Certificate I: Understanding AI and Machine Learning in Africa

Course AIML01: Artificial Intelligence – Past, Present, and Future

Module 2: The Nature of AI

Lecture 2: Connectionist AI – From Perceptrons to Deep Neural Networks

Carnegie Mellon University
Africa

Learning Objectives

1. Explain how connectionist systems process information

2. Explain how these connectionist systems are implemented using artificial neural networks

3. Explain how artificial neural networks evolved from early work on percepton-like architectures to modern high performance deep neural networks

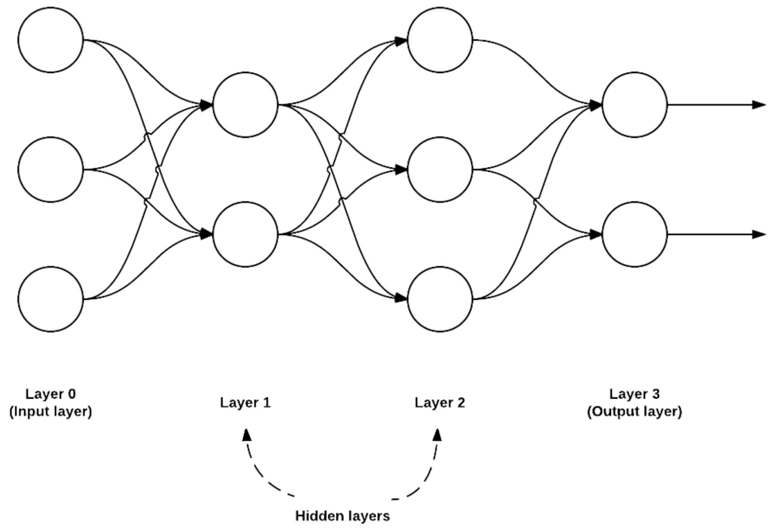
4. Explain how modern artificial networks achieve their high performance

Lecture Contents

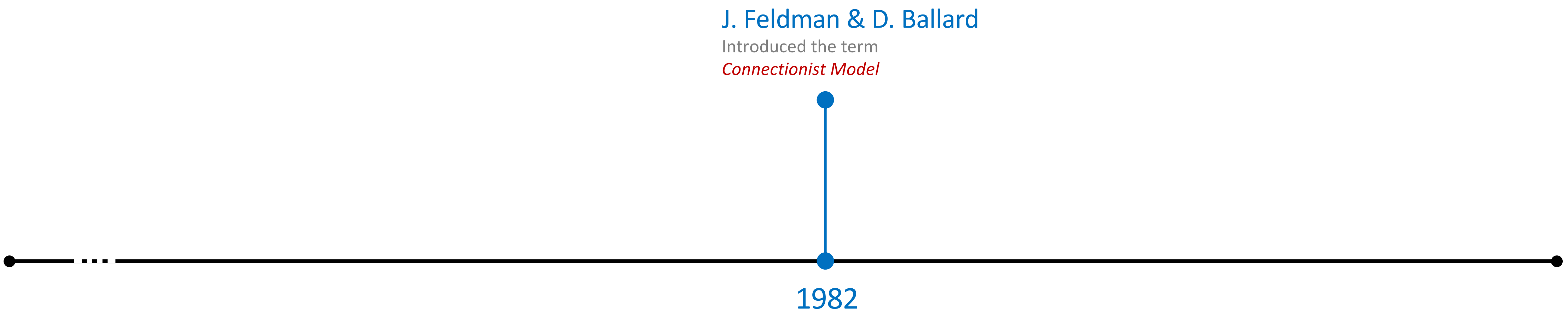
1. Connectionism as a form of information processing
2. Timeline of the major developments in connectionism & artificial neural networks
3. Lecture summary
4. Recommended reading & references

Connectionist AI

- Information represented in a non-symbolic form:
  - Image
  - Sound
  - Signal, …
- Processed by propagating it through an interconnected network of simple processing elements
- Typically implemented as artificial neural networks
- Uses statistical properties rather than logical rules



Credit: Adrian Rosebrock, Deep Learning for Computer Vision, PyImageSearch, 2017



Feldman, J.A. and D.H. Ballard, "Connectionist models and their properties," *Cognitive Science,* 6,205-254, 1982.

Feldman, J.A., "A connectionist model of visual memory," in *Parallel Models of Associative Memory,* G.E. Hinton and J.A. Anderson (eds.), Lawrence Erlbaum Associates, Inc., Publishers, Hillsdale NJ, 1981.

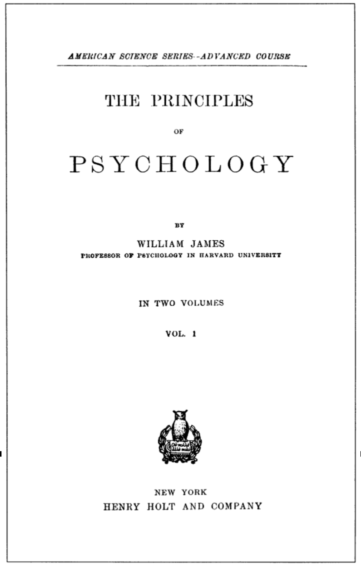
Connectionism

The Principles of Psychology

Connectionist model of associative memory

W. James

1890



AMERICAN SCIENCE SERIES—ADVANCED COURSE

THE PRINCIPLES

OF

PSYCHOLOGY

BY

WILLIAM JAMES

PROFESSOR OF PSYCHOLOGY IN HARVARD UNIVERSITY

IN TWO VOLUMES

VOL. I

NEW YORK

HENRY HOLT AND COMPANY

https://www.jstor.org/stable/1423317

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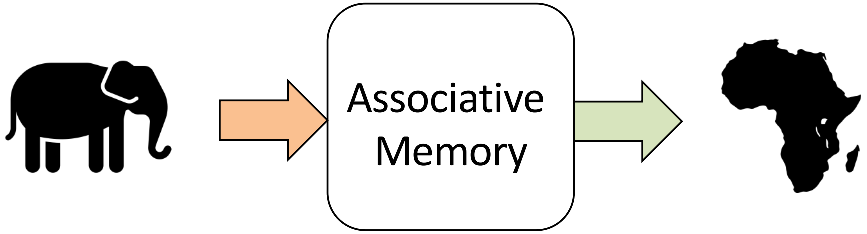

