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Annotated History of Modern AI and Deep Learning

Abstract. Machine learning (ML) is the science of credit assignment: finding patterns in observations that predict the consequences of actions and help to improve future performance. Credit assignment is also required for human understanding of how the world works, not only for individuals navigating daily life, but also for academic professionals like historians who interpret the present in light of past events. Here I focus on the history of modern artificial intelligence (AI) which is dominated by artificial neural networks (NNs) and **deep learning**,^[DL1-4] both conceptually closer to the old field of cybernetics than to what's been called AI since 1956 (e.g., expert systems and logic programming). A modern history of AI will emphasize breakthroughs outside of the focus of traditional AI text books, in particular, mathematical foundations of today's NNs such as the chain rule (1676), the first NNs (linear regression, circa 1800), and the first working deep learners (1965-). From the perspective of 2022, I provide a timeline of the—in hindsight—most important relevant events in the history of NNs, deep learning, AI, computer science, and mathematics in general, crediting those who laid foundations of the field. The text contains numerous hyperlinks to relevant overview sites from my [AI Blog](#). It also debunks certain popular but misleading historic accounts of deep learning, and supplements my previous [deep learning survey](#)^[DL1] which provides hundreds of additional references. Finally, to round it off, I'll put things in a broader historic context spanning the time since the Big Bang until when the universe will be many times older than it is now. The present piece is also the draft of a chapter of my upcoming AI book.

Disclaimer. Some say a history of deep learning should not be written by someone who has helped to shape it—"you are part of history not a historian."^[CONN21] I cannot subscribe to that point of view. Since I seem to know more about deep learning history than others,^{[S20][DL3,DL3a][T22][DL1-2]} I consider it my duty to document and promote this knowledge, even if that seems to imply a conflict of interest, as it means prominently mentioning my own team's work, because (as of 2022) the [most cited NNs](#) are based on it.^[MOST] Future AI historians may correct any era-specific potential bias.

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Introduction

Over time, certain historic events have become more important in the eyes of certain beholders. For example, the Big Bang of 13.8 billion years ago is now widely considered an essential moment in the history of everything. Until a few decades ago, however, it has remained completely unknown to earthlings, who for a long time have entertained quite erroneous ideas about the origins of the universe (see [the final section](#) for more on the world's history). Currently accepted histories of many more limited subjects are results of similarly radical revisions. Here I will focus on the history of artificial intelligence (AI), which also isn't quite what it used to be.

A history of AI written in the 1980s would have emphasized topics such as theorem proving, [\[GOD\]](#)[\[GOD34\]](#)[\[ZU48\]](#)[\[NS56\]](#) logic programming, expert systems, and heuristic search. [\[FEI63,83\]](#)[\[LEN83\]](#) This would be in line with topics of a 1956 conference in Dartmouth, where the term "AI" was coined by John McCarthy as a way of describing an old area of research seeing renewed interest. *Practical AI* dates back at least to 1914, when Leonardo Torres y Quevedo ([see below](#)) built the first working chess end game player^[BRU1-4] (back then chess was considered as an activity restricted to the realms of intelligent creatures). AI *theory* dates back at least to 1931-34 when Kurt Gödel ([see below](#)) identified fundamental limits of any type of computation-based AI. [\[GOD\]](#)[\[BIB3\]](#)[\[GOD21,a,b\]](#)

A history of AI written in the early 2000s would have put more emphasis on topics such as support vector machines and kernel methods, [\[SVM1-4\]](#) Bayesian (actually Laplacian or possibly Saundersonian[\[STI83-85\]](#)) reasoning[\[BAY1-8\]](#)[\[FI22\]](#) and other concepts of probability theory and statistics, [\[MM1-5\]](#)[\[NIL98\]](#)[\[RUS95\]](#) decision trees, [e.g.,](#)[\[MIT97\]](#) ensemble methods, [\[ENS1-4\]](#) swarm intelligence, [\[SW1\]](#) and evolutionary computation. [\[EVO1-7\]](#)[\(\[TUR1\],unpublished\)](#) Why? Because back then such techniques drove many successful AI applications.

A history of AI written in the 2020s must emphasize concepts such as the even older chain rule[\[LEI07\]](#) and deep nonlinear artificial neural networks (NNs) trained by gradient descent, [\[GD\]](#) in particular, feedback-based recurrent networks, which are general computers whose programs are weight matrices. [\[AC90\]](#) Why? Because many of the most famous and most commercial recent AI applications depend on them. [\[DL4\]](#)

Such NN concepts are actually conceptually close to topics of the MACY conferences (1946-1953)[\[MACY51\]](#) and the 1951 *Paris conference on calculating machines and human thought*, now often viewed as the first conference on AI. [\[AI51\]](#)[\[BRO21\]](#)[\[BRU4\]](#) However, before 1956, much of what's now called AI was still called *cybernetics*, with a focus very much in line with [modern AI](#) based on "deep learning" with NNs. [\[DL1-2\]](#)[\[DEC\]](#)

Some of the past NN research was inspired by the human brain, which 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* NNs, which learn better than previous methods to recognize speech or handwriting or video, minimize pain, maximize pleasure, drive cars, etc. [\[MIR\]\(Sec. 0\)](#)[\[DL1-4\]](#)

How can NNs learn all of this? In what follows, I shall highlight essential historic contributions that made this possible. Since virtually all of the fundamental concepts of modern AI were derived in previous millennia, the section titles below emphasize developments only up to the

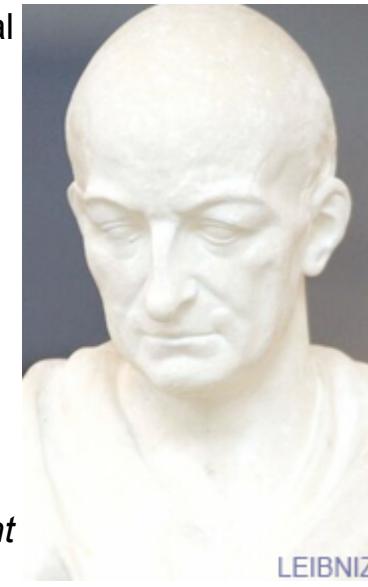
year 2000. However, many of the sections mention the later impact of this work in the new millennium, which brought numerous improvements in hardware and software, a bit like the 20th century brought numerous improvements of the cars invented in the 19th.

The present piece also debunks a frequently repeated, misleading "history of deep learning" [S20][DL3,3a] which ignores most of the pioneering work mentioned below. [T22] See [Footnote 6](#). The title image of the present article is a reaction to an erroneous piece of common knowledge which says [T19] that the use of NNs "*as a tool to help computers recognize patterns and simulate human intelligence had been introduced in the 1980s*," although such NNs appeared long before the 1980s. [T22] Ensuring proper credit assignment in all of science is of great importance to me—just as it should be to all scientists—and I encourage an interested reader to also take a look at some of my letters on this in *Science* and *Nature*, e.g., on the history of aviation, [NASC1-2] the telephone, [NASC3] the computer, [NASC4-7] resilient robots, [NASC8] and scientists of the 19th century. [NASC9]

Finally, to round it off, I'll put things in a broader historic context spanning the time since the Big Bang until when the universe will be many times older than it is now.

1676: The Chain Rule For Backward Credit Assignment

In 1676, [Gottfried Wilhelm Leibniz](#) published the chain rule of differential calculus in a memoir (albeit with a sign error of all things!); Guillaume de l'Hopital described it in his 1696 textbook on Leibniz' differential calculus. [LEI07-10][L84] Today, this rule is central for credit assignment in deep neural networks (NNs). Why? The most popular NNs have nodes or neurons that compute differentiable functions of inputs from other neurons, which in turn compute differentiable functions of inputs from other neurons, and so on. The question is: how will the output of the final function change if we modify the parameters or weights of an earlier function a bit? The chain rule is the basic tool for computing the answer.



LEIBNIZ



CAUCHY

This answer is used by the technique of *gradient descent* (GD), apparently first proposed by Augustin-Louis Cauchy in 1847 [GD] (and much later by Jacques Hadamard [GD]); the stochastic version called SGD is due to Herbert Robbins and Sutton Monro (1951) [STO51-52]. To teach an NN to translate input patterns from a training set into desired output patterns, all NN weights are iteratively changed a bit in the direction of the biggest local improvement, to create a slightly better NN, and so on, until a satisfactory solution is found.

Footnote 1. In 1684, Leibniz was also the first to publish "modern" calculus; [L84][SON18][MAD05][LEI21,a,b] later Isaac Newton was also credited for his unpublished work. [SON18] Their priority dispute, [SON18] however, did not encompass the chain rule. [LEI07-10] Of course, both were building on earlier work: in the 2nd century B.C., Archimedes (perhaps [the greatest scientist ever](#) [ARC06]) paved the way for *infinitesimals* and published special cases of calculus, e.g., for spheres and parabola segments, building on even earlier work in ancient Greece. Fundamental work on calculus was also conducted in the 14th century by Madhava of Sangamagrama and colleagues of the Indian Kerala school. [MAD86-05]

Footnote 2. Remarkably, Leibniz (1646-1714, aka "the world's first computer scientist" [LA14]) also laid foundations of modern computer science. He designed the first machine that could perform all four arithmetic operations (1673), and the first with an *internal memory*. [BL16] He described the principles of *binary computers* (1679) [L79][L03][LA14][HO66][LEI21,a,b] employed by virtually all modern machines. His formal *Algebra of Thought* (1686) [L86][WI48] was deductively equivalent [LE18] to the much later *Boolean Algebra* (1847). [BOO] His *Characteristica Universalis & Calculus Ratiocinator* aimed at answering all possible questions through computation; [WI48] his "*Calculemus!*" is one of the defining quotes of the age of enlightenment. It is quite remarkable that he is also responsible for the chain rule, foundation of "modern" deep learning, a key subfield of modern computer science.

Footnote 3. Some claim that the [backpropagation algorithm](#) (discussed further down; now widely used to train deep NNs) is just the chain rule of Leibniz (1676) & L'Hopital (1696). [CONN21] No, it is the efficient way of applying the chain rule to big networks with differentiable nodes (there are also many inefficient ways of doing this). [T22] It was not published until 1970, as discussed below. [BP1,4,5]

~1800: First NN / Linear Regression / Shallow Learning

In 1805, Adrien-Marie Legendre published what's now often called a linear neural network (NN). Later [Johann Carl Friedrich Gauss](#) was also credited for earlier unpublished work on this done circa 1795.[\[ST181\]](#)

This NN from over 2 centuries ago has two layers: an input layer with several input units, and an output layer. For simplicity, let's assume the latter consists of a single output unit. Each input unit can hold a real-valued number and is connected to the output by a connection with a real-valued weight. The NN's output is the sum of the products of the inputs and their weights. Given a training set of input vectors and desired target values for each of them, the NN weights are adjusted such that the sum of the squared errors between the NN outputs and the corresponding targets is minimized.



LEGENDRE



GAUSS Of course, back then this was not called an NN. It was called the method of least squares, also widely known as linear regression. But it is *mathematically identical* to today's linear NNs: same basic algorithm, same error function, same adaptive parameters/weights. Such simple NNs perform "shallow learning" (as opposed to "deep learning" with many nonlinear layers). In fact, many NN courses start by introducing this method, then move on to more complex, deeper NNs.

Perhaps the first famous example of pattern recognition through shallow learning dates back over 200 years: the re-discovery of the dwarf planet Ceres in 1801 through Gauss, who had data points from previous astronomical observations, then used various tricks to adjust the parameters of a predictor, which essentially learned to generalise from the training data to correctly predict the new location of Ceres.

Footnote 4. Today, students of all technical disciplines are required to take math classes, in particular, analysis, linear algebra, and statistics. In all of these fields, essential results and methods are (at least partially) due to Gauss: the fundamental theorem of algebra, Gauss elimination, the Gaussian distribution of statistics, etc. The so-called "greatest mathematician since antiquity" also pioneered differential geometry, number theory (his favorite subject), and non-Euclidean geometry. Furthermore, he made major contributions to astronomy and physics. Modern engineering including AI would be unthinkable without his results.

