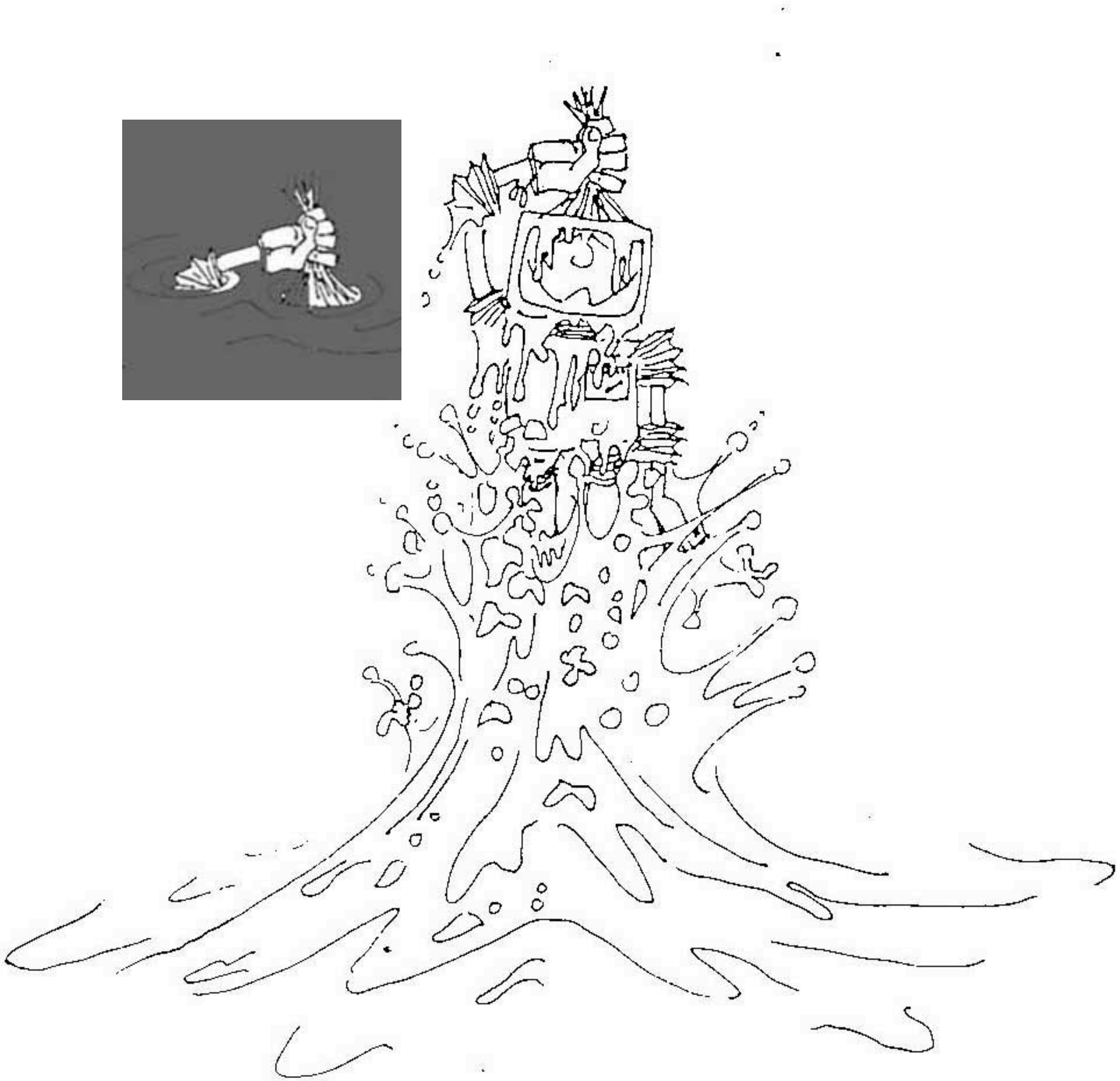


J. Schmidhuber, 1987

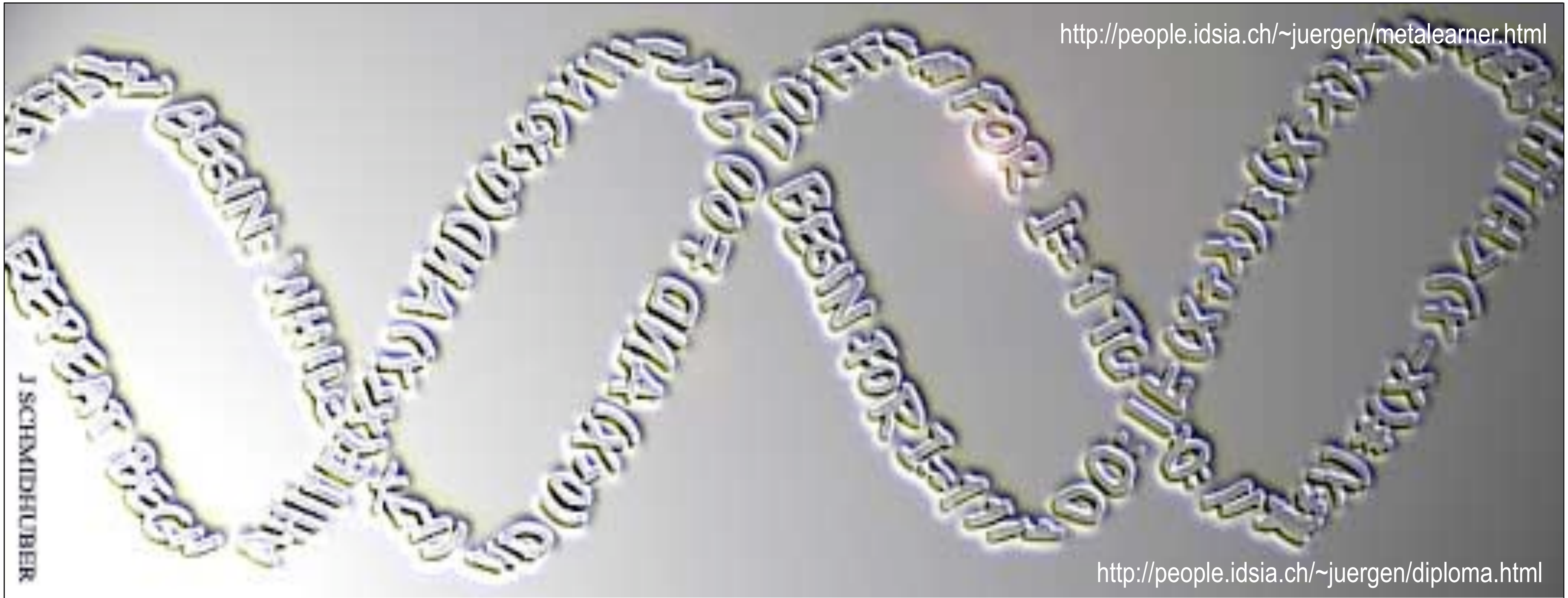
Learning how to Learn Learning Algorithms

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

NNAISENSE

Jürgen Schmidhuber

You_again Shmidhoobuh



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. 1st concrete design of recursively self-improving AI (RSI), trying to make a first step towards superintelligence. Reinforcement-learn to improve learning algorithm itself, and also the meta-learning algorithm, etc…

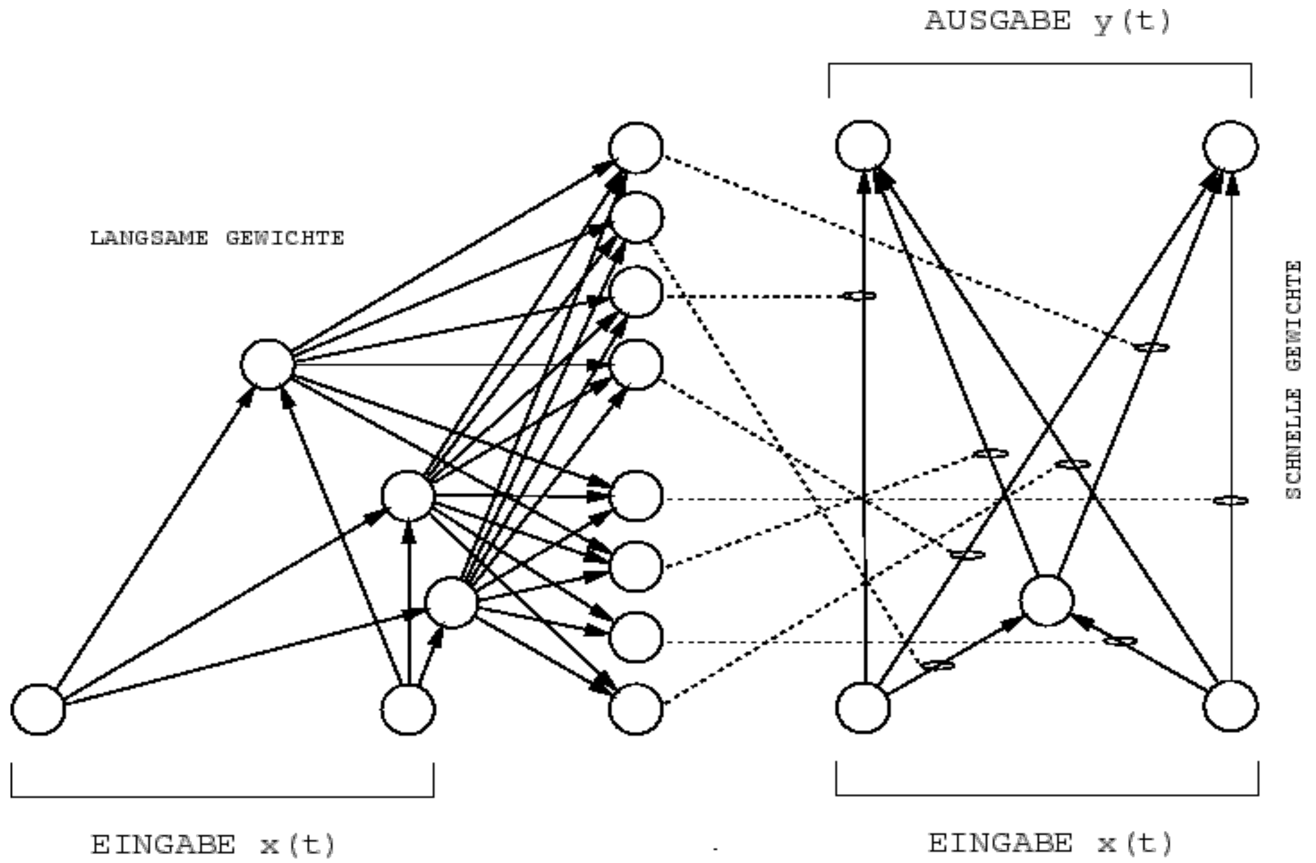
"True" Learning to Learn (L2L) is not just transfer learning! Even a simple feedforward NN can transfer-learn to learn new images faster through pre-training on other image sets

