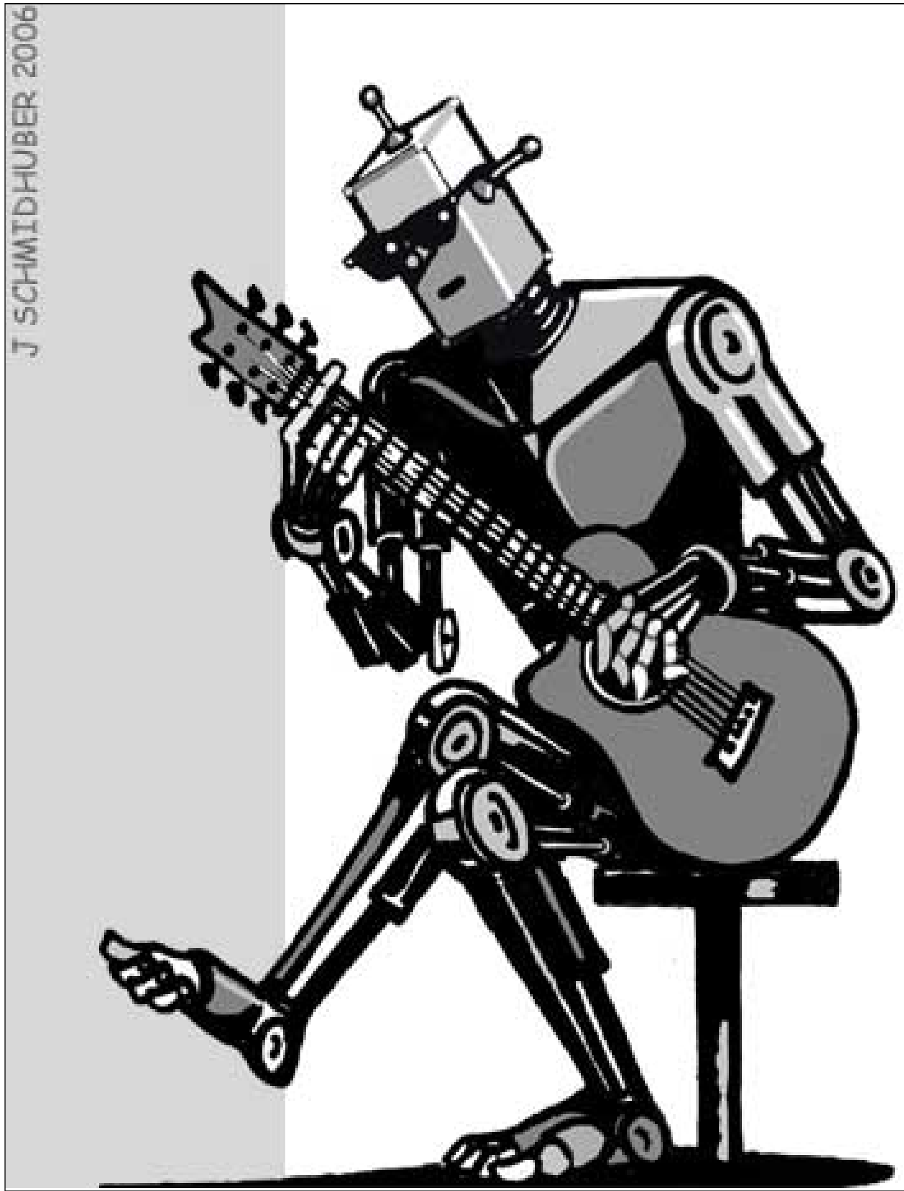

Learning how to Learn Learning Algorithms: Recursive Self-Improvement

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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

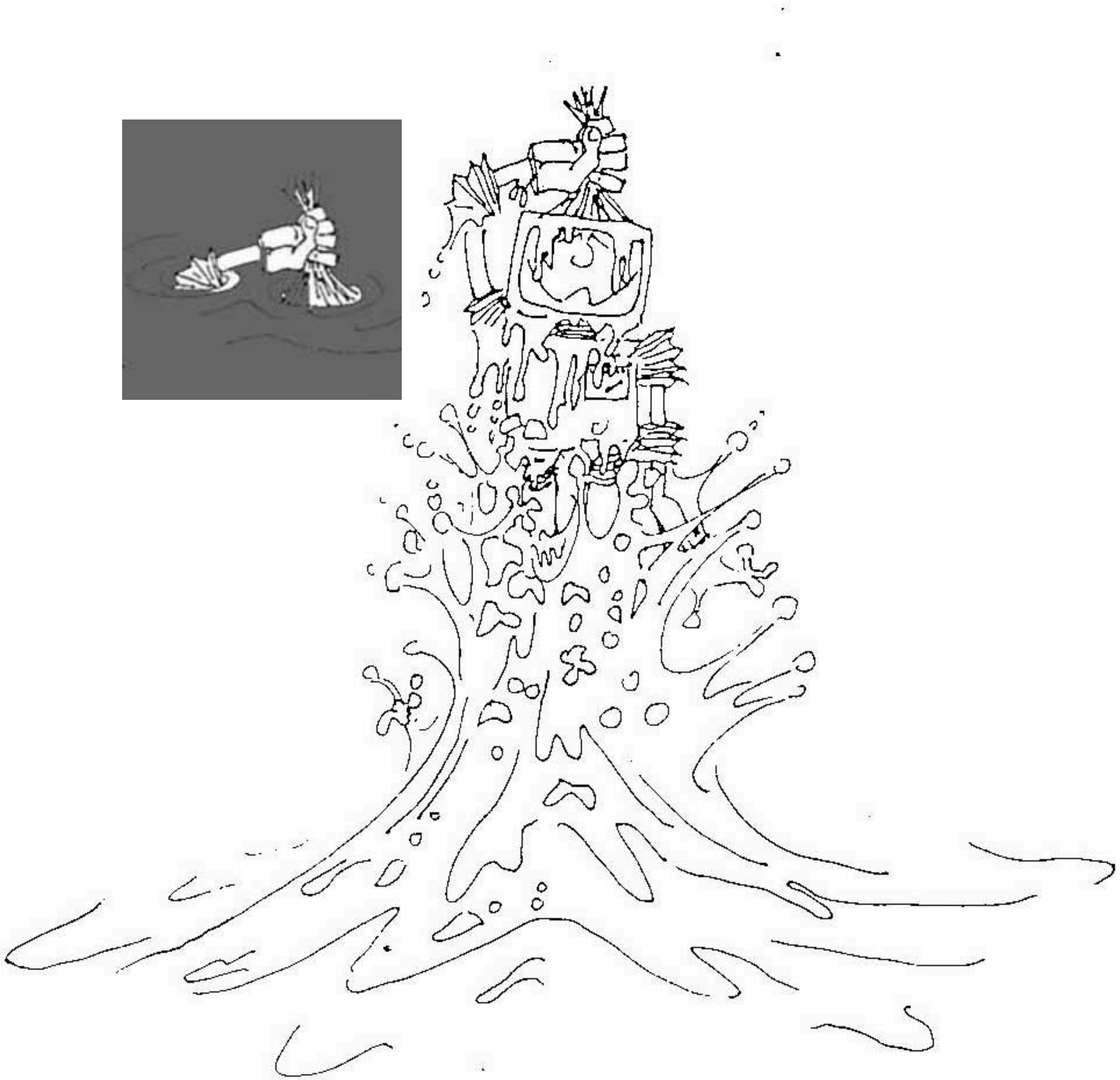
True L2L is not just about learning to adjust a few hyper-parameters such as mutation rates in evolution strategies (e.g., Rechenberg & Schwefel, 1960s)

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):
concrete design of
recursively self-improving AI