Footnote 5. "Shallow learning" with NNs experienced a new wave of popularity in the late 1950s. Rosenblatt's perceptron (1958)[\[R58\]](#) combined a linear NN as above with an output threshold function to obtain a pattern classifier (compare [his more advanced work on multi-layer networks discussed below](#)). Joseph[\[R61\]](#) mentions an even earlier perceptron-like device by Farley & Clark. Widrow & Hoff's similar Adaline learned in 1962.[\[WID62\]](#)

1920-1925: First Recurrent Network Architecture

Like the human brain, but unlike the more limited *feedforward* NNs (FNNs), recurrent NNs (RNNs) have feedback connections, such that one can follow directed connections from certain internal nodes to others and eventually end up where one started. This is essential for implementing a memory of past events during sequence processing.



The first *non-learning* RNN architecture (the Ising model or Lenz-Ising model) was introduced and analyzed by physicists Ernst Ising and Wilhelm Lenz in the 1920s.[\[L20\]\[I24,I25\]\[K41\]\[W45\]\[T22\]](#) It settles into an equilibrium state in response to input conditions, and is the foundation of the first *learning* RNNs (see below).

Non-learning RNNs were also discussed in 1943 by neuroscientists Warren McCulloch und Walter Pitts[\[MC43\]](#) and formally analyzed in 1956 by Stephen Cole Kleene.[\[K56\]](#)



~1972: First Published Learning Artificial RNNs

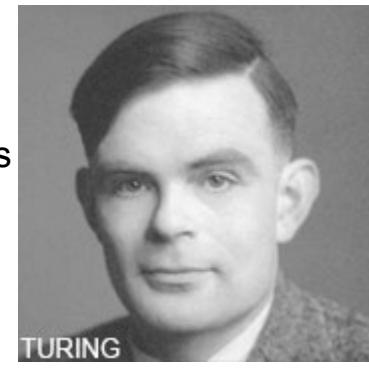
In 1972, Shun-Ichi Amari made the Lenz-Ising recurrent architecture *adaptive* such that it could learn to associate input patterns with output



AMARI
Amari (1972) also had a sequence-processing generalization thereof.
[AMH1]

patterns by changing its connection weights.[AMH1] See also Stephen Grossberg's work on biological networks,[GRO69] David Marr's[MAR71] and Teuvo Kohonen's[KOH72] work, and Kaoru Nakano's learning RNN.[NAK72]

10 years later, the Amari network was republished (and its storage capacity analyzed).[AMH2] Some called it the Hopfield Network (!) or Amari-Hopfield Network.[AMH3] It does not process sequences but settles into an equilibrium in response to static input patterns. However,



TURING

Remarkably, already in 1948, Alan Turing wrote up ideas related to artificial evolution and learning RNNs. This, however, was first published many decades later,[TUR1] which explains the obscurity of his thoughts here.[TUR21] (Margin note: it has been pointed out that the famous "Turing Test" should actually be called the "Descartes Test." [TUR3,a,b][TUR21])

Today, the most popular RNN is the [Long Short-Term Memory \(LSTM\)](#) mentioned below, which has become the [most cited](#) NN of the 20th century.[MOST]

1958: Multilayer Feedforward NN (without Deep Learning)

In 1958, Frank Rosenblatt not only combined linear NNs and threshold functions (see [the section on shallow learning since 1800](#)), he also had more interesting, deeper *multilayer* perceptrons (MLPs).[R58] His MLPs had a non-learning first layer with randomized weights and an adaptive output layer. Although this was not yet deep learning, because only the last layer learned,[DL1] Rosenblatt basically had what much later was rebranded as *Extreme Learning Machines (ELMs)* without proper attribution.[ELM1-2][CONN21][T22]



ROSENBLATT

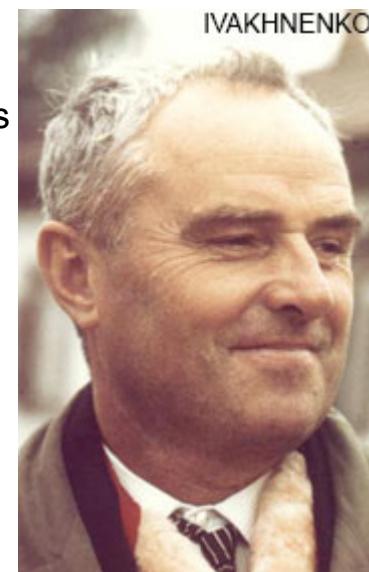
MLPs were also discussed in 1961 by Karl Steinbuch[ST61-95] and Roger David Joseph[R61] (1961). See also Oliver Selfridge's multilayer Pandemonium[SE59] (1959).

Rosenblatt (1962) even wrote about "*back-propagating errors*" in an MLP with a hidden layer[R62] although he did not yet have a general *deep learning* algorithm for deep MLPs. What's now called [backpropagation](#) is quite different and was first published in 1970, [as discussed below.](#)[BP1-BP5][BPA-C]

Today, the most popular FNN is a version of the LSTM-based Highway Net ([mentioned below](#)) called ResNet,[HW1-3] which has become the [most cited](#) NN of the 21st century.[MOST]

1965: First Deep Learning

Successful learning in *deep* feedforward network architectures started in 1965 in the Ukraine (back then the USSR) when Alexey Ivakhnenko & Valentin Lapa introduced the first general, working learning algorithms for deep MLPs with arbitrarily many hidden layers (already containing the now popular multiplicative gates).[DEEP1-2][DL1-2][FDL] A paper of 1971[DEEP2] already described a deep learning net with 8 layers, trained by their highly cited method which was still popular in the new millennium,[DL2] especially in Eastern Europe, where much of Machine Learning was born.[MIR](Sec. 1)[R8]



IVAKHNENKO

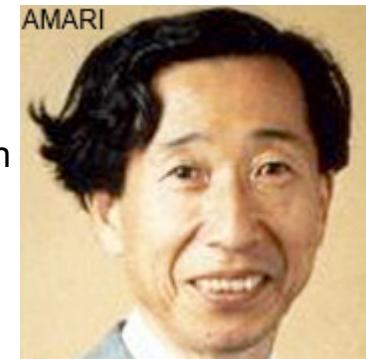
Given a training set of input vectors with corresponding target output vectors, layers are incrementally grown and trained by regression analysis, then pruned with the help of a separate validation set, where regularisation is used to weed out superfluous units. The numbers of layers and units per layer are learned in problem-dependent fashion.

Like later deep NNs, Ivakhnenko's nets learned to create hierarchical, distributed, *internal representations* of incoming data.

He did not call them deep learning NNs, but that's what they were. In fact, the ancient term "*deep learning*" was first introduced to Machine Learning much later by Dechter (1986), and to NNs by Aizenberg et al (2000).^[DL2] (Margin note: our 2005 paper on deep learning^[DL6,6a] was the first machine learning publication with the word combination "*learn deep*" in the title.^[T22])

1967-68: Deep Learning by Stochastic Gradient Descent

Ivakhnenko and Lapa (1965, [see above](#)) trained their deep networks layer by layer. In 1967, however, Shun-Ichi Amari suggested to train MLPs with many layers in non-incremental end-to-end fashion from scratch by stochastic gradient descent (SGD),^[GD1] a method proposed in 1951 by Robbins & Monro.^[STO51-52]



Amari's implementation^[GD2, GD2a] (with his student Saito) learned *internal representations* in a five layer MLP with two modifiable layers, which was trained to classify non-linearly separable pattern classes. Back then compute was billions of times more expensive than today.

See also Iakov Zalmanovich Tsyplkin's even earlier work on gradient descent-based on-line learning for non-linear systems.^[GDa-b]

Remarkably, [as mentioned above](#), Amari also published learning RNNs in 1972.^[AMH1]

1970: Backpropagation. 1982: For NNs. 1960: Precursor.



In 1970, Seppo Linnainmaa was the first to publish what's now known as [backpropagation](#), the famous algorithm for credit assignment in networks of differentiable nodes,^[BP1,4,5] also known as "reverse mode of automatic differentiation." It is now the foundation of widely used NN software packages such as PyTorch and Google's Tensorflow.

In 1982, Paul Werbos proposed to use the method to train NNs,^[BP2] extending ideas in his 1974 thesis.

In 1960, Henry J. Kelley already had a precursor of backpropagation in the field of control theory;^[BPA] see also later work of the early 1960s by Stuart Dreyfus and Arthur E. Bryson.^{[BPB][BPC][R7]} Unlike Linnainmaa's general method,^[BP1] the systems of the 1960s^[BPA-C] backpropagated derivative information through standard Jacobian matrix calculations from one "stage" to the previous one, neither addressing direct links across several stages nor potential additional efficiency gains due to network sparsity.



Backpropagation is essentially an efficient way of implementing Leibniz's chain rule^[LEI07-10] (1676) ([see above](#)) for deep networks.

Cauchy's gradient descent^[GD] uses this to incrementally weaken certain NN connections and strengthen others in the course of many trials, such that the NN behaves more and more like some teacher, which could be a human, or another NN,^[UN-UN2] or something else.

By 1985, compute had become about 1,000 times cheaper than in 1970, and the first desktop computers had just become accessible in wealthier academic labs. An experimental analysis of the known method^[BP1-2] by David E. Rumelhart et al. then demonstrated that backpropagation can yield useful internal representations in hidden layers of NNs.^[RUM] At least

for supervised learning, backpropagation is generally more efficient than Amari's [above-mentioned deep learning through the more general SGD method \(1967\)](#), which learned useful internal representations in NNs about 2 decades earlier.^[GD1-2a]

It took 4 decades until the backpropagation method of 1970^[BP1-2] got widely accepted as a training method for *deep* NNs. Before 2010, many thought that the training of NNs with many layers requires [unsupervised pre-training](#), a methodology introduced [by myself in 1991^{\[UNI\]\[UNO-3\]} \(see below\)](#), and later championed by others (2006).^[UN4] In fact, it was claimed^[VID1] that "nobody in their right mind would ever suggest" to apply plain backpropagation to deep NNs. However, in 2010, our team with my outstanding Romanian postdoc Dan Ciresan^[MLP1-2] showed that [deep FNNs can be trained by plain backpropagation and do not at all require unsupervised pre-training for important applications.](#)^[MLP2]



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 deep FNNs on highly parallel graphics processing units called GPUs (as first done for shallow NNs with few layers by Jung & Oh in 2004^[GPUNN]). A reviewer called this a "[wake-up call to the machine learning community.](#)" Today, everybody in the field is pursuing this approach.

Footnote 6. Unfortunately, several authors who re-published backpropagation in the 1980s did not cite the prior art—not even in later surveys.^[T22] In fact, as mentioned in the introduction, there is a broader, frequently repeated, misleading "history of deep learning"^[S20] which ignores most of the pioneering work mentioned in the previous sections.^{[T22][DLC]} This "alternative history" essentially goes like this: "*In 1969, Minsky & Papert^[M69] showed that shallow NNs without hidden layers are very limited and the field was abandoned until a new generation of neural network researchers took a fresh look at the problem in the 1980s.*"^[S20] However, the 1969 book^[M69] addressed a "problem" of Gauss & Legendre's [shallow learning](#) (circa 1800)^[DL1-2] that had [already been solved 4 years prior](#) by Ivakhnenko & Lapa's popular deep learning method,^{[DEEP1-2][DL2]} and then also by Amari's [SGD for MLPs.](#)^[GD1-2] Minsky neither cited this work nor corrected his book later.^{[HIN](Sec. I)[T22]} And even recent papers promulgate this revisionist narrative of deep learning, apparently to glorify later contributions of their authors (such as the Boltzmann machine^{[BM][HIN][SK75][G63][T22]}) without relating them to the original work,^{[DLC][S20][T22]} although the true history is well-known. Deep learning research was alive and kicking in the 1960s-70s, especially outside of the Anglosphere.^{[DEEP1-2][GD1-3][CNN1][DL1-2][T22]} Blatant misattribution and unintentional^{[PLAG1][CONN21]} or intentional^[FAKE2] plagiarism are still tainting the entire field of deep learning.^[T22] Scientific journals "need to make clearer and firmer commitments to self-correction,"^[SV20] as is already the standard in other scientific fields.