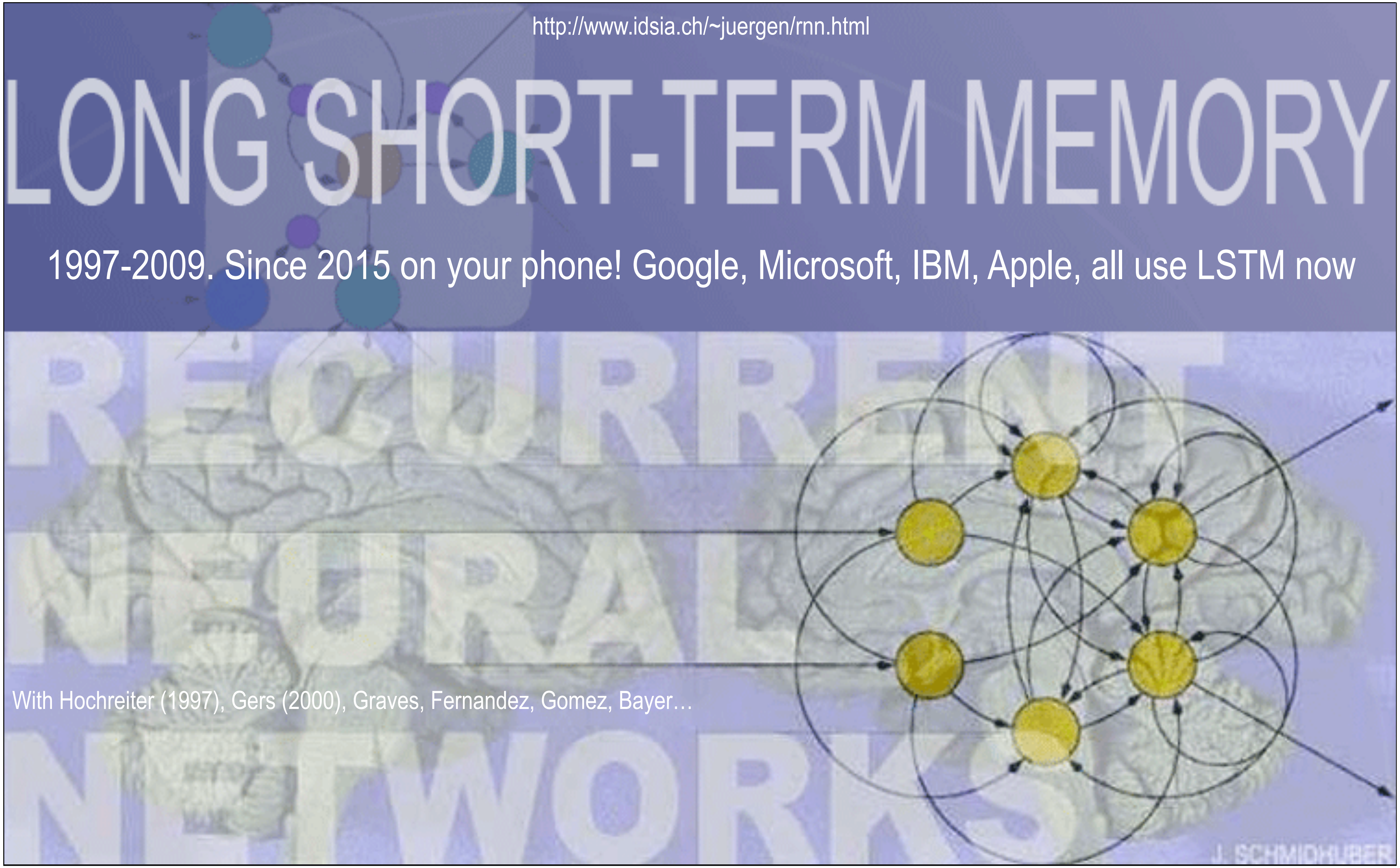
True L2L is not just about learning to adjust a few hyper-parameters such as mutation rates in evolution strategies (e.g., Rechenberg & Schwefel, 1960s)

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)

Looks a bit like supervised L2L but is not yet: 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)

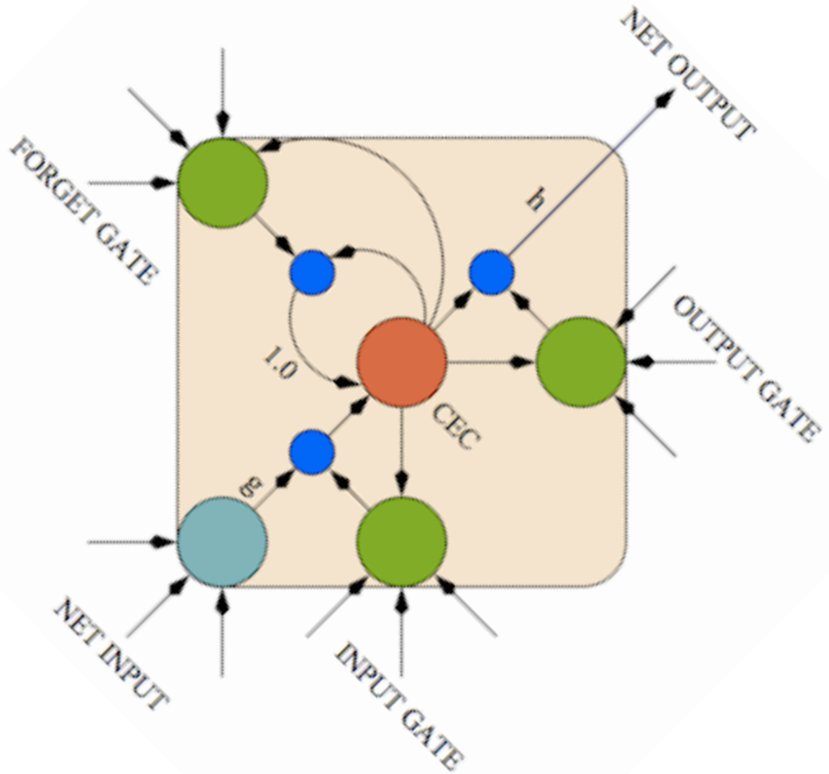



http://www.idsia.ch/~juergen/rnn.html
LONG SHORT-TERM MEMORY
1997-2009. Since 2015 on your phone! Google, Microsoft, IBM, Apple, all use LSTM now
RECURRENT
NEURAL
NETWORKS
With Hochreiter (1997), Gers (2000), Graves, Fernandez, Gomez, Bayer…
J. SCHMIDHUBER

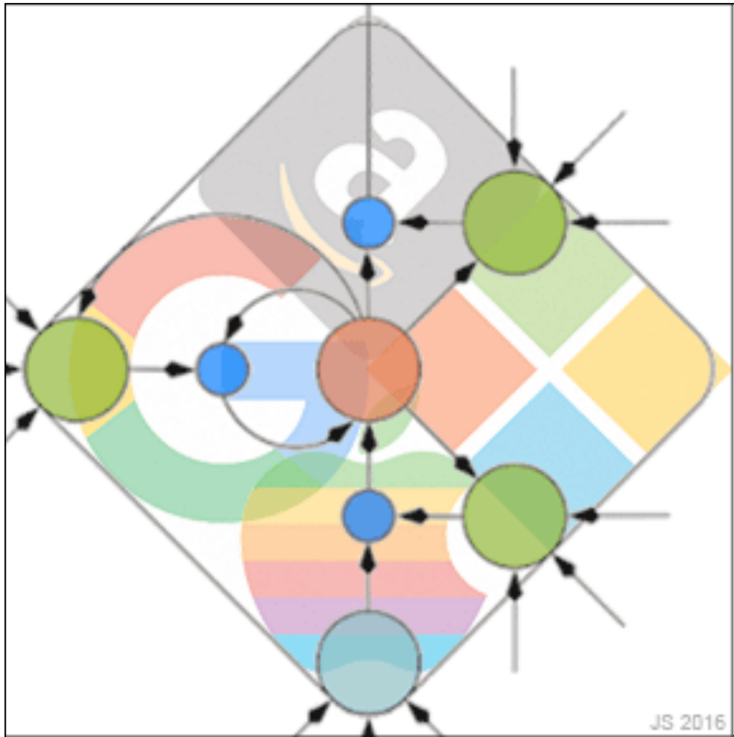
Today's LSTM has fast weights in the forget gates! LSTM shaped by:

Ex-PhD students (TUM & IDSIA) Sepp Hochreiter (PhD 1999), Felix Gers (PhD 2001, forget gates for recurrent units), Alex Graves (e.g., CTC, PhD 2008), Daan Wierstra (PhD 2010), Justin Bayer (2009, evolving LSTM-like architectures)

But few would say that LSTM by itself is a metalerner!



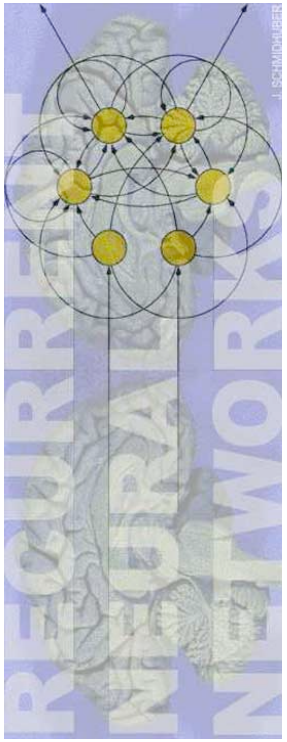
LSTM cell

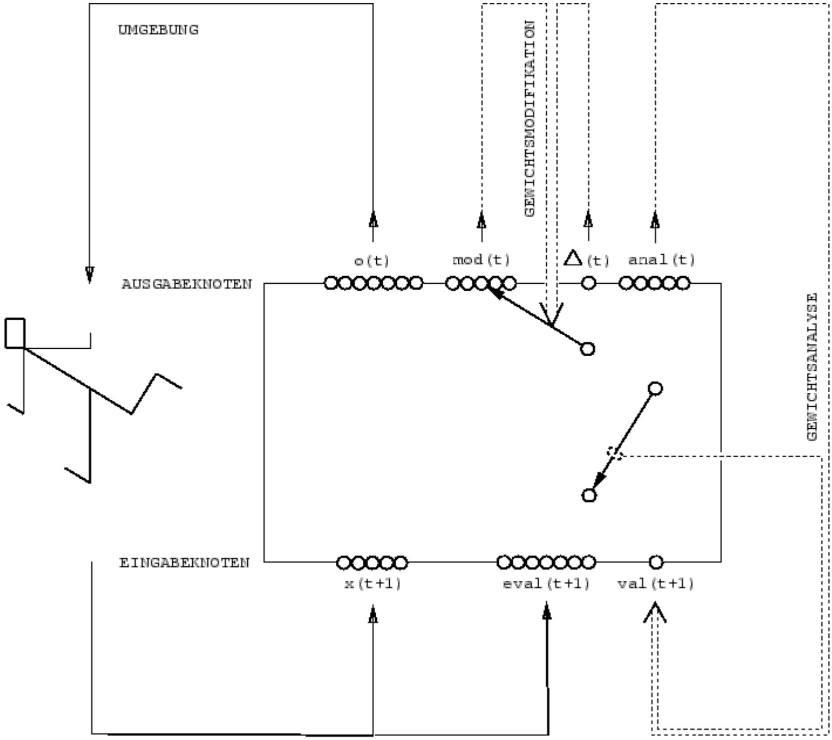


2015: Dramatic improvement of Google's speech recognition through LSTM & CTC (2006), now on 2 billion Android phones. Similar for Microsoft. 2016: LSTM on almost 1 billion Apple iPhones, e.g., Siri. 2016: Google's greatly improved Google Translate uses LSTM; also Amazon's Echo. 2017: Facebook uses LSTM for over 4 billion translations each day

Otherwise this would also be metalearning: Almost 30% of the awesome computational power for inference in all those Google datacenters is used for LSTM (Jouppi et al, 2017); 5% for CNNs.