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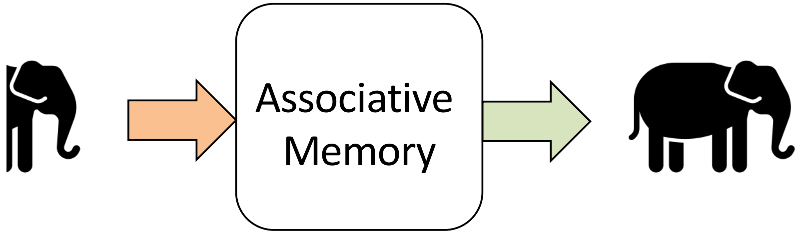

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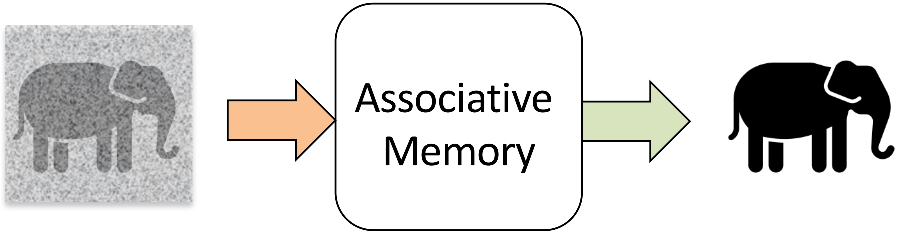

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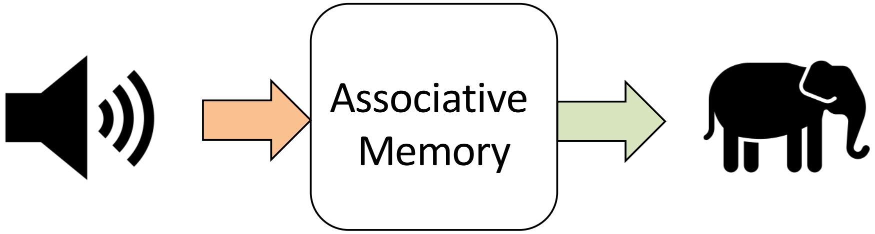

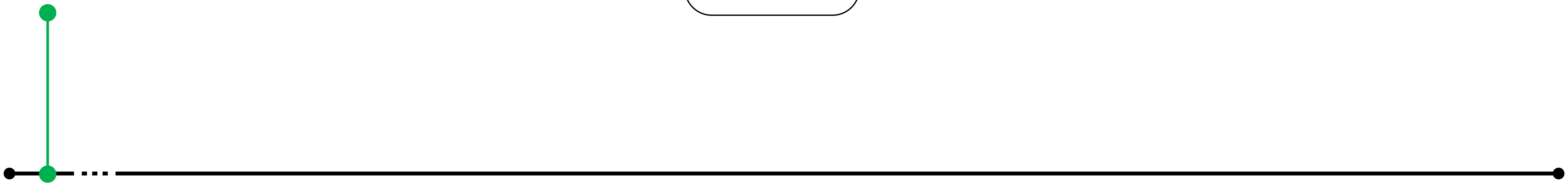

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Hebbian Learning

The Organization of Behavior

D. Hebb

Hebbian learning:

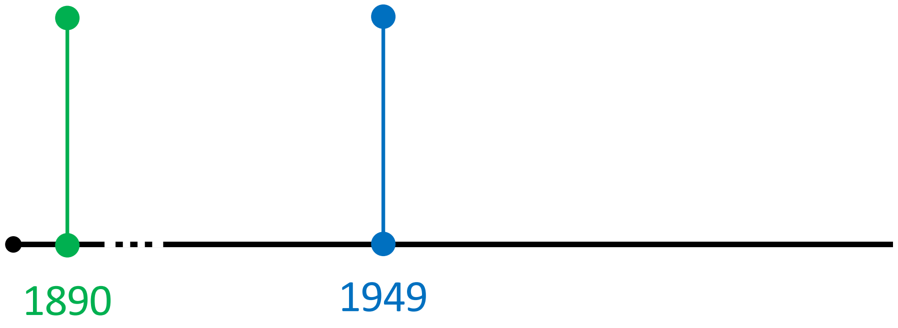
Unsupervised neural training process

The synaptic strength — the bond between connecting neurons — is increased if both neurons are active at the same time

Neurons that fire together, wire together

1890

1949



The introduction to Donald Hebb's book also contains one of the first usages of the term connectionism

Introduction xix

Any frequently repeated, particular stimulation will lead to the slow development of a "cell-assembly," a diffuse structure comprising cells in the cortex and diencephalon (and also, perhaps, in the basal ganglia of the cerebrum), capable of acting briefly as a closed system, delivering facilitation to other such systems and usually having a specific motor facilitation A series of such events constitutes a "phase sequence"—the thought process *Each assembly action may be aroused by a preceding* assembly, by a sensory event, or—normally—by both The central facilitation from one of these activities on the next is the prototype of "attention" The theory proposes that in this central facilitation, and its varied relationship to sensory processes, lies the answer to an issue that is made inescapable by Humphrey's (1940) penetrating review of the problem of the direction of thought.

