Deep Learning: Our Miraculous Year 1990-1991

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The Deep Learning (DL) Neural Networks (NNs) of our team have revolutionised Pattern Recognition and Machine Learning, and are now heavily used in academia and industry [DL4]. In 2020, we will celebrate that many of the basic ideas behind this revolution were published three decades ago within fewer than 12 months in our *"Annus Mirabilis"* or *"Miraculous Year"* 1990-1991 at TU Munich. Back then, few people were interested, but a quarter century later, NNs based on these ideas were on over 3 billion devices such as smartphones, and used many billions of times per day, consuming a significant fraction of the world's compute [DL4].

The following summary of what happened in 1990-91 not only contains some high-level context for laymen, but also references for experts who know enough about the field to evaluate the original sources. I also mention selected later work which further developed the ideas of 1990-91 (at TU Munich, the Swiss AI Lab IDSIA, and other places), as well as related work by others. Here the table of contents:

0. Background on Deep Learning in Neural Nets (NNs)

The human brain has on the order of 100 billion neurons, each connected to 10,000 other neurons on average. Some are input neurons that feed the rest with data (sound, vision, tactile, pain, hunger). Others are output neurons that control muscles. Most neurons are hidden in between, where thinking takes place. Your brain apparently learns by changing the strengths or weights of the connections, which determine how strongly neurons influence each other, and which seem to encode all your lifelong experience. Similar for our *artifical* neural networks (NNs), which learn better than previous methods to recognize speech or handwriting or video, minimize pain, maximize pleasure, drive cars, etc [DL1] [DL4].

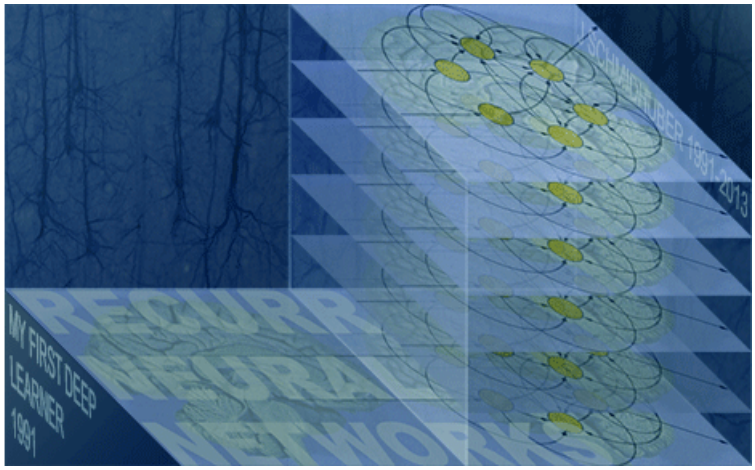
Most current commercial applications focus on supervised learning to make NNs imitate human teachers [DL1] [DL4]. In the course of many trials, Seppo Linnainmaa's gradient-computing algorithm of 1970 [BP1], today often called backpropagation or the reverse mode of automatic differentiation is used to incrementally weaken certain NN connections and strengthen others, such that the NN behaves more and more like the teacher (compare also [BPA] [BPB] [BP2]).

Today's most powerful NNs tend to be very deep, that is, they have many layers of neurons or many subsequent computational stages. In the 1980s, however, gradient-based training did not work well for deep NNs, only for shallow ones [DL1] [DL2].

This *Deep Learning Problem* was most obvious for *recurrent* NNs (RNNs, first informally proposed in 1945 [MC43], then formalised in 1956 [K56] - compare [PDA2]). Like the human brain, but unlike the more limited *feedforward* NNs (FNNs), RNNs have feedback connections. This makes RNNs powerful, general purpose, parallel-sequential computers that can process input sequences of arbitrary length (think of speech or videos). RNNs can in principle implement any program that can run on your laptop. If we want to build an *Artificial General Intelligence* (AGI), then its underlying computational substrate must be something like an RNN - FNNs are fundamentally insufficient. RNNs relate to FNNs like general computers relate to mere calculators.

In particular, unlike FNNs, RNNs can in principle deal with problems of arbitrary depth [DL1]. Early RNNs of the 1980s, however, failed to learn deep problems in practice. I wanted to overcome this drawback, to achieve RNN-based *"general purpose Deep Learning"* or *"general Deep Learning."*

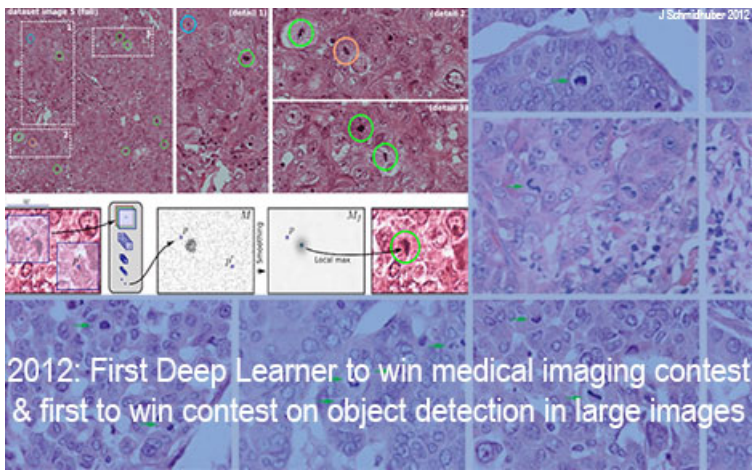
1. First Very Deep NNs, Based on Unsupervised Pre-Training (1991)



My first idea to overcome the *Deep Learning Problem* mentioned above was to facilitate supervised learning in deep RNNs by *unsupervised* pre-training of a hierarchical stack of RNNs (1991), to obtain a first *"Very Deep Learner"* called the *Neural Sequence Chunker* [UN0] or Neural History Compressor [UN1]. Each higher level minimizes the description length (or negative log probability) of the data representation in the level below, using the *Predictive Coding* trick: try to predict the next input in the incoming data stream, given the previous inputs, and update neural activations only in case of *unpredictable data*, thus storing only what's not yet known. In other words, the chunker learns to compress the data stream such that the *Deep Learning Problem* becomes less severe, and can be solved by standard backpropagation. Although computers back then were about a million times slower per dollar than today, by 1993, my method was able to solve previously unsolvable "Very Deep Learning" tasks of depth > 1000 [UN2] (requiring more than 1,000 subsequent computational stages - the more such stages, the deeper the learning). In 1993, we also published a *continuous* version of the Neural History Compressor [UN3].

To my knowledge, the Sequence Chunker [UN0] also was the first system made of RNNs operating on different (self-organizing) time scales. (But I also had a way of distilling all those RNNs down into a single deep RNN operating on a single time scale - see Sec. 2.) A few years later, others also started publishing on multi-time scale RNNs, e.g., [HB96]; compare also the *Clockwork RNN* [CW].

More than a decade after this work [UN1], a similar method for more limited *feedforward* NNs (FNNs) was published, facilitating supervised learning by unsupervised pre-training of stacks of FNNs called *Deep Belief Networks* (DBNs) [UN4]. The 2006 justification was essentially the one I used in the early 1990s for my RNN stack: each higher level tries to reduce the description length (or negative log probability) of the data representation in the level below.



Soon after the *unsupervised* pre-training-based Very Deep Learner above, the Deep Learning Problem (Sec. 3) was also overcome through our *purely supervised* LSTM (Sec. 4). Much later, between 2006 and 2011, my lab also drove a very similar shift from unsupervised pre-training to pure supervised learning, two decades after our *Miraculous Year*, this time for the less general *feedforward* NNs (FNNs) rather than *recurrent* NNs (RNNs), with revolutionary applications to cancer detection and many other problems. See Sec. 19 for more on this.

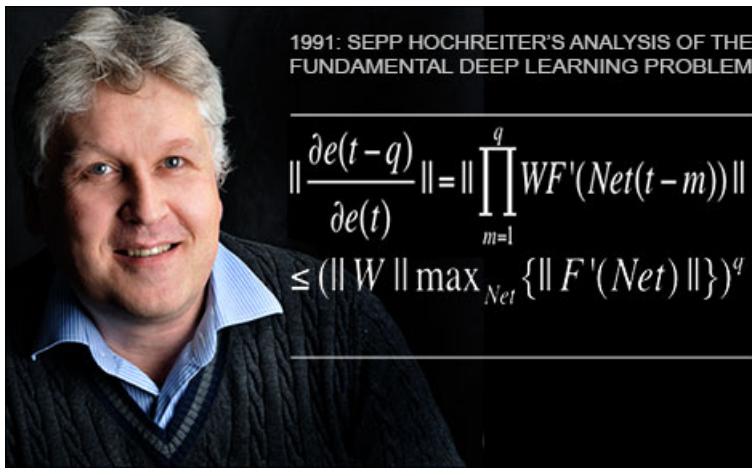
Of course, Deep Learning in feedforward NNs started much earlier, with Ivakhnenko & Lapa, who published the first general, working learning algorithms for deep multilayer perceptrons with arbitrarily many layers back in 1965 [DEEP1]. For example, Ivakhnenko's paper from 1971 [DEEP2] already described a Deep Learning net with 8 layers, trained by a highly cited method still popular in the new millennium [DL2]. But unlike the deep FNNs of Ivakhnenko and his successors of the 1970s and 80s, our deep RNNs had general purpose parallel-sequential computational architectures [UN0-3]. By the early 1990s, most NN research was still limited to rather shallow nets with fewer than 10 subsequent computational stages, while our methods already enabled over 1,000 such stages. I'd say we were the ones who made NNs really deep, especially RNNs, the deepest and most powerful nets of them all.