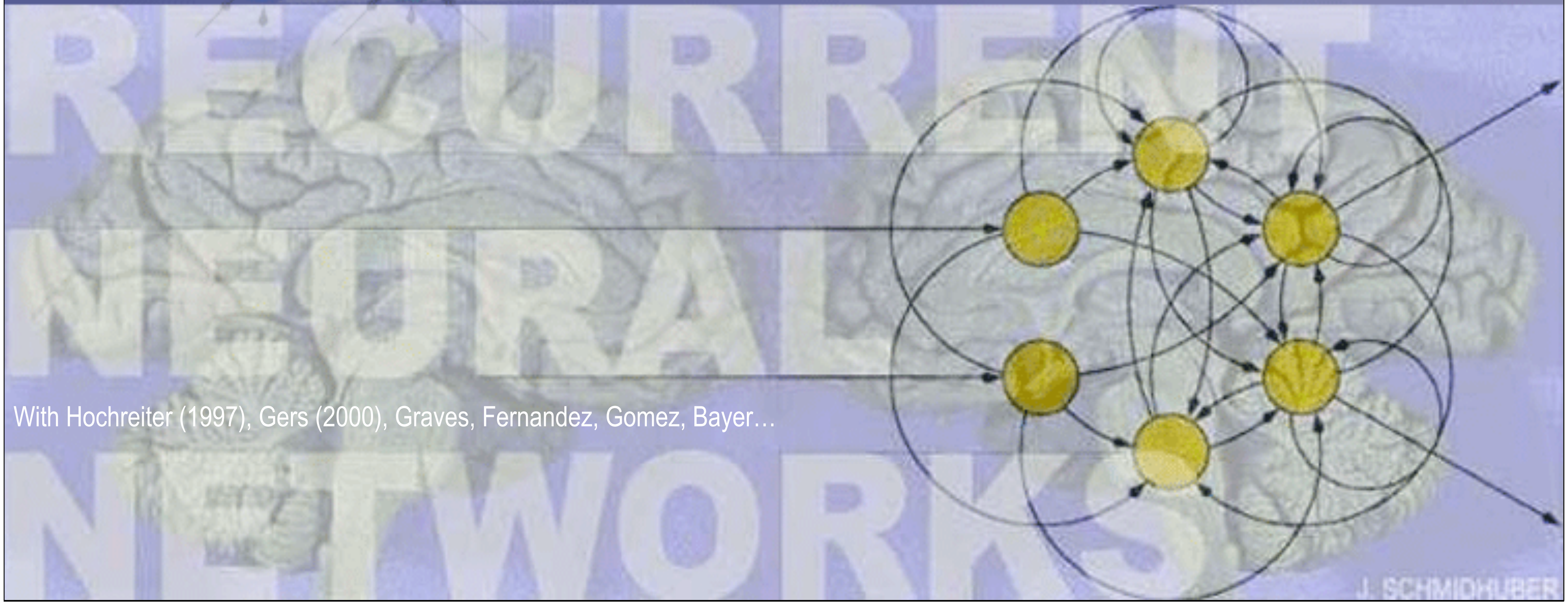
http://people.idsia.ch/~juergen/metalearner.html

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

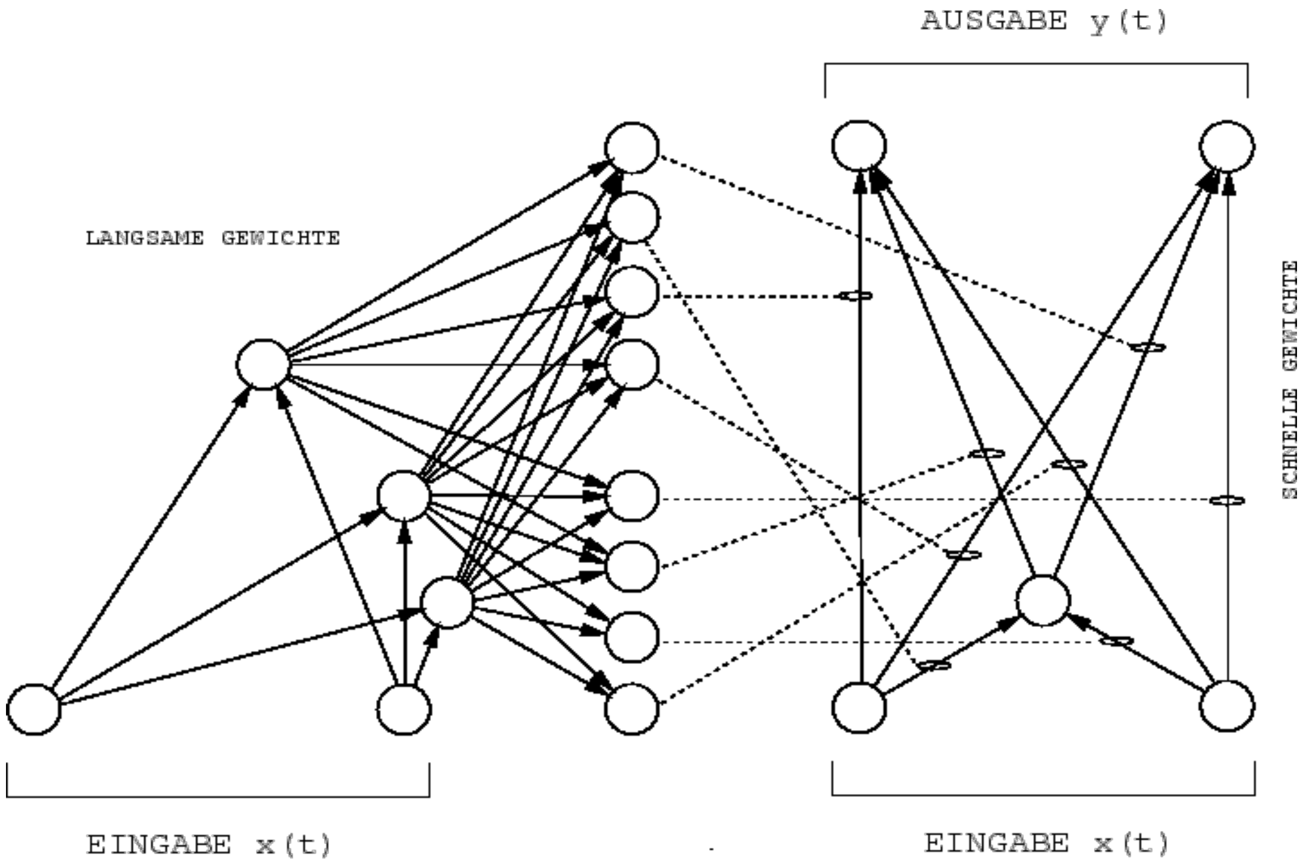
LONG SHORT-TERM MEMORY

1997-2009. Since 2015 on your phone! Google, Microsoft, IBM, Apple, all use LSTM now

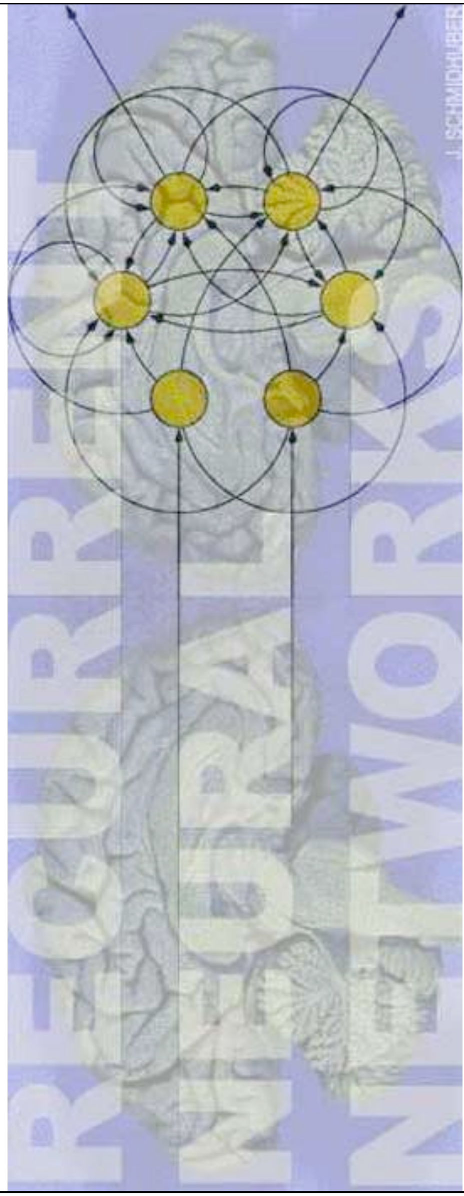


With Hochreiter (1997), Gers (2000), Graves, Fernandez, Gomez, Bayer…

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)