1979: First Deep Convolutional NN (1969: ReLUs)

Computer Vision was revolutionized in [the 2010s](#) by a particular feedforward NN called the convolutional NN (CNN).^[CNN1-4] The basic CNN architecture with alternating convolutional and downsampling layers is due to Kunihiko Fukushima (1979). He called it Neocognitron.^[CNN1]

Remarkably, already 10 years earlier, Fukushima also introduced [rectified linear units](#) (ReLUs) for NNs (1969).^[RELU1] They are now widely used in CNNs and other NNs.

In 1987, NNs with convolutions were combined by Alex Waibel with weight sharing and [backpropagation](#) (see [above](#)),^[BP1-2] and applied to speech.^[CNN1a] Waibel did not call this CNNs but TDNNs.



A popular downsampling variant called max-pooling was introduced by Yamaguchi et al. for TDNNs in 1990^[CNN3a] and by Juan Weng et al. for higher-dimensional CNNs in 1993.^[CNN3]

Since 1989, Yann LeCun's team has contributed improvements of CNNs, especially for images.^{[CNN2,4][T22]} Baldi and Chauvin (1993) had the first application of CNNs with backpropagation to biomedical/biometric images.^[BA93]



CNNs became more popular in the ML community much later in 2011 when my own team greatly sped up the training of deep CNNs (Dan Ciresan et al., 2011).^[GPUCNN1,3,5] Our fast GPU-based^{[GPUNN][GPUCNN5]} CNN of 2011^[GPUCNN1] known as **DanNet**^{[DAN,DAN1][R6]} was a practical breakthrough, much deeper and faster than earlier GPU-accelerated CNNs of 2006.^[GPUCNN] In 2011, DanNet became the first pure deep CNN to win computer vision contests.^[GPUCNN2-3,5]

Competition ^[GPUCNN5]	Date/Deadline	Image size	Improvement	Winner
ICDAR 2011 Chinese handwriting	May 15, 2011	variable	3.8% / 28.9%	DanNet ^[GPUCNN1-3]
IJCNN 2011 traffic signs	Aug 06, 2011	variable	68.0% (superhuman)	DanNet ^{[DAN,DAN1][R6]}
ISBI 2012 image segmentation	Mar 01, 2012	512x512	26.1%	DanNet ^[GPUCNN3a]
ICPR 2012 medical imaging	Sep 10, 2012	2048x2048x3	8.9%	DanNet ^[GPUCNN8]
ImageNet 2012	Sep 30, 2012	256x256x3	41.4%	AlexNet ^[GPUCNN4]
MICCAI 2013 Grand Challenge	Sep 08, 2013	2048x2048x3	26.5%	DanNet ^[GPUCNN8]
ImageNet 2014	Aug 18, 2014	256x256x3		VGG Net ^[GPUCNN9]
ImageNet 2015	Sep 30, 2015	256x256x3	15.8%	ResNet, ^[HW2] a Highway Net ^[HW1] with open gates

For a while, DanNet enjoyed a monopoly. From 2011 to 2012 it won every contest it entered, winning four of them in a row (15 May 2011, 6 Aug 2011, 1 Mar 2012, 10 Sep 2012).^[GPUCNN5] In particular, at IJCNN 2011 in Silicon Valley, DanNet blew away the competition and achieved the first superhuman visual pattern recognition^[DAN1] in an international contest. DanNet was also the first deep CNN to win: a Chinese handwriting contest (ICDAR 2011), an image segmentation contest (ISBI, May 2012), a contest on object detection in large images (ICPR, 10 Sept 2012), and—at the same time—a medical imaging contest on cancer detection.^[GPUCNN8] In 2010, we introduced DanNet to Arcelor Mittal, the world's largest steel producer, and were able to greatly improve steel defect detection.^[ST] To the best of my knowledge, this was the first deep learning breakthrough in heavy industry. In July 2012, our CVPR paper on DanNet^[GPUCNN3] hit the computer vision community. 5 months later, the similar GPU-accelerated AlexNet won the ImageNet^[IM09] 2012 contest.^{[GPUCNN4-5][R6]} Our CNN image scanners were 1000 times faster than previous methods.^[SCAN] This attracted tremendous interest from the healthcare industry. Today IBM, Siemens, Google and many startups are pursuing this approach. The VGG network (ImageNet 2014 winner)^[GPUCNN9] and other highly cited CNNs^[RCNN1-3] further extended the DanNet of 2011.^{[MIR](Sec. 19)[MOST]}

ResNet, the ImageNet 2015 winner^[HW2] (Dec 2015) and currently the most cited NN,^[MOST] is a version (with open gates) of our earlier Highway Net (May 2015).^{[HW1-3][R5]} The Highway Net (see below) is actually the feedforward net version of our vanilla LSTM (see below).^[LSTM2] It was the first working, really deep feedforward NN with hundreds of layers (previous NNs had at most a few tens of layers).

1980s-90s: Graph NNs / Stochastic Delta Rule (Dropout) /...

NNs with rapidly changing "fast weights" were introduced by v.d. Malsburg (1981) and others.^[FAST,a,b] Deep learning architectures that can manipulate structured data such as graphs^[T22] were proposed in 1987 by Pollack^[PO87-90] and extended/improved by Sperduti, Goller, and Küchler in the early 1990s.^{[SP93-97][GOL][KU][T22]} See also our graph NN-like, Transformer-like Fast

Weight Programmers of 1991 [FWP0-1][FWP6][FWP] which learn to continually rewrite mappings from inputs to outputs (addressed below), and the work of Baldi and colleagues. [BA96-03] Today, graph NNs are used in numerous applications.

Werbos, [BP2][BPTT1] Williams, [BPTT2][CUB0-2] and others [ROB87][BPTT3][DL1] analyzed ways of implementing gradient descent [GD][STO51-52][GDa-b][GD1-2a] in RNNs. Kohonen's self-organising maps became popular. [KOH82-89]

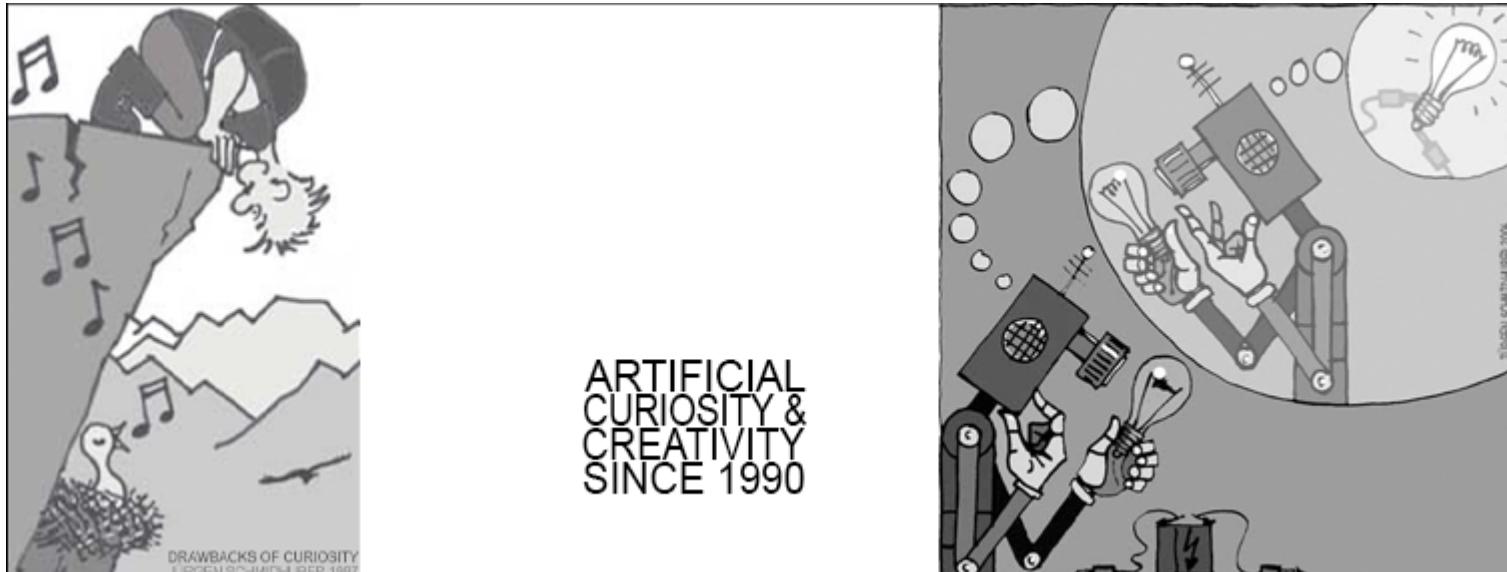
The 80s and 90s also saw various proposals of biologically more plausible deep learning algorithms that—unlike backpropagation—are local in space and time. [BB2][NAN1-4][NHE][HEL] See overviews [MIR](Sec. 15, Sec. 17) and recent renewed interest in such methods. [NAN5][FWPMETA6][HIN22]

In 1990, Hanson introduced the Stochastic Delta Rule, a stochastic way of training NNs by backpropagation. Decades later, a version of this became popular under the moniker "dropout." [Drop1-4][GPUCNN4]

Many additional papers on NNs (including RNNs) were published in the 1980s and 90s—see the numerous references in the 2015 survey. [DL1] Here, however, we mostly limit ourselves to the—in hindsight—most essential ones, given the present (ephemeral?) perspective of 2022.

Feb 1990: Generative Adversarial Networks / Curiosity

Generative Adversarial Networks (GANs) have become very popular. [MOST] They were first published in 1990 in Munich under the moniker *Artificial Curiosity*. [AC90-20][GAN1] Two dueling NNs (a probabilistic generator and a predictor) are trying to maximize each other's loss in a minimax game. [AC](Sec. 1) The generator (called the controller) generates probabilistic outputs (using stochastic units [AC90] like in the much later StyleGANs [GAN2]). The predictor (called the world model) sees the outputs of the controller and predicts environmental reactions to them. Using gradient descent, the predictor NN *minimizes* its error, while the generator NN tries to make outputs that *maximize* this error: one net's loss is the other net's gain. [AC90] (The world model can also be used for continual **online action planning**. [AC90][PLAN2-3][PLAN])



4 years before a 2014 paper on GANs, [GAN1] my well-known 2010 survey [AC10] summarised the generative adversarial NNs of 1990 as follows: a "*neural network as a predictive world model is used to maximize the controller's intrinsic reward, which is proportional to the model's prediction errors*" (which are minimized).