The kind of cortical organization discussed in the preceding paragraph is what is regarded as essential to adult waking behavior It is proposed also that there is an alternate, "intrinsic" organization, occurring in sleep and in infancy, which consists of hypersynchrony in the firing of cortical cells But besides these two forms of cortical organization there may be disorganization It is assumed that the assembly depends completely on a very delicate timing which might be disturbed by metabolic changes as well as by sensory events that do not accord with the pre-existent central process When this is transient, it is called emotional disturbance, when chronic, neurosis or psychosis

The theory is evidently a form of connectionism, one of the switchboard variety, though it does not deal in direct connections between afferent and efferent pathways not an "S-R" psychology, if R means a *muscular* response The connections serve rather to establish autonomous central activities, which then are the basis of further learning In accordance with modern physiological ideas, the theory also utilizes local field processes and gradients, following the lead particularly of Marshall and Talbot (1942) It does not, further, make any single nerve cell or pathway essential to any habit or perception Modern physiology has presented psychology with new opportunities for the synthesis of divergent theories and previously unrelated data, and it is my intent to take such advantage of these opportunities as I can.

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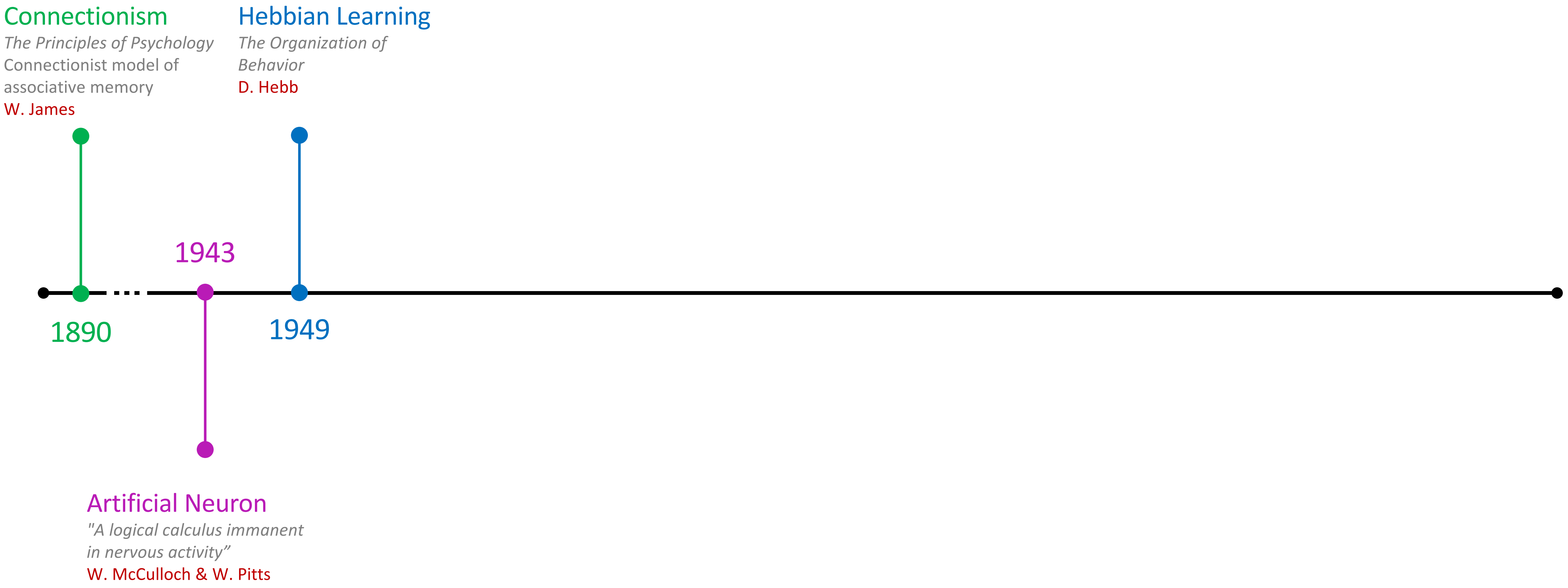
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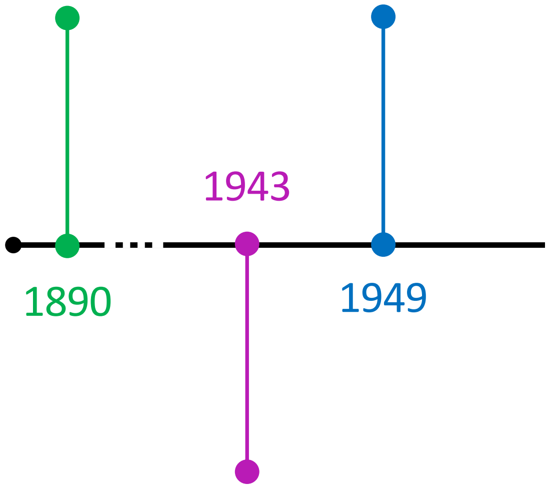

Artificial Neuron

"A logical calculus immanent in nervous activity"
W. McCulloch & W. Pitts

Any statement within propositional logic can be represented by a network of simple processing units, i.e., a connectionist system

LOGICAL CALCULUS FOR NERVOUS ACTIVITY 105

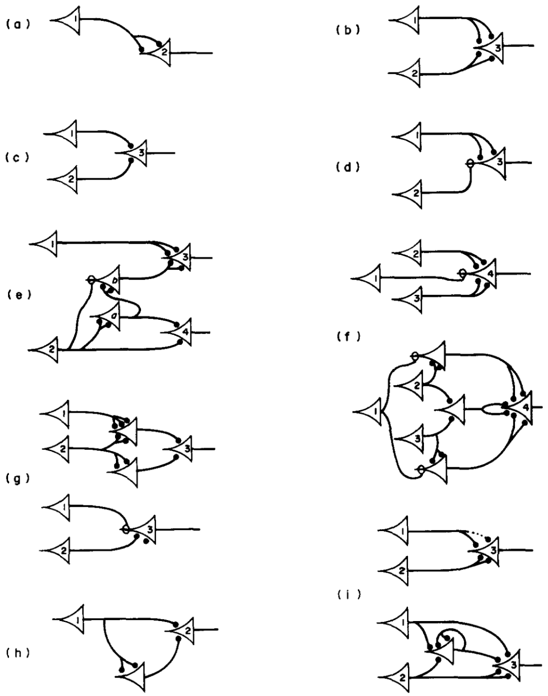

Figure 1. The neuron c_i is always marked with the numeral i upon the body of the cell, and the corresponding action is denoted by "N" with i s subscript, as in the text:

W. S. McCulloch and W. Pitts. A logical calculus of ideas immanent in nervous activity. Bulletin of Mathematical Biophysics, 5:115–133, 1943.

