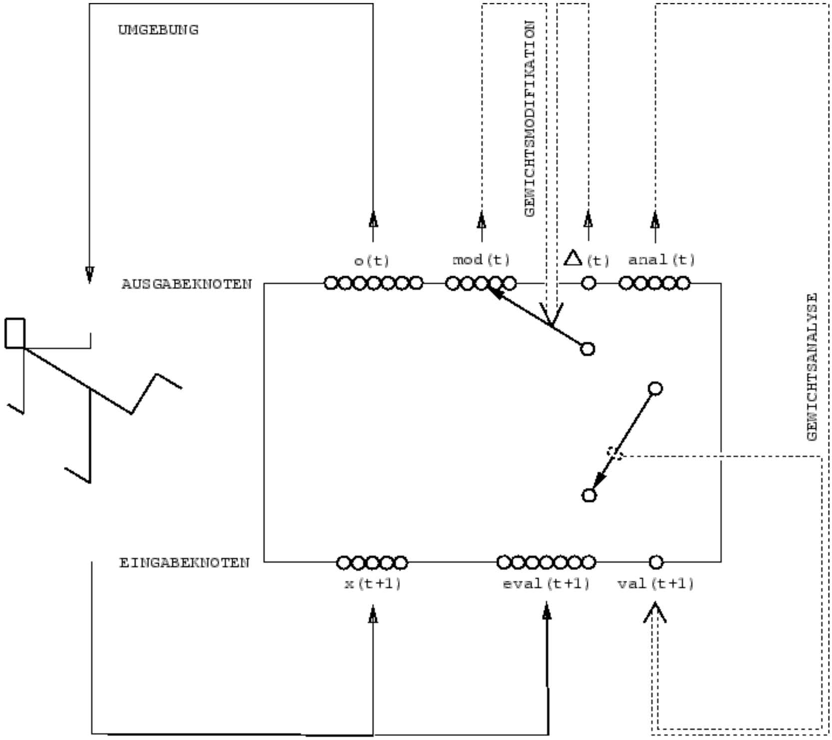
Robot learns to
balance 1 or 2 poles
through 3D joint



Gomez & Schmidhuber:
Co-evolving recurrent
neurons learn deep
memory POMDPs.
GECCO 2005

http://www.idsia.ch/~juergen/evolution.html





1993: Gradient-based meta-RNNs that can learn to run their own weight change algorithm: J. Schmidhuber. A self-referential weight matrix. ICANN 1993

This was before LSTM. In 2001, however, Sepp Hochreiter taught a meta-LSTM to learn a learning algorithm for quadratic functions that was faster than backprop

Success-story algorithm (SSA) for self-modifying code (since 1994)

E.g., Schmidhuber, Zhao, Wiering: MLJ 28:105-130, 1997

R(t): Reward until time t. Stack of past check points $v_1 v_2 v_3$ … with self-mods in between. SSA undoes selfmods after v_i that are not followed by long-term reward acceleration up until t (now):

$R(t)/t <$
$[R(t)-R(v_1)] / (t-v1) <$
$[R(t)-R(v_2)] / (t-v_2) <$…

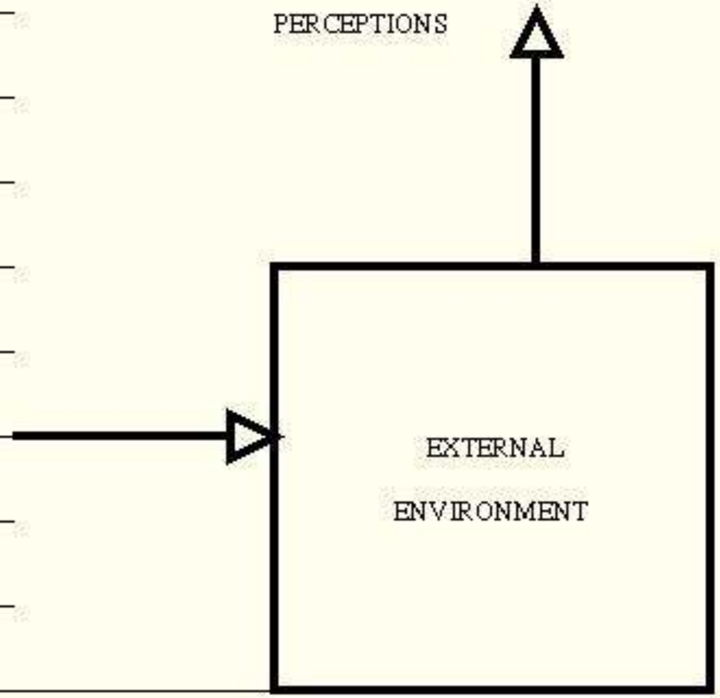
INTERNAL STATE

ADDRESSES	0	1	2	3	4	5	6	7	8	9	10	11	12
CONTENTS	5321	−44	810	−2	−3322	5	7	3	0	−189	2	237	6

INSTRUCTION POINTER

PARAMETERS

0 = ADD(a1, a2, a3)	0.001	0.0014	0.9	0.24	0.001	0.0014	0.9	0.9
1 = MUL(a1, a2, a3)	0.001	0.0014	0.04	0.01	0.001	0.0014	0.04	0.04
2 = SUB(a1, a2, a3)	0.99	0.0014	0.01	0.01	0.99	0.0014	0.01	0.01
3 = JMPLEQ(a1, a2, a3)	0.001	0.99	0.01	0.01	0.001	0.99	0.01	0.01
4 = MOVEAGENT(a1, a2)	0.001	0.0014	0.01	0.7	0.001	0.0014	0.01	0.01
5 = InvokeSSA()	0.004	0.0014	0.01	0.01	0.004	0.0014	0.01	0.01
6 = INCPROB(a1, a2)	0.001	0.0014	0.01	0.01	0.001	0.0014	0.01	0.01
7 = DECPROB(a1, a2)	0.001	0.0014	0.01	0.01	0.001	0.0014	0.01	0.01