The 2014 GANs are an instance of this where the trials are very short (like in bandit problems) and the environment simply returns 1 or 0 depending on whether the controller's (or generator's) output is in a given set. [AC20][AC][T22](Sec. XVII)

Other early adversarial machine learning settings [S59][H90] were very different—they neither involved unsupervised NNs nor were about modeling data nor used gradient descent. [AC20]



JÜRGEN SCHMIDHUBER

The 1990 principle has been widely used for exploration in Reinforcement Learning [SIN5][OUD13] [PAT17][BUR18] and for synthesis of realistic images, [GAN1,2] although the latter domain was recently taken over by Rombach et al.'s *Latent Diffusion*, another method published in Munich, [DIF1] building on Jarzynski's earlier work in physics from the previous millennium [DIF2] and more recent papers. [DIF3-5]

In 1991, I published yet another ML method based on two adversarial NNs called **Predictability Minimization** for creating disentangled representations of partially redundant data, applied to images in 1996. [PM0-2][AC20][R2][MIR](Sec. 7)

April 1990: NNs Generate Subgoals / Work on Command

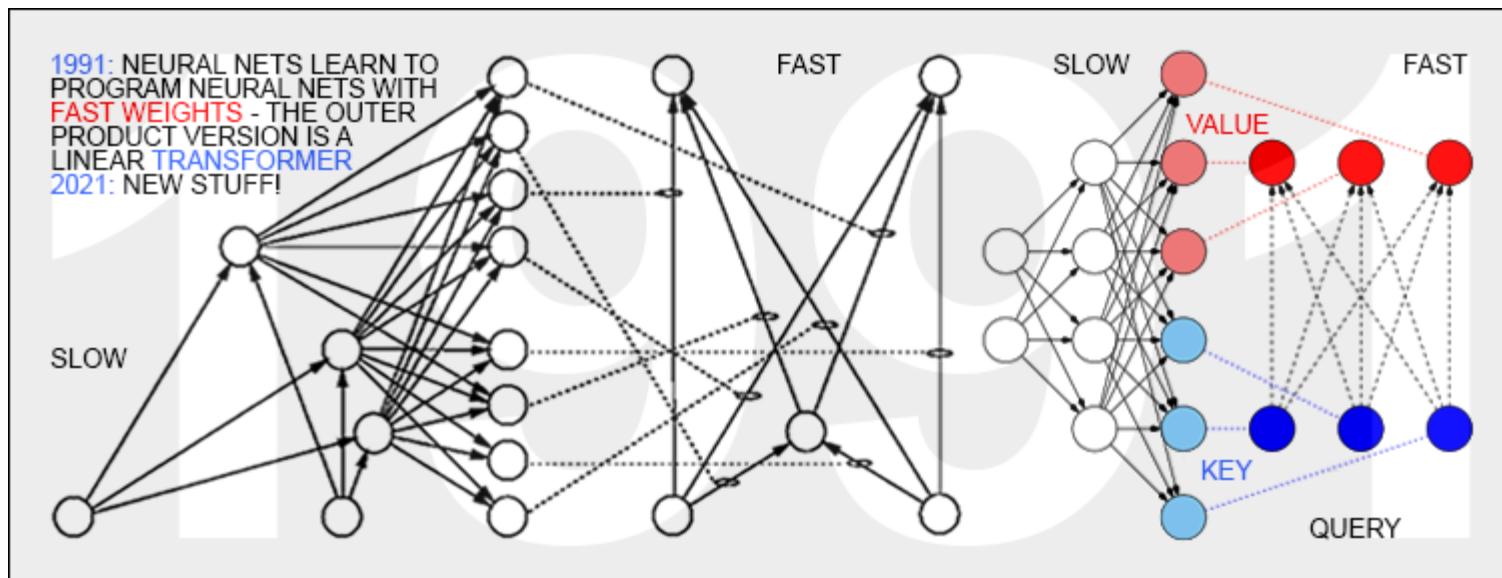
Most NNs of recent centuries were dedicated to simple pattern recognition, not to high-level reasoning, which is now considered a remaining grand challenge. [LEC] The early 1990s, however, saw first exceptions: NNs that learn to *decompose* complex spatio-temporal observation sequences into compact but meaningful *chunks* [UN0-3] (see further below), and NN-based planners of hierarchical action sequences for *compositional learning*, [HRL0] as discussed next. This work injected concepts of traditional "symbolic" hierarchical AI [NS59][FU77] into end-to-end differentiable "sub-symbolic" NNs.

In 1990, our NNs learned to generate hierarchical action plans with end-to-end differentiable NN-based subgoal generators for Hierarchical Reinforcement Learning (HRL). [HRL0] Soon afterwards, this was also done with recurrent NNs that learn to generate sequences of subgoals. [HRL1-2][PHD][MIR](Sec. 10) An RL machine gets extra *command inputs* of the form (*start, goal*). An evaluator NN learns to predict the current 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. The system is learning action plans at multiple levels of abstraction and multiple time scales and solves (at least in principle) what recently (2022) has been called an "open problem." [LEC]

Compare other NNs that have "worked on command" since April 1990, in particular, for learning selective attention, [ATT0-3] artificial curiosity and self-invented problems, [PP][PPa,1,2][AC] upside-down reinforcement learning [UDRL1-2] and its generalizations. [GGP]

March 1991: Transformers with Linearized Self-Attention

Recently, Transformers [TR1] have been all the rage, e.g., generating human-sounding texts. [GPT3] Transformers with "linearized self-attention" [TR5-6] were first published in March 1991 [FWP0-1] [FWP6][FWP] (apart from normalisation—see tweet of 2022 for 30-year anniversary). These so-called "Fast Weight Programmers" or "Fast Weight Controllers" [FWP0-1] separated storage and control like in traditional computers, but in an end-to-end-differentiable, adaptive, fully neural way (rather than in a hybrid fashion [PDA1-2][DNC]). The "self-attention" in standard Transformers [TR1-4] combines this with a projection and softmax (using attention terminology like the one I introduced in 1993 [ATT][FWP2][R4]).



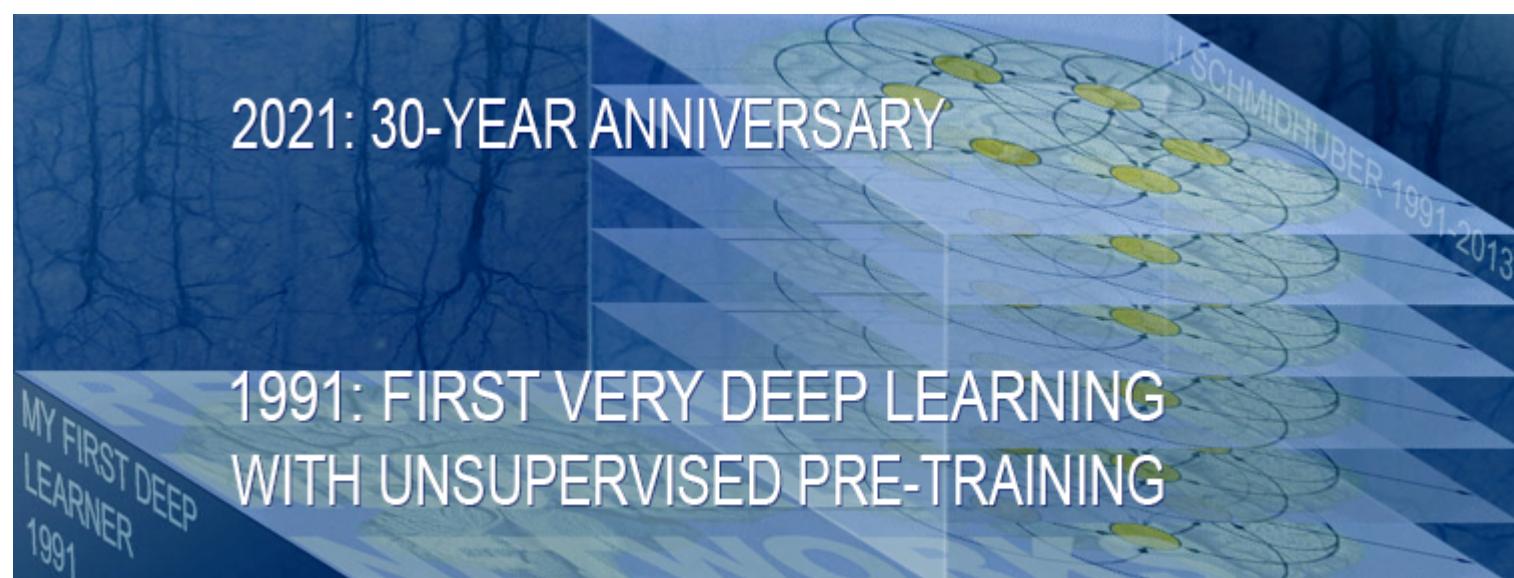
Today's Transformers heavily use [unsupervised pre-training](#)^[UNO-3] (see [next section](#)), another deep learning methodology first published in our [Annus Mirabilis of 1990-1991](#).^{[MIR][MOST]}

The [1991 fast weight programmers](#) also led to meta-learning self-referential NNs that can run their own weight change algorithm or learning algorithm on themselves, and improve it, and improve the way they improve it, and so on. This work since 1992^{[FWPMETA1-9][HO1]} extended my 1987 diploma thesis,^[META1] which introduced algorithms not just for learning but also for [meta-learning or learning to learn](#),^[META] to learn better learning algorithms through experience. This became very popular in the 2010s^[DEC] when computers were a million times faster.

April 1991: Deep Learning by Self-Supervised Pre-Training

Today's most powerful NNs tend to be very deep, that is, they have many layers of neurons or many subsequent computational stages.^[MIR] Before the 1990s, however, gradient-based training did not work well for deep NNs, only for shallow ones^[DL1-2] (but see a 1989 paper^[MOZ]). This *Deep Learning Problem* was most obvious for *recurrent* NNs. 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 data or videos). RNNs can in principle implement any program that can run on your laptop or any other computer in existence. If we want to build an *Artificial General Intelligence* (AGI), then its underlying computational substrate must be something more like an RNN than an FNN as FNNs are fundamentally insufficient; RNNs and similar systems are to FNNs as general computers are to pocket calculators. In particular, unlike FNNs, RNNs can in principle deal with problems of arbitrary depth.^[DL1] Before the 1990s, however, RNNs failed to learn deep problems in practice.^{[MIR](Sec. 0)}

To overcome this drawback through RNN-based "general deep learning," I built a self-supervised RNN hierarchy that learns representations at multiple levels of abstraction and multiple self-organizing time scales:^[LEC] the *Neural Sequence Chunker*^[UNO] or *Neural History Compressor*.^[UN1] Each RNN tries to solve the *pretext task* of predicting its next input, sending only unexpected inputs (and therefore also targets) to the next RNN above. The resulting compressed sequence representations greatly facilitate downstream *supervised* deep learning such as sequence classification.



Although computers back then were about a million times slower per dollar than today, by 1993, the *Neural History Compressor* above 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] (See also recent work on

unsupervised NN-based abstraction.^[OBJ1-5])

More than a decade after this work,^[UN1] a similar unsupervised 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.^{[HIN][T22][MIR]}

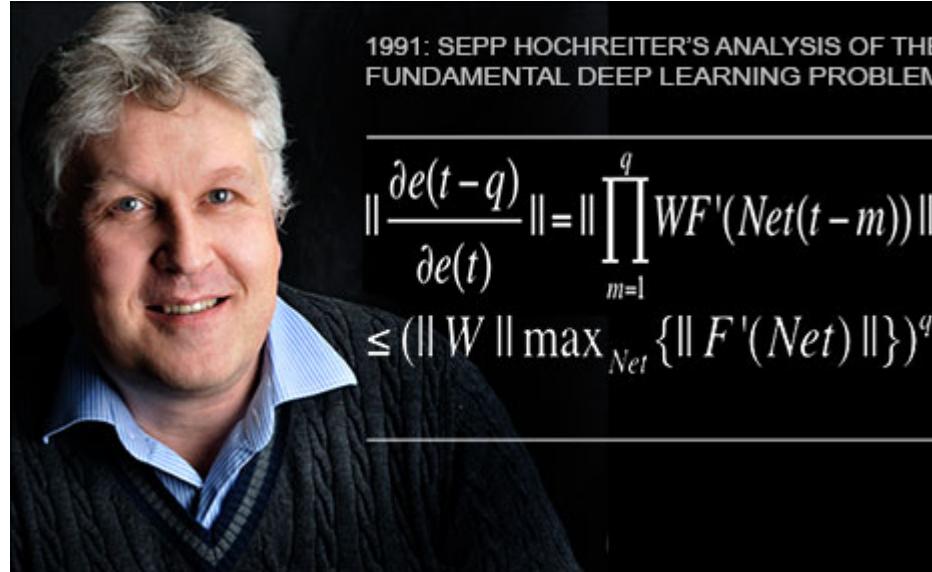
April 1991: Distilling one NN into another NN

The hierarchical internal representations of the neural history compressor above can be collapsed into a single recurrent NN (RNN), using my [NN distillation procedure of 1991](#).^{[UNO-1][MIR]} Here the knowledge of a teacher NN is "distilled" 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). NN distillation was also republished many years later,^{[DIST2][MIR][HIN][T22]} and is widely used today.