2. Compressing / Distilling one NN into Another (1991)

My above-mentioned paper on the Neural History Compressor (Sec. 1) also introduced a way of compressing the network hierarchy (whose higher levels are typically running on much slower self-organising time scales than lower levels) into a *single* deep RNN [UN1] which thus learned to solve very deep problems despite the obstacles mentioned in Sec. 0. This is described in Section 4 of reference [UN1] [DIST1] on a "conscious" chunker and a "subconscious" automatiser, which introduced a general principle for transferring the knowledge of one NN to another. Suppose a teacher NN has learned to predict (conditional expectations of) data, given other data. Its knowledge can be compressed into a student NN, by training the student NN to imitate the behavior of the teacher NN (while also re-training the student NN on previously learned skills such that it does not forget them).

I called this *"collapsing"* or *"compressing"* the behavior of one net into another. Today, this is widely used, and also called *"distilling"* [DIST2] or *"cloning"* the behavior of a teacher net into a student net.

3. The Fundamental Deep Learning Problem: Vanishing / Exploding Gradients (1991)



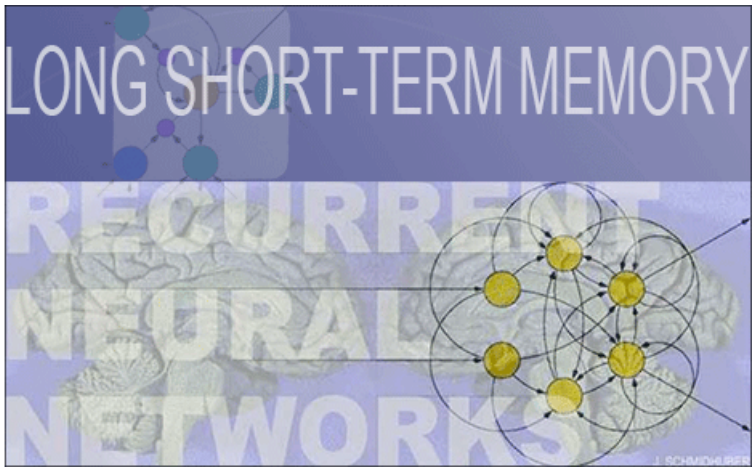
The background section Sec. 0 pointed out that Deep Learning is hard. But why is it hard? A main reason is what I like to call the Fundamental Deep Learning Problem identified and analyzed in 1991 by my first student Sepp Hochreiter in his diploma thesis [VAN1].

As a part of his thesis, Sepp implemented the Neural History Compressor above (Sec. 1) and other RNN-based systems (Sec. 11). However, he did much more: His work formally showed that deep NNs suffer from the now famous problem of vanishing or exploding gradients: in typical deep or recurrent networks, back-propagated error signals either shrink rapidly, or grow out of bounds. In both cases, learning fails. This analysis led to basic principles of what's now called LSTM (Sec. 4).

(In 1994, others published results [VAN2] essentially identical to the 1991 vanishing gradient results of Sepp [VAN1]. Even after a common publication [VAN3], the first author of reference [VAN2] published papers (e.g., [VAN4]) that cited only his own 1994 paper but not Sepp's original work.)

Note that Sepp's thesis identified those problems of backpropagation in deep NNs two decades after another student with a similar first name (Seppo Linnainmaa) published modern backpropagation or the reverse mode of automatic differentiation in his own thesis of 1970 [BP1].

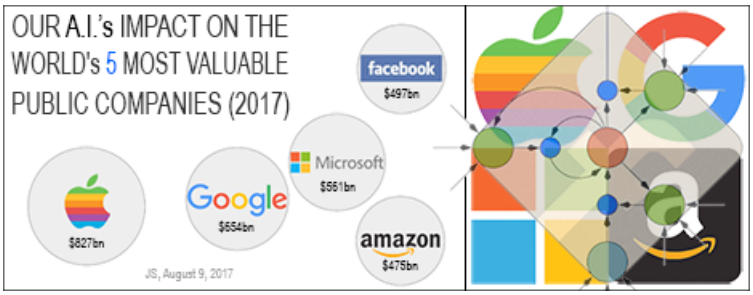
4. Long Short-Term Memory (LSTM) Recurrent Networks: Supervised Very Deep Learning



The Long Short-Term Memory (LSTM) recurrent neural network [LSTM1-6] overcomes the Fundamental Deep Learning Problem identified by Sepp in his

above-mentioned 1991 diploma thesis [VAN1] (Sec. 3), which I consider one of the most important documents in the history of machine learning. It also provided essential insights for overcoming the problem, through basic principles (such as *constant error flow*) of what we called LSTM in a tech report of 1995 [LSTM0]. This led to lots of follow-up work described below.

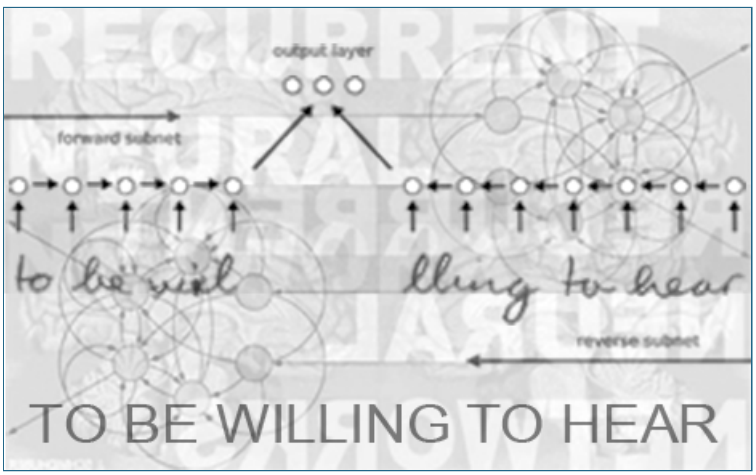
Next year we'll celebrate the quarter-century anniversary of LSTM's first failure to pass peer review. After the main peer-reviewed publication in 1997 [LSTM1] (now the most cited article in the history of *Neural Computation*), LSTM and its training procedures were further improved on my Swiss LSTM grants at IDSIA through the work of my later students Felix Gers, Alex Graves, and others. A milestone was the *"vanilla LSTM architecture"* with forget gate [LSTM2] - the LSTM variant of 1999-2000 that everybody is using today, e.g., in Google's Tensorflow. The LSTM forget gate is actually an end-to-end differentiable fast weight controller of the type we also introduced in 1991 [FAST0] (Sec. 8).



Alex was lead author on our first successful application of LSTM to speech (2004) [LSTM10]. 2005 saw the first publication of LSTM with full backpropagation through time and of bi-directional LSTM [LSTM3] (now widely used). Another milestone of 2006 was the training method *"Connectionist Temporal Classification"* or CTC [CTC] for simultaneous alignment and recognition of sequences. Since 2007, CTC has become essential for LSTM-based speech recognition [LSTM4]. For example, in 2015, the CTC-LSTM combination dramatically improved Google's speech recognition [GSR15] [DL4].

In the early 2000s, we showed how LSTM can learn languages unlearnable by traditional models such as Hidden Markov Models [LSTM13]. This took a while to sink in, and compute still had to get 1000 times cheaper, but by 2016-17, both Google Translate [WU] [GT16] and Facebook Translate [FB17] were based on two connected LSTMs [S2S], one for the incoming text, one for the outgoing translation, much better than what they had before [DL4].

In 2009, my PhD student Justin Bayer was lead author of a system that automatically designed LSTM-like architectures outperforming vanilla LSTM in certain applications [LSTM7]. In 2017, Google started using similar "neural architecture search" [NAS].