VARIABLE PROBABILITY DISTRIBUTIONS

INTERNAL STATE

ADDRESSES	0	1	2	3	4	5	6	7	8	9	10	11	12
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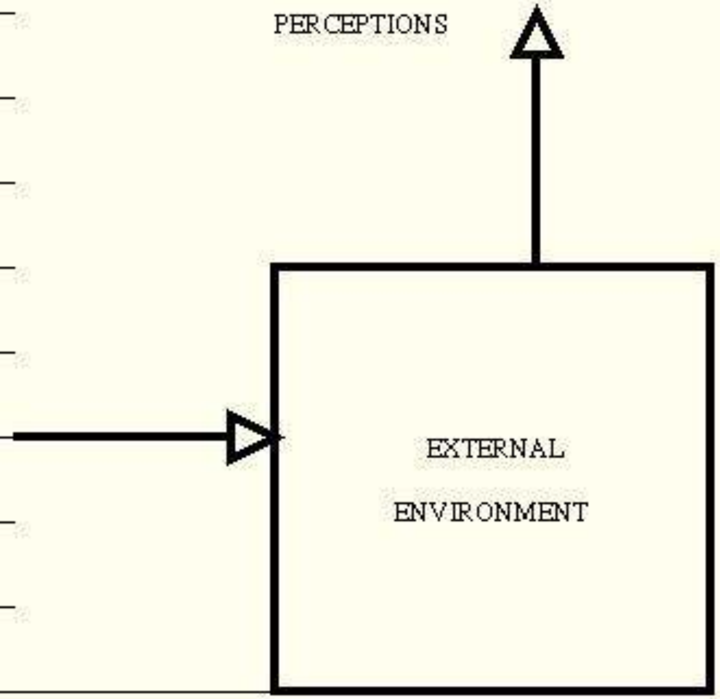
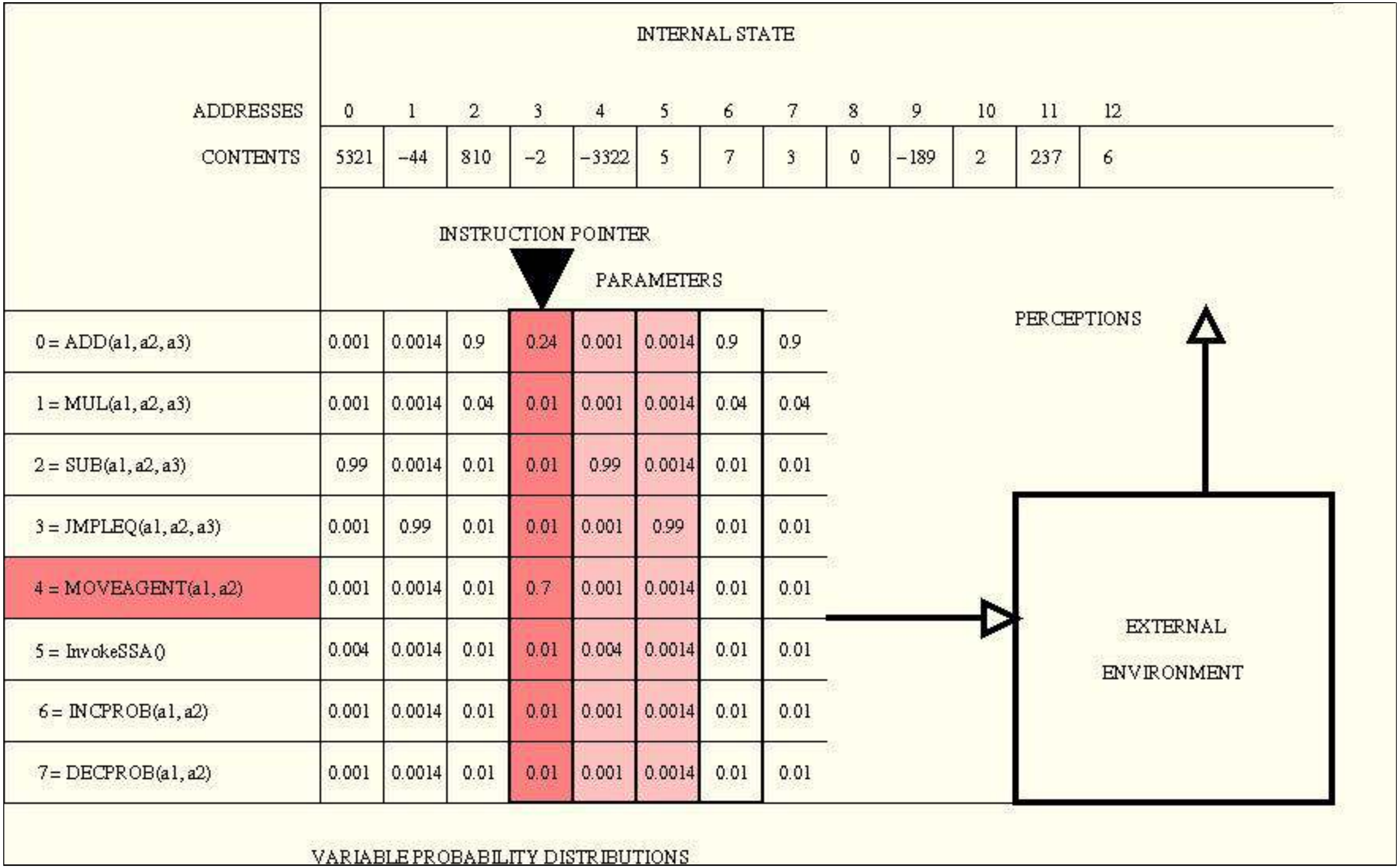