LSTM / CTC also used by

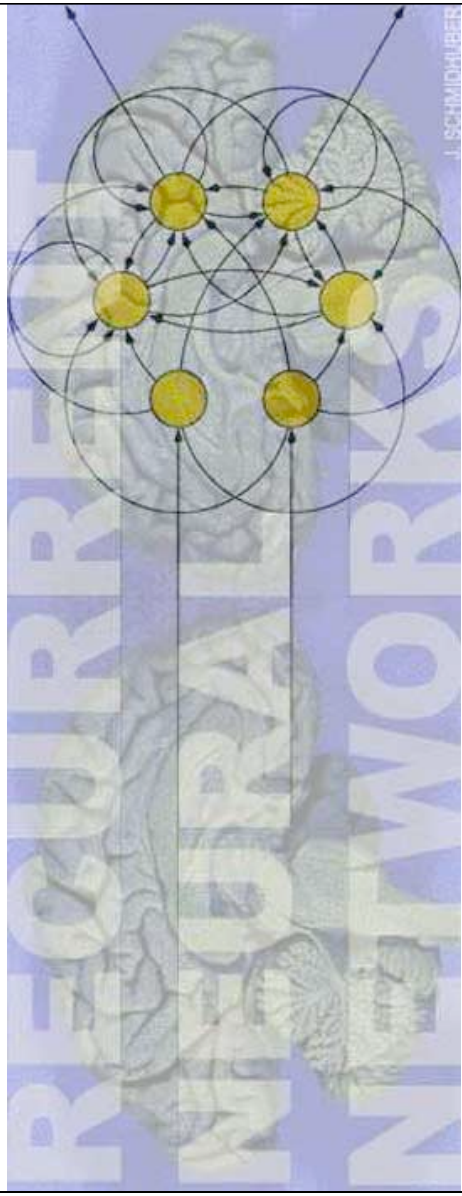




1992-1993: Gradient-based meta-RNNs that can learn to run their own weight change algorithm, e.g.: J. Schmidhuber. A self-referential weight matrix. ICANN 1993. Based on TR at U Colorado, 1992.

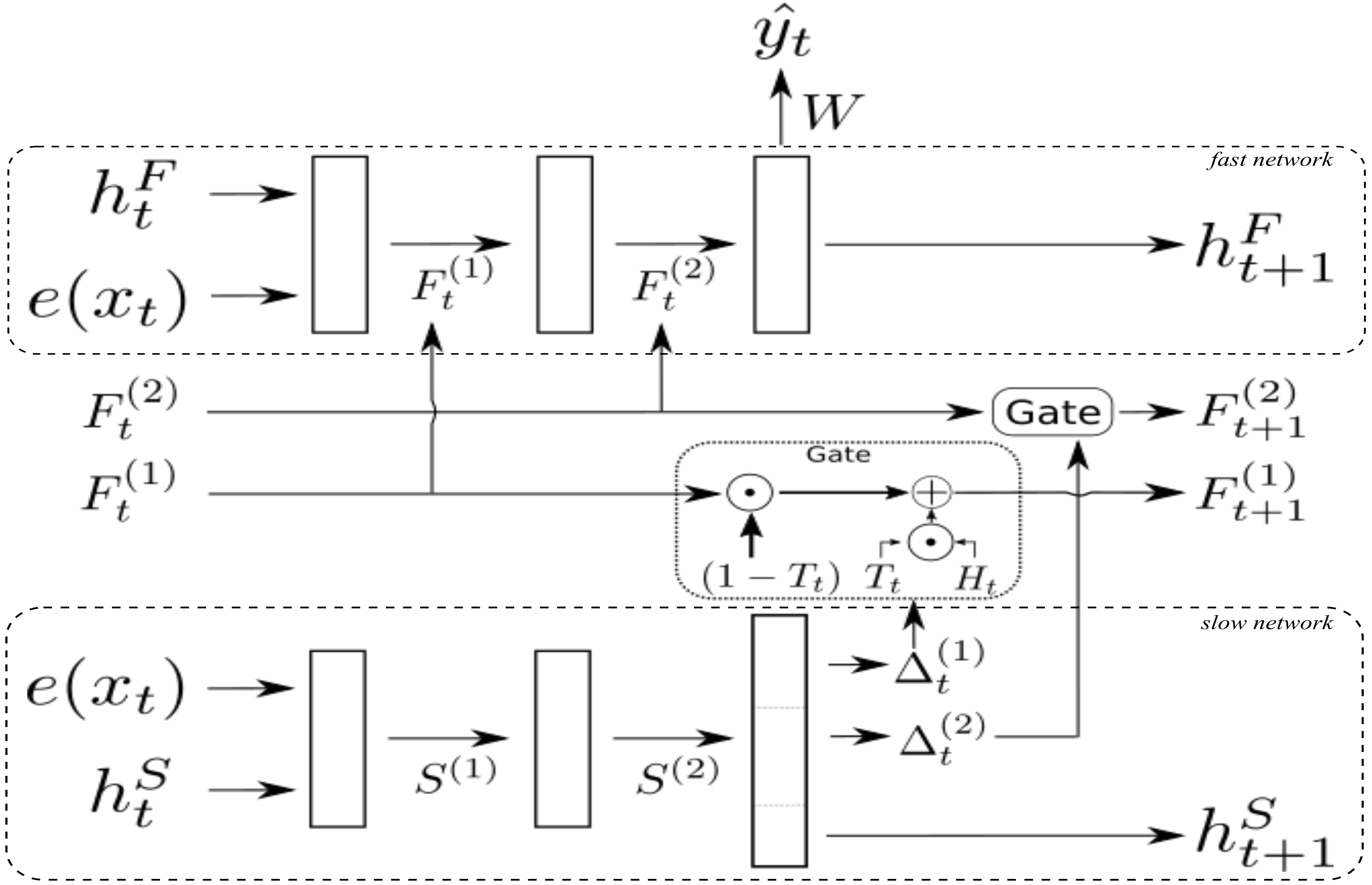
An RNN, but no LSTM yet. In 2001, however, Sepp Hochreiter taught a meta-LSTM to learn a learning algorithm for quadratic functions that was faster than backprop

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



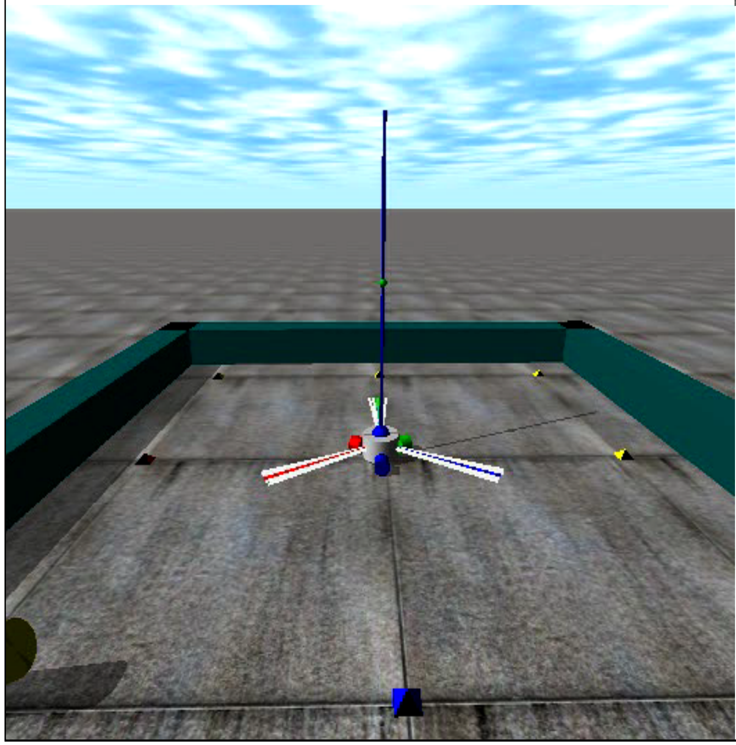
Schmidhuber, ICANN 1993: Reducing the ratio between learning complexity and number of time-varying variables in fully recurrent nets.

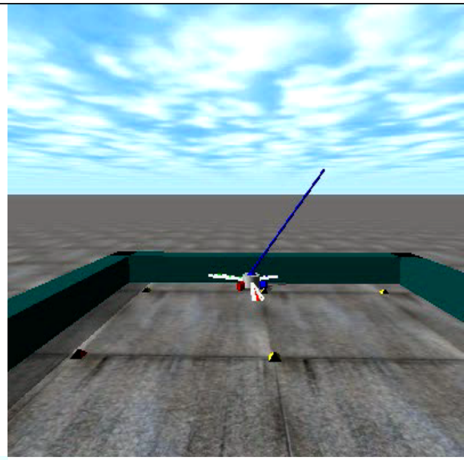
Similar NIPS 2016 paper by Ba et al. See I. Schlag at NIPS Metalearning Symposium 2017!



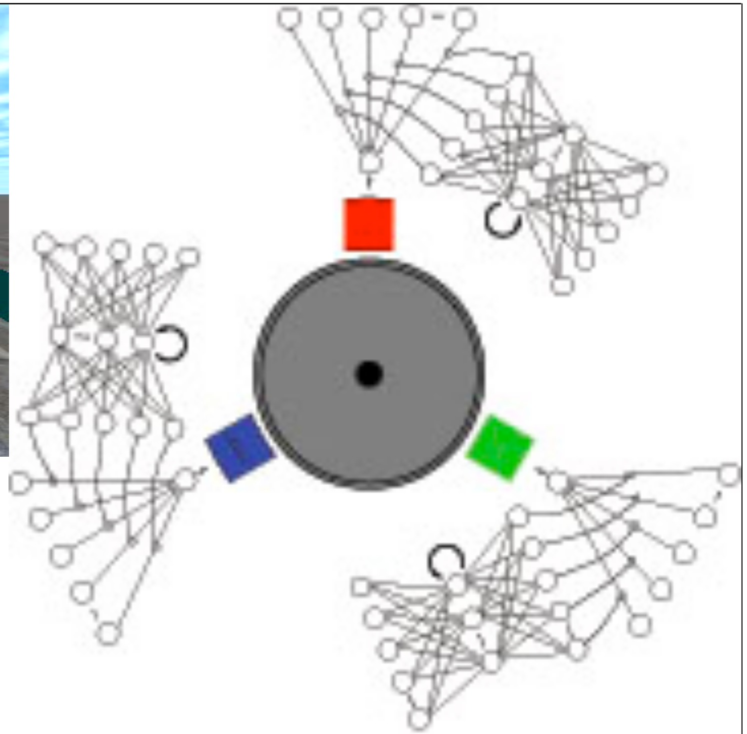
New fast weight addressing scheme: Imanol Schlag @ NIPS Meta-learning Workshop 2017