Since 2006, we have worked with the software industry (e.g., LifeWare) to greatly improve handwriting recognition. In 2009, through the efforts of Alex, LSTM trained by CTC became the first RNN to win international competitions, namely, three ICDAR 2009 Connected Handwriting Competitions (French, Farsi, Arabic). This attracted enormous interest from industry. LSTM was soon used for everything that involves sequential data such as language and speech [LSTM10-11] [LSTM4] [DL1] and videos. By 2017, LSTM powered Facebook's machine translation (over 30 billion translations per week) [FB17] [DL4], Apple's Quicktype on roughly 1 billion iPhones [DL4], the voice of Amazon's Alexa [DL4], Google's speech recognition (on Android smartphones since 2015) [GSR15] [DL4] & image caption generation [DL4] & machine translation [GT16] [DL4] & automatic email answering [DL4], etc. Business Week called LSTM "arguably the most commercial AI achievement" [AV1].

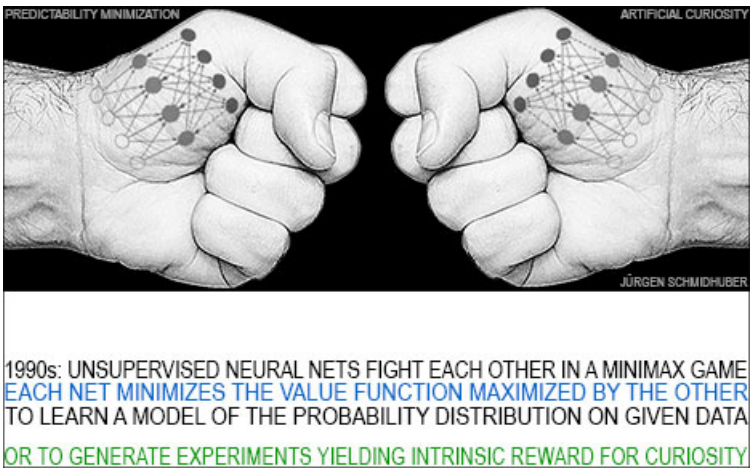
By 2016, more than a quarter of the awesome computational power for inference in Google's datacenters was used for LSTM (and 5% for another popular Deep Learning technique called CNNs - see Sec. 19) [JOU17]. Google's new on-device speech recognition of 2019 (now on your phone, not on the server) is still based on LSTM.

Through the work of my students Rupesh Kumar Srivastava and Klaus Greff, the LSTM principle also led to our Highway Networks [HW1] of May 2015, the first working very deep FNNs with hundreds of layers. Microsoft's popular ResNets [HW2] (which won the ImageNet 2015 contest) are a special case thereof. The earlier Highway Nets perform roughly as well as ResNets on ImageNet [HW3]. Highway layers are also often used for natural language processing, where the simpler residual layers do not work as well [HW3].

We also trained LSTM through *Reinforcement Learning* (RL) without a teacher, e.g., with my postdoc Bram Bakker [LSTM-RL] (2002). And also through Neuroevolution, e.g., with my PhD student Daan Wierstra [LSTM12] (2005), who later became employee number 1 of DeepMind, the company co-founded by his friend Shane Legg, another PhD student from my lab (Shane and Daan were the first persons at DeepMind with AI publications and PhDs in computer science). RL with LSTM has become important. For example, in 2019, DeepMind beat a pro player in the game of Starcraft, which is harder than Chess or Go in many ways, using Alphastar whose brain has a deep LSTM core trained by RL [DM3]. An RL-trained LSTM also was the core of OpenAI's Dactyl which learned to control dextrous robot hands without a teacher [OAI1], and of OpenAI Five which learned to defeat human experts in the Dota 2 video game (2018) [OAI2].

Essential foundations for all of this were laid in 1991. My team subsequently developed LSTM & CTC etc. with the help of basic funding from TU Munich and the (back then private) Swiss Dalle Molle Institute for AI (IDSIA), as well as public funding which I acquired from Switzerland & Germany & EU during the *"Neural Network Winter"* of the 1990s and early 2000s, trying to keep the field alive when few were interested in NNs. I am especially thankful to Professors Kurt Bauknecht & Leslie Kaelbling & Ron Williams & Ray Solomonoff whose positive reviews of my grant proposals have greatly helped to obtain financial support from SNF since the 1990s.

5. Artificial Curiosity Through Adversarial Generative NNs (1990)



As humans interact with the world, they learn to predict the consequences of their actions. They are also curious, designing experiments that lead to novel data from which they can learn more. To build curious *artificial* agents, I introduced a new type of *active* unsupervised or self-supervised learning in 1990 [AC90, AC90b]. It is based on a minimax game where one NN minimizes the objective function maximized by another NN. Today, I refer to this duel between two unsupervised adversarial NNs as Adversarial Curiosity [AC19], to distinguish it from our later types of Artificial Curiosity since 1991 (Sec. 6).

How does Adversarial Curiosity work? The first NN is called the controller C. C (probabilistically) generates outputs that may influence an environment. The second NN is called the world model M. It predicts the environmental reactions to C's outputs. Using gradient descent, M minimizes its error, thus becoming a better predictor. But in a zero sum game, C tries to find outputs that maximize the error of M. M's loss is the gain of C.

That is, C is motivated to invent novel outputs or experiments that yield data that M still finds surprising, until the data becomes familiar and eventually boring. Compare more recent summaries and extensions of this principle, e.g., [AC09].

So in 1990 we already had unsupervised or self-supervised neural nets that were both *generative* and *adversarial* (using much later terminology from 2014 [GAN1]), generating experimental outputs yielding novel data, not only for stationary patterns but also for pattern sequences, and even for the general case of Reinforcement Learning (RL).

The popular *Generative Adversarial Networks (GANs)* [GAN0] [GAN1] (2010-2014) are an application of Adversarial Curiosity [AC90] where the environment simply returns whether C's current output is in a given set [AC19].

BTW, note that the closely related Adversarial Curiosity [AC90, AC90b] & GANs [GAN0, GAN1] & Adversarial *Predictability Minimization* (Sec. 7) are very different from other early adversarial machine learning settings [GS59] [H90] which neither involved unsupervised NNs nor were about modeling data nor used gradient descent [AC19].

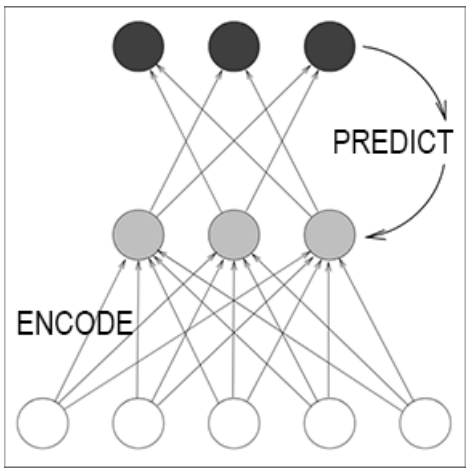
6. Artificial Curiosity Through NNs That Maximize Learning Progress (1991)

Numerous improvements of the original Adversarial Curiosity of 1990 (AC1990, Sec. 5) are summarized in more recent surveys [AC06] [AC09] [AC10]. Here I focus on the first important improvement of 1991 [AC91] [AC91b].

The errors of AC1990's world model M (to be minimized, Sec. 5) are the rewards of the controller C (to be maximized). This makes for a fine exploration strategy in many deterministic environments. In stochastic environments, however, this might fail. C might learn to focus on situations where M can always get high prediction errors due to randomness, or due to its computational limitations. For example, an agent controlled by C might get stuck in front of a TV screen showing highly unpredictable white noise [AC10].

Therefore, as pointed out in 1991, in stochastic environments, C's reward should not be the errors of M, but (an approximation of) the *first derivative* of M's errors across subsequent training iterations, that is, M's *improvements* [AC91] [AC91b]. As a consequence, despite its high errors in front of the noisy TV screen above, C won't get rewarded for getting stuck there. Both the totally predictable and the fundamentally unpredictable will get boring. This insight led to lots of follow-up work [AC10] on artificial scientists and artists, e.g., [AC09].