VARIABLE PROBABILITY DISTRIBUTIONS



INTERNAL STATE
ADDRESSES 0 1 2 3 4 5 6 7 8 9 10 11 12
CONTENTS 5321 −44 810 −2 −3322 5 7 3 0 −189 2 237 6
INSTRUCTION POINTER
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0 = ADD(a1, a2, a3) 0.001 0.0014 0.9 0.24 0.001 0.0014 0.9 0.9
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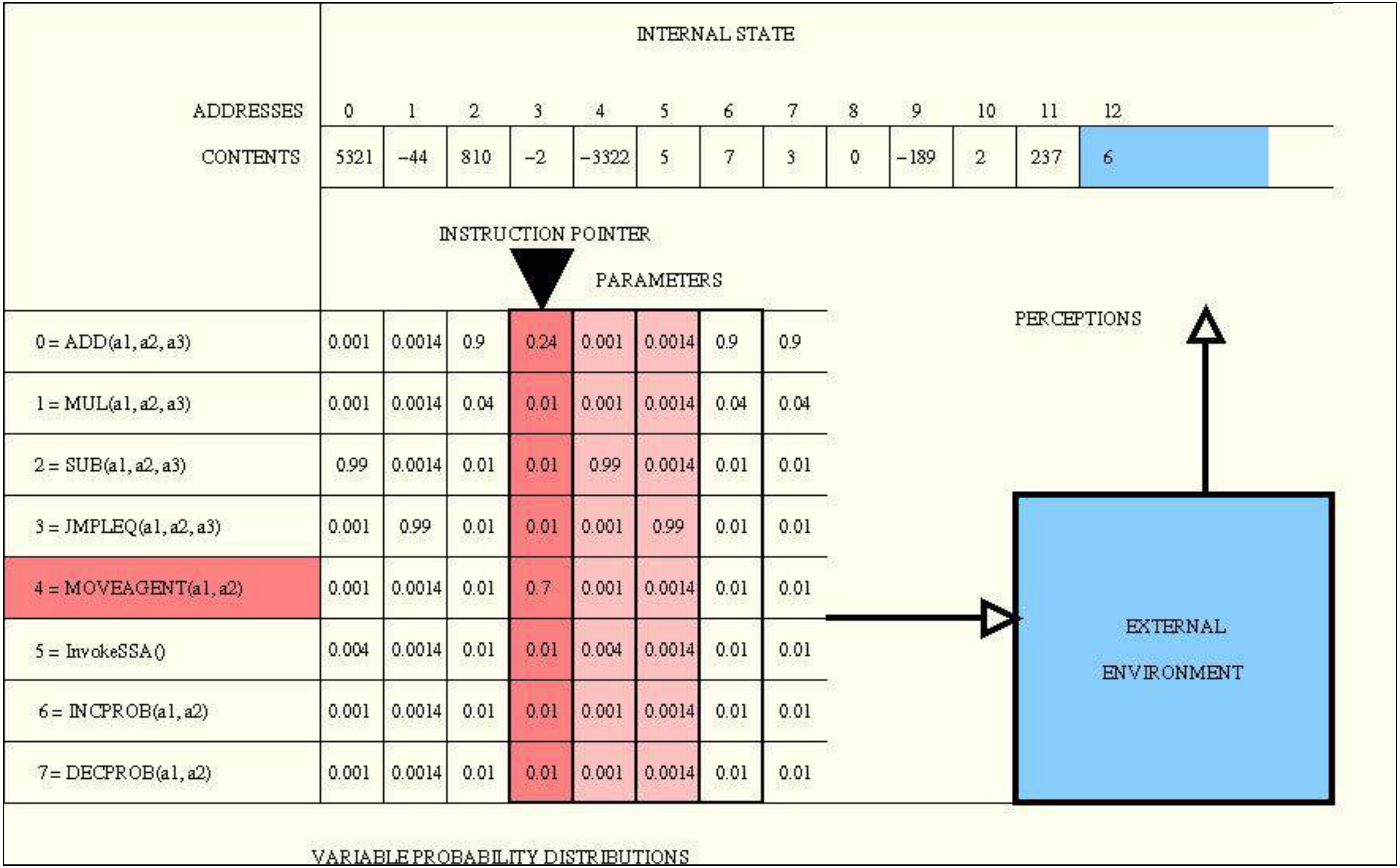
PERCEPTIONS
EXTERNAL
ENVIRONMENT
VARIABLE PROBABILITY DISTRIBUTIONS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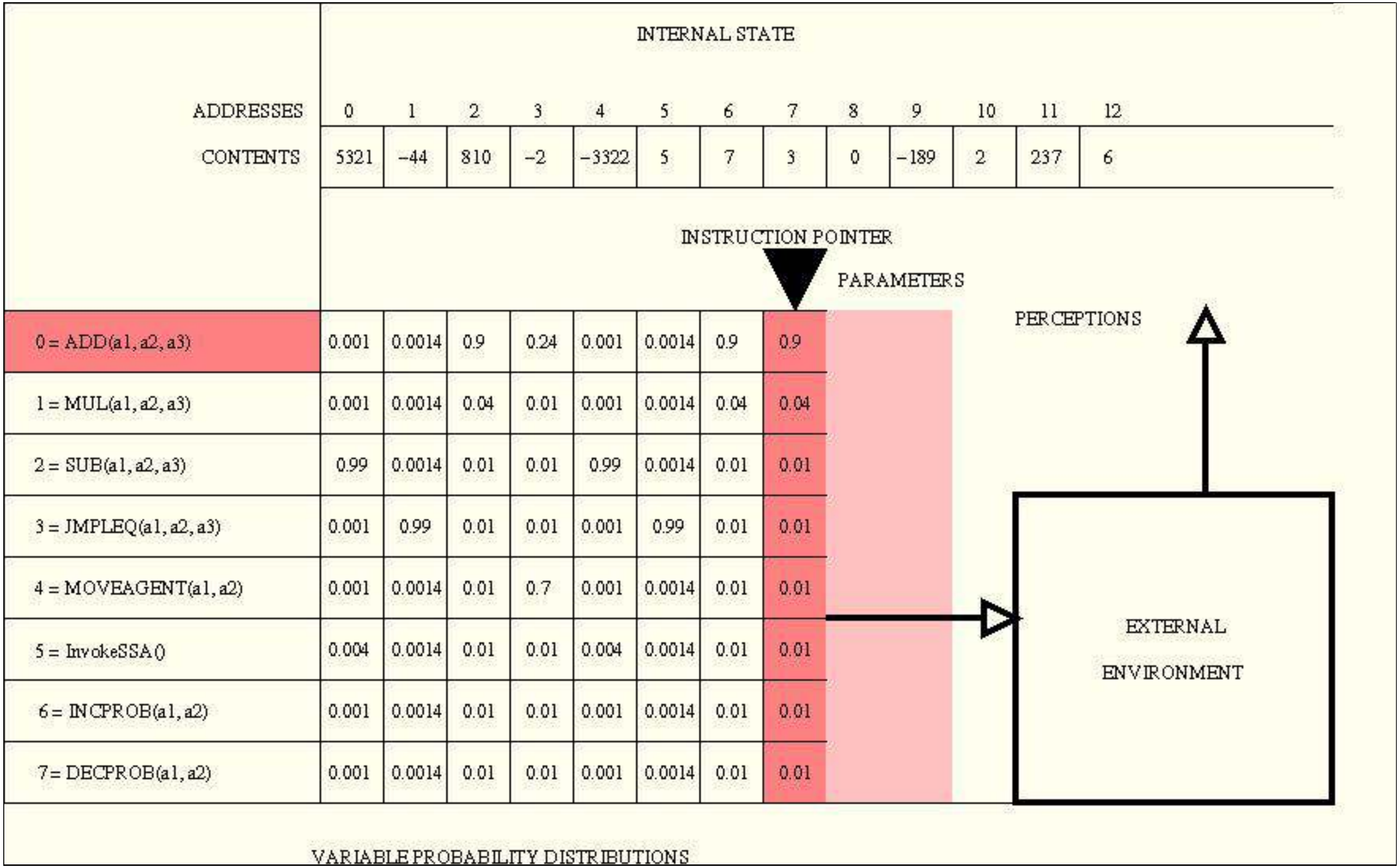
PERCEPTIONS
EXTERNAL
ENVIRONMENT
VARIABLE PROBABILITY DISTRIBUTIONS


INTERNAL STATE
ADDRESSES
CONTENTS

ADDRESSES	0	1	2	3	4	5	6	7	8	9	10	11	12
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INSTRUCTION POINTER
PARAMETERS
PERCEPTIONS