2005:
Reinforcement-
Learning or
Evolving RNNs
with Fast Weights



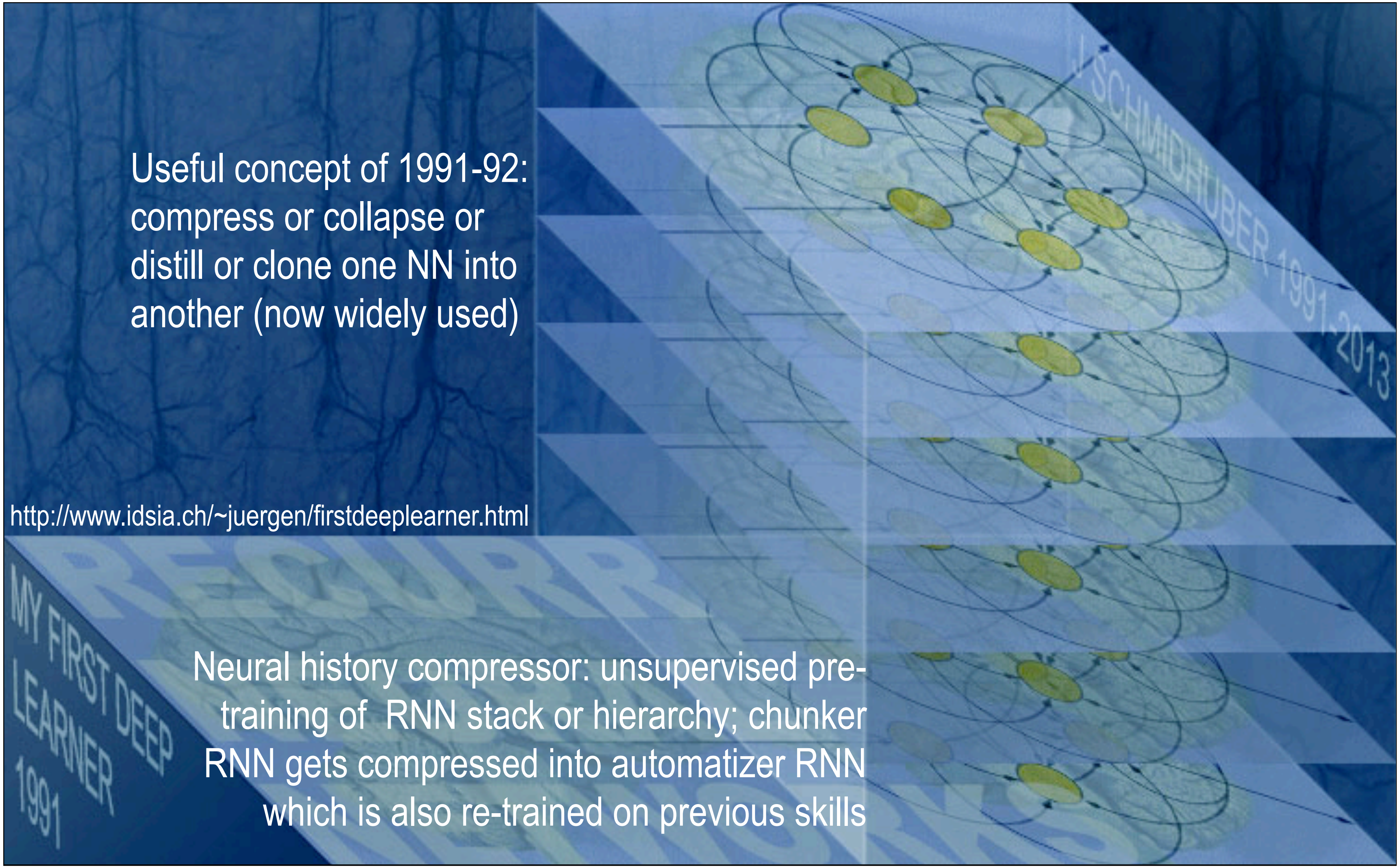


Robot learns to
balance 1 or 2 poles
through 3D joint



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

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



Useful concept of 1991-92: compress or collapse or distill or clone one NN into another (now widely used)

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

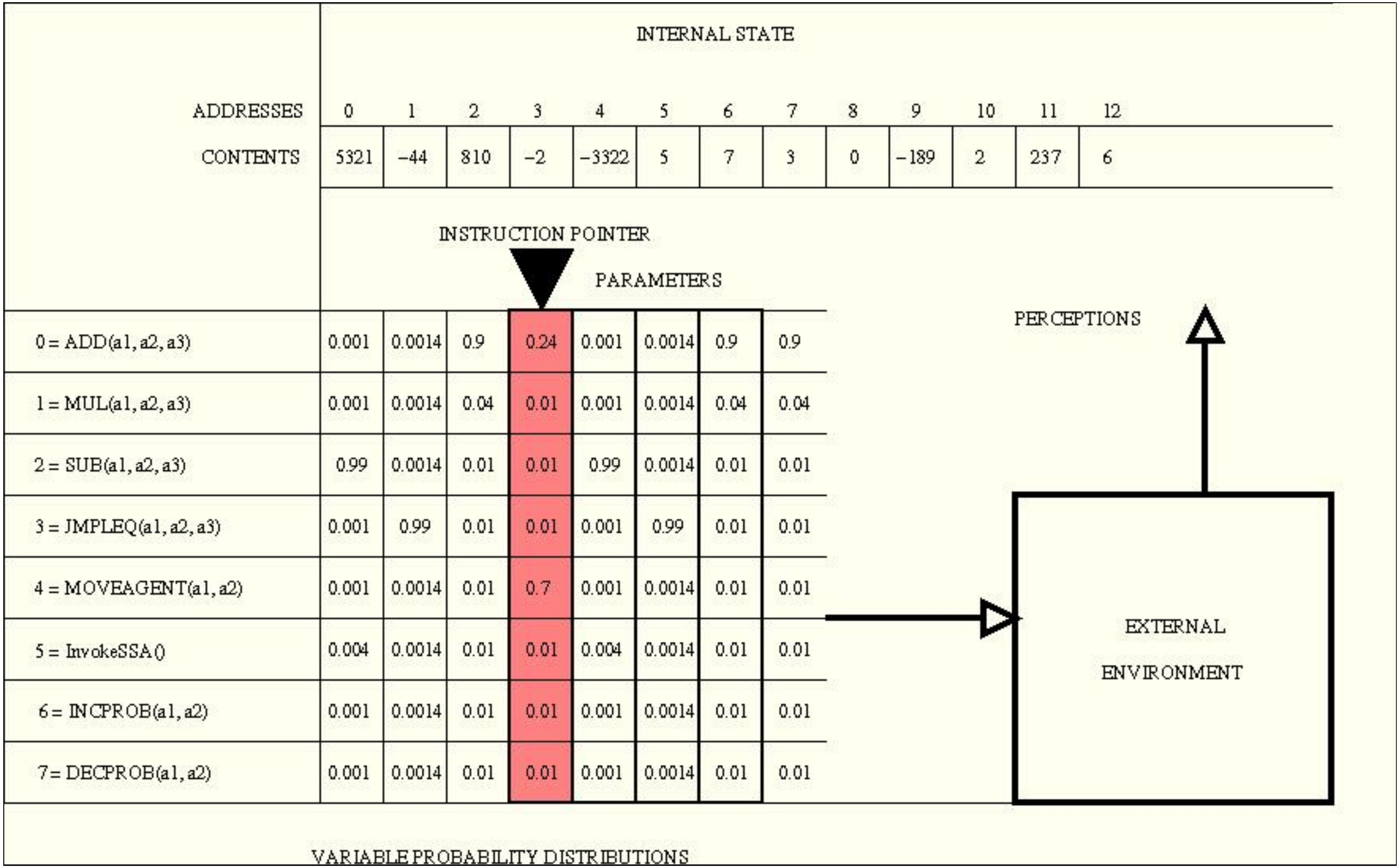
Neural history compressor: unsupervised pre-training of RNN stack or hierarchy; chunker RNN gets compressed into automatizer RNN which is also re-trained on previous skills

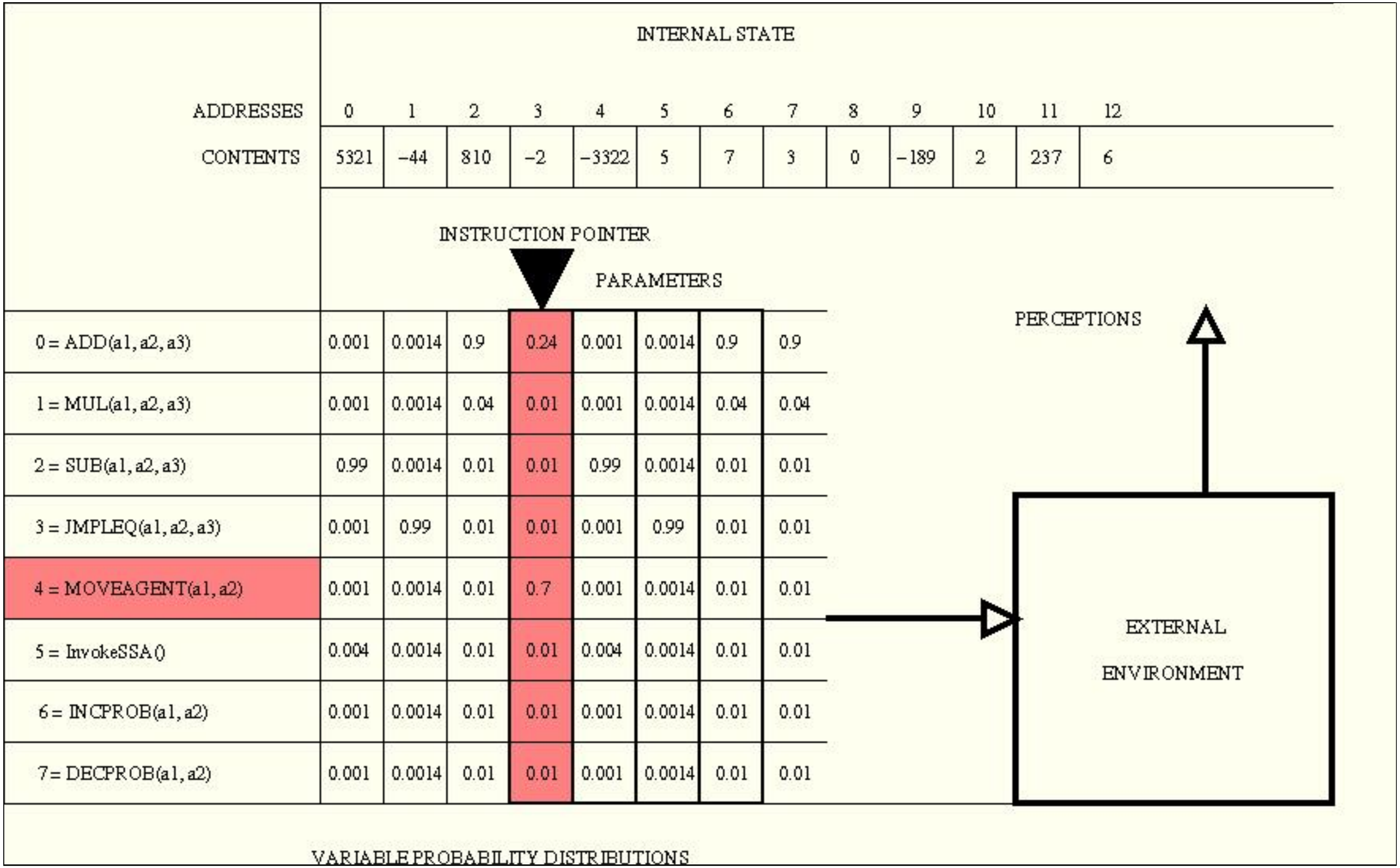
Success-story algorithm (SSA) for self-modifying code (since 1994)