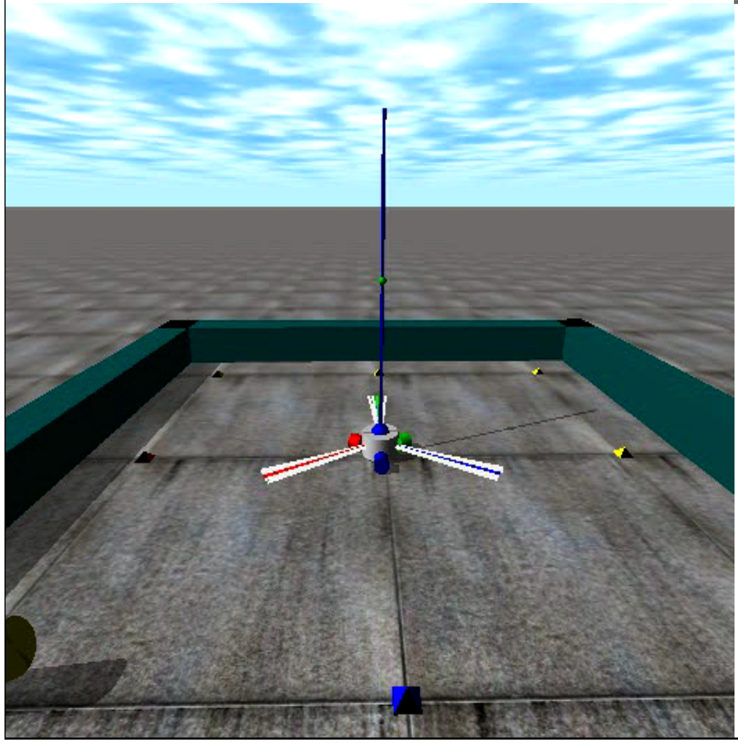
1993: More elegant Hebb-inspired addressing to go from (#hidden) to $(\#\text{hidden})^2$ temporal variables: gradient-based RNN learns to control internal end-to-end differentiable spotlights of attention for fast differentiable memory rewrites – again fast weights

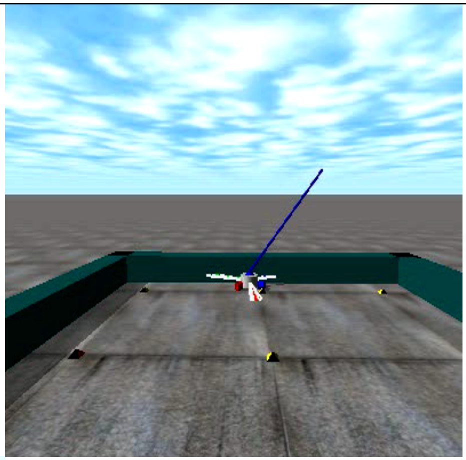


Schmidhuber, ICANN 1993: Reducing the ratio between learning complexity and number of time-varying variables in fully recurrent nets.

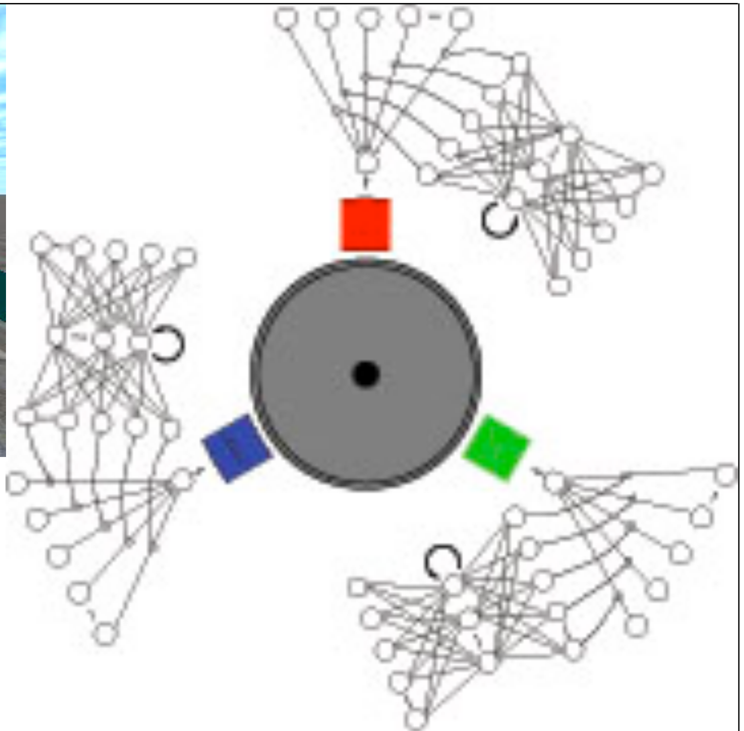
Similar to NIPS 2016 paper by Ba, Hinton, Mnih, Leibo, Ionesco

2005: Reinforcement-Learning or Evolving RNNs with Fast Weights



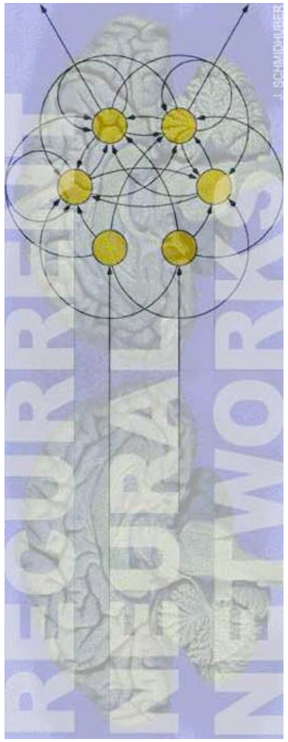


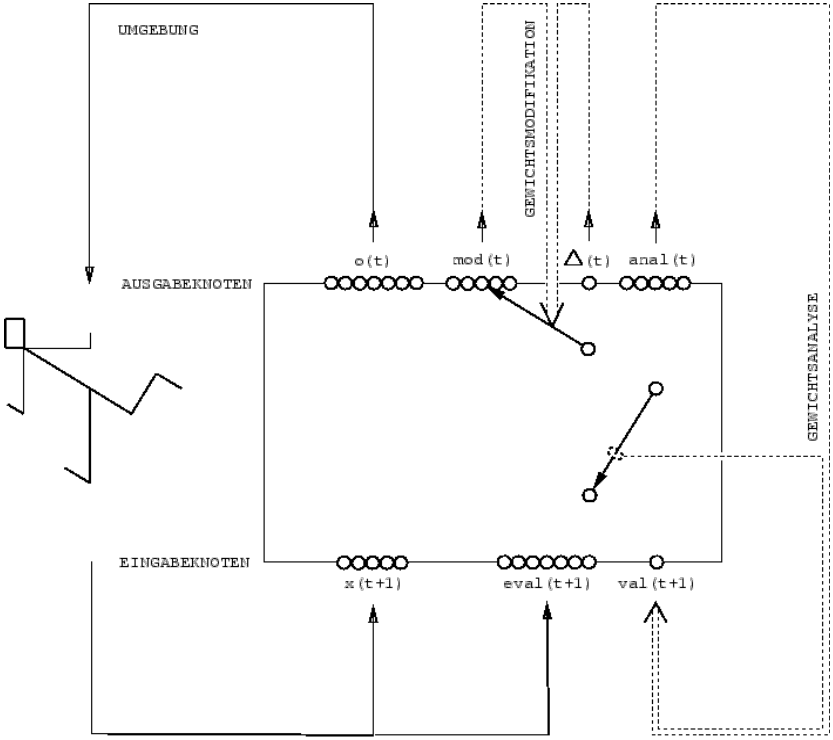
Robot learns to balance 1 or 2 poles through 3D joint



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):