Today, unsupervised pre-training is heavily used by *Transformers*^[TR1-6] for natural language processing and other domains. Remarkably, [Transformers with linearized self-attention](#) were also first published^[FWP0-6] in our [Annus Mirabilis of 1990-1991](#),^{[MIR][MOST]} together with unsupervised/self-supervised pre-training for deep learning.^[UNO-3] See the [previous section](#).

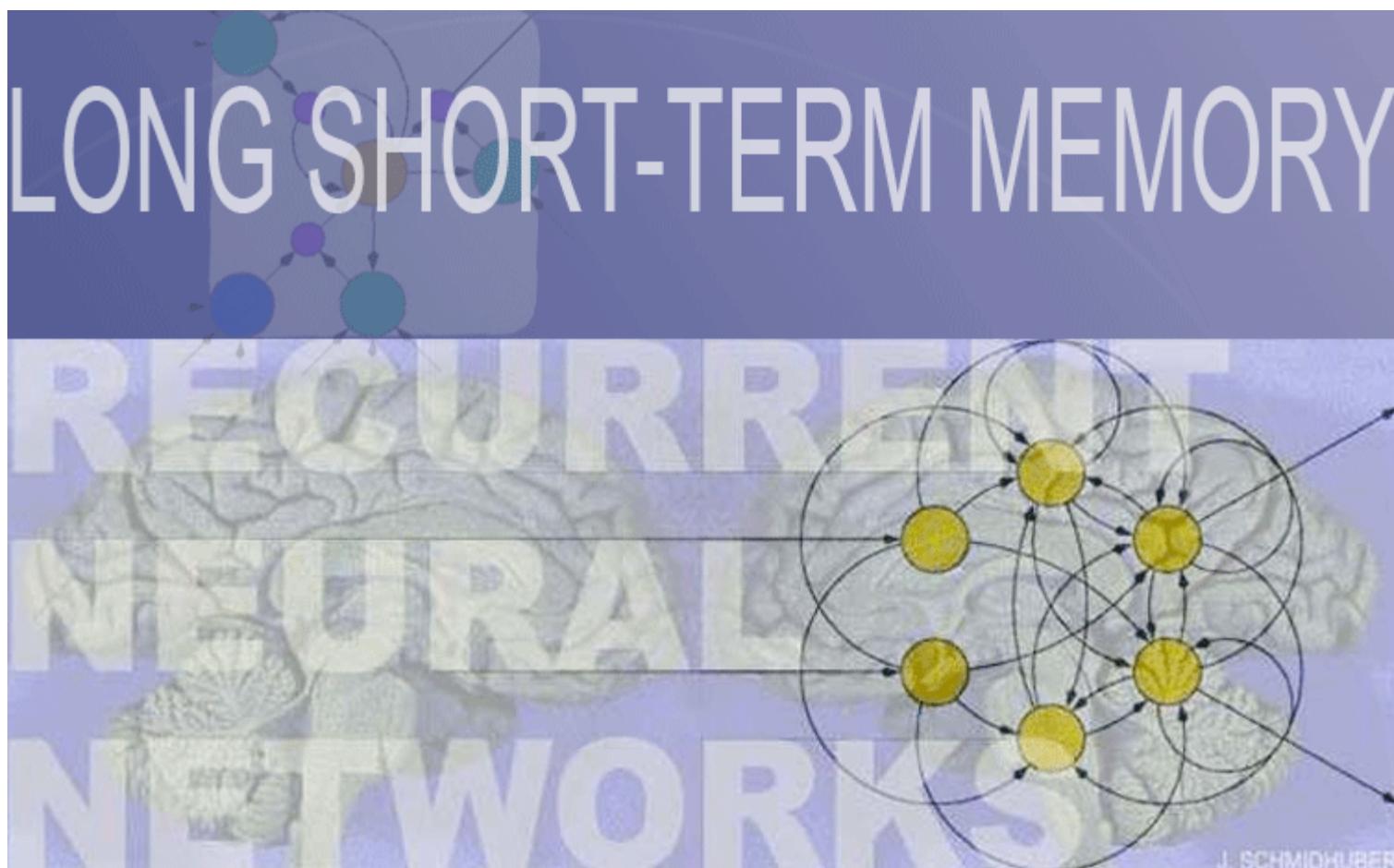
June 1991: Fundamental Problem: Vanishing Gradients

Deep learning is hard because of the [Fundamental Deep Learning Problem](#) identified and analyzed in 1991 by my first student Sepp Hochreiter in his diploma thesis which I had the pleasure to supervise.^[VAN1] First he implemented the [Neural History Compressor above](#) but then did much more: he 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 (compare^[VAN2]). This analysis led to basic principles of what's now called LSTM (see below).



June 1991: Roots of LSTM / Highway Nets / ResNets

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] 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.^[LSTMO] After the main peer-reviewed publication in 1997^{[LSTM1][25y97]} (now the most cited NN article of the 20th century^[MOST]), 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. Alex was lead author of 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. Our team successfully applied CTC-trained LSTM to speech in 2007^[LSTM4] (also with hierarchical LSTM stacks^[LSTM14]). This led to the first superior end-to-end neural speech recognition. It was very different from hybrid methods since the late 1980s which combined NNs and traditional approaches such as Hidden Markov Models (HMMs).^{[BWJ][BRI][BOU][HYB12][T22]} 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 speech^{[LSTM10-11][LSTM4][DL1]} and videos. In 2015, the CTC-LSTM combination dramatically improved Google's speech recognition on the Android smartphones.^[GSR15] Many other companies adopted this.^[DL4] Google's new [on-device speech recognition](#) of 2019 ([now on your phone, not on the server](#)) is still based on LSTM.

1995: Neural Probabilistic Language Model

The first superior end-to-end neural machine translation was also based on LSTM. In 1995, we already had an excellent neural probabilistic text model^[SNT] whose basic concepts were reused in 2003^{[NPM][T22]}—see also Pollack's earlier work on embeddings of words and other structures^{[PO87][PO90]} as well as Nakamura and Shikano's 1989 word category prediction model.^[NPMA] In 2001, we showed that LSTM can learn languages unlearnable by traditional models such as HMMs,^[LSTM13] i.e., a neural "subsymbolic" model suddenly excelled at learning "symbolic" tasks. Compute still had to get 1000 times cheaper, but by 2016, Google Translate^[GT16]—whose whitepaper^[WU] mentions LSTM over 50 times—was based on two connected LSTMs,^[S2S] one for incoming texts, and one for outgoing translations—much better than what existed before.^[DL4] By 2017, LSTM also powered Facebook's machine translation (over 30 billion translations per week—the most popular youtube video needed years to achieve only 10 billion clicks),^{[FB17][DL4]} Apple's Quicktype on roughly 1 billion iPhones,^[DL4] the voice of Amazon's Alexa,^[DL4] Google's [image caption generation](#)^[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 above](#)).^[JOU17] And of course, our LSTM is also massively used in healthcare and medical diagnosis—a simple Google Scholar search turns up innumerable medical articles that have "LSTM" in their title.^[DEC]

HIGHWAY NETWORKS: FIRST NEURAL NETWORKS WITH OVER 100 LAYERS

BASED ON LSTM PRINCIPLE

SPECIAL CASE: RESNETS

JS 2015

Through the work of my students Rupesh Kumar Srivastava and Klaus Greff, the LSTM principle also led to our [Highway Network](#)^[HW1] of May 2015, the first working very deep FNN with hundreds of layers (previous NNs had at most a few tens of layers). Microsoft's ResNet^[HW2] (which won the [ImageNet 2015 contest](#)) is a version thereof (ResNets are Highway Nets whose gates are always open). The earlier Highway Nets perform roughly as well as their ResNet versions on ImageNet.^[HW3] Variants of highway gates are also used for certain algorithmic tasks where the pure residual layers do not work as well.^[NDR]

The LSTM / Highway Net Principle is the Core of Modern Deep Learning

Deep learning is all about NN depth.^[DL1] In the 1990s, [LSTMs](#) brought essentially *unlimited* depth to supervised *recurrent* NNs; in the 2000s, the LSTM-inspired [Highway Nets](#) brought it to *feedforward* NNs. LSTM has become the most cited NN of the 20th century; the Highway Net version called ResNet the most cited NN of the 21st.^[MOST] (Citations, however, are a highly questionable measure of true impact.^[NAT1])

1980s-: NNs for Learning to Act Without a Teacher

The previous sections have mostly focused on deep learning for passive pattern recognition/classification. However, NNs are also relevant for Reinforcement Learning (RL),^{[KAE96][BER96][TD3][UNI][GM3][LSTMPG]} the most general type of learning. General RL agents must discover, without the aid of a teacher, how to interact with a dynamic, initially unknown, partially observable environment in order to maximize their expected cumulative reward signals.^[DL1] There may be arbitrary, a priori unknown delays between actions and perceivable consequences. The RL problem is as hard as any problem of computer science, since any task with a computable description can be formulated in the general RL framework.^[UNI]

Certain RL problems can be addressed through non-neural techniques invented long before the 1980s: Monte Carlo (tree) search (MC, 1949),^[MOC1-5] dynamic programming (DP, 1953),^[BEL53] artificial evolution (1954),^{[EVO1-7][TUR1],unpublished} alpha-beta-pruning (1959),^[S59] control theory and system identification (1950s),^{[KAL59][GLA85]} stochastic gradient descent (SGD, 1951),^[STO51-52] and universal search techniques (1973).^[AIT7]

Deep FNNs and RNNs, however, are useful tools for *improving* certain types of RL. In the 1980s, concepts of function approximation and NNs were combined with system identification,^{[WER87-89][MUN87][NGU89]} DP and its online variant called Temporal Differences (TD),^[TD1-3] artificial evolution,^[EVONN1-3] and policy gradients.^{[GD1][PG1-3]} Many additional references on this can be found in Sec. 6 of the 2015 survey.^[DL1]

When there is a Markovian interface^[PLAN3] to the environment such that the current input to the RL machine conveys all the information required to determine a next optimal action, RL with DP/TD/MC-based FNNs can be very successful, as shown in 1994^[TD2] (master-level backgammon player) and the 2010s^[DM1-2a] (superhuman players for Go, chess, and other games).

For more complex cases without Markovian interfaces, where the learning machine must consider not only the present input, but also the history of previous inputs, our combinations of RL algorithms and LSTM^{[LSTM-RL][RPG]} have become standard, in particular, our [LSTM trained by policy gradients](#) (2007).^{[RPG07][RPG][LSTMPG]}



For example, in 2018, a PG-trained LSTM was the core of OpenAI's famous [Dactyl](#) which learned to control a dexterous robot hand without a teacher.[\[OAI1\]](#)[\[OAI1a\]](#) Similar for video games: in 2019, DeepMind (co-founded by a student from my lab) famously beat a pro player in the game of Starcraft, which is theoretically harder than Chess or Go[\[DM2\]](#) in many ways, using [AlphaStar](#) whose brain has a [deep LSTM core](#) trained by PG.[\[DM3\]](#) An RL LSTM (with 84% of the model's total parameter count) also was the core of the famous [OpenAI Five](#) which learned to [defeat human experts](#) in the Dota 2 video game (2018).[\[OAI2\]](#) Bill Gates called this a "*huge milestone in advancing artificial intelligence*".[\[OAI2a\]](#)[\[MIR\]\(Sec. 4\)](#)[\[LSTMPG\]](#)