J. Schmidhuber. On learning how to learn learning strategies. TR FKI-198-94, 1994.

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
PERCEPTIONS
EXTERNAL ENVIRONMENT
VARIABLE PROBABILITY DISTRIBUTIONS



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

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
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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

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

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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
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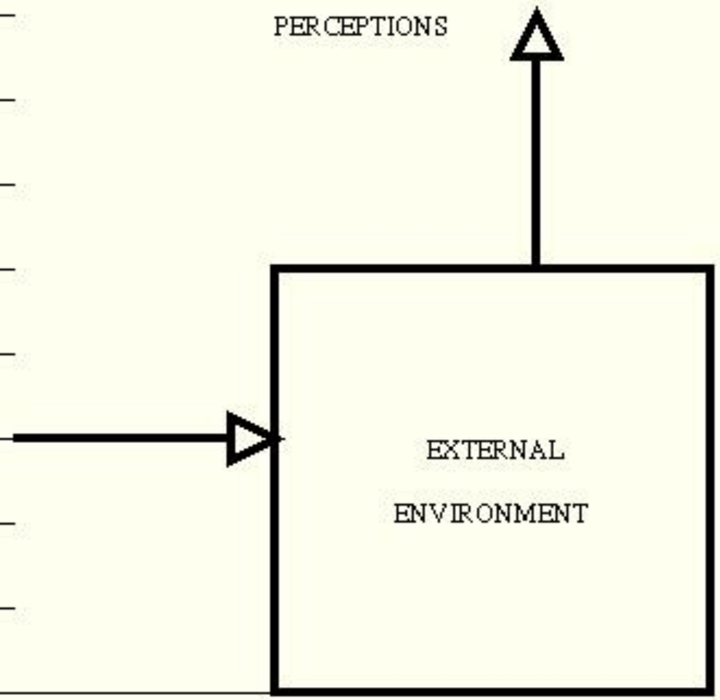
7 = DECPROB(a1, a2)	0.001	0.0014	0.01	0.01	0.001	0.0014	0.01	0.01



VARIABLE PROBABILITY DISTRIBUTIONS

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

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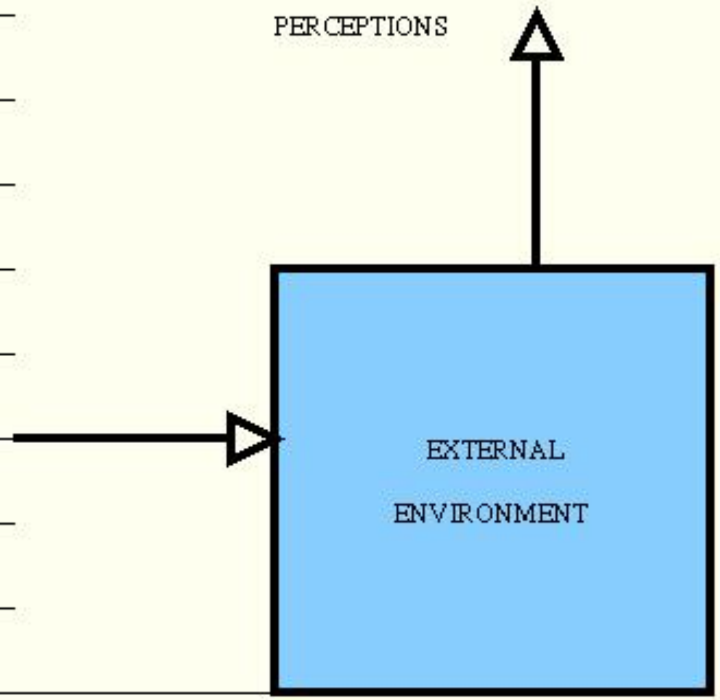
7 = DECPROB(a1, a2)	0.001	0.0014	0.01	0.01	0.001	0.0014	0.01	0.01



VARIABLE PROBABILITY DISTRIBUTIONS

INTERNAL STATE

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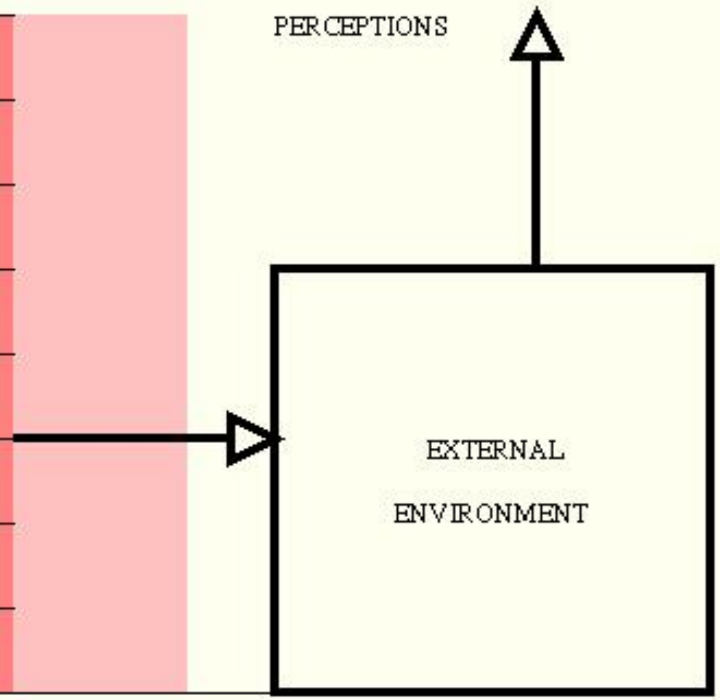
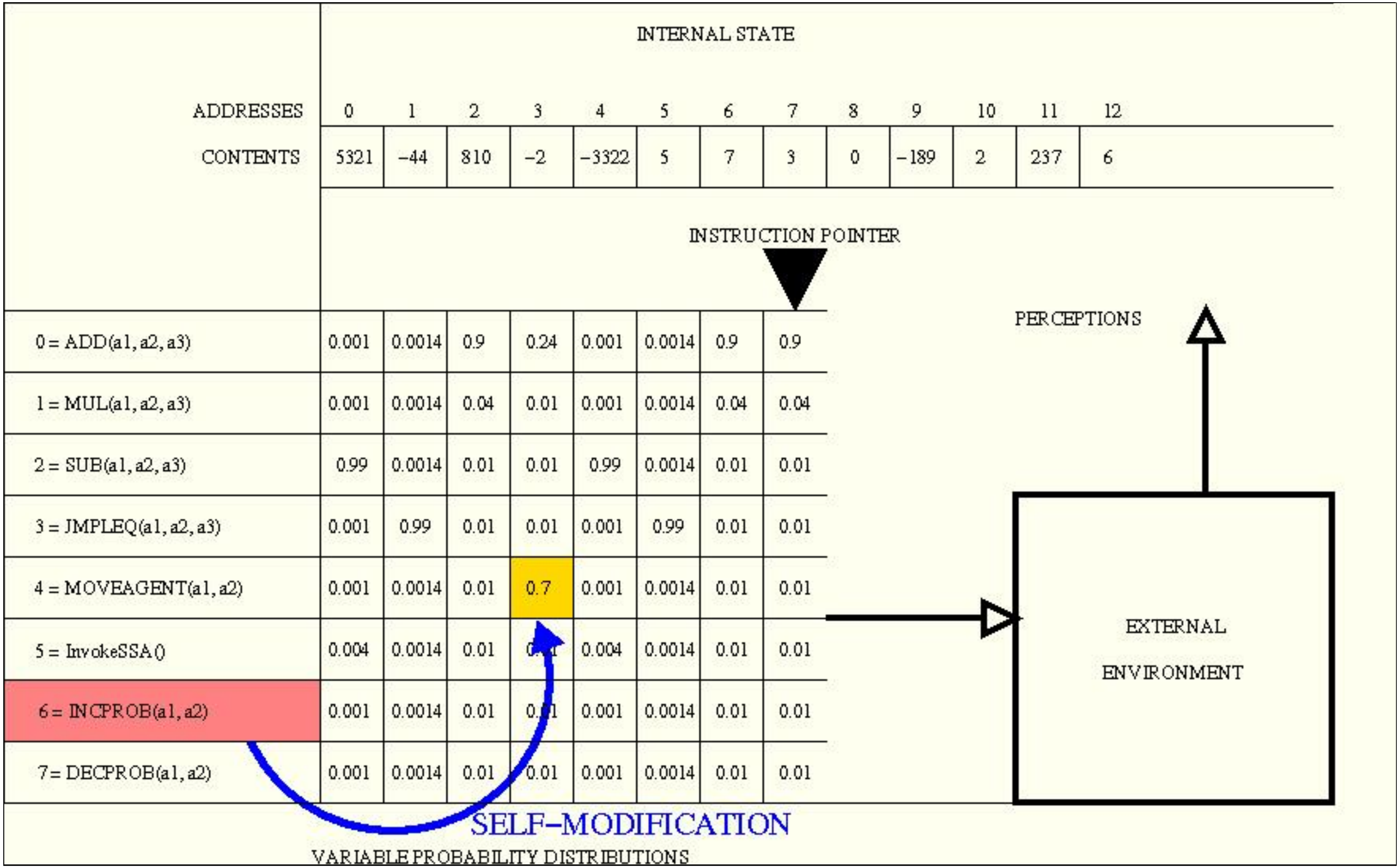
7 = DECPROB(a1, a2)	0.001	0.0014	0.01	0.01	0.001	0.0014	0.01	0.01