$R(t)/t <$
$[R(t)-R(v_1)] / (t\text{-}v1) <$
$[R(t)-R(v_2)] / (t\text{-}v_2) <$…

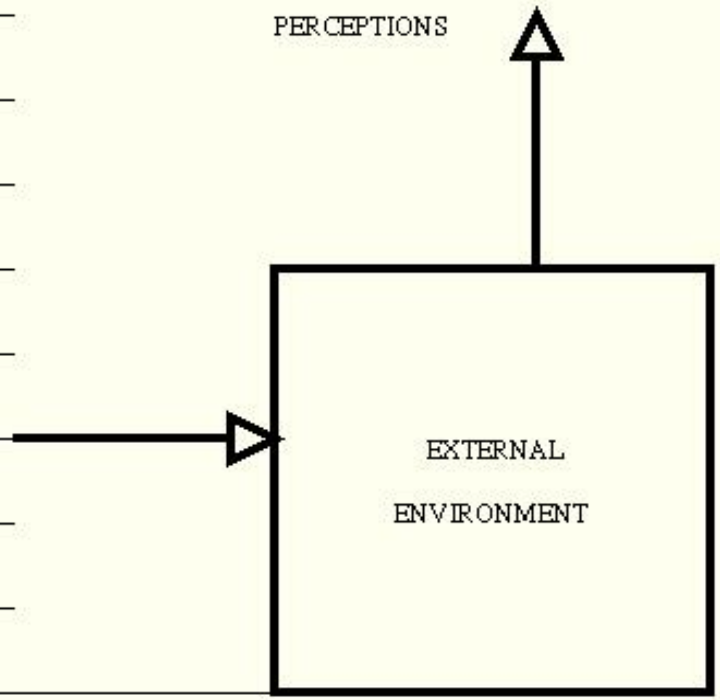
INTERNAL STATE

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

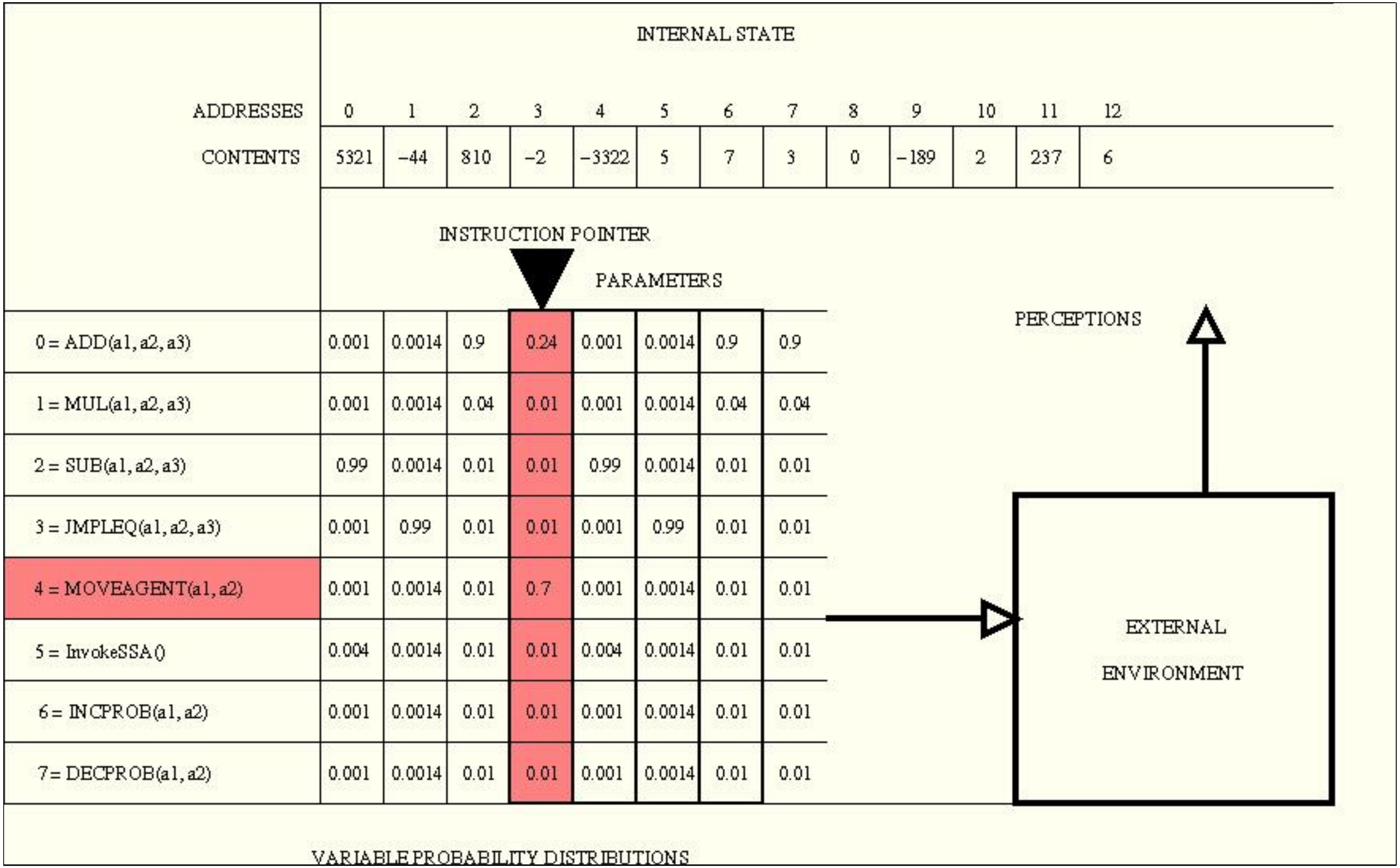
INSTRUCTION POINTER

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
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
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7 = DECPROB(a1, a2) 0.001 0.0014 0.01 0.01 0.001 0.0014 0.01 0.01
VARIABLE PROBABILITY DISTRIBUTIONS
PERCEPTIONS
EXTERNAL ENVIRONMENT

INTERNAL STATE

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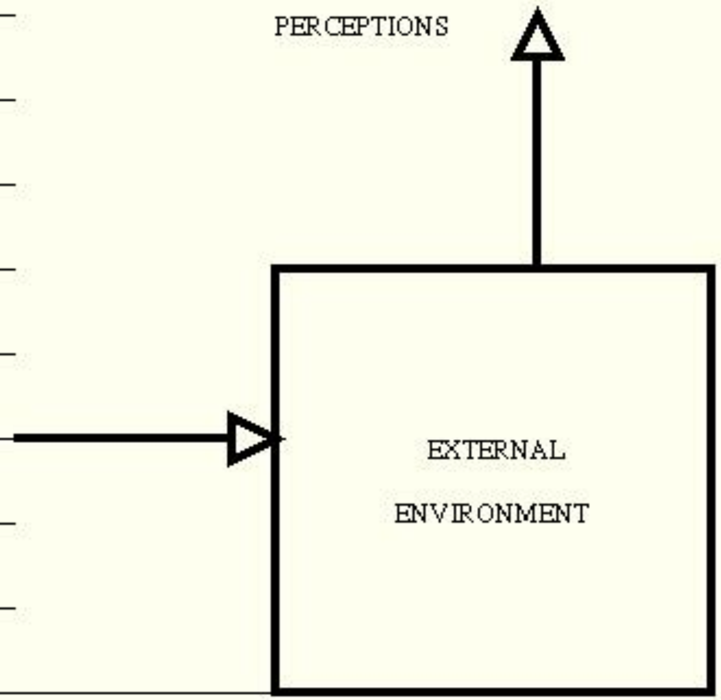

VARIABLE PROBABILITY DISTRIBUTIONS

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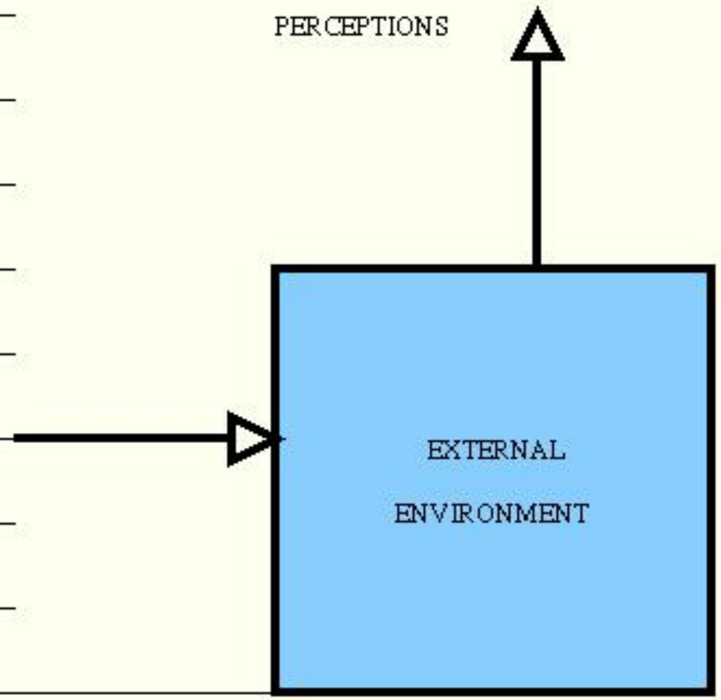