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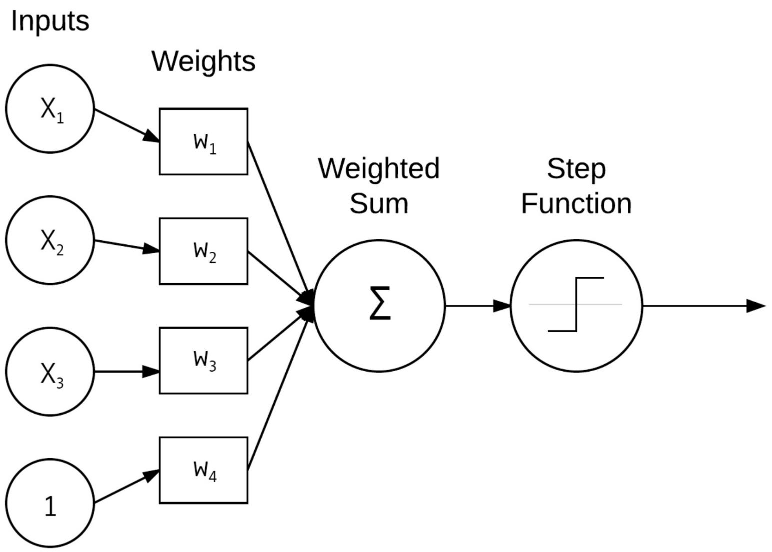

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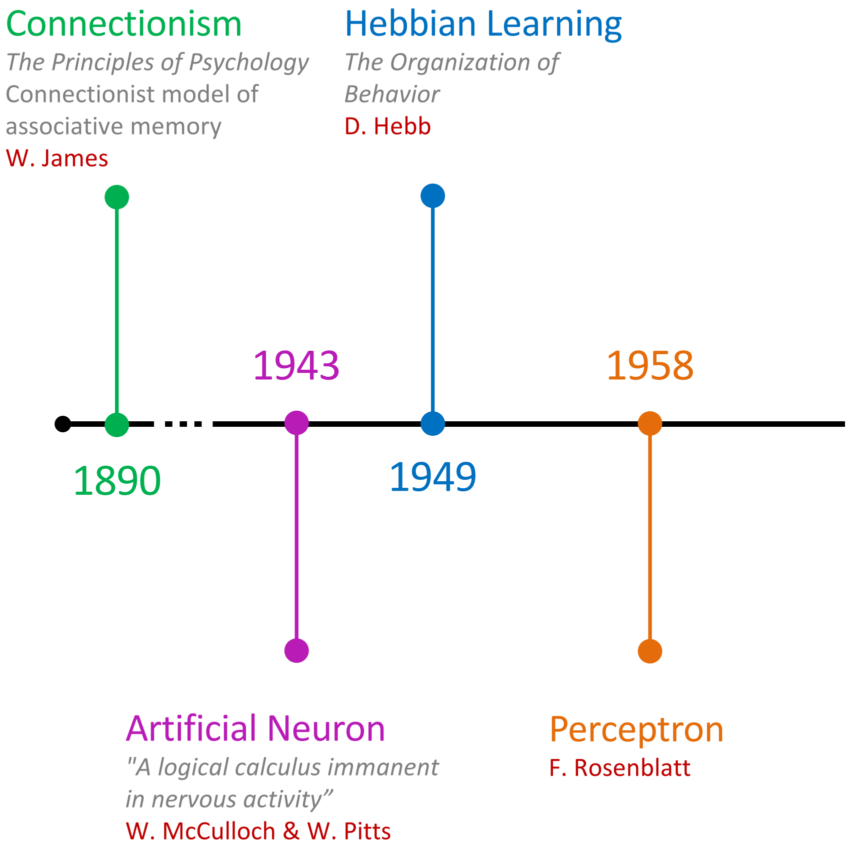
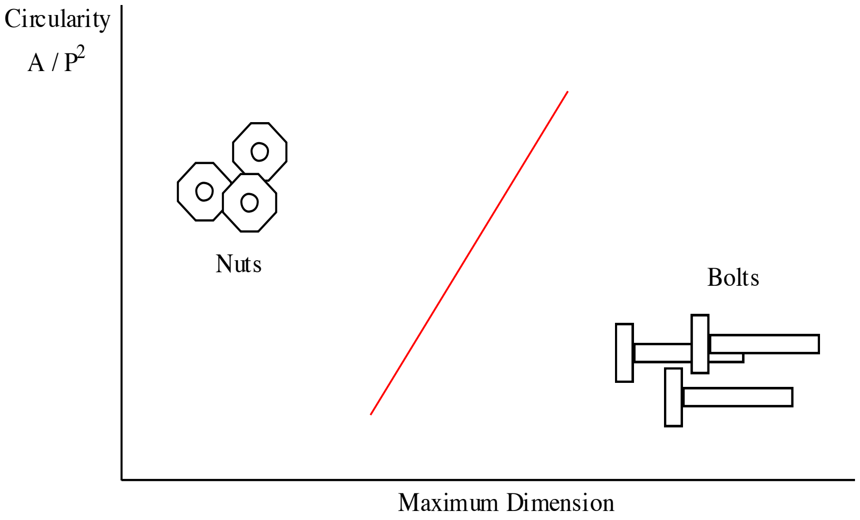
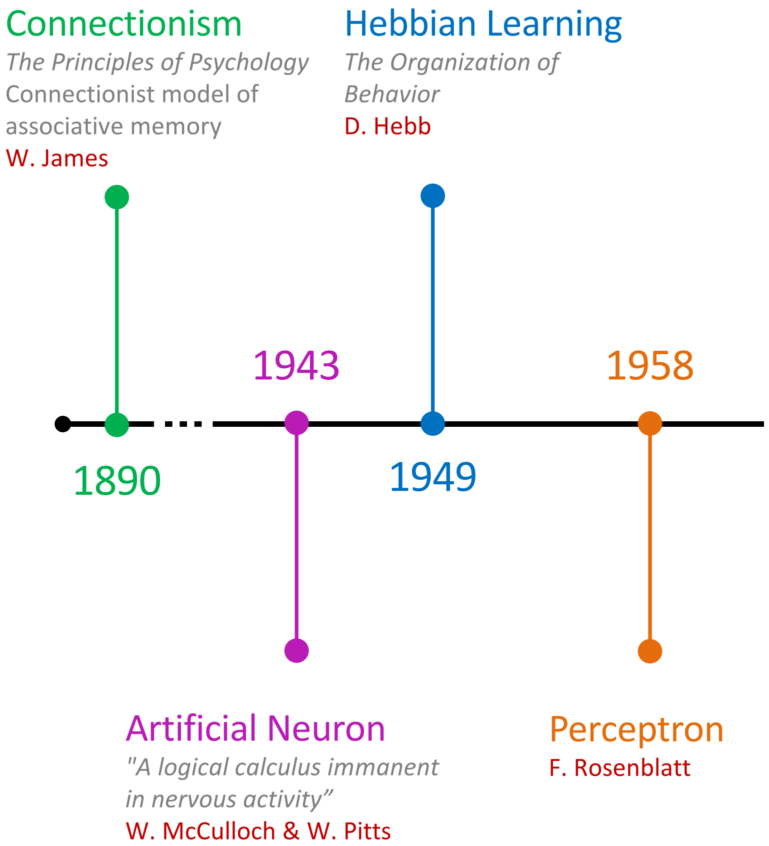