VARIABLE PROBABILITY DISTRIBUTIONS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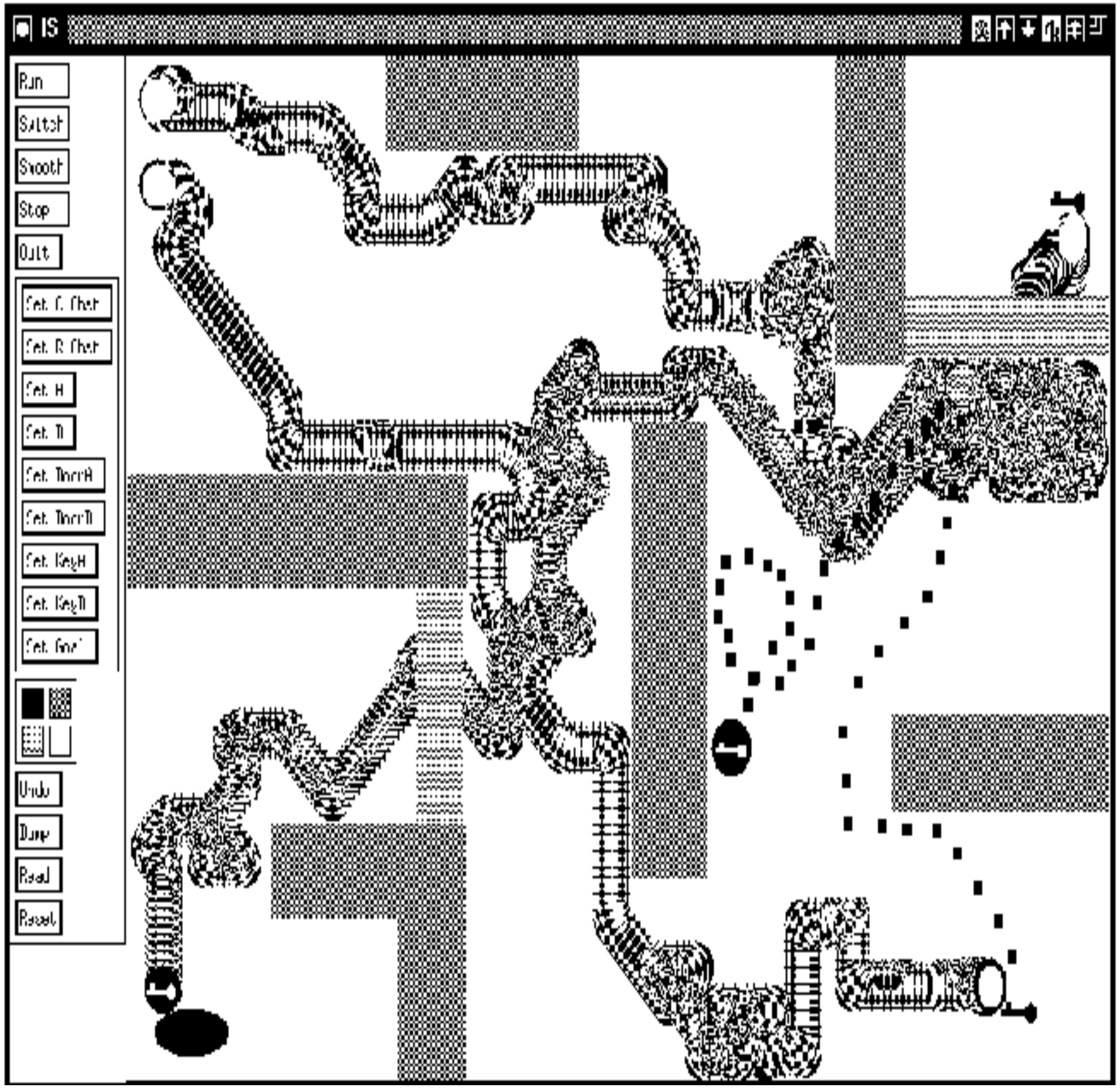
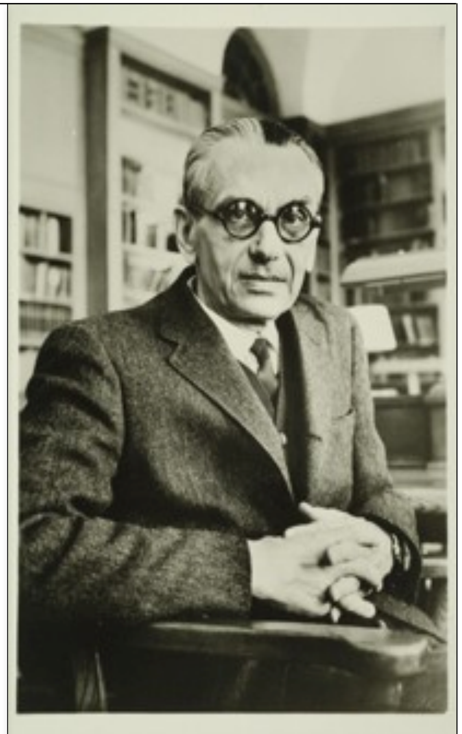
PERCEPTIONS
EXTERNAL
ENVIRONMENT
SELF−MODIFICATION
VARIABLE PROBABILITY DISTRIBUTIONS

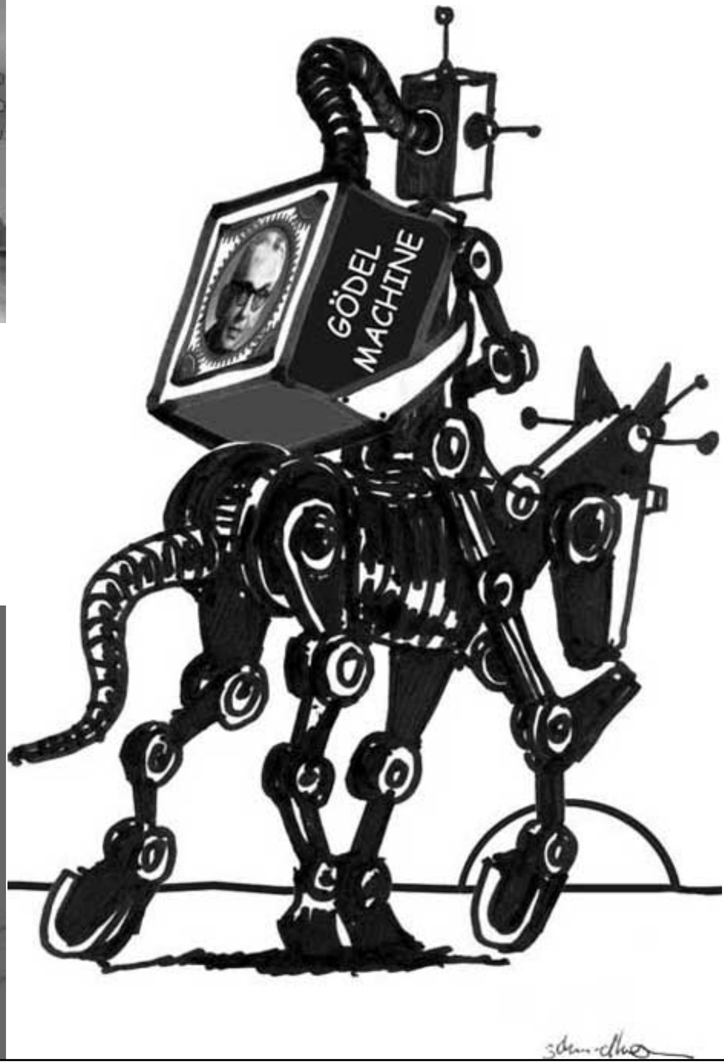


1997: Lifelong meta-RL with self-modifying policies and success-story algorithm: 2 agents, 2 doors, 2 keys. 1st southeast wins 5, the other 3. Through recursive self-modifications only: from 300,000 steps per trial down to 5,000.

Kurt Gödel, father of theoretical computer science and of AI theory, exhibited the limits of math and computation and AI (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



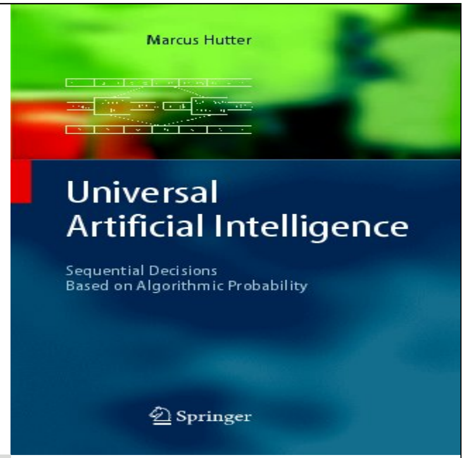


Gödel Machine (2003): agent-controlling program that speaks about itself, ready to rewrite itself in arbitrary fashion once it has found a proof that the rewrite is useful, given a user-defined utility function

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

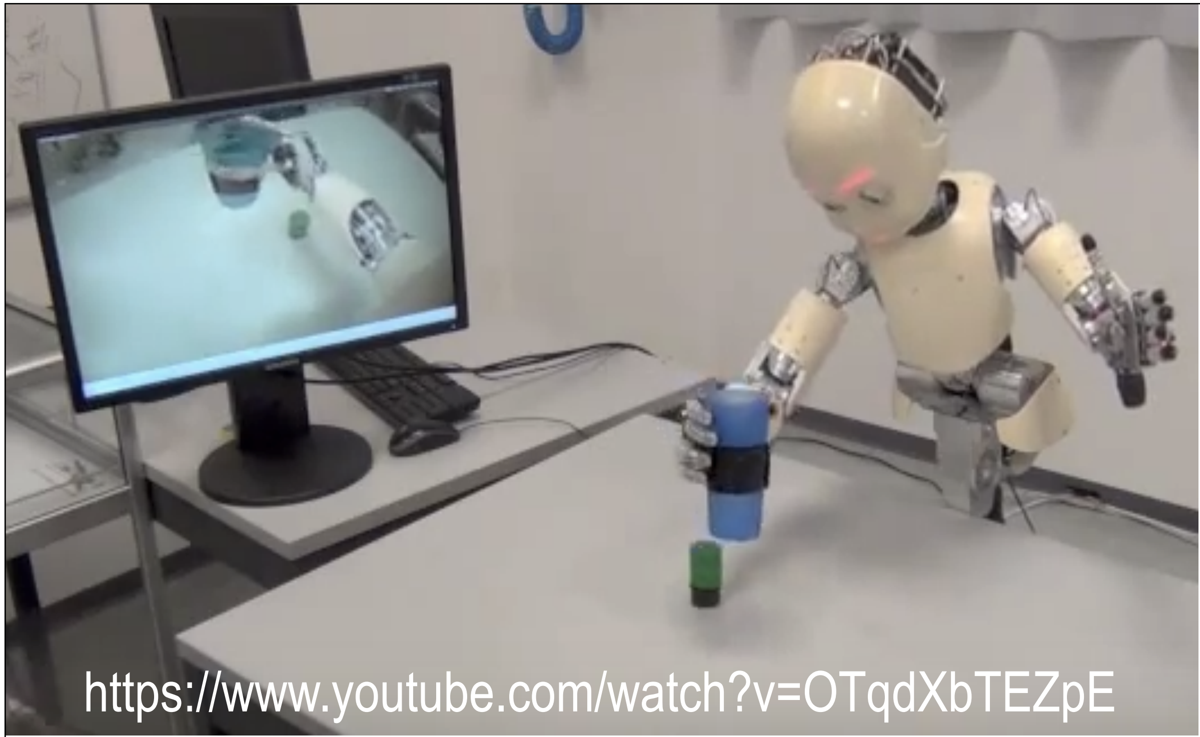


Given $f:X\rightarrow Y$ and $x\in X$, search proofs to find program q that provably computes f(z) for all $z\in X$ within time bound $t_q(z)$; spend most time on f(x)-computing q with best current bound