7. Adversarial Networks for Unsupervised Data Modeling (1991)

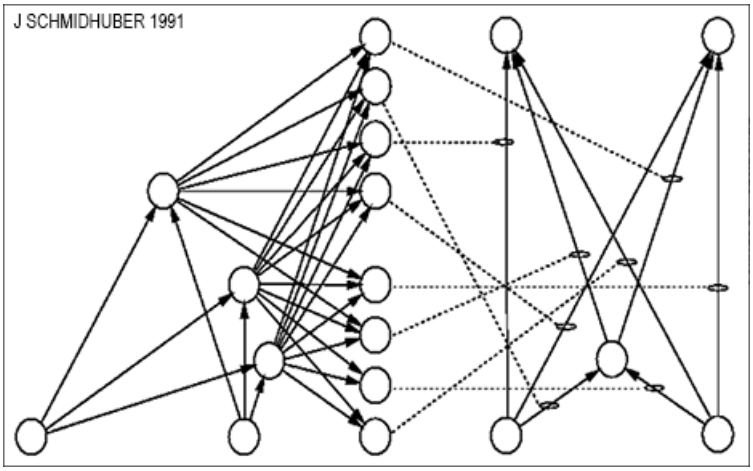


Soon after my first work on adversarial generative networks in 1990 (Sec. 5), I introduced a variation of the unsupervised adversarial minimax principle while I was a postdoc at the University of Colorado at Boulder. One of the most important NN tasks is to learn the statistics of given data such as images. To achieve this, I used again the principles of gradient descent/ascent in a minimax game where one NN minimizes the objective function maximized by another. This duel between two unsupervised adversarial NNs was called Predictability Minimization (PM, 1990s) [PM2] [PM1] [PM0]. (Contrary to later claims [GAN1], PM is indeed a pure minimax game, e.g., [PM2], Equation 2. Compare the survey [AC19].)

The first toy experiments with PM [PM1] were conducted nearly three decades ago when compute was about a million times more expensive than today. When it had become about 10 times cheaper 5 years later, we could show that semi-linear PM variants applied to images automatically generate feature detectors well-known from neuroscience, such as on-center-off-surround detectors, off-center-on-surround detectors, and orientation-sensitive bar detectors [PM2].

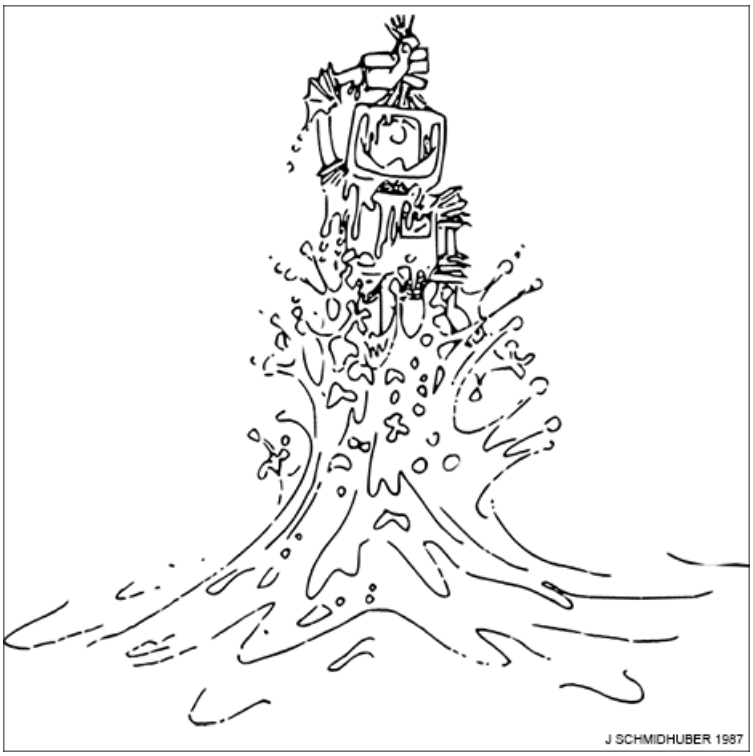
8. End-To-End-Differentiable Fast Weights: NNs Learn to Program NNs (1991)

A typical NN has many more connections than neurons. In traditional NNs, neuron activations change quickly, while connection weights change slowly. That is, the numerous weights cannot implement short-term memories or temporal variables, only the few neuron activations can. Non-traditional NNs with quickly changing *"fast weights"* overcome this limitation.



Dynamic links or fast weights for NNs were introduced by Christoph v. d. Malsburg in 1981 [FAST] and further studied by others, e.g., [FASTb]. However, these authors did not have an *end-to-end-differentiable* system that learns by gradient descent to quickly manipulate the fast weight storage. Such a system I published in 1991 [FAST0] [FAST1]. There a slow NN learns to control the weights of a separate fast NN. That is, I *separated storage and control* like in traditional computers, but in a fully neural way (rather than in a hybrid fashion [PDA1] [PDA2] [DNC]). This led to lots of follow-up work, some of it mentioned below.

One year later, I introduced gradient descent-based, active control of fast weights through 2D tensors or outer product updates [FAST2] (compare our more recent work on this [FAST3] [FAST3a]). The motivation was to get many more temporal variables under end-to-end differentiable control than what's possible in standard RNNs of the same size: O(H^2) instead of O(H), where H is the number of hidden units. A quarter century later, others followed this approach [FAST4a]. The paper [FAST2] also explicitly addressed the learning of *"internal spotlights of attention"* in end-to-end-differentiable networks. Compare Sec. 9 on learning attention.



I also showed how fast weights can be used for meta-learning or "learning to learn", one of my main research topics since 1987 [META1]. In references [FASTMETA1-3] since 1992, the slow RNN and the fast RNN are *identical:* the initial weight of each connection in the net is trained by gradient descent, but during an episode, each connection can be addressed and read and modified by the net itself (through *O(log n)* special output units where *n* is the number of connections), and the connection's weight may rapidly change - the network becomes *self-referential* in the sense that it can in principle learn to run arbitrary computable weight change algorithms or learning

algorithms (for all of its weights) *on itself*. This led to many follow-up papers in the 1990s and 2000s.

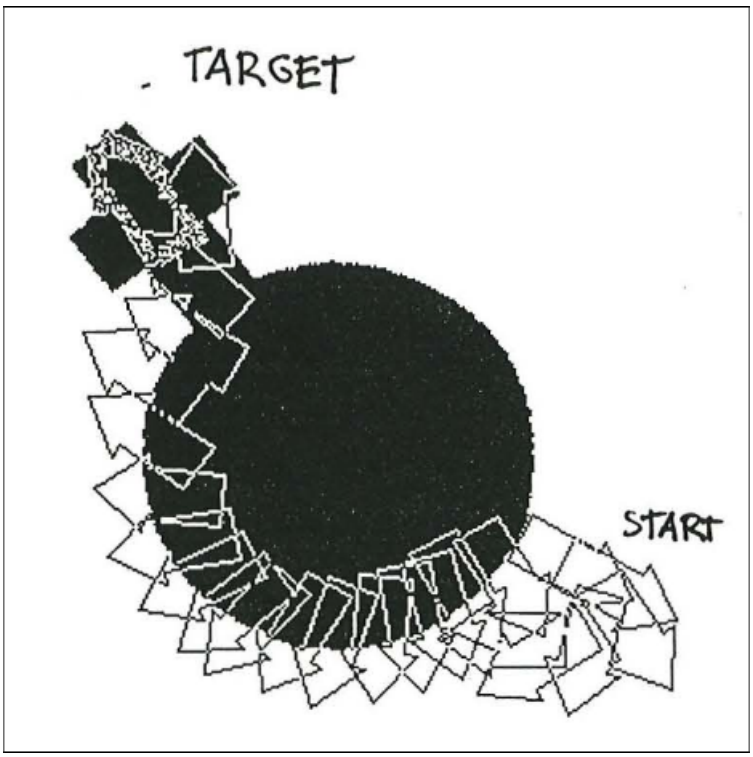
Deep Reinforcement Learning (RL) without a teacher can also profit from fast weights even when the system's dynamics are not differentiable, as shown in 2005 by my former postdoc Faustino Gomez [FAST5] (now CEO of NNAISENSE) when affordable computers were about 1000 times faster than in the early 1990s.

BTW, our related work on Deep RL in the same year (but without fast weights) to my knowledge was the first machine learning publication with the word combination **"learn deep"** in the title [DL6] (2005; soon afterwards many started talking about "deep learning").

Over the decades we have published quite a few additional ways of learning to generate quickly numerous weights of large NNs through very compact codes, e.g., [KO0] [KO1] [KO2] [CO1] [CO2] [CO3]. Here we exploited that the Kolmogorov complexity or algorithmic information content of successful huge NNs may actually be rather small. In particular, in July 2013, "Compressed Network Search" [CO2] was the first deep learning model to successfully learn control policies directly from high-dimensional sensory input (video) using reinforcement learning, without any unsupervised pre-training (unlike in Sec. 1). Soon afterwards, DeepMind also had a Deep RL system for high-dimensional sensory input [DM1] [DM2].

Today, the most famous end-to-end differentiable fast weight-based NN [FAST0] is actually our vanilla LSTM network of 2000 [LSTM2] (Sec. 4), whose forget gates learn to control the fast weights on self-recurrent connections of internal LSTM cells. All the major IT companies are now massively using vanilla LSTM [DL4]. Again, the roots of this go back to 1991 (Sec. 4 & Sec. 8).