VARIABLE PROBABILITY DISTRIBUTIONS

INTERNAL STATE

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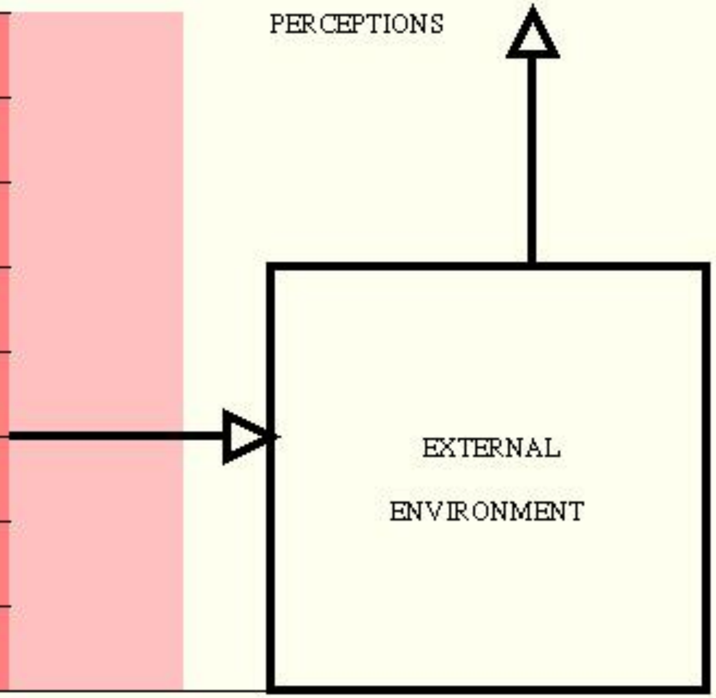
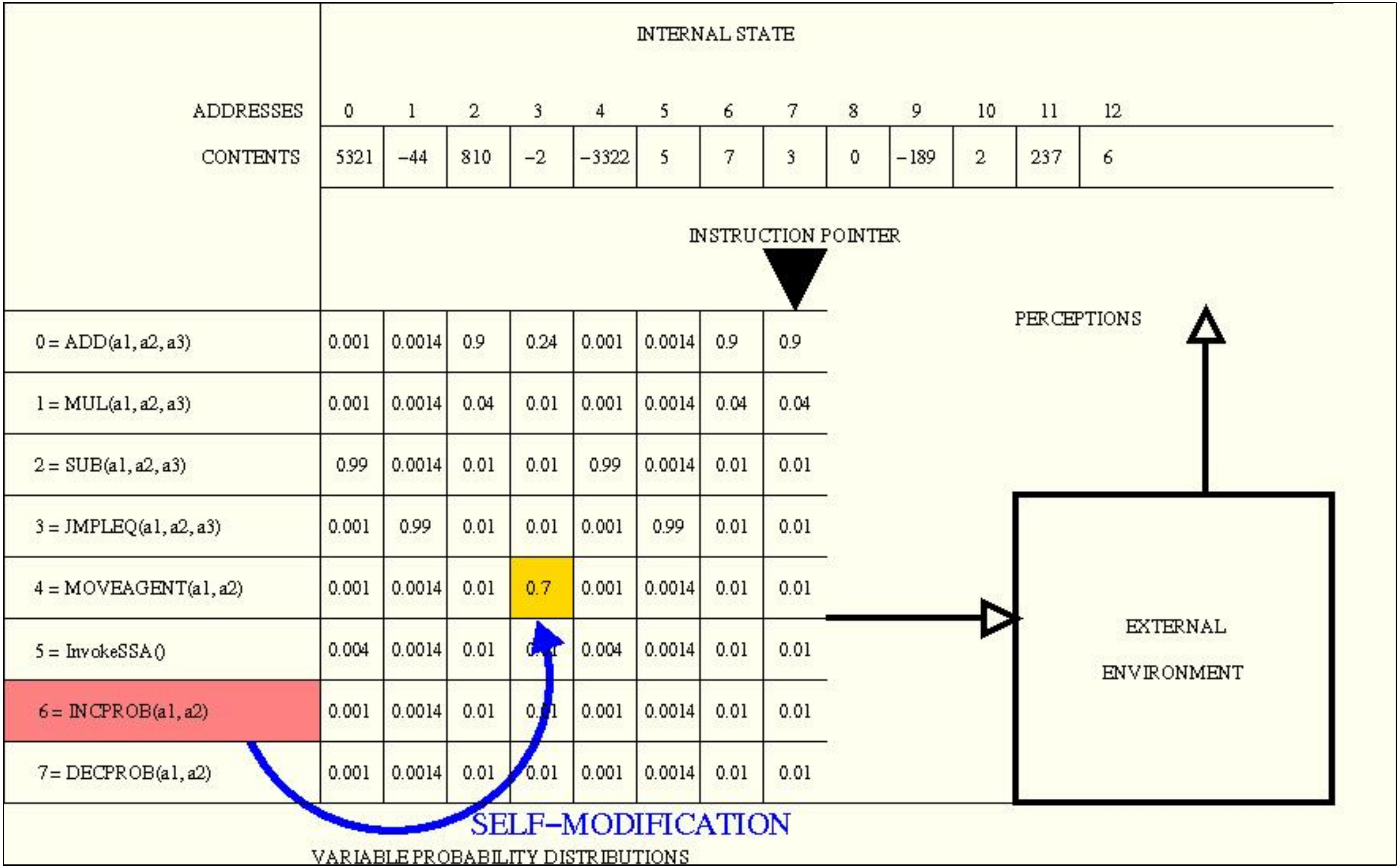