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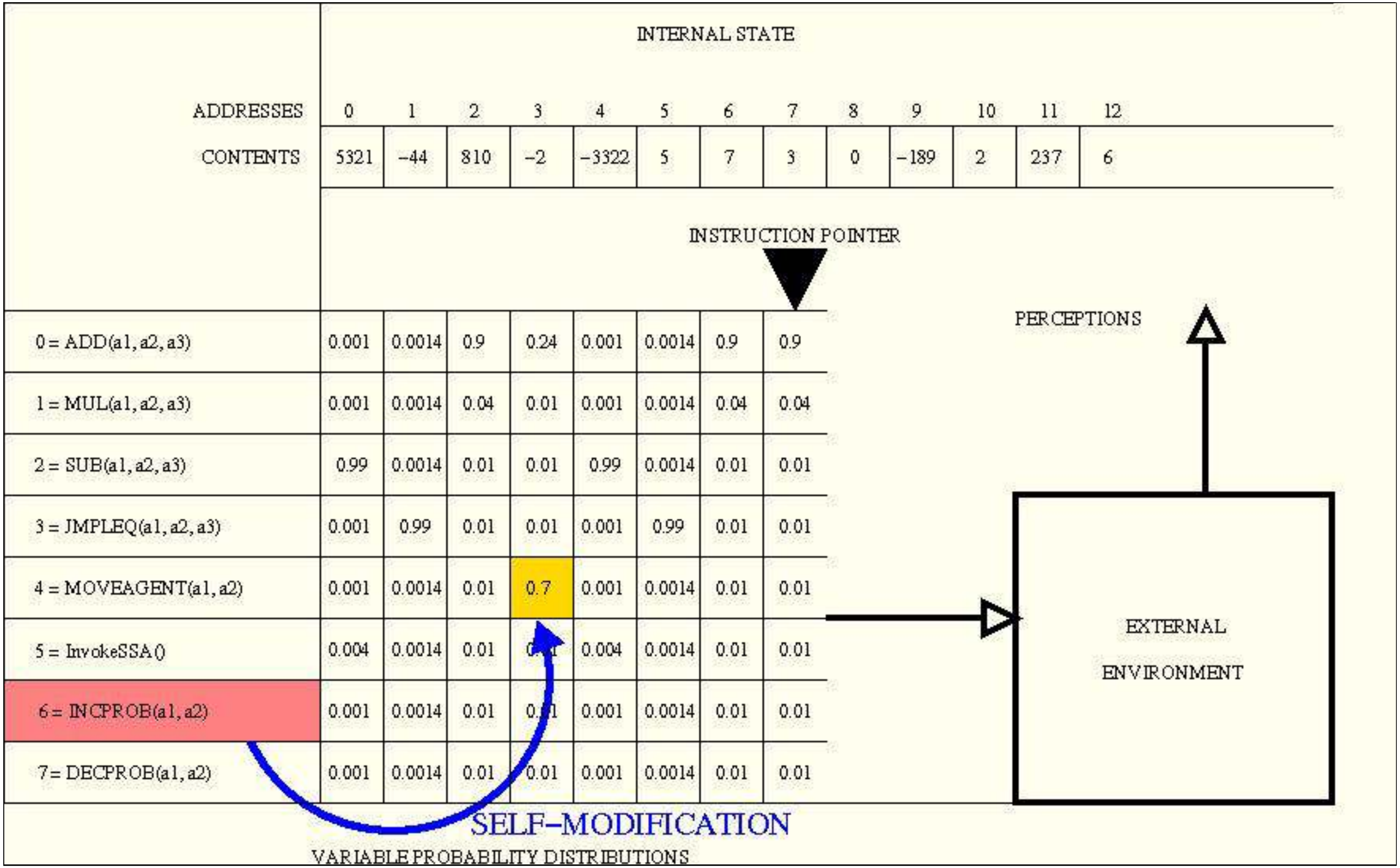
EXTERNAL
ENVIRONMENT
VARIABLE PROBABILITY DISTRIBUTIONS


INTERNAL STATE
ADDRESSES 0 1 2 3 4 5 6 7 8 9 10 11 12
CONTENTS 5321 −44 810 −2 −3322 5 7 3 0 −189 2 237 6
INSTRUCTION POINTER
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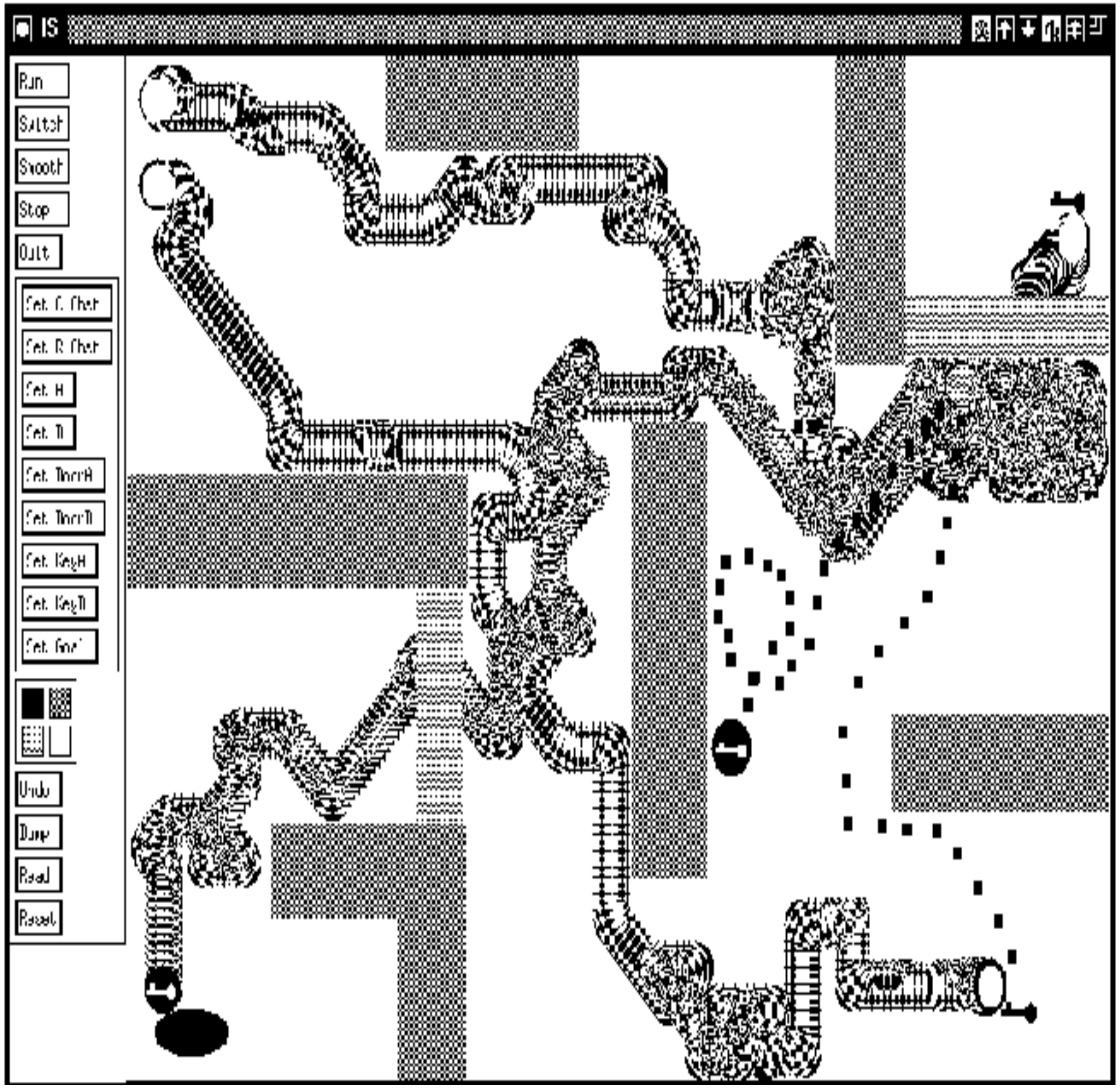
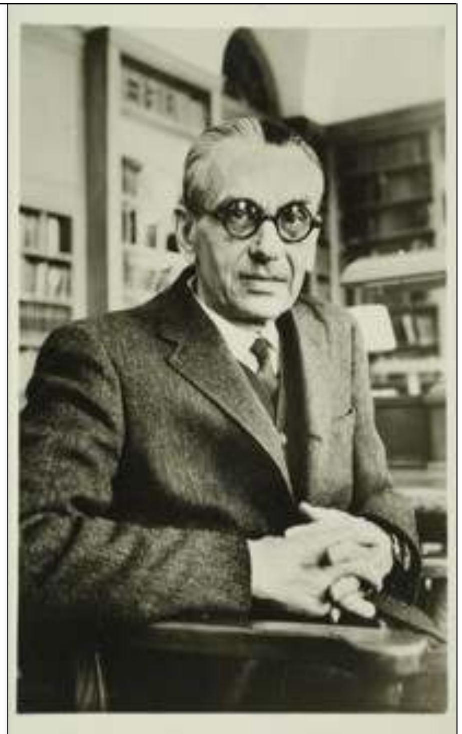
PERCEPTIONS
EXTERNAL ENVIRONMENT
SELF−MODIFICATION
VARIABLE PROBABILITY DISTRIBUTIONS