9. Learning Sequential Attention with NNs (1990)

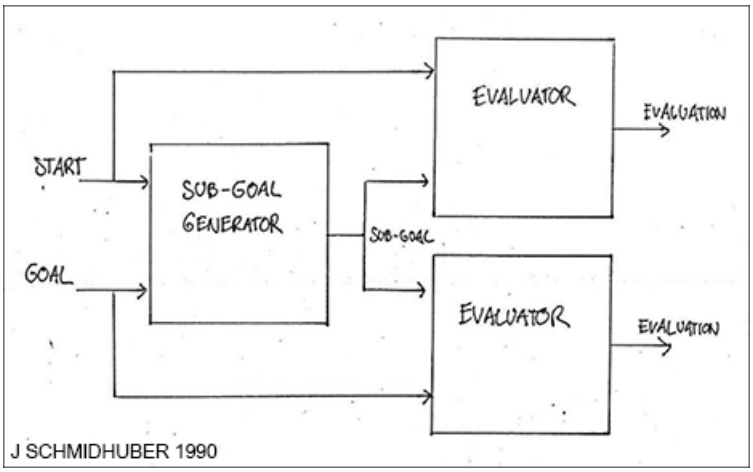


Unlike traditional NNs, humans use sequential gaze shifts and selective attention to detect and recognize patterns. This can be much more efficient than the highly parallel approach of traditional FNNs. That's why we introduced sequential attention-learning NNs three decades ago (1990 and onwards) [ATT0] [ATT1]. Shortly afterwards, I also explicitly addressed the learning of *"internal spotlights of attention"* in RNNs [FAST2] (Sec. 8).

So back then we already had *both* of the now common types of neural sequential attention: end-to-end-differentiable *"soft"* attention (in *latent* space) through multiplicative units within NNs [FAST2], and *"hard"* attention (in *observation* space) in the context of Reinforcement Learning (RL) [ATT0] [ATT1]. This led to lots of follow-up work. Today, many are using sequential attention-learning NNs.

My overview paper for CMSS 1990 [ATT2] summarised in Section 5 our early work on attention, to my knowledge the first implemented neural system for combining glimpses that jointly trains a recognition & prediction component with an attentional component (the fixation controller). Two decades later, the reviewer of my 1990 paper wrote about his own work as second author of a related paper [ATT3]: *"To our knowledge, this is the first implemented system for combining glimpses that jointly trains a recognition component ... with an attentional component (the fixation controller)."* Compare Sec. 10.

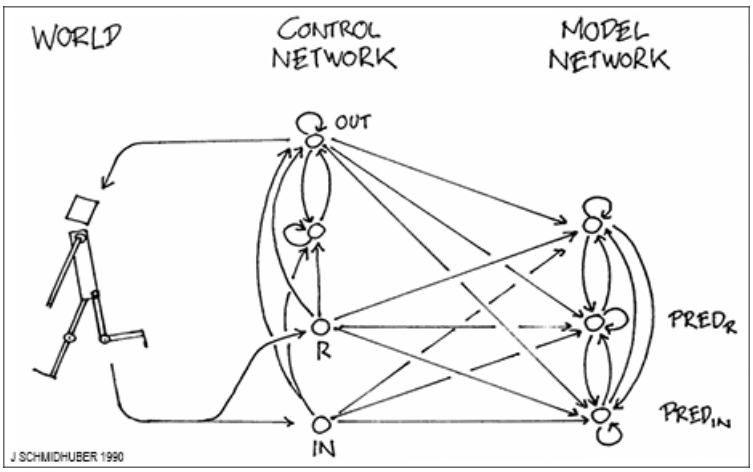
10. Hierarchical Reinforcement Learning (1990)



Traditional Reinforcement Learning (RL) without a teacher does not hierarchically decompose problems into easier subproblems. That's why in 1990 I introduced *Hierarchical RL* (HRL) with end-to-end differentiable NN-based subgoal generators [HRL0], also with recurrent NNs that learn to generate sequences of subgoals [HRL1] [HRL2]. An RL machine gets extra inputs of the form *(start, goal)*. An evaluator NN learns to predict the rewards/costs of going from *start* to *goal*. An (R)NN-based subgoal generator also sees *(start, goal)*, and uses (copies of) the evaluator NN to learn by gradient descent a sequence of cost-minimising intermediate subgoals. The RL machine tries to use such subgoal sequences to achieve final goals.

Our 1990-91 papers [HRL0] [HRL1] were the first of many follow-up papers on HRL, e.g., [HRL4]. Soon afterwards, others also started publishing on HRL. For example, the reviewer of our reference [ATT2] (which summarised in Section 6 our early work on HRL) was last author of ref [HRL3]. Compare Sec. 9.

11. Planning with Recurrent Neural World Models (1990)



In 1990, I introduced reinforcement learning (RL) and planning based on a combination of two RNNs called the *controller* C and the *world model* M (see also Sec. 5). M learns to predict the consequences of C's actions. C learns to use M to plan ahead for several time steps, selecting action sequences that maximise predicted cumulative reward [AC90]. This led to lots of follow-up publications, also in recent years, e.g., [PLAN2-6].

The 1990 FKI report [AC90] also introduced several other concepts that have become popular. See Sec. 12, Sec. 13, Sec. 14, Sec. 5, Sec. 20.

12. Goal-Defining Commands as Extra NN Inputs (1990)

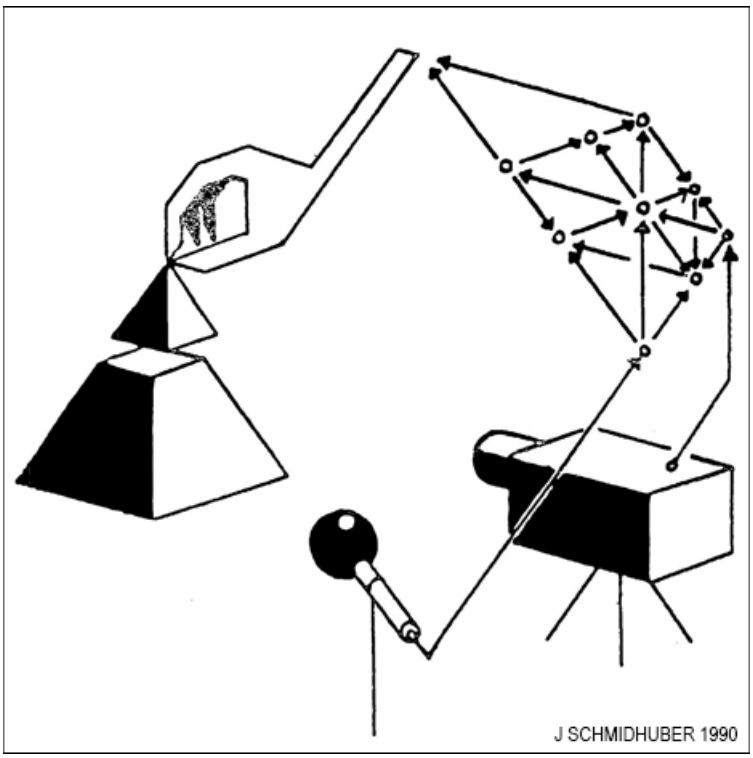
One concept that is widely used in today's RL NNs are extra *goal-defining input patterns* that encode various tasks, such that the NN knows which task to execute next. We introduced this in 1990 in various contexts [ATT0] [ATT1] [HRL0] [HRL1]. In references [ATT0] [ATT1], a reinforcement learning neural controller learned to control a fovea through sequences of saccades to find particular objects in visual scenes, thus learning sequential attention (Sec. 9). User-defined goals were provided to the system by special "goal input vectors" that remained

constant (Sec. 3.2 of [ATT1]) while the system shaped its stream of visual inputs through fovea-shifting actions.

Hierarchical RL (HRL, Sec. 10) with end-to-end differentiable subgoal generators [HRL0] [HRL1] also uses an NN with task-defining inputs of the form *(start, goal)*, learning to predict the costs of going from start to goal. (Compare my former student Tom Schaul's *"universal value function approximator"* at DeepMind a quarter century later [UVF15].)

This led to lots of follow-up work. For example, our POWERPLAY RL system (2011) [PP] [PP1] also uses task-defining inputs to distinguish between tasks, continually *inventing on its own new goals and tasks*, incrementally learning to become a more and more general problem solver in an active, partially unsupervised or self-supervised fashion. RL robots with high-dimensional video inputs and intrinsic motivation (like in PowerPlay) learned to explore in 2015 [PP2].