Credit: David Vernon, Machine Vision, Prentice-Hall, 1991



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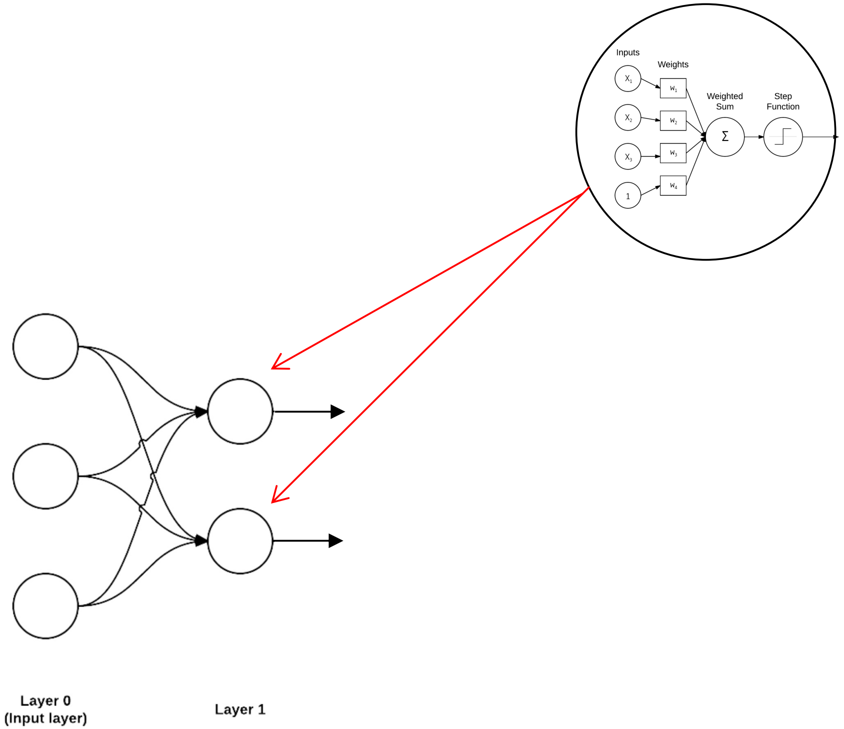
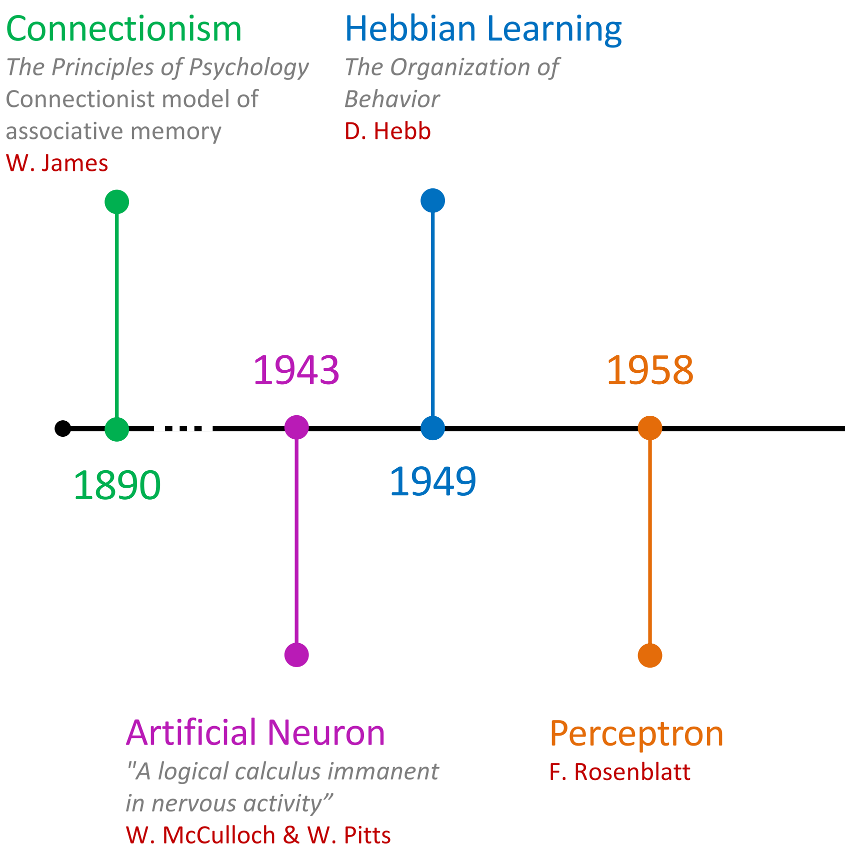
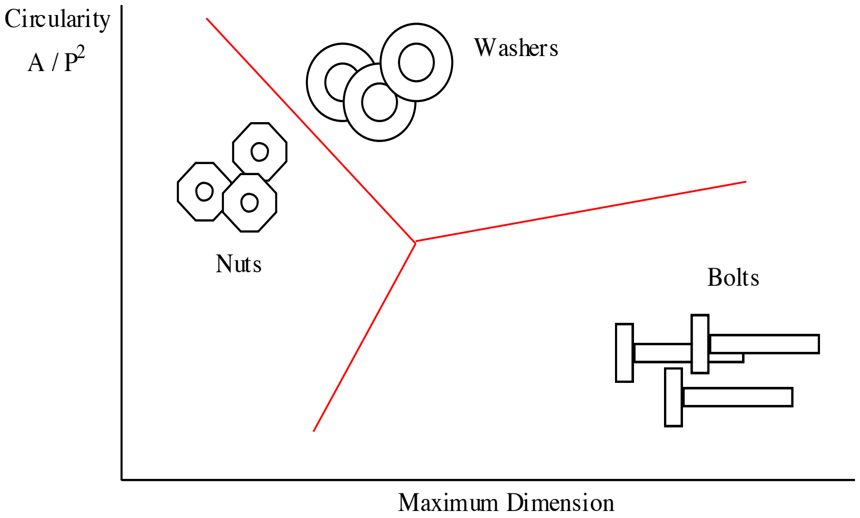