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

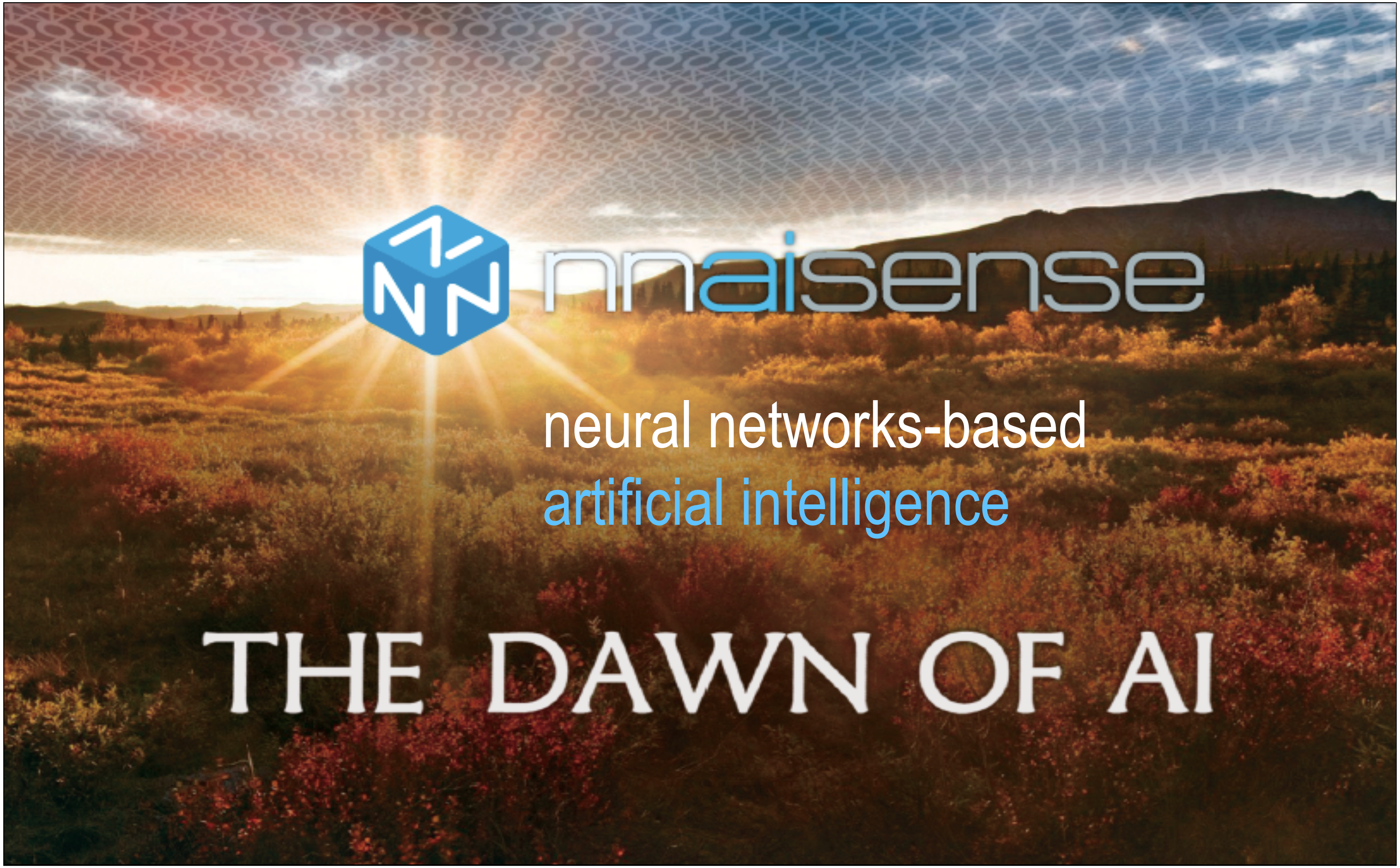
As fast as fastest f-computer, save for factor $1+\varepsilon$ and f-specific const. independent of x!


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



Continual curiosity-driven skill acquisition from high-dimensional video inputs for humanoid robots. Kompella, Stollenga, Luciw, Schmidhuber. Artificial Intelligence, 2015

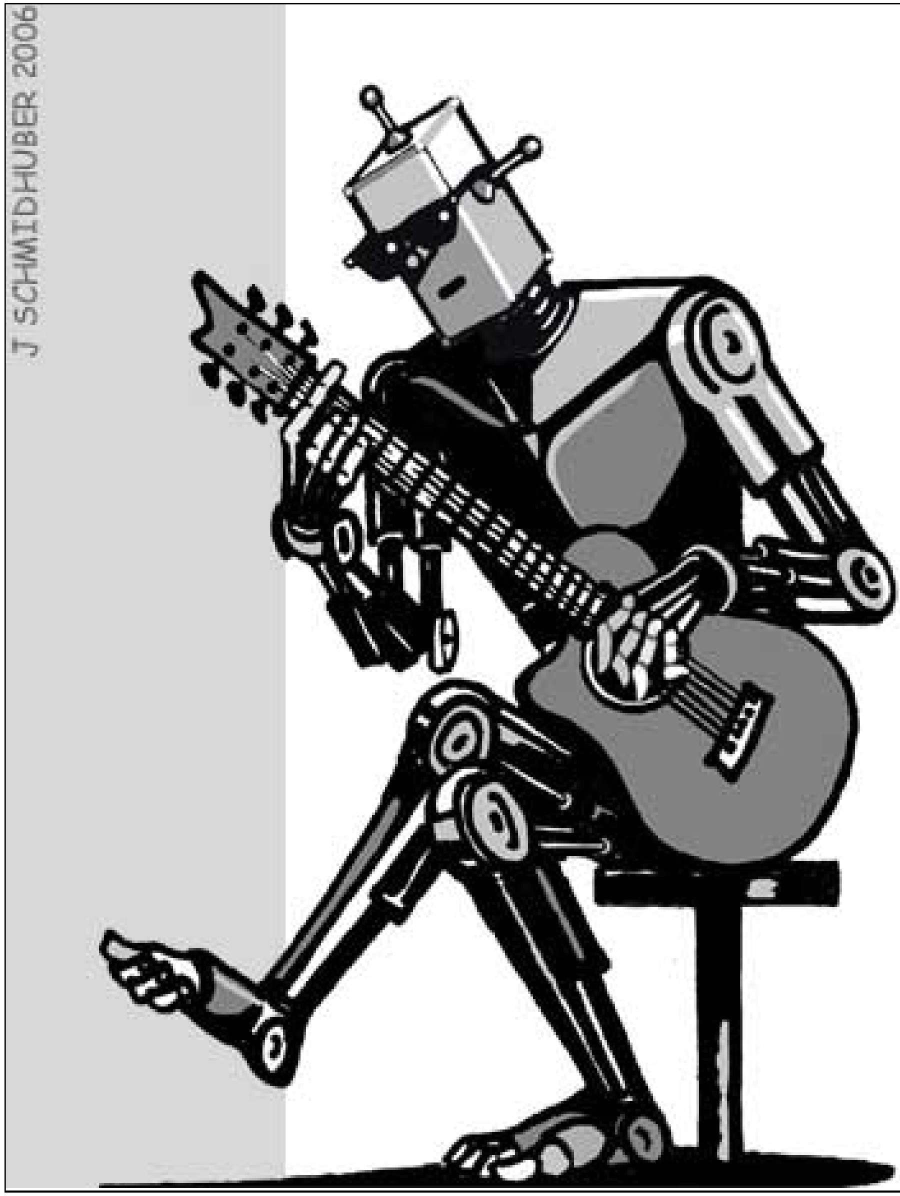

YouTube
AAAI 2013 BEST STUDENT VIDEO AWARD
Mit M Stollenga, K Frank, J Leitner, L Pape, A Foerster, J Koutnik


nnaisense
neural networks-based
artificial intelligence
THE DAWN OF AI

http://people.idsia.ch/~juergen/erc2017.html

www.nnaisense.com

1. 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. Schmidhuber. A self-referential weight matrix. ICANN 1993. Based on TR CU-CS-627-92, Univ. Colorado, 1992. (Supervised gradient-based RSI.)
3. Schmidhuber. On learning how to learn learning strategies. TR FKI-198-94, 1994. (RL)
4. Schmidhuber and J. Zhao and M. Wiering. Simple principles of metalearning. TR IDSIA-69-96, 1996. (Meta-RL and RSI based on 3.)
5. Schmidhuber, J. Zhao, N. Schraudolph. Reinforcement learning with self-modifying policies. In *Learning to learn*, Kluwer, pages 293-309, 1997. (Meta-RL based on 3.)
6. 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. (Partially based on 3.)
7. 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 Schmidhuber. Metalearning. Scholarpedia, 5(6):4650, 2010.
9. More under http://people.idsia.ch/~juergen/metalearner.html