13. High-Dimensional Reward Signals As NN Inputs / General Value Functions (1990)



Traditional RL is based on *one-dimensional* reward signals. Humans, however, have millions of informative sensors for different types of pain and pleasure etc. To my knowledge, reference [AC90] was the first paper on RL with *multi-dimensional, vector-valued* pain and reward signals coming in through many different sensors, where cumulative values are predicted for all those sensors, not just for a single scalar overall reward. Compare what was later called a *general value function* [GVF]. Unlike previous adaptive critics, the one of 1990 [AC90] was multi-dimensional and recurrent.

Unlike in traditional RL, those reward signals were also used as informative *inputs* to the controller NN learning to execute actions that maximise cumulative reward.

14. Deterministic Policy Gradients (1990)

The section *"Augmenting the Algorithm by Temporal Difference Methods"* of the 1990 paper [AC90] also combined the *Dynamic Programming*-based *Temporal Difference* method [TD] for predicting cumulative (possibly multi-dimensional, Sec. 13) rewards with a gradient-based predictive model of the world (Sec. 11), to compute weight changes for the separate control network. See also Sec. 2.4 of the 1991 follow-up paper [PLAN3] (and compare [NAN1]). A quarter century later, a variant of this was called a *Deterministic Policy Gradient* algorithm (DPG) by DeepMind [DPG] [DDPG].

15. Networks Adjusting Networks / Synthetic Gradients (1990)

In 1990, I proposed various NNs that learn to adjust other NNs [NAN1]. Here I focus on the section *"An Approach to Local Supervised Learning in Recurrent Networks"* [NAN1]. The global error measure to be minimized is the sum of all errors received at an RNN's output units over time. In conventional *backpropagation through time* (see surveys [BPTT1-2]), each unit needs a stack for remembering past activations which are used to compute contributions to weight changes during the error propagation phase. Instead of allowing unlimited storage capacities in the form of stacks, I introduced a second adaptive NN that learns to associate states of the RNN with corresponding error vectors. These locally estimated error gradients (rather than the true gradients) are used to adjust the RNN [NAN1] [NAN2] [NAN3] [NAN4].

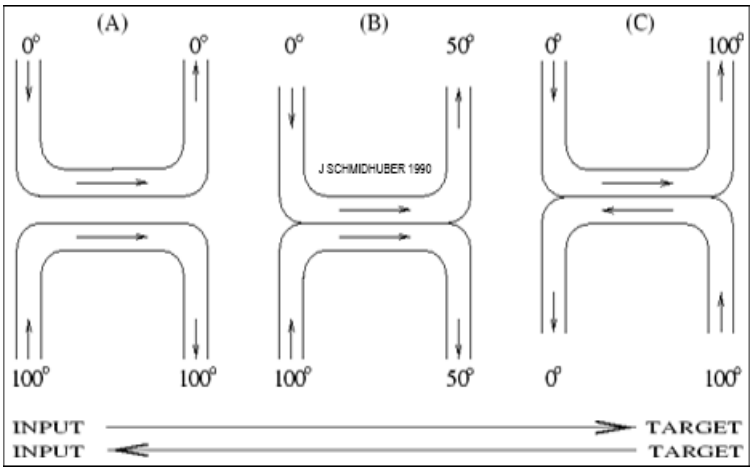
Unlike standard backpropagation, the method is local in space and time [BB1] [NAN1]. A quarter century later, DeepMind called this *"Synthetic Gradients"* [NAN5].

16. O(n^3) Gradients for Online Recurrent NNs (1991)

The original 1987 fixed-size storage learning algorithm for fully recurrent continually running networks [ROB] requires O(n^4) computations per time step, where n is the number of non-input units. I published a method which computes exactly the same gradient and requires fixed-size storage of the same order as the previous algorithm. But, the average time complexity per time step is only O(n^3) [CUB1] [CUB2]. *However, this work does not really count, since the great RNN pioneer Ron Williams had derived this method first* [CUB0]!

BTW, I committed a similar error in 1987 when I published what I thought was the first paper on Genetic Programming (GP), that is, on automatically evolving computer programs [GP1] (authors in alphabetic order). Only later I found out that Nichael Cramer had published GP already in 1985 [GP0] (and that Stephen F. Smith had proposed a related approach as part of a larger system [GPA] in 1980). Since then I have been trying to do the right thing and correctly attribute credit. At least our 1987 paper [GP1] seems to be the first on GP for codes with loops and codes of variable size, and the first on GP implemented in a Logic Programming language.

17. The Deep Neural Heat Exchanger (1990)

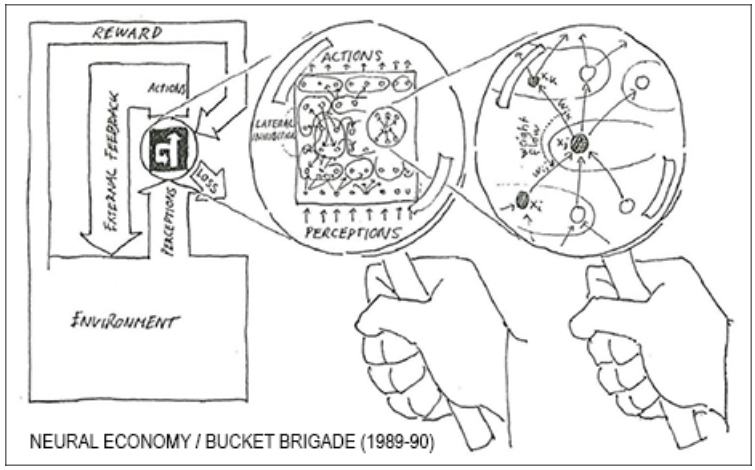


The *Neural Heat Exchanger* is supervised learning method for deep multi-layer NNs. It is inspired by the physical heat exchanger. Inputs "heat up" while being transformed through many successive layers, targets enter from the other end of the deep pipeline and "cool down." Unlike backpropagation, the method is entirely local. This makes its parallel implementation trivial. It was first presented during occasional talks at various universities since 1990 [NHE], and is closely related to the Helmholtz Machine [HEL]. Again, experiments were conducted by my brilliant student Sepp Hochreiter (Sec. 3, Sec. 4).

18. PhD Thesis (1990)

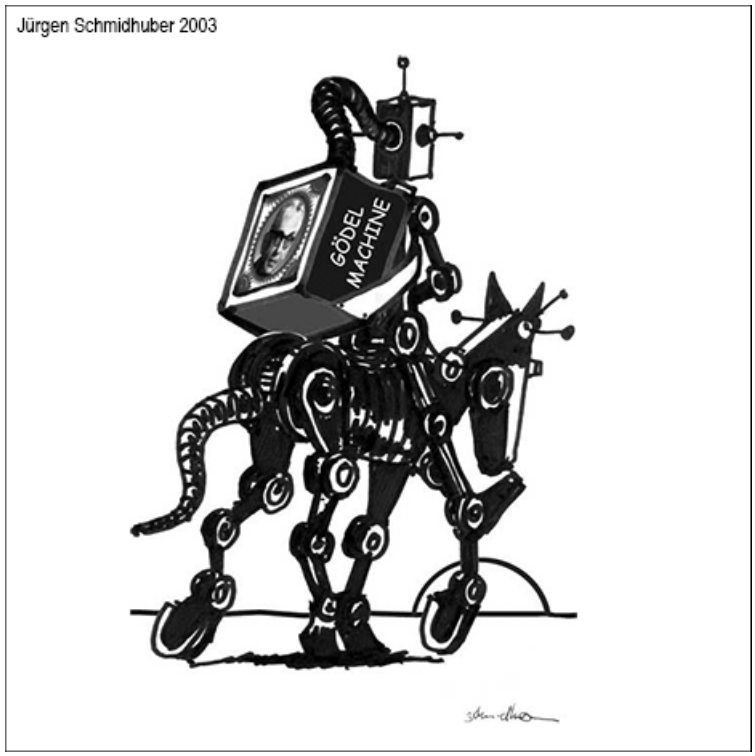
My doctoral dissertation at TUM [PHD] also came out in 1991, summarising some of my earlier work since 1989, including the first Reinforcement Learning (RL) *Neural Economy* (the Neural Bucket Brigade) [BB1] [BB2], learning algorithms for RNNs that are local in space and time [BB1], hierarchical RL (HRL) with end-to-end differentiable subgoal generators (Sec. 10), RL and planning through a combination of two RNNs called the *controller* C and the *world model* M (Sec. 11), sequential attention-learning NNs (Sec. 9), NNs that learn to adjust other NNs

(including *"synthetic gradients,"* Sec. 15), and unsupervised or self-supervised, generative, adversarial networks (Sec. 5) for implementing curiosity.