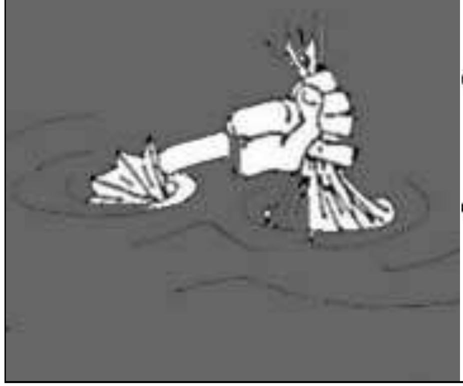
1997: Lifelong meta-learning with self-modifying policies and success-story algorithm: 2 agents, 2 doors, 2 keys. 1st southeast wins 5, the other 3. Through recursive self-modifications only: from 300,000 steps per trial down to 5,000.

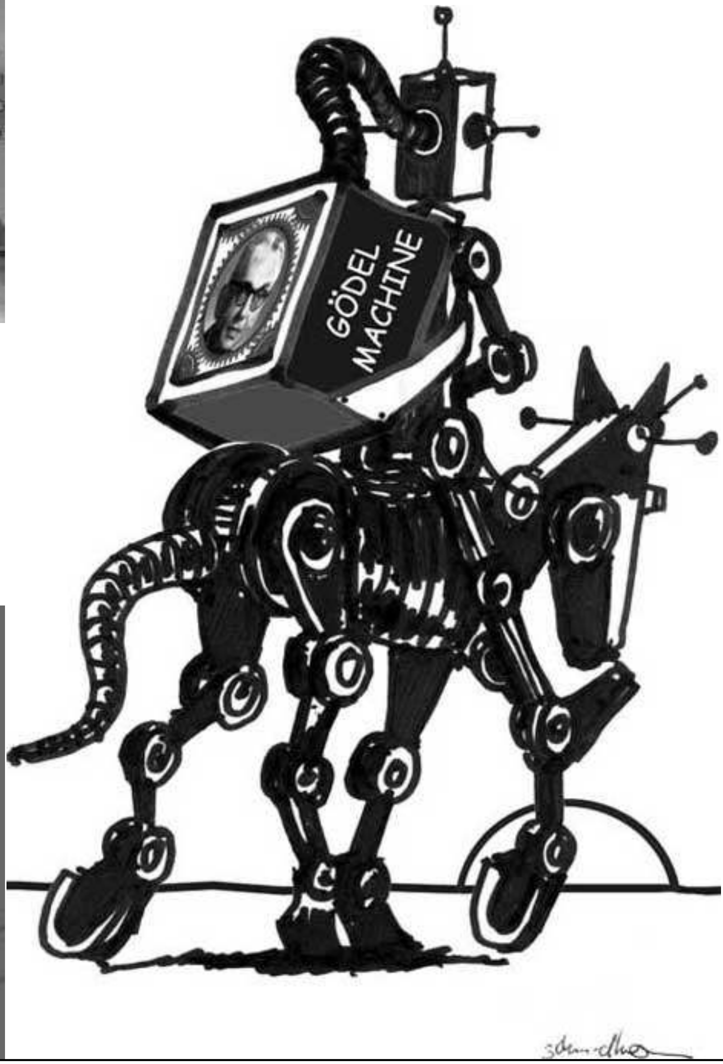
Kurt Gödel, father of theoretical computer science, exhibited the limits of math and computation (1931) by creating a formula that speaks about itself, claiming to be unprovable by a computational theorem prover: either formula is true but unprovable, or math is flawed in an algorithmic sense

Universal problem solver Gödel machine uses self reference trick in a new way



goedelmachine.com



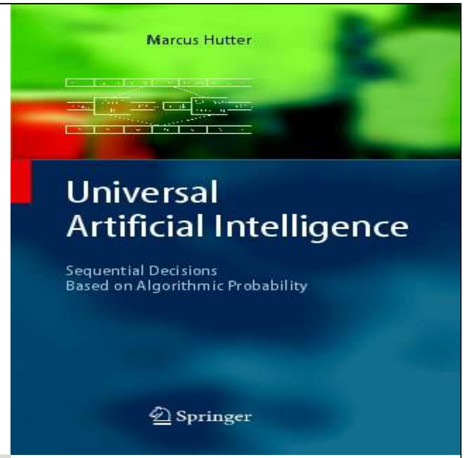


Gödel Machine (2003): agent-controlling program that speaks about itself, ready to rewrite itself in arbitrary fashion once it has found a proof that the rewrite is useful, given a user-defined utility function

Theoretically optimal self-improver!

Initialize Gödel Machine by Marcus Hutter's asymptotically fastest method for all well-defined problems