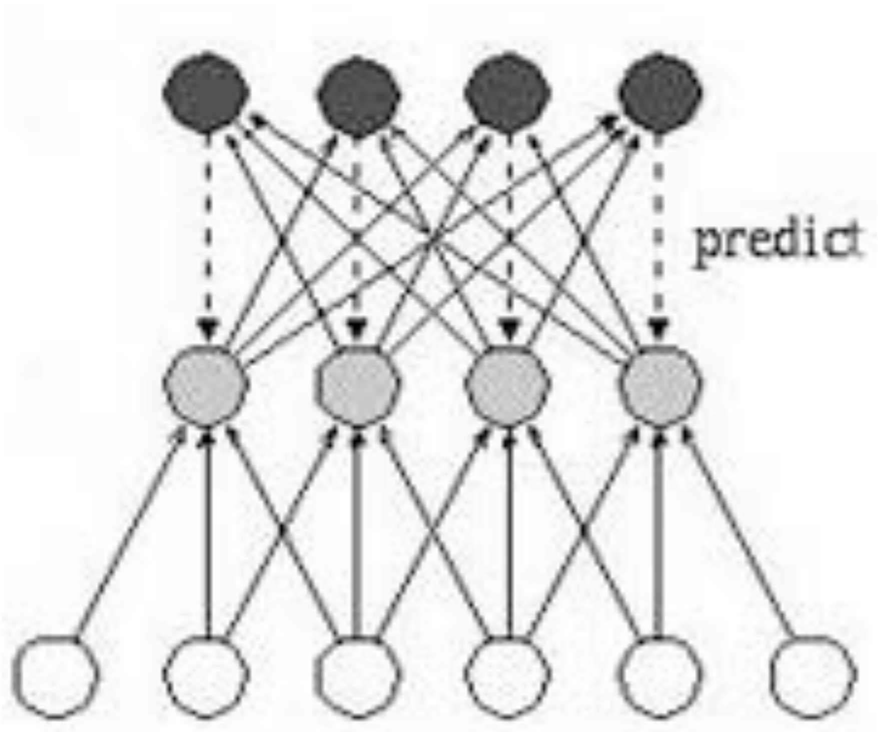


Learning how to Learn Learning Algorithms: Extra Slides

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

NNAISENSE

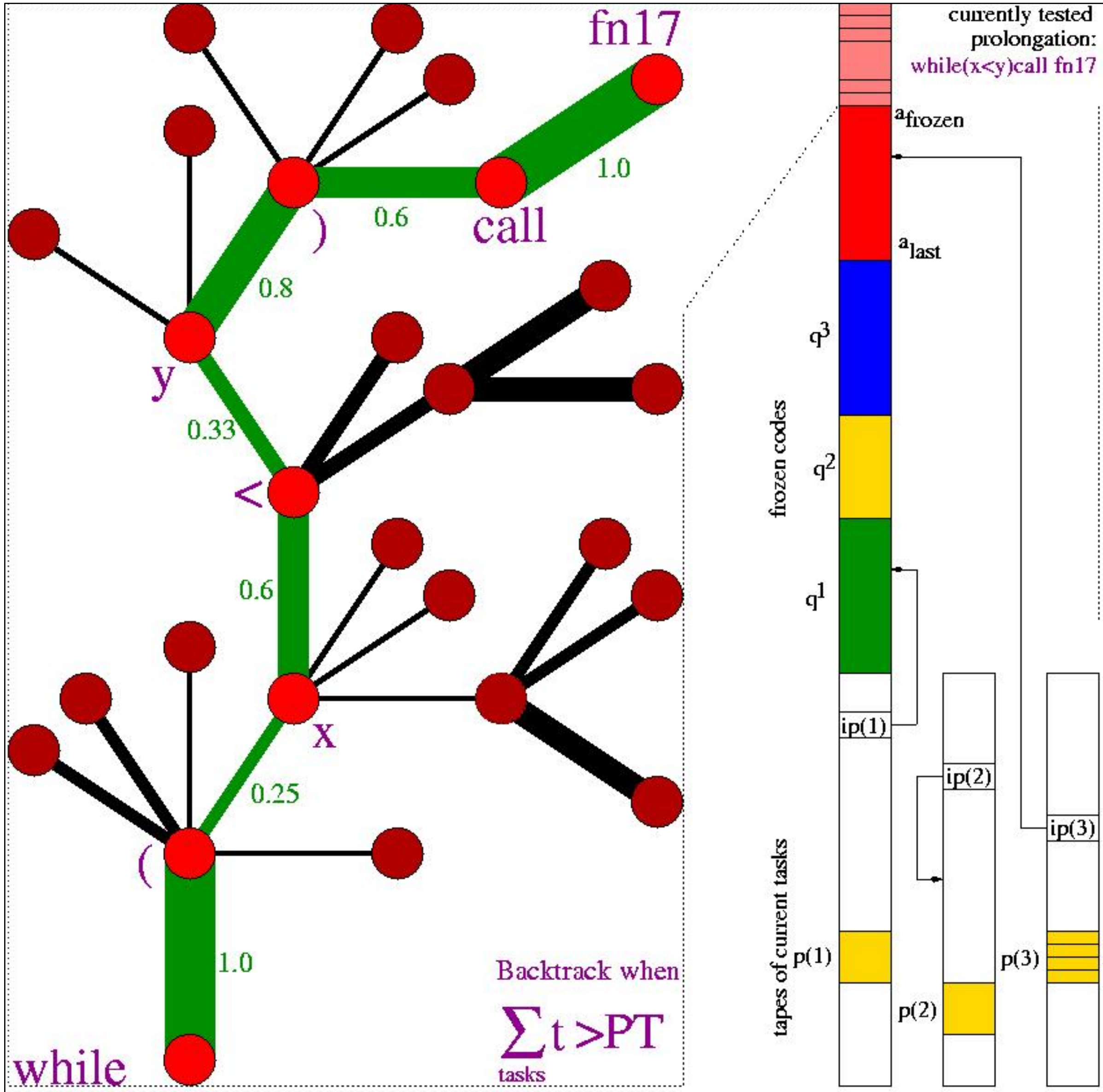
1990s: Predictability Minimization: 2 unsupervised nets fight in minimax game to model a given data distribution



Encoder maximizes objective minimized by predictor. Saddle point = ideal factorial code. Next: similar for Reinforcement Learning!

1997-2002: **What's interesting? Exploring the predictable**
http://people.idsia.ch/~juergen/interest.html

Two reinforcement learning adversaries called "left brain" and "right brain" are intrinsically motivated to outwit or surprise the other by proposing an experiment such that the other agrees on the experimental protocol but disagrees on the predicted outcome, which is an internal abstraction of complex spatio-temporal events generated through the execution the self-invented experiment. After execution, the surprised loser pays a reward to the winner in a zero sum game. This motivates the two brain system to focus on the "interesting" things, losing interest in boring aspects of the world that are consistently predictable by both brains, as well as seemingly random aspects of the world that are currently still hard to predict by any brain. This type of artificial curiosity can help to speed up the intake of external reward.

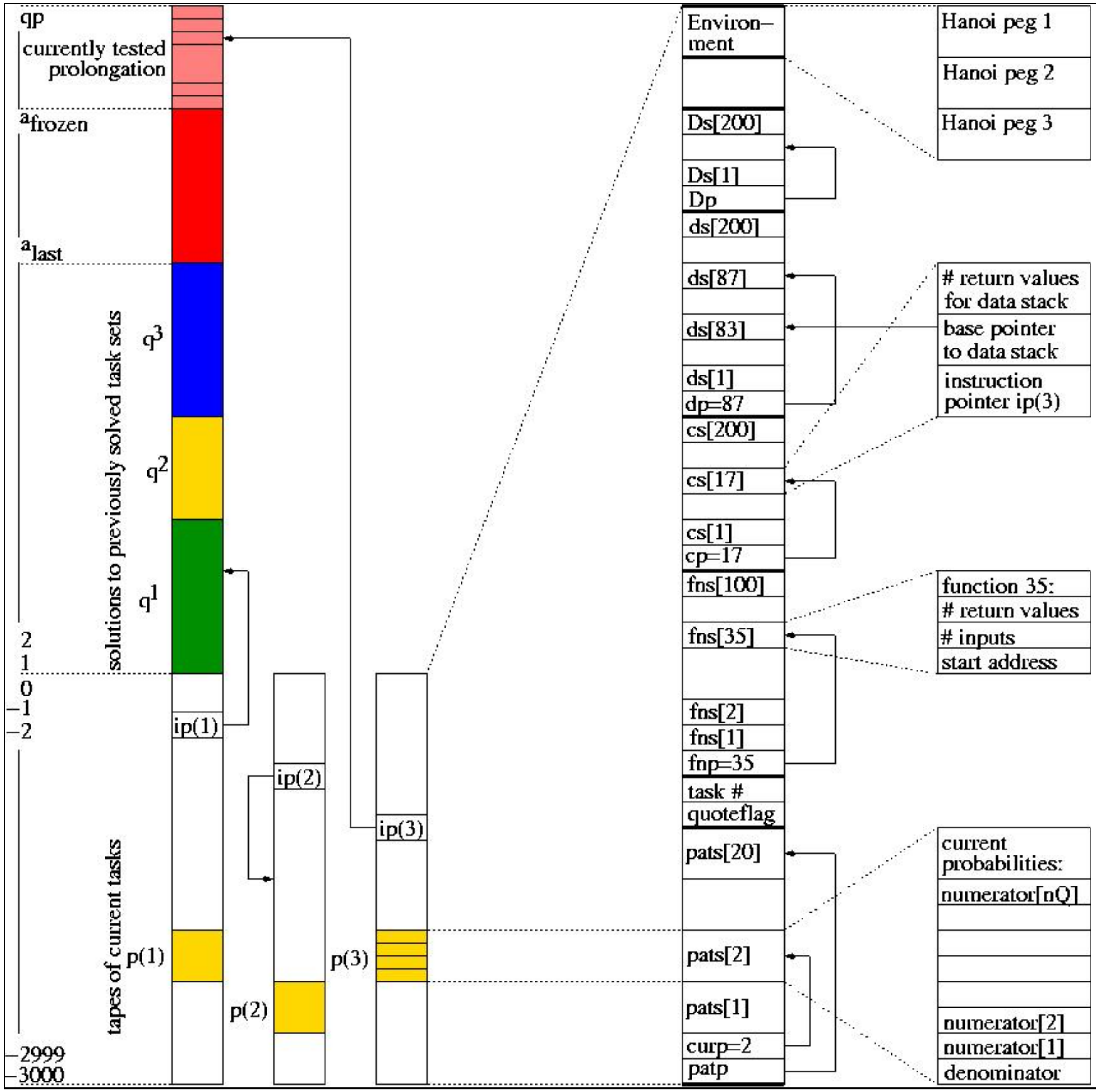


Super-deep program learner: Optimal Ordered Problem Solver OOPS (Schmidhuber, MLJ, 2004, extending Levin's universal search, 1973)

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

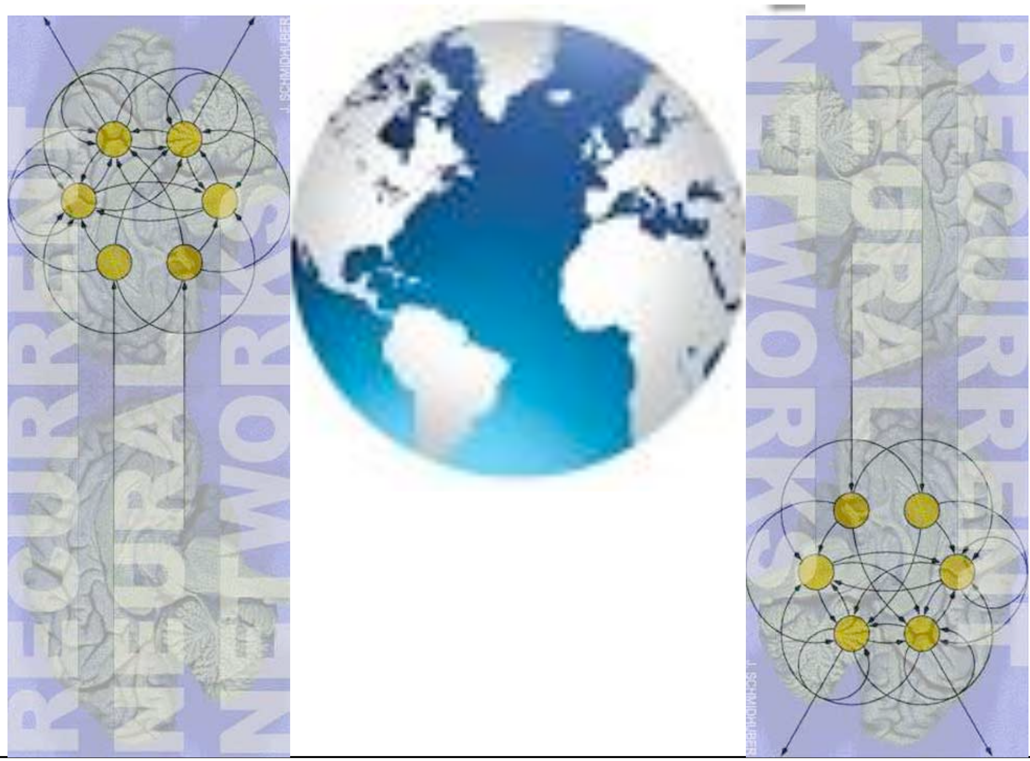
Towers of Hanoi: incremental solutions

- +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