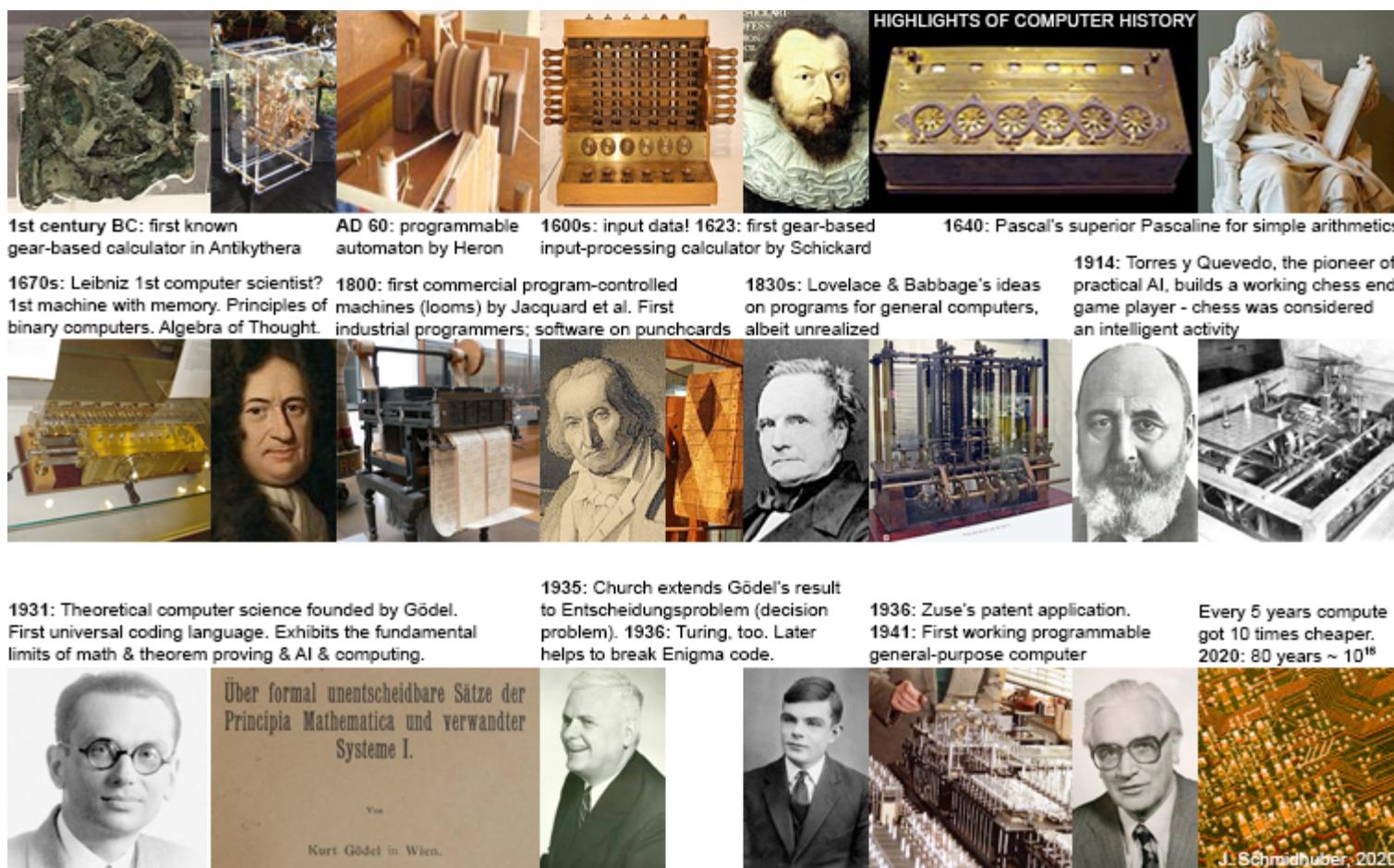
The future of RL will be about learning/composing/planning with compact spatio-temporal abstractions of complex input streams—about commonsense reasoning[\[MAR15\]](#) and *learning to think*.[\[PLAN4-5\]](#) How can NNs learn to represent percepts and action plans in a hierarchical manner, at multiple levels of abstraction, and multiple time scales?[\[LEC\]](#) We published answers to these questions in 1990-91: self-supervised [neural history compressors](#)[\[UN\]](#)[\[UN0-3\]](#) learn to represent percepts at multiple levels of abstraction and multiple time scales ([see above](#)), while end-to-end differentiable NN-based subgoal generators[\[HRL3\]](#)[\[MIR\]\(Sec. 10\)](#) learn hierarchical action plans through gradient descent ([see above](#)). More sophisticated ways of learning to think in abstract ways were published in 1997[\[AC97\]](#)[\[AC99\]](#)[\[AC02\]](#) and 2015-18.[\[PLAN4-5\]](#)

It's the Hardware, Stupid!

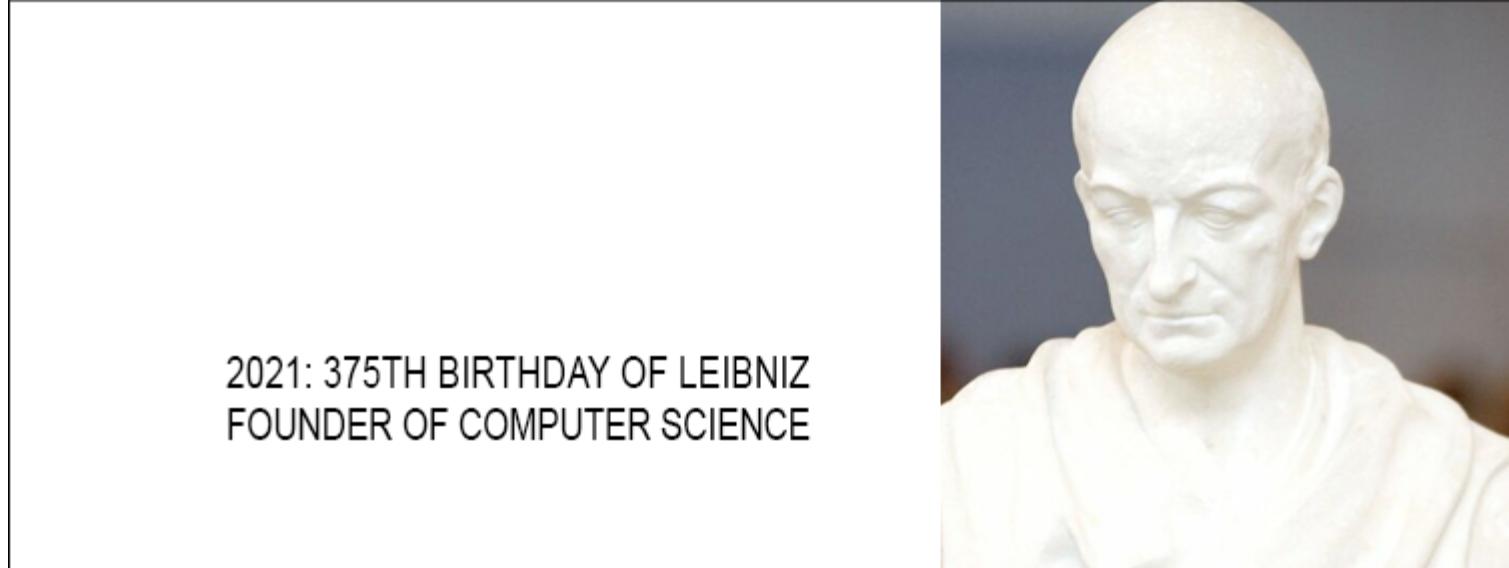
The recent breakthroughs of deep learning algorithms from the past millennium (see previous sections) would have been impossible without continually improving and accelerating computer hardware. Any history of AI and deep learning would be incomplete without mentioning this evolution, which has been running for at least two millennia.

The first known gear-based computational device was the Antikythera mechanism (a kind of astronomical clock) in Ancient Greece over 2000 years ago.

Perhaps the world's first *practical programmable machine* was an automatic theatre made in the 1st century[\[SHA7a\]](#)[\[RAU1\]](#) by Heron of Alexandria (who apparently also had the first known working steam engine—the *Aeolipile*).



The 9th century music automaton by the Banu Musa brothers in Baghdad was perhaps the first machine with a *stored* program. [\[BAN\]\[KOE1\]](#) It used pins on a revolving cylinder to store programs controlling a steam-driven flute—compare Al-Jazari's programmable drum machine of 1206. [\[SHA7b\]](#)



The 1600s brought more flexible machines that computed answers in response to *input data*. The first data-processing gear-based special purpose calculator for simple arithmetics was built in 1623 by [Wilhelm Schickard](#), one of the candidates for the title of "father of automatic computing," followed by the superior Pascaline of Blaise Pascal (1642). In 1673, the already mentioned [Gottfried Wilhelm Leibniz](#) (called "the smartest man who ever lived" [\[SMO13\]](#)) designed the first machine (the step reckoner) that could perform all four arithmetic operations, and the first with a memory. [\[BL16\]](#) He also described the principles of binary computers governed by punch cards (1679), [\[L79\]\[L03\]\[LA14\]\[HO66\]](#) and published the chain rule [\[LEI07-10\]](#) (see above), essential ingredient of deep learning and modern AI.

The first *commercial* program-controlled machines (punch card-based looms) were built in France circa 1800 by Joseph-Marie Jacquard and others—perhaps the first "modern" programmers who wrote the world's first *industrial* software. They inspired Ada Lovelace and her mentor Charles Babbage (UK, circa 1840). He planned but was unable to build a programmable, general purpose computer (only his *non-universal special purpose calculator* led to a working 20th century replica).

In 1914, the Spaniard Leonardo Torres y Quevedo (mentioned in the [introduction](#)) became the 20th century's first AI pioneer when he built the first working chess end game player (back then chess was considered as an activity restricted to the realms of intelligent creatures). The machine was still considered impressive decades later when another AI pioneer—Norbert Wiener [\[WI48\]](#)—played against it at the 1951 Paris AI conference. [\[AI51\]\[BRO21\]\[BRU4\]](#)



Between 1935 and 1941, [Konrad Zuse](#) created the world's first working programmable general-purpose computer: the Z3. The corresponding patent of 1936 [\[ZU36-38\]\[RO98\]](#) [\[ZUS21\]](#) described the digital circuits required by programmable physical hardware, predating

Claude Shannon's 1937 thesis on digital circuit design.^[SHA37] Unlike Babbage, Zuse used Leibniz' principles of *binary computation* (1679)^{[L79][LA14][HO66][L03]} instead of traditional *decimal computation*. This greatly simplified the hardware.^[LEI21,a,b] Ignoring the inevitable storage limitations of any physical computer, the *physical hardware* of Z3 was indeed *universal* in the modern sense of the *purely theoretical but impractical* constructs of Gödel^{[GOD][GOD34,21,21a]} (1931-34), Church^[CHU] (1935), Turing^[TUR] (1936), and Post^[POS] (1936). Simple arithmetic tricks can compensate for Z3's lack of an explicit conditional jump instruction.^[RO98] Today, most computers are *binary* like Z3.



Z3 used *electromagnetic relays* with visibly moving switches. The first *electronic* special purpose calculator (whose moving parts were electrons too small to see) was the binary ABC (US, 1942) by John Atanasoff (the "*father of tube-based computing*"^[NASC6a]). Unlike the gear-based machines of the 1600s, ABC used vacuum tubes—today's machines use the transistor principle patented by Julius Edgar Lilienfeld in 1925.^[LIL1-2] But unlike Zuse's Z3, ABC was not freely programmable. Neither was the *electronic* Colossus machine by Tommy Flowers (UK, 1943-45) used to break the Nazi code.^[NASC6]

The first general working programmable machine built by someone other than Zuse (1941)^[RO98] was Howard Aiken's decimal MARK I (US, 1944). The much faster decimal ENIAC by Eckert and Mauchly (1945/46) was programmed by rewiring it. Both data *and* programs were stored in electronic memory by the "Manchester baby" (Williams, Kilburn & Tootill, UK, 1948) and the 1948 upgrade of ENIAC, which was reprogrammed by entering numerical instruction codes into read-only memory.^[HAI14b]

Since then, computers have become much faster through integrated circuits (ICs). In 1949, Werner Jacobi at Siemens filed a patent for an IC semiconductor with several transistors on a common substrate (granted in 1952).^[IC49-14] In 1958, Jack Kilby demonstrated an IC with external wires. In 1959, Robert Noyce presented a monolithic IC.^[IC14] Since the 1970s, graphics processing units (GPUs) have been used to speed up computations through parallel processing. ICs/GPUs of today (2022) contain many billions of transistors (almost all of them of Lilienfeld's 1925 FET type^[LIL1-2]).