VARIABLE PROBABILITY DISTRIBUTIONS



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
PERCEPTIONS
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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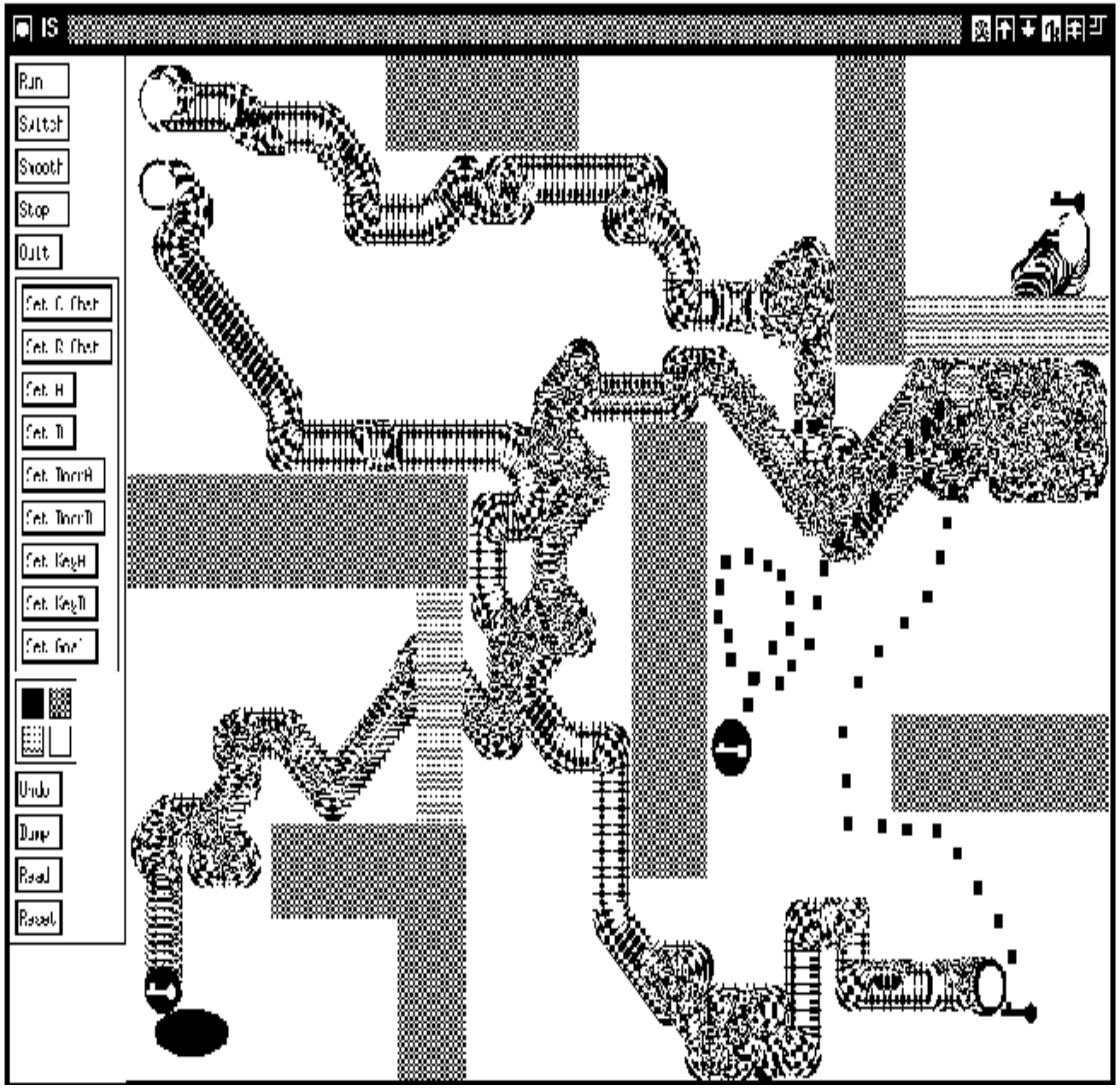
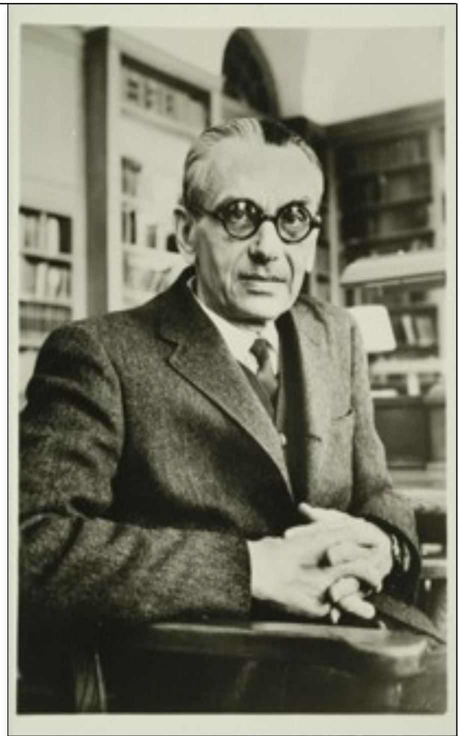
7 = DECPROB(a1, a2) 0.001 0.0014 0.01 0.01 0.001 0.0014 0.01 0.01
EXTERNAL ENVIRONMENT
SELF−MODIFICATION
VARIABLE PROBABILITY DISTRIBUTIONS

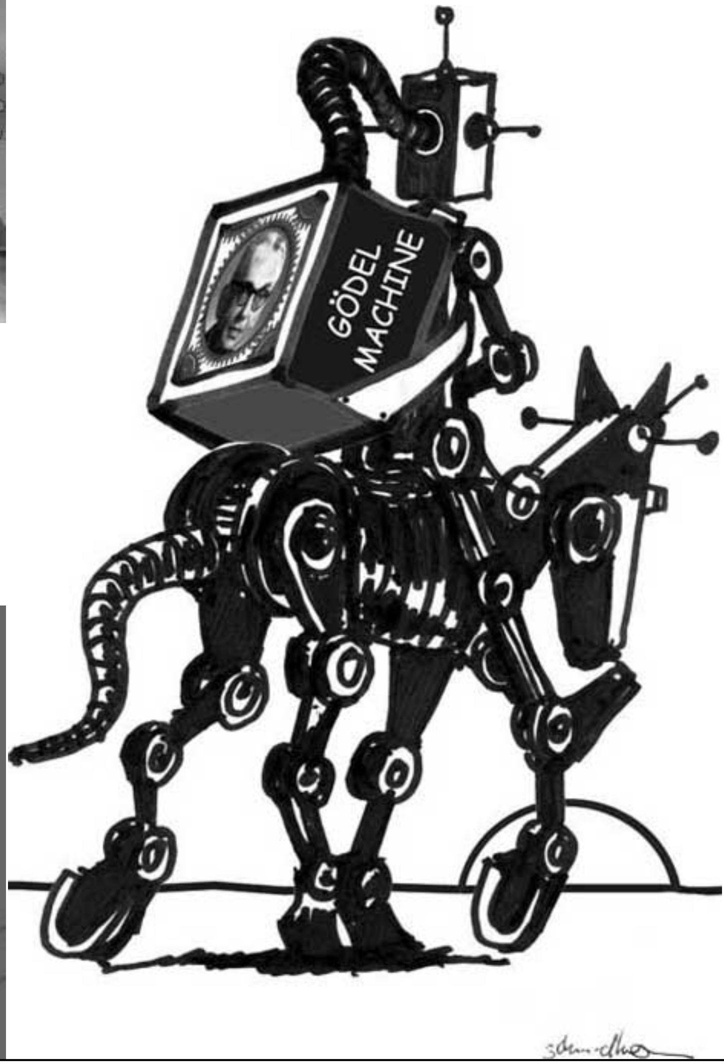


1997: Lifelong meta-learning with self-modifying policies and success-story algorithm: 2 agents, 2 doors, 2 keys. 1st southeast wins 5, the other 3. Through recursive self-modifications only: from 300,000 steps per trial down to 5,000.

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



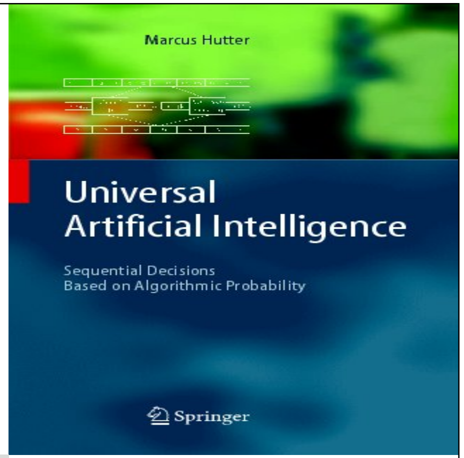


Gödel Machine (2003): agent-controlling program that speaks about itself, ready to rewrite itself in arbitrary fashion once it has found a proof that the rewrite is useful, given a user-defined utility function

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 $f: X \to Y$ 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