Inputs
Weights
X_1
X_2
X_3
1
w_1
w_2
w_3
w_4
Weighted Sum
Σ
Step Function
Layer 0 (Input layer)
Layer 1





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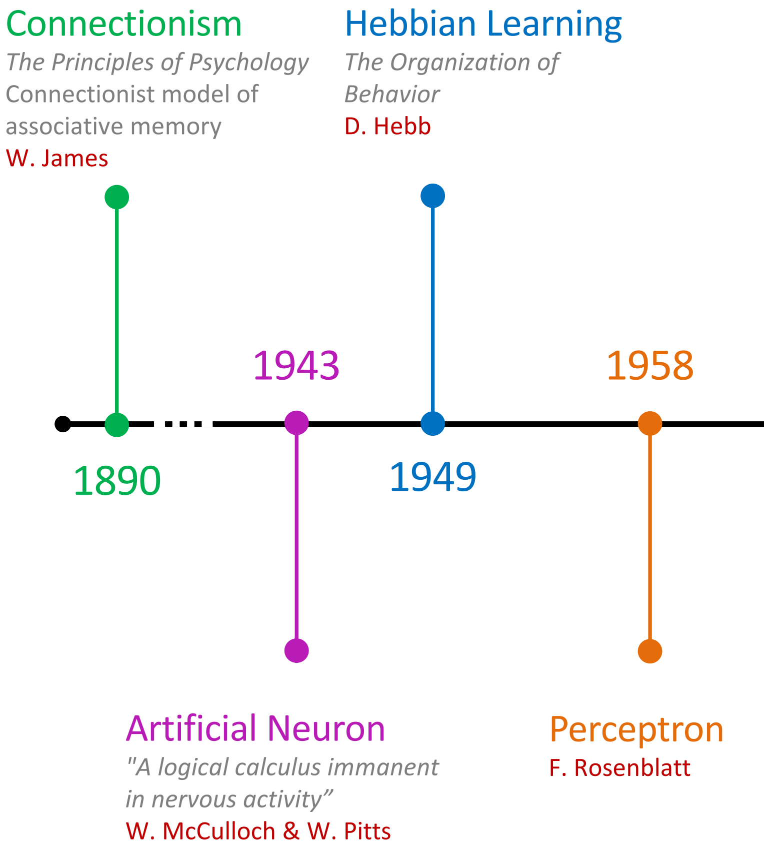
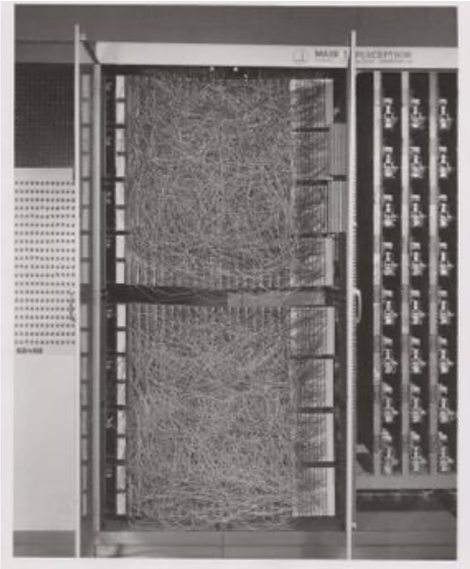