In 1941, Zuse's Z3 could perform roughly one elementary operation (e.g., an addition) per second. Since then, every 5 years, compute got 10 times cheaper (note that his law is much older than Moore's Law which states that the number of transistors^[LIL1-2] per chip doubles every 18 months). As of 2021, 80 years after Z3, modern computers can execute about 10 million billion instructions per second for the same (inflation-adjusted) price. The naive extrapolation of this exponential trend predicts that the 21st century will see cheap computers with a thousand times the *raw computational power of all human brains combined*.^[RAW]

Where are the physical limits? According to Bremermann (1982),^[BRE] a computer of 1 kg of mass and 1 liter of volume can execute at most 10^{51} operations per second on at most 10^{32} bits. The trend above will hit the Bremermann limit roughly 25 decades after Z3, circa 2200. However, since there are only 2×10^{30} kg of mass in the solar system, the trend is bound to break within a few centuries, since the speed of light will greatly limit the acquisition of additional mass, e.g., in form of other solar systems, through a function polynomial in time, as previously noted back in 2004.^{[OOPS2][ZUS21]}

Physics seems to dictate that future efficient computational hardware will have to be brain-like, with many compactly placed processors in 3-dimensional space, sparsely connected by many short and few long wires, to minimize total connection cost (even if the "wires" are actually light beams).^[DL2] The basic architecture is essentially the one of a deep, sparsely connected, 3-dimensional RNN, and Deep Learning methods for such RNNs are expected to become even much more important than they are today.^[DL2]

Don't Neglect the Theory of AI Since 1931

The core of modern AI and deep learning is mostly based on simple math of recent centuries: calculus/linear algebra/statistics. Nevertheless, to efficiently implement this core on the modern hardware mentioned in the previous section, and to roll it out for billions of people, lots of software engineering was necessary, based on lots of smart algorithms invented in the past century. There is no room here to mention them all. However, at least I'll list some of the most important highlights of the theory of AI and computer science in general.

In the early 1930s, Gödel founded modern theoretical computer science.^{[GOD][GOD34][LEI21,21a]} He introduced a *universal coding language* (1931-34).^{[GOD][GOD34-21a]} It was based on the integers, and allows for formalizing the operations of any digital computer in axiomatic form. Gödel used it to represent both data (such as axioms and theorems) and programs^[VAR13] (such as proof-generating sequences of operations on the data). He famously constructed formal statements that talk about the computation of other formal statements—especially self-referential statements which imply that they are not decidable, given a computational theorem prover that systematically enumerates all possible theorems from an enumerable set of axioms. Thus he identified fundamental limits of algorithmic theorem proving, computing, and any type of computation-based AI.^{[GOD][BIB3][MIR](Sec. 18)[GOD21,21a]}



Like most great scientists, Gödel built on earlier work. He combined Georg Cantor's diagonalization trick^[CAN] (which showed in 1891 that there are different types of infinities) with the foundational work by Gottlob Frege^[FRE] (who introduced the first formal language in 1879), Thoralf Skolem^[SKO23] (who introduced primitive recursive functions in 1923) and Jacques Herbrand^[GOD86] (who identified limitations of Skolem's approach). These authors in turn built on the formal *Algebra of Thought* (1686) by Gottfried Wilhelm Leibniz^{[L86][WI48]} (see above), which is deductively equivalent^[LE18] to the later *Boolean Algebra* of 1847.^[BOO]

In 1935, Alonzo Church derived a corollary / extension of Gödel's result by demonstrating that Hilbert & Ackermann's *Entscheidungsproblem* (decision problem) does not have a general solution.^[CHU] To do this, he used his alternative universal coding language called *Untyped Lambda Calculus*, which forms the basis of the highly influential programming language LISP. In 1936, Alan M. Turing introduced yet another universal model: the *Turing Machine*.^[TUR] He rederived the above-mentioned result.^{[CHU][TUR][HIN][GOD21,21a][TUR21][LEI21,21a]} In the same year of 1936, Emil Post published yet another independent universal model of computing.^[POS] Today we know many such models.

Konrad Zuse not only created the world's first working programmable general-purpose computer,^{[ZU36-38][RO98][ZUS21]} he also designed *Plankalkül*, the first high-level programming language.^{[BAU][KNU]} He applied it to chess in 1945^[KNU] and to theorem proving in 1948.^[ZU48] Compare Newell & Simon's later work on theorem proving (1956).^[NS56] Much of early AI in the 1940s-70s was actually about theorem proving and deduction in Gödel style^{[GOD][GOD34,21,21a]} through expert systems and logic programming.

In 1964, Ray Solomonoff combined Bayesian (actually Laplacian^[STI83-85]) probabilistic reasoning and theoretical computer science^{[GOD][CHU][TUR][POS]} to derive a mathematically optimal (but computationally infeasible) way of learning to predict future data from past observations.^{[AIT1][AIT10]} With Andrej Kolmogorov, he founded the theory of *Kolmogorov complexity* or algorithmic information theory (AIT),^[AIT1-22] going beyond traditional information theory^{[SHA48][KUL]} by formalizing the concept of Occam's razor, which favors the simplest explanation of given data, through the concept of the shortest program computing the data. There are many computable, time-bounded versions of this concept,^{[AIT7][AIT5][AIT12-13][AIT16-17]} as well as applications to NNs.^{[KO2][CO1-3]}

In the early 2000s, Marcus Hutter (while working under my Swiss National Science Foundation

grant^[UNI]) augmented Solomonoff's universal predictor^{[AIT1][AIT10]} by an optimal action selector (a universal AI) for reinforcement learning agents living in initially unknown (but at least computable) environments.^[AIT20,22] He also derived the asymptotically fastest algorithm for all well-defined computational problems,^[AIT21] solving any problem as quickly as the unknown fastest solver of such problems, save for an additive constant that does not depend on the problem size.

The even more general optimality of the self-referential 2003 Gödel Machine^[GM3-9] is not limited to *asymptotic* optimality.

Nevertheless, such mathematically optimal AIs are not yet practically feasible for various reasons. Instead, practical modern AI is based on suboptimal, limited, yet not extremely well-understood techniques such as NNs and deep learning, the focus of the present article. But who knows what kind of AI history will prevail 20 years from now?

The Broader Historic Context from Big Bang to Far Future

Credit assignment is about finding patterns in historic data and figuring out how certain events were enabled by previous events. Historians do it. Physicists do it. AIs do it, too. Let's take a step back and look at AI in the broadest historical context: all time since the Big Bang. In 2014, I found a beautiful pattern of exponential acceleration in it,^[OMG] which I have presented in many talks since then, and which also made it into Sibylle Berg's award-winning book "GRM: Brainfuck."^[OMG2] Previously published patterns of this kind span much shorter time intervals: just a few decades or centuries or at most millennia.^[OMG1]

It turns out that from a human perspective, the most important events since the beginning of the universe are neatly aligned on a timeline of exponential speed up (error bars mostly below 10 percent). In fact, history seems to converge in an Omega point in the year 2040 or so. I like to call it Omega, because a century ago, Teilhard de Chardin called Omega the point where humanity will reach its next level.^[OMG0] Also, Omega sounds much better than "Singularity"^[SING1-2]—it sounds a bit like "Oh my God."^[OMG]

Let's start with the Big Bang 13.8 billion years ago. We divide this time by 4 to obtain about 3.5 billion years. Omega is 2040 or so. At Omega minus 3.5 billion years, something very important happened: life emerged on this planet.

And we take again a quarter of this time. We come out 900 million years ago when something very important happened: animal-like, mobile life emerged.

And we divide again by 4. We come out 220 million years ago when mammals were invented, our ancestors.

And we divide again by 4. 55 million years ago the first primates emerged, our ancestors.

And we divide again by 4. 13 million years ago the first hominids emerged, our ancestors. I don't know why all these divisions by 4 keep hitting these defining moments in history. But they do. I also tried thirds, and fifths, and harmonic proportions, but only quarters seem to work.

And we divide again by 4. 3.5 million years ago something very important happened: the dawn of technology, as *Nature* called it: the first stone tools.

And we divide by 4. 800 thousand years ago the next great tech breakthrough happened: controlled fire.

And we divide by 4. 200 thousand years ago, anatomically modern man became prominent, our ancestor.

And we divide by 4. 50 thousand years ago, behaviorally modern man emerged, our ancestor,

$\Omega = 2040 \text{ or so} - 13.8 \text{ B years: Big Bang}$	
$\Omega - 1/4 \text{ of this time: }$	$\Omega - 3.5 \text{ B years: first life on Earth}$
$\Omega - 1/4 \text{ of this time: }$	$\Omega - 0.9 \text{ B years: first animal-like mobile life}$
$\Omega - 1/4 \text{ of this time: }$	$\Omega - 220 \text{ M years: first mammals (our ancestors)}$
$\Omega - 1/4 \text{ of this time: }$	$\Omega - 55 \text{ M years: first primates (our ancestors)}$
$\Omega - 1/4 \text{ of this time: }$	$\Omega - 13 \text{ M years: first hominids (our ancestors)}$
$\Omega - 1/4 \text{ of this time: }$	$\Omega - 3.5 \text{ M years: first stone tools (dawn of tech)}$
$\Omega - 1/4 \text{ of this time: }$	$\Omega - 850 \text{ K years: controlled fire (next big tech)}$
$\Omega - 1/4 \text{ of this time: }$	$\Omega - 210 \text{ K years: anatomically modern man}$
$\Omega - 1/4 \text{ of this time: }$	$\Omega - 50 \text{ K years: behaviorally modern man}$
$\Omega - 1/4 \text{ of this time: }$	$\Omega - 13 \text{ K years: neolithic revolution, civilization}$
$\Omega - 1/4 \text{ of this time: }$	$\Omega - 3.3 \text{ K years: iron age, 1st population explosion}$
$\Omega - 1/4 \text{ of this time: }$	$\Omega - 800 \text{ years: first guns & rockets (in China)}$
$\Omega - 1/4 \text{ of this time: }$	$\Omega - 200 \text{ years: industrial revolution}$
$\Omega - 1/4 \text{ of this time: }$	$\Omega - 50 \text{ years (around 1990): information revolution, WWW, cell phones & PCs for all, Cold War ends, Modern AI starts, Miraculous Year ...}$
$\Omega - 1/4 \text{ of this time: }$	$\Omega - 13 \text{ years (2030 or so): cheap AIs with one human brain power? And then what?}$
$\Omega - 1/4 \text{ of this time: }$	$\Omega - 3 \text{ years: ??}$
$\Omega - 1/4 \text{ of this time: }$	$\Omega - 9 \text{ months: ????$
$\Omega - 1/4 \text{ of this time: }$	$\Omega - 2 \text{ months: ???????}$
$\Omega - 1/4 \text{ of this time: }$	$\Omega - 2 \text{ weeks: ??????????????}$

Finally multiply Ω by 4! At the age of **55 B years**, the visible cosmos will be permeated by intelligence. After Ω , AIs will have plenty of time to go where the physical resources are, to make more and bigger AIs.

and started colonizing the world.

And we divide again by 4. We come out 13 thousand years ago when something very important happened: domestication of animals, agriculture, first settlements—the begin of civilisation. Now we see that all of civilization is just a flash in world history, just one millionth of the time since the Big Bang. Agriculture and spacecraft were invented almost at the same time.

And we divide by 4. 3,300 years ago saw the onset of the 1st population explosion in the Iron Age.

And we divide by 4. Remember that the convergence point Omega is the year 2040 or so. Omega minus 800 years—that was in the 13th century, when iron and fire came together in form of guns and cannons and rockets in China. This has defined the world since then and the West remains quite behind of the license fees it owes China.