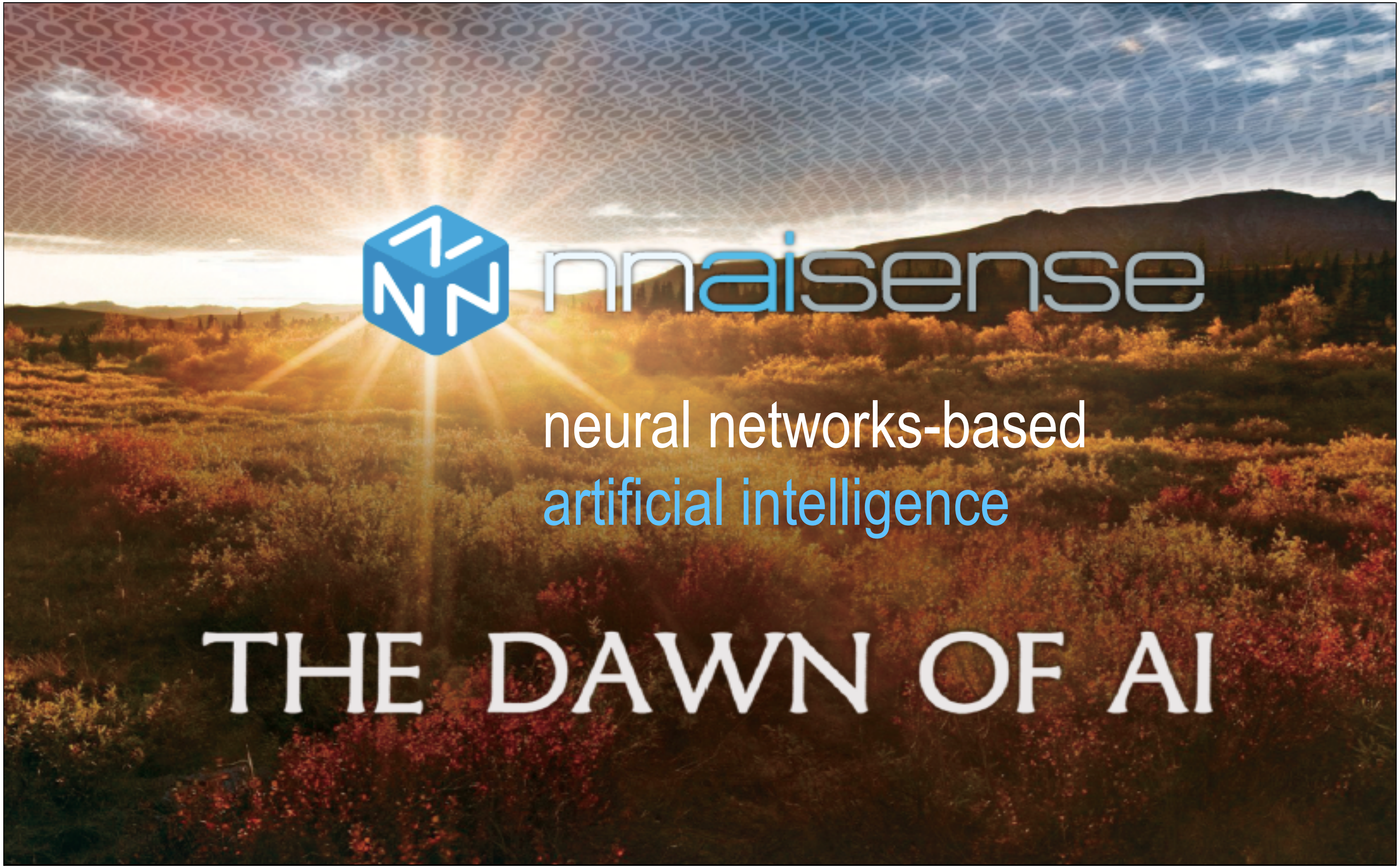
$n^3+10^{1000}=n^3+O(1)$

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

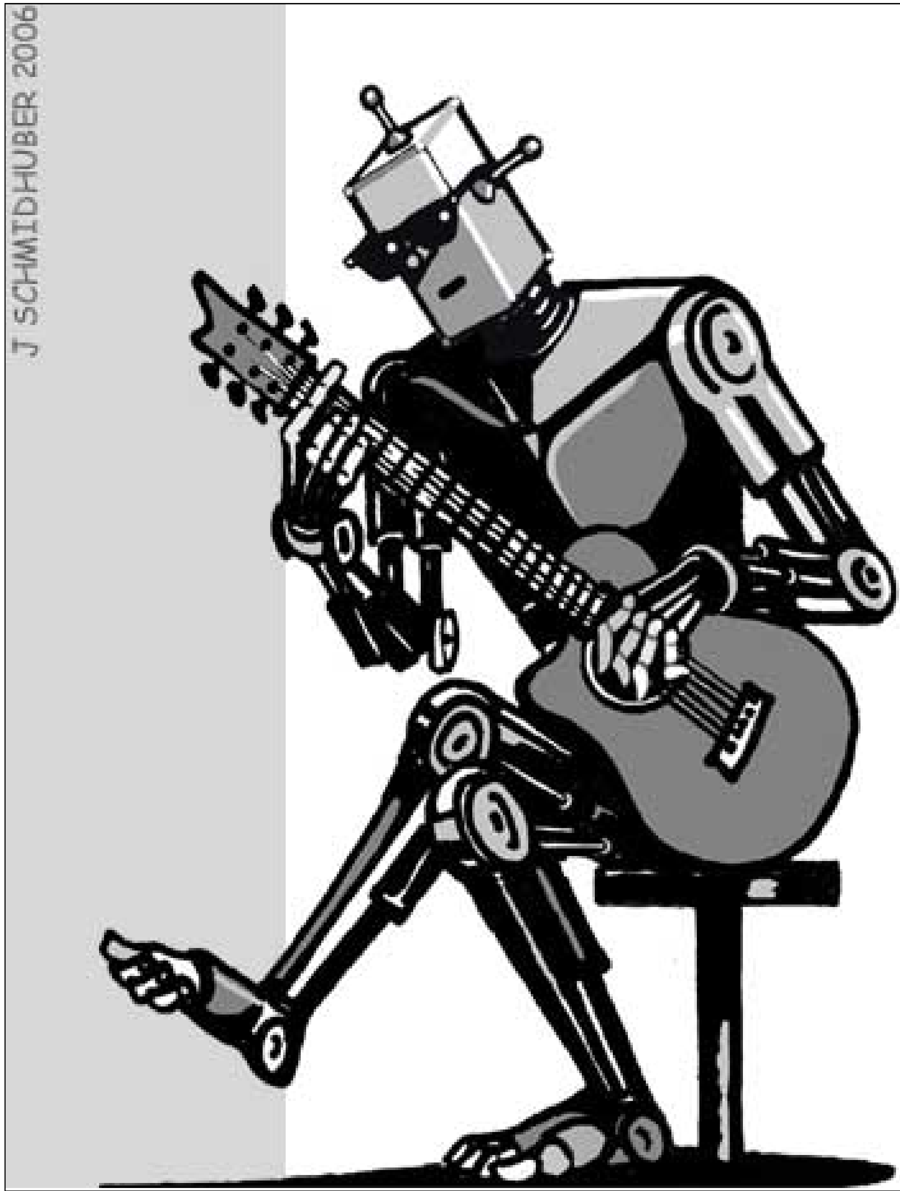
PowerPlay not only solves but also continually invents problems at the borderline between what's known and unknown - training an increasingly general problem solver by continually searching for the simplest still unsolvable problem

POWER PLAY

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


nnaisense
neural networks-based
artificial intelligence
THE DAWN OF AI

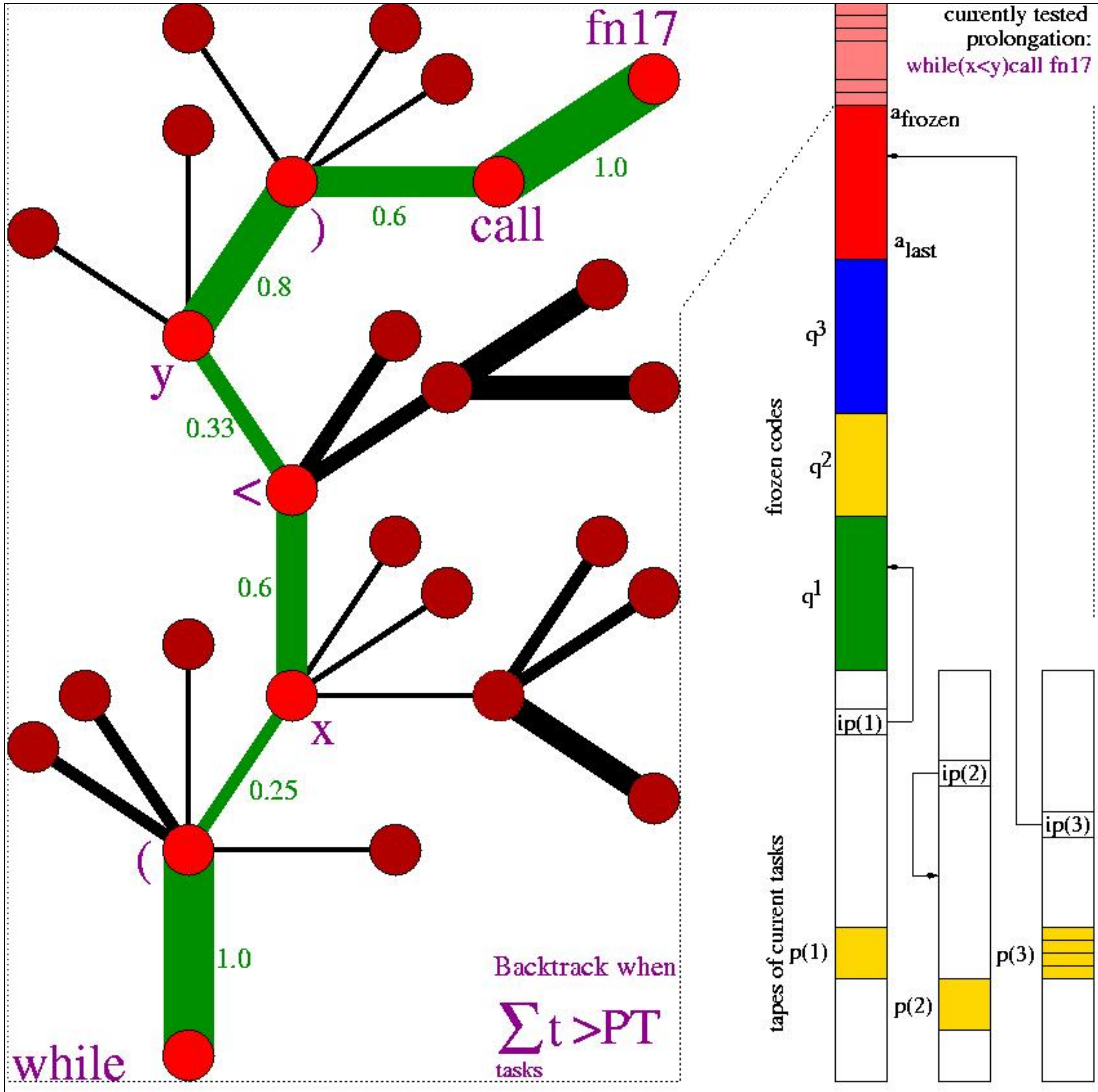
NIPS 2016 demo:
Reinforcement learning to park
Cooperation NNAISENSE - AUDI