The Mark 1 Perceptron Machine



https://wiki.pathmind.com/multilayer-perceptron

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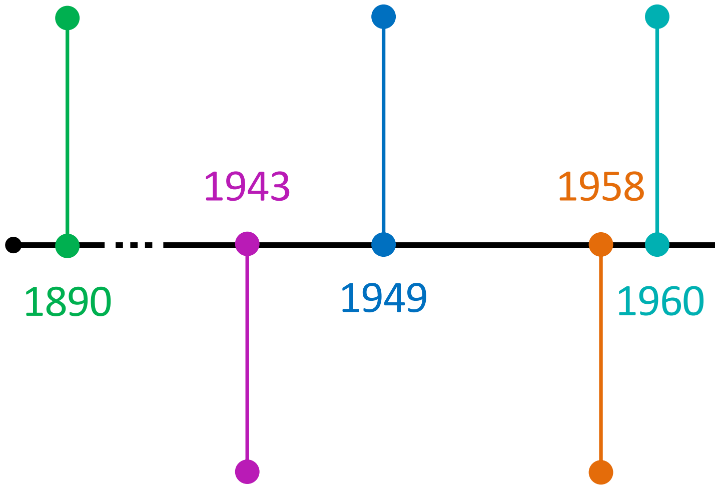

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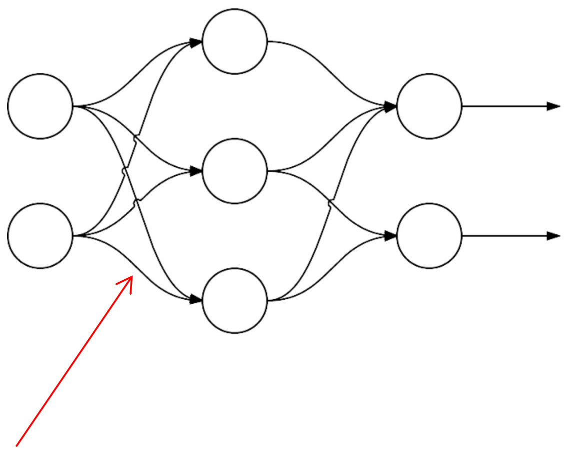
Perceptron
F. Rosenblatt

Multilayer Perceptron



No learning algorithm existed to allow the adjustment of the weights of connections between the input units and the hidden units

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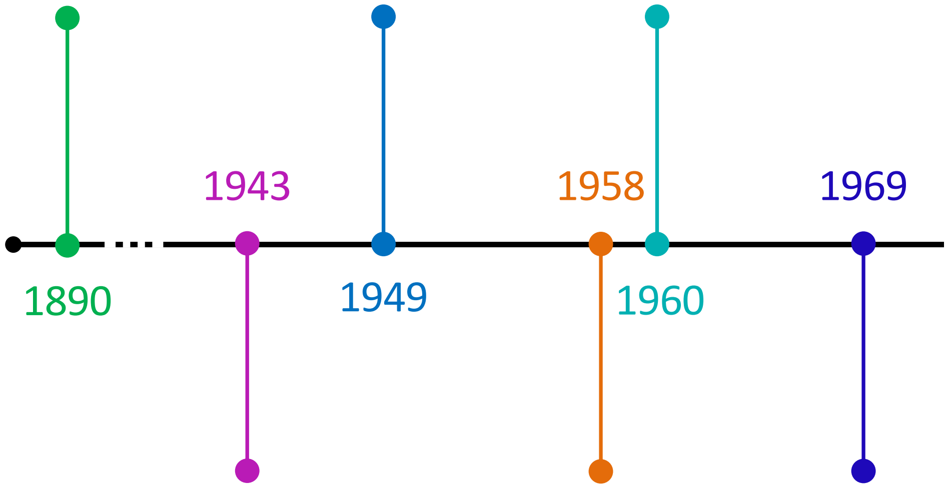

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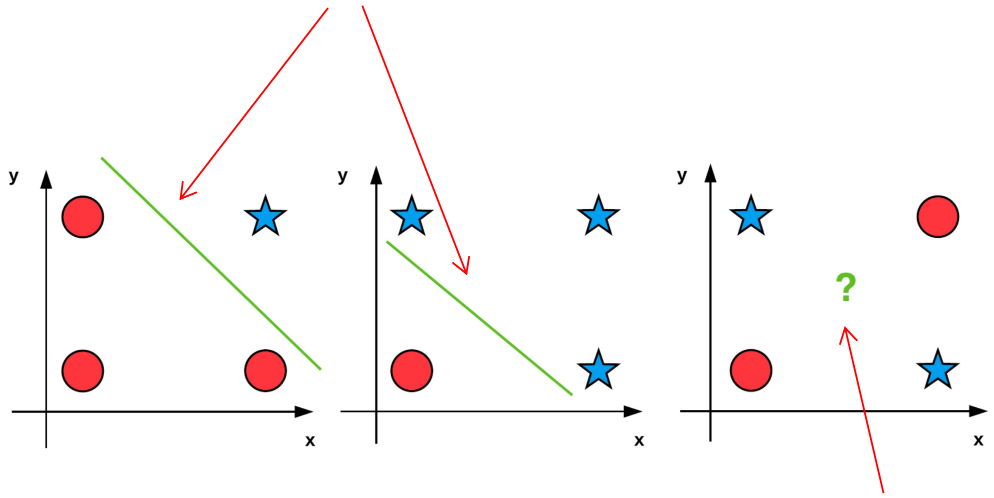
F. Rosenblatt