And we divide again by 4. Omega minus 200 years—we hit the mid 19th century, when iron and fire came together in ever more sophisticated form to power the industrial revolution through improved steam engines, based on the work of Beaumont, Papin, Newcomen, Watt, and others (1600s-1700s, going beyond the first simple steam engines by Heron of Alexandria^[RAU1] in the 1st century). The telephone (e.g., Meucci 1857, Reis 1860, Bell 1876)^[NASC3] started to revolutionize communication. The germ theory of disease (Pasteur & Koch, late 1800s) revolutionized healthcare and made people live longer on average. And circa 1850, the fertilizer-based agricultural revolution (Sprengel & von Liebig, early 1800s) helped to trigger the 2nd population explosion, which peaked in the 20th century, when the world population quadrupled, letting the 20th century stand out among all centuries in the history of mankind, driven by the Haber-Bosch process for creating *artificial* fertilizer, without which the world could feed at most 4 billion people.^[HAB1-2]

And we divide again by 4. Omega minus 50 years—that's more or less the year 1990, the end of the 3 great wars of the 20th century: WW1, WW2, and the Cold War. The 7 most valuable public companies were all Japanese (today most of them are US-based); however, both China and the US West Coast started to rise rapidly, setting the stage for the 21st century. A digital nervous system started spanning the globe through cell phones and the wireless revolution (based on radio waves discovered in the 1800s) as well as cheap personal computers for all. The WWW was created at the European particle collider in Switzerland by Tim Berners-Lee. And Modern AI started also around this time: the [first truly self-driving cars](#) were built in the 1980s in Munich by the team of Ernst Dickmanns (by 1994, their robot cars were driving in highway traffic, up to 180 km/h).^[AUT] Back then, I worked on my 1987 diploma thesis,^[META1] which introduced algorithms not just for learning but also for [meta-learning or learning to learn](#),^[META] to learn better learning algorithms through experience (now a very popular topic^[DEC]). And then came our [Miraculous Year 1990-91](#)^[MIR] at TU Munich, the root of today's most cited NNs^[MOST] and of modern deep learning through self-supervised/unsupervised learning ([see above](#)),^{[UNJ][UN0-3]} the LSTM/Highway Net/ResNet principle (now in your pocket on your smartphone—[see above](#)),^{[DL4][DEC][MOST]} artificial curiosity and generative adversarial NNs for agents that invent their own problems ([see above](#)),^{[AC90-AC20][PP-PP2][SA17]} Transformers with linearized self-attention ([see above](#)),^{[FWP0-6][TR5-6]} distilling teacher NNs into student NNs ([see above](#)),^{[UNJ][UN0-3]} learning action plans at multiple levels of abstraction and multiple time scales ([see above](#)),^{[HRL0-2][LEC]} and other exciting stuff. Much of this has become very popular, and improved the lives of billions of people.^{[DL4][DEC][MOST]}

And we divide again by 4. Omega minus 13 years—that's a point in the near future, more or less the year 2030, when many predict that cheap AIs will have a human brain power. Then the final 13 years or so until Omega, when incredible things will happen ([take all of this with a grain of salt, though](#)^[OMG1]).

But of course, time won't stop with Omega. Maybe it's just human-dominated history that will end. After Omega, many curious meta-learning AIs that invent their own goals (which have existed in my lab for decades^{[ACJ][AC90,AC90b]}) will quickly improve themselves, restricted only by the fundamental limits of computability and physics.

What will supersmart AIs do? Space is hostile to humans but friendly to appropriately designed robots, and offers many more resources than our thin film of biosphere, which receives less than a billionth of the sun's energy. While some curious AIs will remain fascinated with life, at least as long as they don't fully understand it,^{[ACM16][FA15][SP16][SA17]} most will be more interested in the incredible new opportunities for robots and software life out there in space. Through innumerable self-replicating robot factories in the asteroid belt and beyond they will transform the solar system and then within a few hundred thousand years the entire galaxy and within tens of billions of years the rest of the reachable universe. Despite the light-speed limit, the expanding AI sphere will have plenty of time to colonize and shape the entire visible cosmos.

Let me stretch your mind a bit. The universe is still young, only 13.8 billion years old. Remember when we kept dividing by 4? Now let's multiply by 4! Let's look ahead to a time when the cosmos will be 4 times older than it is now: about 55 billion years old. By then, the visible cosmos will be permeated by intelligence. Because after Omega, most AIs will have to go where most of the physical resources are, to make more and bigger AIs. Those who don't won't have an impact.[\[ACM16\]](#)[\[FA15\]](#)[\[SP16\]](#)



1997: A COMPUTER SCIENTIST'S VIEW OF LIFE, THE UNIVERSE, AND EVERYTHING
THE SIMPLEST AND FASTEST WAY OF COMPUTING ALL POSSIBLE COMPUTABLE METAVERSES
ALGORITHMIC THEORY OF EVERYTHING YIELDS PHYSICAL, PHILOSOPHICAL, AND THEOLOGICAL CONSEQUENCES

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555+ References (and many more in the survey[\[DL1\]](#))

[25y97] In 2022, we are celebrating the following works from a quarter-century ago. 1. Journal paper on [Long Short-Term Memory](#), the most cited neural network (NN) of the 20th century (and basis of the [most cited NN of the 21st](#)). 2. First paper on physical, philosophical and theological consequences of the simplest and fastest way of computing [all possible metaverses](#) (= computable universes). 3. Implementing [artificial curiosity and creativity](#) through generative adversarial agents that learn to design *abstract, interesting* computational experiments. 4. Journal paper on [meta-reinforcement learning](#). 5. Journal paper on [hierarchical Q-learning](#). 6. First paper on reinforcement learning to play soccer: start of a series. 7. Journal papers on flat minima & low-complexity NNs that generalize well. 8. Journal paper on [Low-Complexity Art](#), the Minimal Art of the Information Age. 9. Journal paper on probabilistic incremental program evolution.

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in the title (2005). *The deep reinforcement learning & neuroevolution developed in Schmidhuber's lab solved problems of depth 1000 and more.*^[DL6] Soon after its publication, everybody started talking about "deep learning." Causality or correlation?

[DL7] "Deep Learning ... moving beyond shallow machine learning since 2006!" Web site deeplearning.net of Y. Bengio's MILA (2015, retrieved May 2020; compare the version in the [Internet Archive](#)), referring to Hinton's^[UN4] and Bengio's^[UN5] *unsupervised* pre-training for deep NNs^[UN4] (2006) although [this type of deep learning dates back to Schmidhuber's work of 1991.](#)^{[UN1-2][UN]}

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[DM3] S. Stanford. DeepMind's AI, AlphaStar Showcases Significant Progress Towards AGI. Medium ML Memoirs, 2019. *AlphaStar has a "deep LSTM core."*

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called keys and values for self-attention^[TR1-6]). The similar Transformers^[TR1-2] combine this with projections and softmax and are now widely used in natural language processing. For long input sequences, their efficiency was improved through Transformers with linearized self-attention^[TR5-6] which are formally equivalent to Schmidhuber's 1991 outer product-based Fast Weight Programmers (apart from normalization). In 1993, he introduced the attention terminology^[FWP2] now used in this context,^[ATT] and extended the approach to RNNs that program themselves. See [tweet of 2022](#).

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highway net computes $g(x)x + t(x)h(x)$, where x is the data from the previous layer. (Like LSTM with forget gates^[LSTM2] for RNNs.) Resnets^[HW2] are a version of this where the gates are always open: $g(x)=t(x)=\text{const}=1$. Highway Nets perform roughly as well as ResNets^[HW2] on ImageNet.^[HW3] Variants of highway gates are also used for certain algorithmic tasks, where the simpler residual layers do not work as well.^[INDR] [More](#).

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bootstraps itself. 1992-: gradient descent-based neural metalearning. 1994-: Meta-Reinforcement Learning with self-modifying policies. 1997: Meta-RL plus artificial curiosity and intrinsic motivation. 2002-: asymptotically optimal metalearning for curriculum learning. 2003-: mathematically optimal Gödel Machine. 2020: new stuff!

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the much earlier [Fast Weight Programmers](#)). Most of this started with the [Annus Mirabilis of 1990-1991](#). [\[MIR\]](#)

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Relevant threads with many comments at reddit.com/r/MachineLearning, the largest machine learning forum with over 800k subscribers in 2019 (note that Jürgen Schmidhuber's name is often misspelled):

[R1] Reddit/ML, 2019. [Hinton, LeCun, Bengio receive ACM Turing Award. This announcement contains more comments about Schmidhuber than about any of the awardees](#).

[R2] Reddit/ML, 2019. [J. Schmidhuber really had GANs in 1990](#).

[R3] Reddit/ML, 2019. [NeurIPS 2019 Bengio Schmidhuber Meta-Learning Fiasco. Schmidhuber started metalearning \(learning to learn—now a hot topic\) in 1987](#) [\[META1\]\[META\]](#) long before Bengio who suggested in public at N(eur)IPS 2019 that he did it before Schmidhuber.

[R4] Reddit/ML, 2019. [Five major deep learning papers by G. Hinton did not cite similar earlier work by J. Schmidhuber](#).

[R5] Reddit/ML, 2019. [The 1997 LSTM paper by Hochreiter & Schmidhuber has become the most cited deep learning research paper of the 20th century](#).

[R6] Reddit/ML, 2019. [DanNet, the CUDA CNN of Dan Ciresan in J. Schmidhuber's team, won 4 image recognition challenges prior to AlexNet](#).

[R7] Reddit/ML, 2019. [J. Schmidhuber on Seppo Linnainmaa, inventor of backpropagation in 1970](#).

[R8] Reddit/ML, 2019. J. Schmidhuber on Alexey Ivakhnenko, godfather of deep learning 1965.

[R9] Reddit/ML, 2019. We find it extremely unfair that Schmidhuber did not get the Turing award. That is why we dedicate this song to Juergen to cheer him up.

[R11] Reddit/ML, 2020. Schmidhuber: Critique of Honda Prize for Dr. Hinton

[R12] Reddit/ML, 2020. J. Schmidhuber: Critique of Turing Award for Drs. Bengio & Hinton & LeCun

[R15] Reddit/ML, 2021. J. Schmidhuber's work on fast weights from 1991 is similar to linearized variants of Transformers

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[UN0] J. Schmidhuber. Neural sequence chunkers. Technical Report FKI-148-91, Institut für Informatik, Technische Universität München, April 1991. [PDF](#). *Unsupervised/self-supervised learning and predictive coding is used in a deep hierarchy of recurrent neural networks (RNNs) to find compact internal representations of long sequences of data, across multiple time scales and levels of abstraction. Each RNN tries to solve the pretext task of predicting its next input, sending only unexpected inputs to the next RNN above. The resulting compressed sequence representations greatly facilitate downstream supervised deep learning such as sequence classification. By 1993, the approach solved problems of depth 1000 [UN2] (requiring 1000 subsequent computational stages/layers—the more such stages, the deeper the learning). A variant collapses the hierarchy into a single deep net. It uses a so-called conscious chunker RNN which attends to unexpected events that surprise a lower-level so-called subconscious automatiser RNN. The chunker learns to understand the surprising events by predicting them. The automatiser uses a neural knowledge distillation procedure to compress and absorb the formerly conscious insights and behaviours of the chunker, thus making them subconscious. The systems of 1991 allowed for much deeper learning than previous methods.* [More](#).

[UN1] J. Schmidhuber. Learning complex, extended sequences using the principle of history compression. *Neural Computation*, 4(2):234-242, 1992. Based on TR FKI-148-91, TUM, 1991. [\[UN0\]](#) [PDF](#). *First working Deep Learner based on a deep RNN hierarchy (with different self-organising time scales), overcoming the vanishing gradient problem through unsupervised pre-training and predictive coding (with self-supervised target generation). Also: compressing or distilling a teacher net (the chunker) into a student net (the automatizer) that does not forget its old skills—such approaches are now widely used.* [More](#).

[UN2] J. Schmidhuber. Habilitation thesis, TUM, 1993. [PDF](#). *An ancient experiment on "Very Deep Learning" with credit assignment across 1200 time steps or virtual layers and unsupervised / self-supervised pre-training for a stack of recurrent NN can be found here* (depth > 1000).

[UN3] J. Schmidhuber, M. C. Mozer, and D. Prelinger. [Continuous history compression](#). In H. Hüning, S. Neuhauser, M. Raus, and W. Ritschel, editors, *Proc. of Intl. Workshop on Neural Networks, RWTH Aachen*, pages 87-95. Augustinus, 1993.

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