IDSIA 2002 on my SNF grant

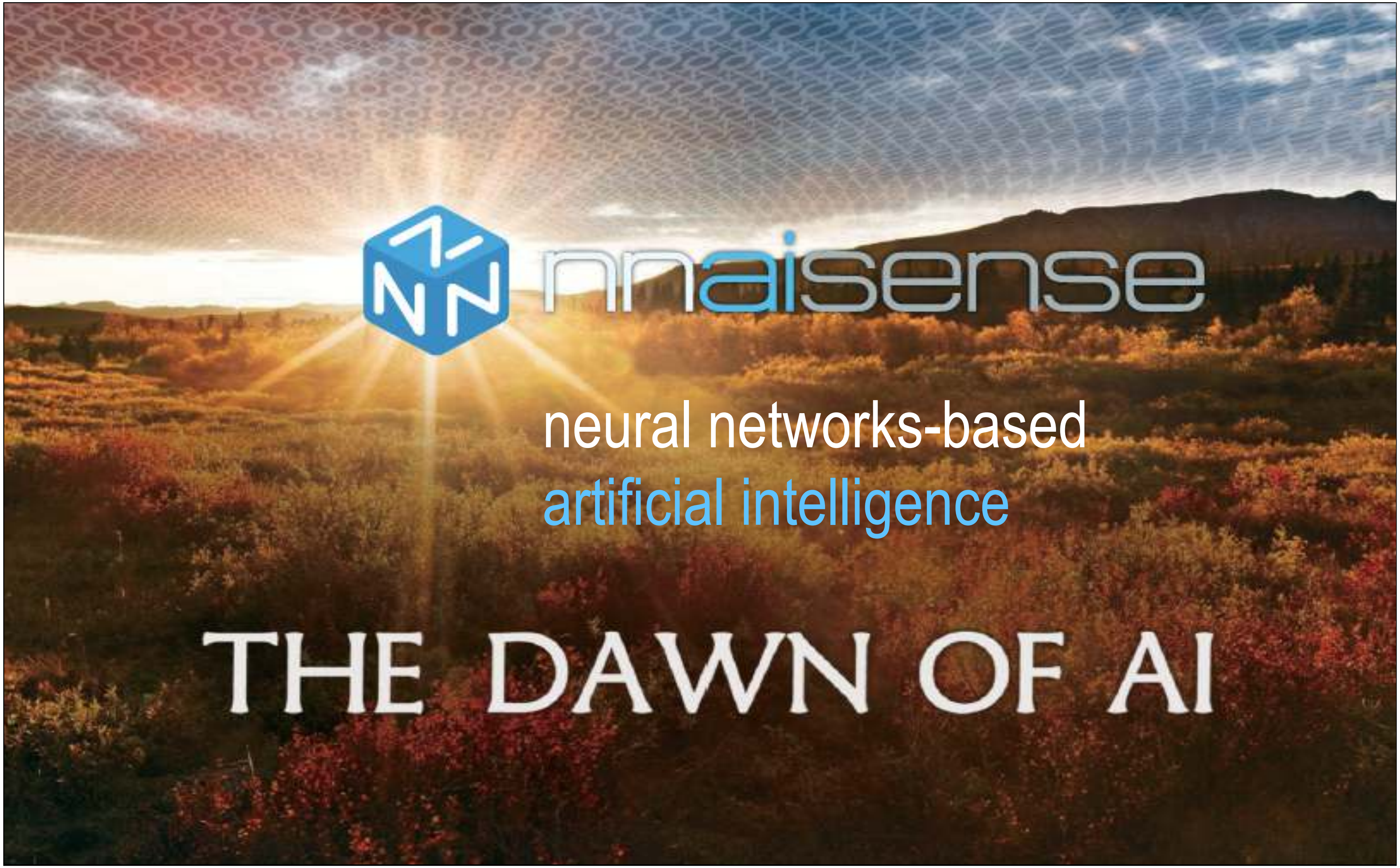


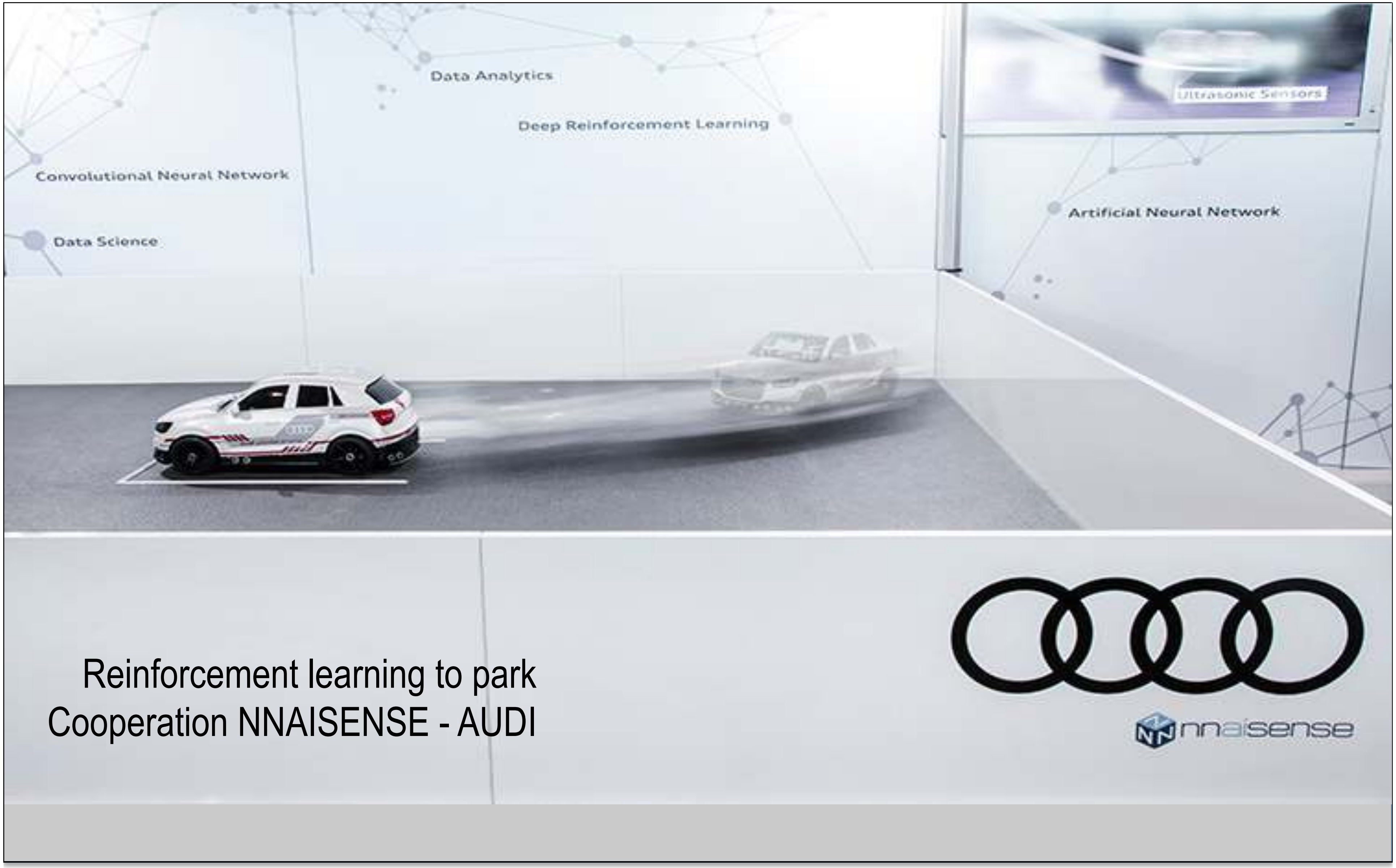
Given $f{:}X \rightarrow Y$ and $x \in X$, search proofs to find program q that provably computes f(z) for all $z \in X$ within time bound $t_q(z)$; spend most time on f(x)-computing q with best current bound

$n^3+10^{1000}=n^3+O(1)$

As fast as fastest f-computer, save for factor $1+\varepsilon$ and f-specific const. independent of x!