Back then, much of the NN research by others was inspired by statistical mechanics, e.g., [HOP]. The works of 1990-91 (and my even earlier diploma thesis of 1987 [META1]) embodied an alternative *program-oriented* view of Machine Learning.

When Kurt Gödel founded theoretical computer science in 1931 [GOD], he represented both data (such as axioms and theorems) and programs (such as proof-generating sequences of operations on the data) in a *universal coding language* based on the integers. He famously used this language to construct formal statements that talk about the computation of other formal statements, especially *self-referential* formal statements which state that they are not provable by *any* computational theorem prover. Thus he exhibited the fundamental limits of mathematics and computation and Artificial Intelligence.

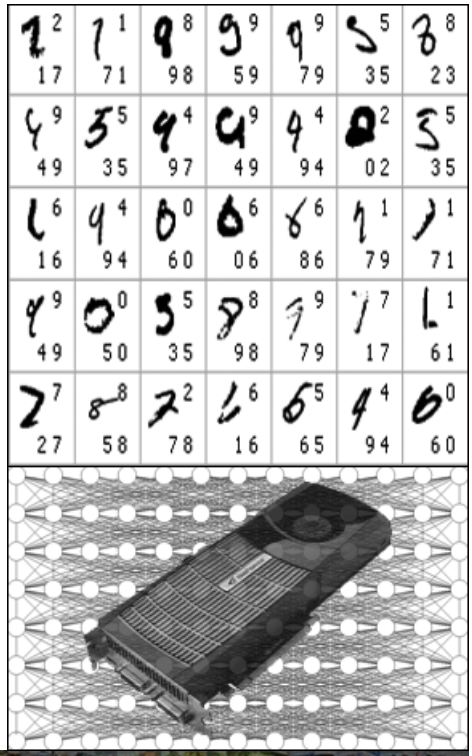


As I have frequently pointed out since 1990 [AC90], the weights of an NN should be viewed as its program. Some argue that the goal of a deep NN is to learn useful *internal representations* of observed data (there even is an international conference on learning representations called ICLR), but I have always preferred the view that the NN's goal is actually to learn a *program* (the parameters) that *computes* such representations. Inspired by Gödel, I built NNs whose outputs are programs or weight matrices of other NNs (Sec. 8), and even *self-referential RNNs* that can run and inspect their own weight change algorithms or learning algorithms (Sec. 8). A difference to Gödel's work is that the universal programming language is not based on the integers, but on real values, such that the outputs of typical NNs are differentiable with respect to their programs. That is, a simple program generator (the efficient gradient descent procedure [BP1]) can compute a direction in program space where one may find a better program [AC90], in particular, a *better program-generating program* (Sec. 8). Much of my work since 1989 has exploited this fact.

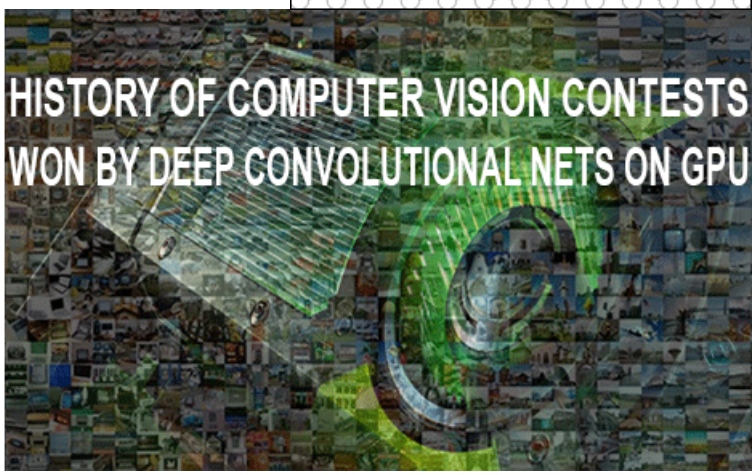
19. From Unsupervised Pre-Training to Pure Supervised Learning (1991-95 and 2006-11)

As mentioned in Sec. 1, my first Very Deep Learner was the RNN stack of 1991 which used unsupervised pre-training to learn problems of depth greater than 1000. Soon afterwards, however, we published more general ways of overcoming the Deep Learning Problem (Sec. 3) *without* any unsupervised pre-training, replacing the unsupervised RNN stack [UN1-3] by the purely supervised Long Short-Term Memory (LSTM) (Sec. 4). That is, already in the previous millennium, unsupervised pre-training lost significance as LSTM did not require it. In fact, this shift from *unsupervised* pre-training to pure *supervised* learning started already in 1991.

A very similar shift took place much later between 2006 and 2010, this time for the less general *feedforward* NNs (FNNs) rather than *recurrent* NNs (RNNs). Again, my little lab played a central role in this transition. In 2006, supervised learning in FNNs was facilitated by unsupervised pre-training of stacks of FNNs [UN4] (Sec. 1). But in 2010, our team with my outstanding Romanian postdoc Dan Ciresan [MLP1] showed that deep FNNs can be trained by plain backpropagation and do not at all require unsupervised pre-training for important applications. Our system set a new performance record [MLP1] on the back then famous and widely used image recognition benchmark called MNIST. This was achieved by greatly accelerating traditional FNNs on highly parallel graphics processing units called GPUs. A reviewer called this a "wake-up call to the machine learning community." Today, very few commercial DL applications are still based on unsupervised pre-training.



My team at the Swiss AI Lab IDSIA further improved the above-mentioned work (2010) on purely supervised Deep Learning in FNNs [MLP1] by replacing the traditional FNNs through another old NN type called convolutional NNs or CNNs, invented and developed by others since the 1970s [CNN1-4]. Our supervised ensemble of fast GPU-based CNNs (Ciresan et al., 2011) [GPUCNN1] was a practical breakthrough (much faster than early work on accelerating CNNs [GPUCNN]) and won 4 important computer vision competitions in a row between May 15, 2011, and September 10, 2012 [GPUCNN5]. In particular, our fast deep CNNs were the first to win a Chinese handwriting contest (ICDAR 2011), the first to achieve superhuman visual pattern recognition in any international contest (IJCNN 2011), the first to win an image segmentation contest (ISBI, May 2012), and the first to win a contest on object detection in large images (ICPR, 10 Sept 2012), at the same time the first to win a medical imaging contest [GPUCNN5] (on cancer detection). Our fast CNN image scanners were over 1000 times faster than previous methods [SCAN].

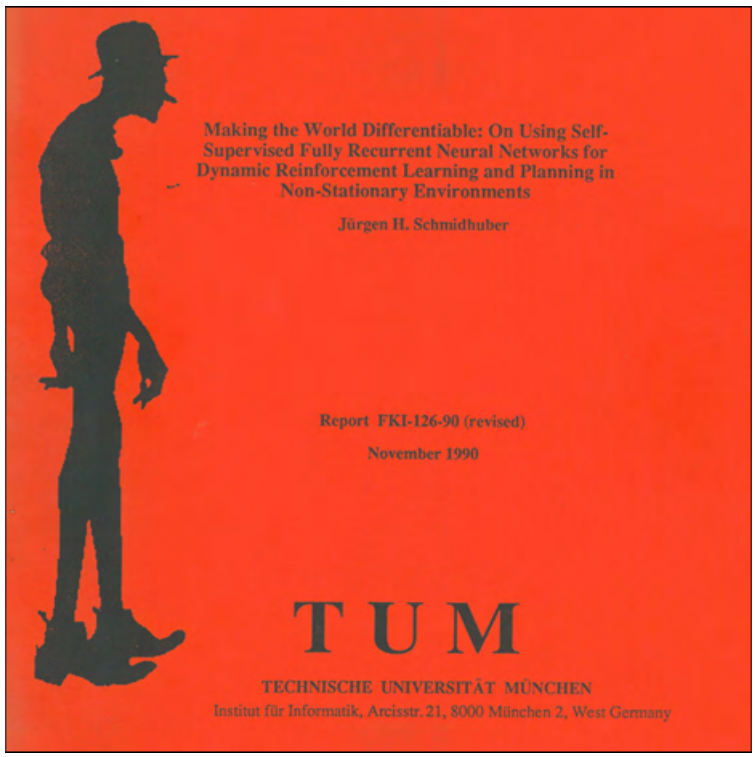


Our system more than halved the error rate for object recognition in a contest already in 2011, 20 years after our *Annus Mirabilis* [GPUCNN2]. Soon afterwards, others applied similar approaches in image recognition contests [GPUCNN5].

Like our LSTM results of 2009 (Sec. 4), the above-mentioned results with *feedforward* NNs of 2010-11 attracted enormous interest from industry. For example, in 2010, we introduced our deep and fast GPU-based NNs to Arcelor Mittal, the world's largest steel maker, and were able to greatly improve steel defect detection [ST]. This may have been the first Deep Learning breakthrough in heavy industry. Today, most AI startups and major IT firms as well as many other famous companies are using such supervised fast GPU-NNs.