Learning how to Learn Learning Algorithms: Extra Slides

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

NNAISENSE

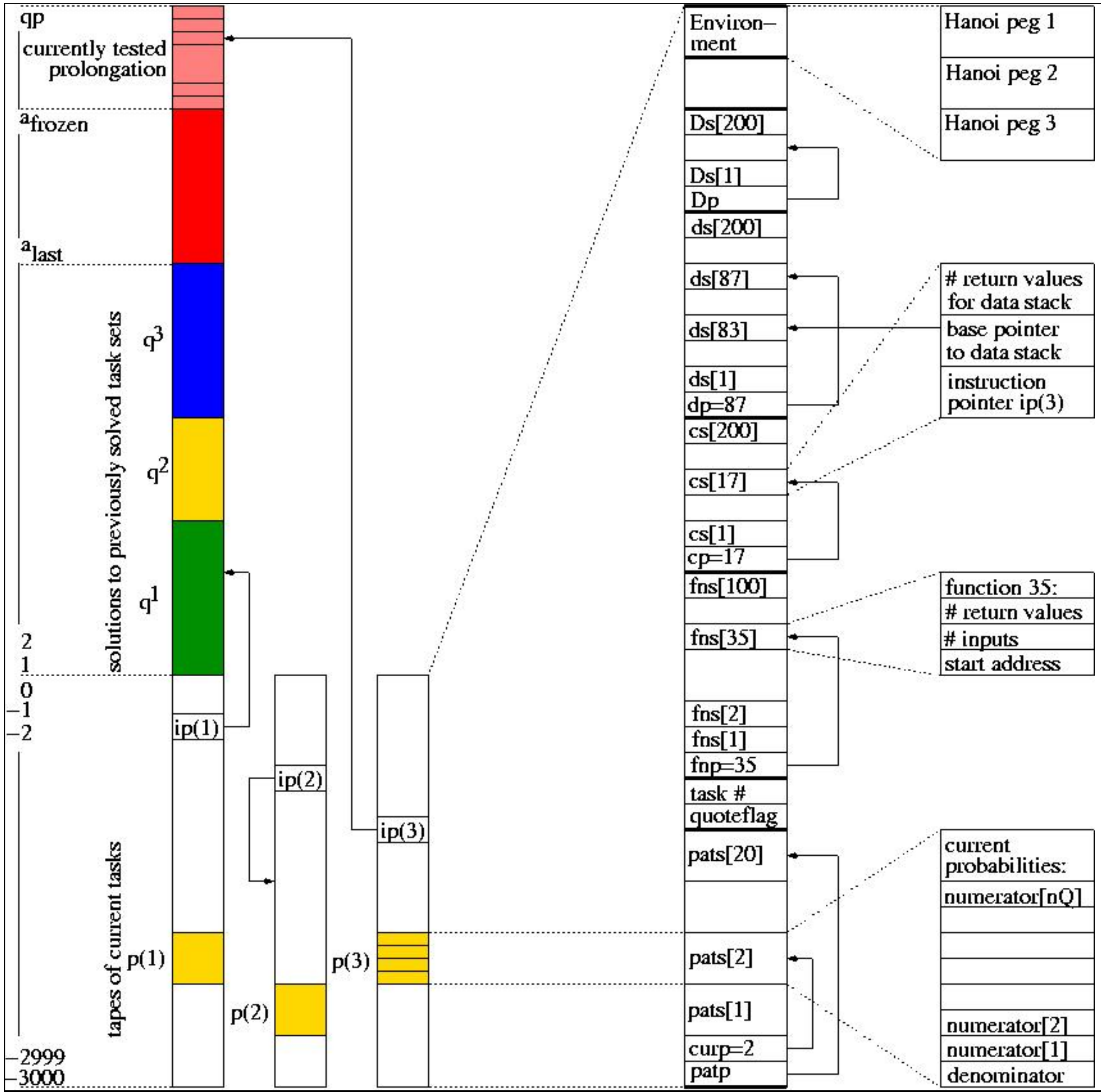


Super-deep program learner:
Optimal Ordered Problem Solver
OOPS (Schmidhuber, MLJ, 2004, extending Levin's universal search, 1973)

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

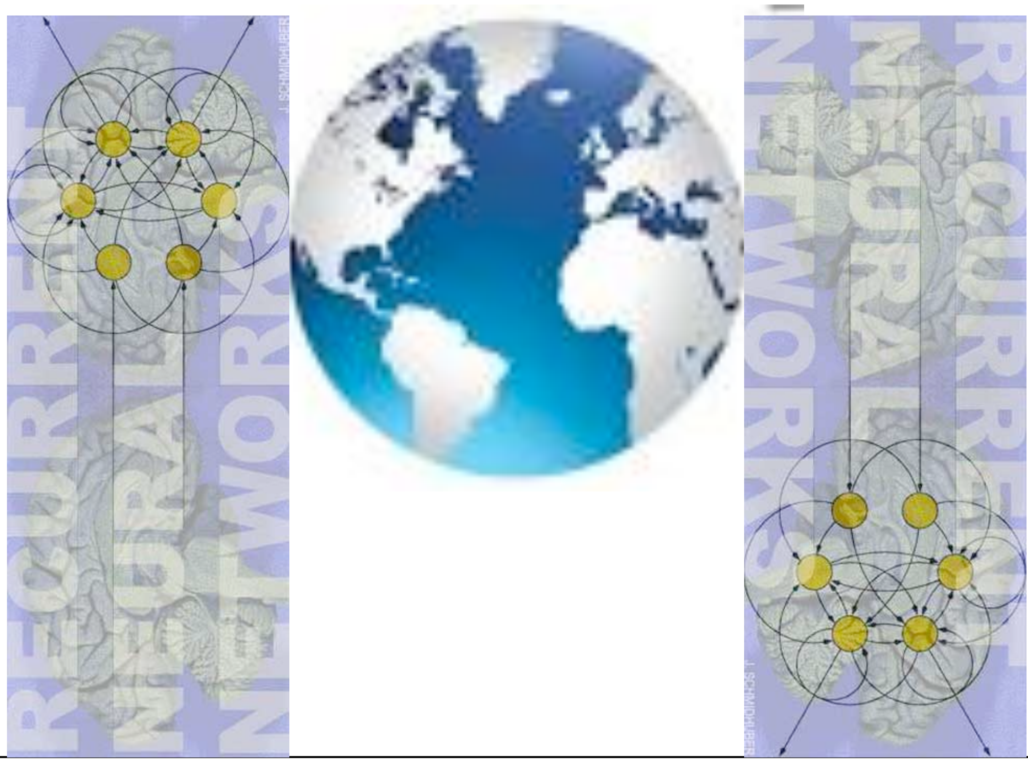
Towers of Hanoi: incremental solutions

- +1ms, n=1: *(movdisk)*
- 1 day, n=1,2: *(c4 c3 cpn c4 by2 c3 by2 exec)*
- 3 days, n=1,2,3: *(c3 dec boostq defnp c4 calltp c3 c5 calltp endnp)*
- 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