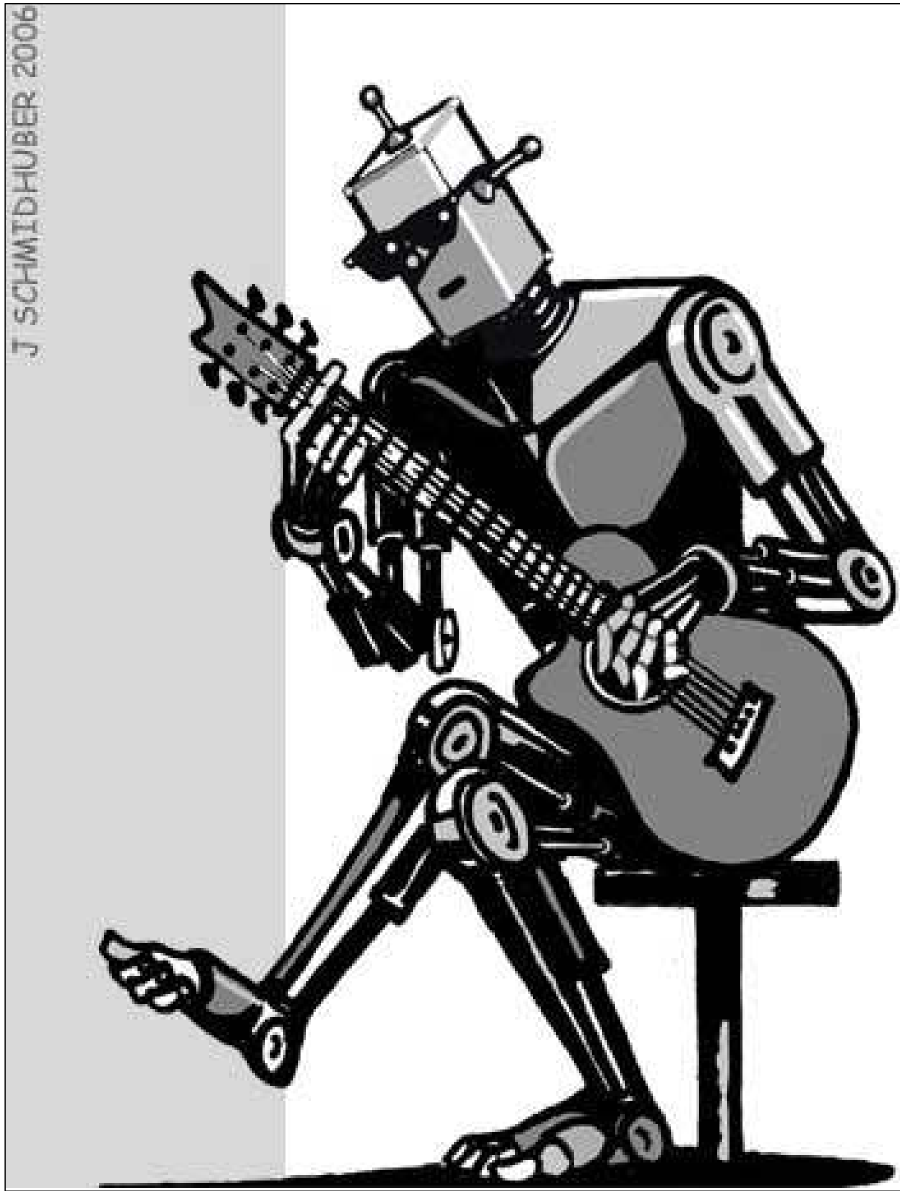

PowerPlay not only solves but also continually
invents problems at the borderline between what's
known and unknown - training an increasingly
general problem solver by continually searching for
the simplest still unsolvable problem
POWER
PLAY


nnaisense
neural networks-based
artificial intelligence
THE DAWN OF AI



Reinforcement learning to park
Cooperation NNAISENSE - AUDI

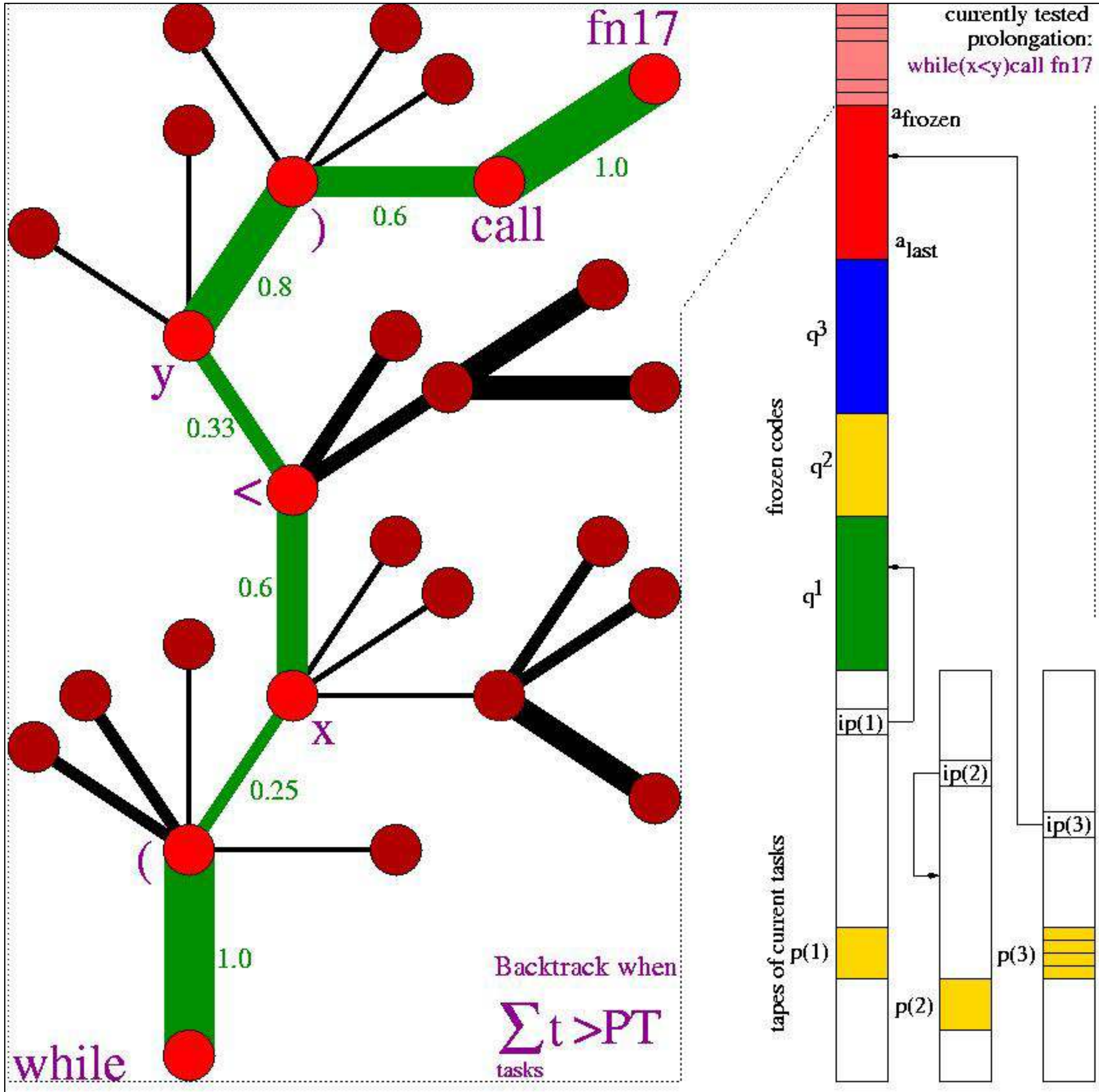
1. J. Schmidhuber. Evolutionary principles in self-referential learning, or on learning how to learn: The meta-meta-... hook. Diploma thesis, TUM, 1987. (First concrete RSI.)
2. J. Schmidhuber. A self-referential weight matrix. ICANN 1993
3. J. Schmidhuber. On learning how to learn learning strategies. TR FKI-198-94, 1994.
4. J. Schmidhuber and J. Zhao and M. Wiering. Simple principles of metalearning. TR IDSIA-69-96, 1996. (Based on 3.)
5. J. Schmidhuber, J. Zhao, N. Schraudolph. Reinforcement learning with self-modifying policies. In *Learning to learn*, Kluwer, pages 293-309, 1997. (Based on 3.)
6. J. Schmidhuber, J. Zhao, and M. Wiering. Shifting inductive bias with success-story algorithm, adaptive Levin search, and incremental self-improvement. Machine Learning 28:105-130, 1997. (Based on 3.)
7. J. Schmidhuber. Gödel machines: Fully Self-Referential Optimal Universal Self-Improvers. In *Artificial General Intelligence,* p. 119-226, 2006. (Based on TR of 2003.)
8. T. Schaul and J. Schmidhuber. Metalearning. Scholarpedia, 5(6):4650, 2010.
9. More under http://people.idsia.ch/~juergen/metalearner.html