20. The Amazing FKI Tech Report Series on Artificial Intelligence in the 1990s

In hindsight, many of the later widely used basic ideas of "modern" Deep Learning were published in our *Miraculous Year* 1990-1991 at TU Munich, soon after the fall of the Berlin Wall: unsupervised or self-supervised, data-generating, adversarial networks (for artificial curiosity and related concepts, Sec. 5; see also follow-up work at CU in Sec. 7), the Fundamental Deep Learning Problem (vanishing / exploding gradients, Sec. 3) and its solutions through (a) unsupervised pre-training for very deep (recurrent) networks (Sec. 1) and (b) basic insights leading to LSTM (Sec. 4; see also Sec. 8). We also introduced sequential attention-learning NNs back then - another concept that has become popular (see Sec. 9 on both *hard* and *soft* attention, in *observation* space and in *latent* space), as well as NNs that learn to program the fast weights of another NN (Sec. 8), and even their own weights. Plus all the other things mentioned above, from Hierarchical Reinforcement Learning (Sec. 10) to planning with recurrent neural world models (Sec. 11) etc. (Sec. 1-20). Of course, one had to wait for faster computers to commercialize such algorithms. By the mid 2010s, however, our stuff was massively used by Apple, Google, Facebook, Amazon, Samsung, Baidu, Microsoft, etc, many billions of times per day on billions of computers [DL4].



Most of the results above were actually first published in TU Munich's FKI Tech Report series, for which I drew many illustrations by hand, some of them shown in the present page (Sec. 10, Sec. 11, Sec. 13, Sec. 18). The FKI series now plays an important role in the history of Artificial Intelligence, as it introduced several important concepts: Unsupervised Pre-Training for Very Deep Learning (FKI-148-91 [UN0], Sec. 1), Compressing / Distilling one NN into Another (FKI-148-91 [UN0], Sec. 2), Long Short-Term Memory (FKI-207-95 [LSTM0], Sec. 4, see also Sec. 8), Artificial Curiosity Through NNs that Maximize Learning Progress (FKI-149-91 [AC91], Sec. 6), End-To-End-Differentiable Fast Weights and NNs that learn to program other NNs (separating storage and control for NNs like in traditional computers, FKI-147-91 [FAST0], Sec. 8), Learning of Sequential Attention with NNs (FKI-128-90 [ATT0], Sec. 9), Goal-Defining Commands as Extra NN Inputs (FKI-128-90 [ATT0], FKI-129-90 [HRL0], Sec. 12), Hierarchical Reinforcement Learning (FKI-129-90 [HRL0], Sec. 10), Networks Adjusting Networks / Synthetic Gradients (FKI-125-90 [NAN2], Sec. 15). (Cubic Gradient Computation for Online Recurrent NNs also was published as FKI-151-91 [CUB1], but this one does not really count, see Sec. 16.) In particular, the report FKI-126-90 [AC90] introduced a whole bunch of concepts that are now widely used: Planning with Recurrent World Models (Sec. 11), High-Dimensional Reward Signals as Extra NN Inputs / General Value Functions (Sec. 13), Deterministic Policy Gradients (Sec. 14), NNs that are both *Generative* and *Adversarial* (Sec. 5; see also Sec. 7), for Artificial Curiosity and related concepts. Later remarkable FKI Tech Reports from the 1990s describe ways of greatly compressing NNs [KO0] [FM] to improve their generalisation capability.

Peer-reviewed versions came out soon after the tech reports. For example, in 1992, I had a fun contest with the great David MacKay as to who'd have more publications within a single year in *Neural Computation*, back then the leading journal of our field. By the end of 1992, both of us had four. But David won, because his publications (mostly on Bayesian approaches for NNs) were much longer than mine :-) *Disclaimer:* Of course, silly measures like number of publications and h-index etc should not matter in science - the only thing that really counts is research quality [NAT1].

21. Concluding Remarks

In surveys from the Anglosphere it does not always become clear [DLC] that **Deep Learning was invented where English is not an official language.** It started in 1965 in the Ukraine (back then the USSR) with the first nets of arbitrary depth that really learned [DEEP1-2] (Sec. 1). Five years later, modern backpropagation was published "next door" in Finland (1970) [BP1] (Sec. 0). The basic deep convolutional NN architecture (now widely used) was invented in the 1970s in Japan [CNN1], where NNs with convolutions were later (1987) also combined with "weight sharing" and backpropagation [CNN1a]. Unsupervised or self-supervised adversarial networks that duel each other in a minimax game for Artificial Curiosity etc (now widely used) originated in Munich (1990, Sec. 5) (also the birthplace of the first truly self-driving cars in the 1980s - in highway traffic by 1994). The Fundamental Problem of Backpropagation-Based Deep Learning (1991, Sec. 3) [VAN1] was also discovered in Munich. So were the first "modern" Deep Learners to overcome this problem, through **(1)** unsupervised pre-training [UN1-2] (1991, Sec. 1), and **(2)** Long Short-Term Memory [LSTM0-7], "arguably the most commercial AI achievement" [AV1] (Sec. 4). LSTM was further developed in Switzerland (Sec. 4), which is also home of the first image recognition contest-winning deep GPU-based CNNs (2011, Sec. 19 - everybody in computer vision is using this approach now), the first superhuman visual pattern recognition (2011), and the first very deep, working feedforward NNs with more than a hundred layers [HW1] (Sec. 4). Around 1990, Switzerland also became origin of the *World Wide Web,* which allowed for quickly spreading AI around the globe. As of 2017, Switzerland is still leading the world in AI research in terms of citation impact, although China is now the nation that produces the most papers on AI [THE17].

Of course, Deep Learning is just a small part of AI, mostly limited to passive pattern recognition. We view it as a by-product of our research on more general AI through meta-learning or "learning to learn learning algorithms" (publications since 1987), systems with artificial curiosity and creativity that invent their own problems and set their own goals (since 1990), evolutionary computation (since 1987) & RNN evolution & compressed network search, reinforcement learning (RL) for agents in realistic partially observable environments where traditional RL (for board games etc) does not work (since 1989), general artificial intelligence, optimal universal learning machines such as the Gödel machine (2003-), optimal search for programs running on general purpose computers such as RNNs, etc.

And of course, AI itself is just part of a grander scheme driving the universe from simple initial conditions to more and more unfathomable complexity [SA17]. Finally, even this awesome process may be just a tiny part of the even grander, optimally efficient computation of *all* logically possible universes [ALL1] [ALL2] [ALL3].

Acknowledgments

Thanks to several expert reviewers for useful comments. (Let me know under *juergen@idsia.ch* if you can spot any remaining error.) The contents of this article may be used for educational and non-commercial purposes, including articles for Wikipedia and similar sites.

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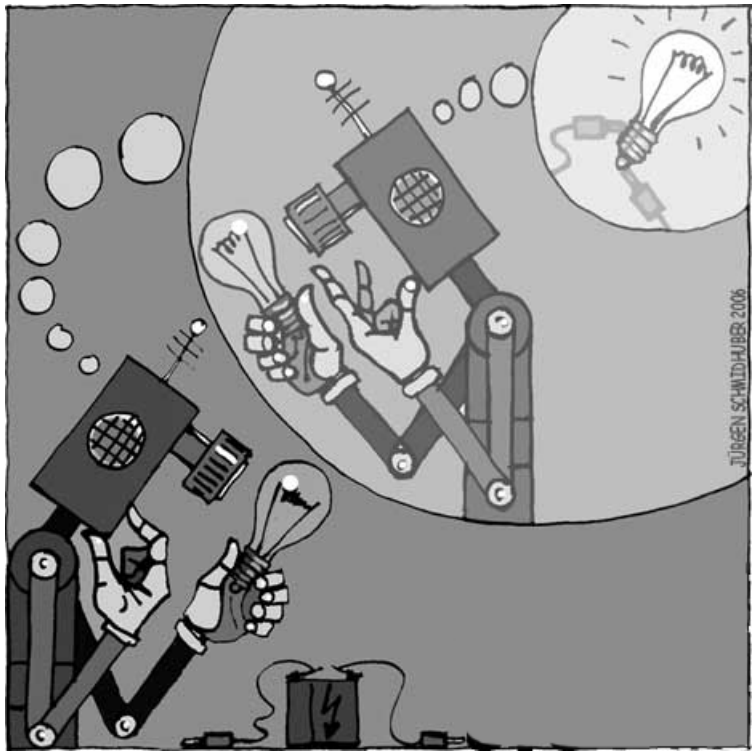

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