Learning how to Learn Learning Algorithms: Extra Slides

Jürgen Schmidhuber
The Swiss AI Lab IDSIA
Univ. Lugano & SUPSI
http://www.idsia.ch/~juergen

NNAISENSE

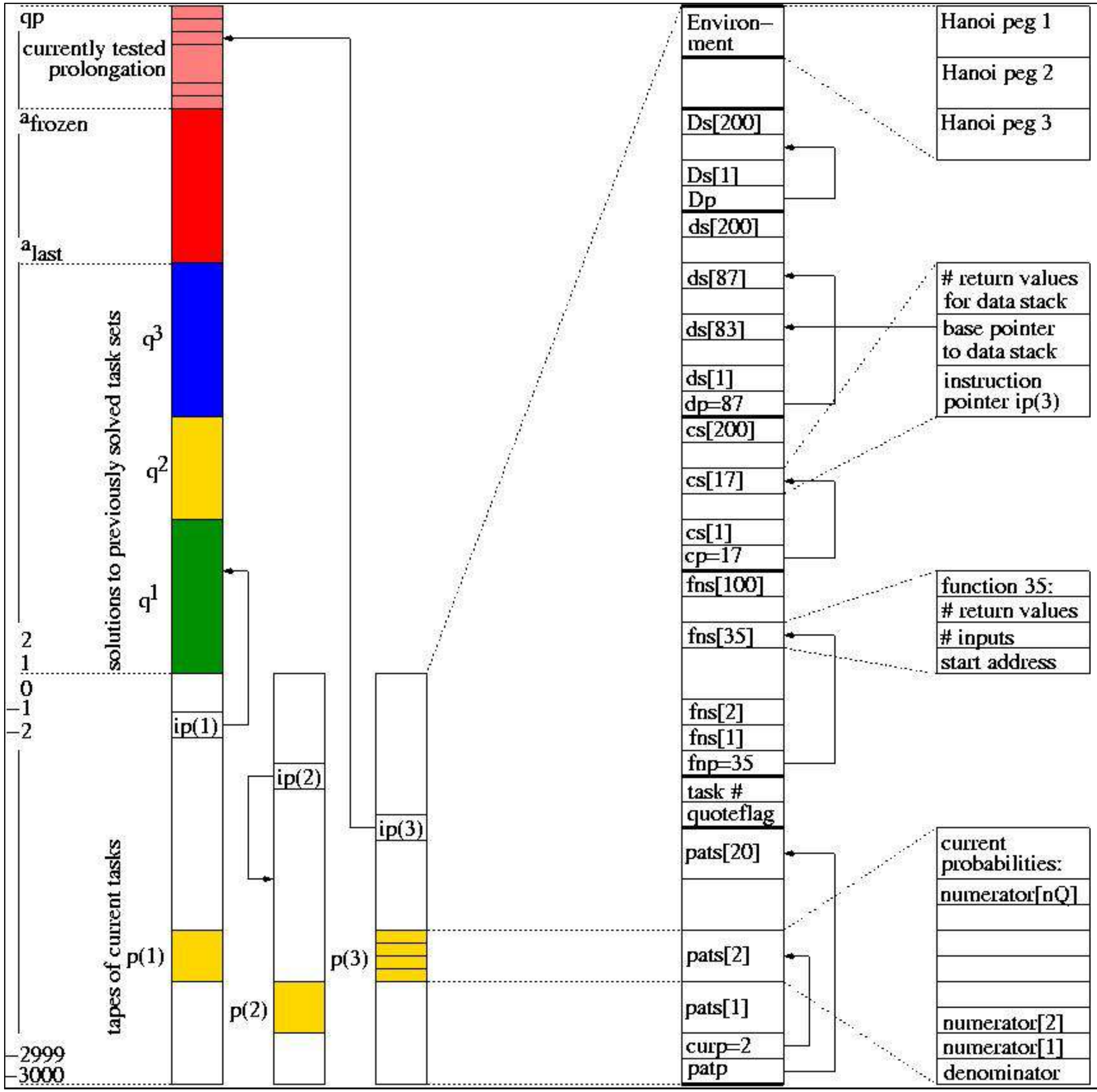


Super-deep program learner: Optimal Ordered Problem Solver OOPS (Schmidhuber, MLJ, 2004, extending Levin's universal search, 1973)

Time-optimal incremental search and algorithmic transfer learning in program space

Branches of search tree are program prefixes

Node-oriented backtracking restores partially solved task sets & modified memory components on error or when $\sum t > PT$



61 primitive instructions operating on stack-like and other internal data structures. For example:

push1(), not(x), inc(x), add(x,y), div(x,y), or(x,y), exch_stack(m,n), push_prog(n), movstring(a,b,n), delete(a,n), find(x), define function(m,n), callfun(fn), jumpif(val,address), quote(), unquote(), boost_probability(n,val) ….

Programs are integer sequences; data and code look the same; makes functional programming easy

Towers of Hanoi: incremental solutions

- +1ms, n=1: *(movdisk)*
- 1 day, n=1,2: *(c4 c3 cpn c4 by2 c3 by2 exec)*
- 3 days, n=1,2,3: *(<u>c3 dec boostq defnp c4 calltp c3 c5 calltp endnp</u>)*
- 4 days: n=4, n=5, …, n=30: *by same double-recursive program*
- Profits from 30 earlier context-free language tasks (1^n2^n)*: transfer learning*
- 93,994,568,009 prefixes tested
- 345,450,362,522 instructions
- 678,634,413,962 time steps
- longest single run: 33 billion steps (5% of total time)! Much deeper than recent memory-based "deep learners" …
- top stack size for restoring storage: < 20,000

What the found Towers of Hanoi solver does:

- *(c3 dec boostq defnp c4 calltp c3 c5 calltp endnp)*
- Prefix increases P of double-recursive procedure: Hanoi(Source,Aux,Dest,n): IF n=0 exit; ELSE BEGIN Hanoi(Source,Dest,Aux,n-1); move top disk from Aux to Dest; Hanoi(Aux,Source,Dest,n-1); END
- Prefix boosts instructions of previoulsy frozen program, which happens to be a previously learned solver of a context-free language (1^n2^n). This rewrites search procedure itself: Benefits of metalearning!
- Prefix probability 0.003; suffix probability $3*10^{-8}$; total probability $9*10^{-11}$
- Suffix probability without prefix execution: $4*10^{-14}$
- That is, Hanoi does profit from 1^n2^n experience and incremental learning (OOPS excels at algorithmic transfer learning): speedup factor 1000

J.S.: IJCNN 1990, NIPS 1991: Reinforcement Learning with Recurrent Controller & Recurrent World Model

Learning and planning with recurrent networks

RNNAIssance
2014-2015

On Learning to Think: Algorithmic Information Theory for Novel Combinations of Reinforcement Learning RNN-based Controllers (RNNAIs) and Recurrent Neural World Models

http://arxiv.org/abs/1511.09249