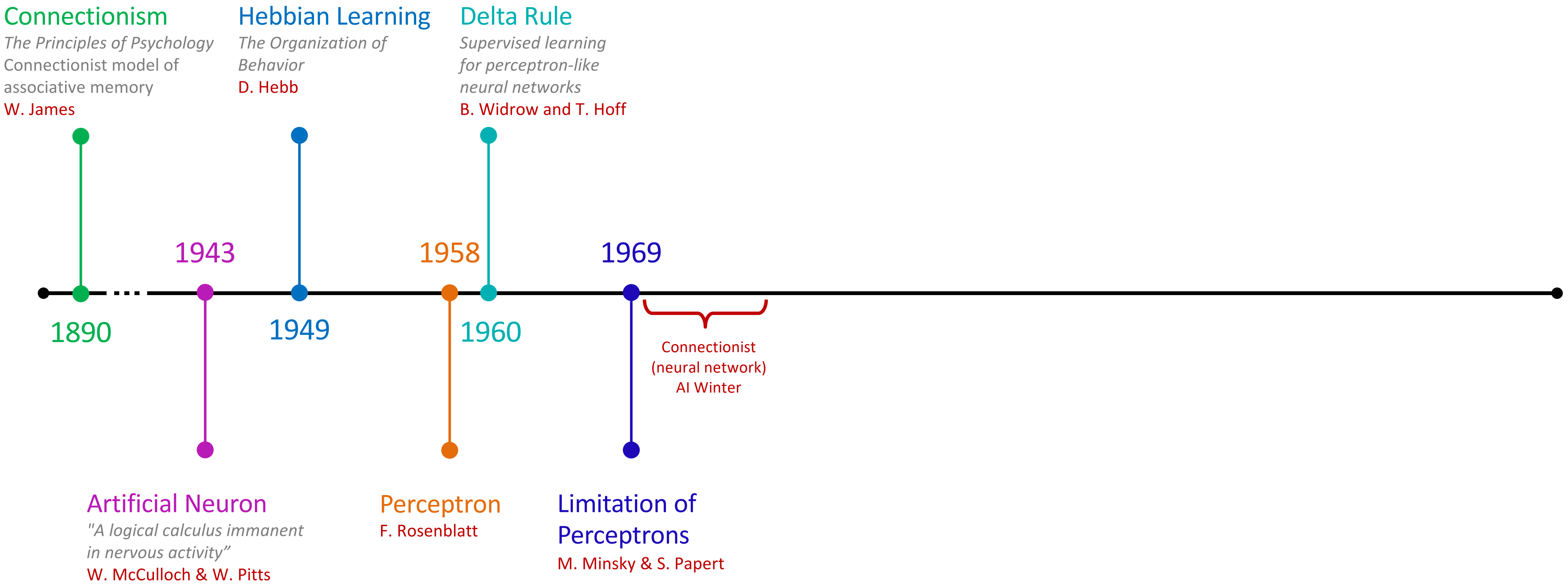
Limitation of Perceptrons
M. Minsky & S. Papert

Linear separability: each class can be separated by a line
Perceptron neural networks can be trained to separate these classes



Cannot separate these classes with a single line
Perceptron neural networks cannot be trained to separate these classes

Research on neural networks and connectionism suffered considerably as a result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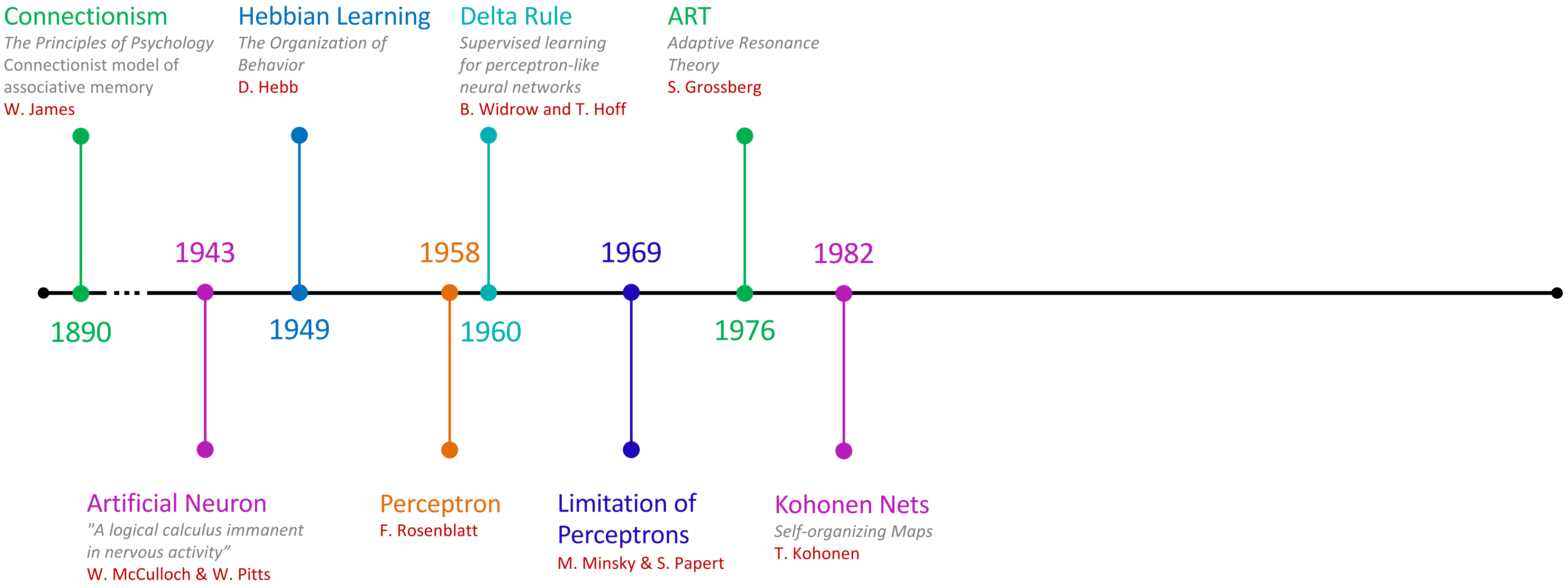
1969
Connectionist (neural network) AI Winter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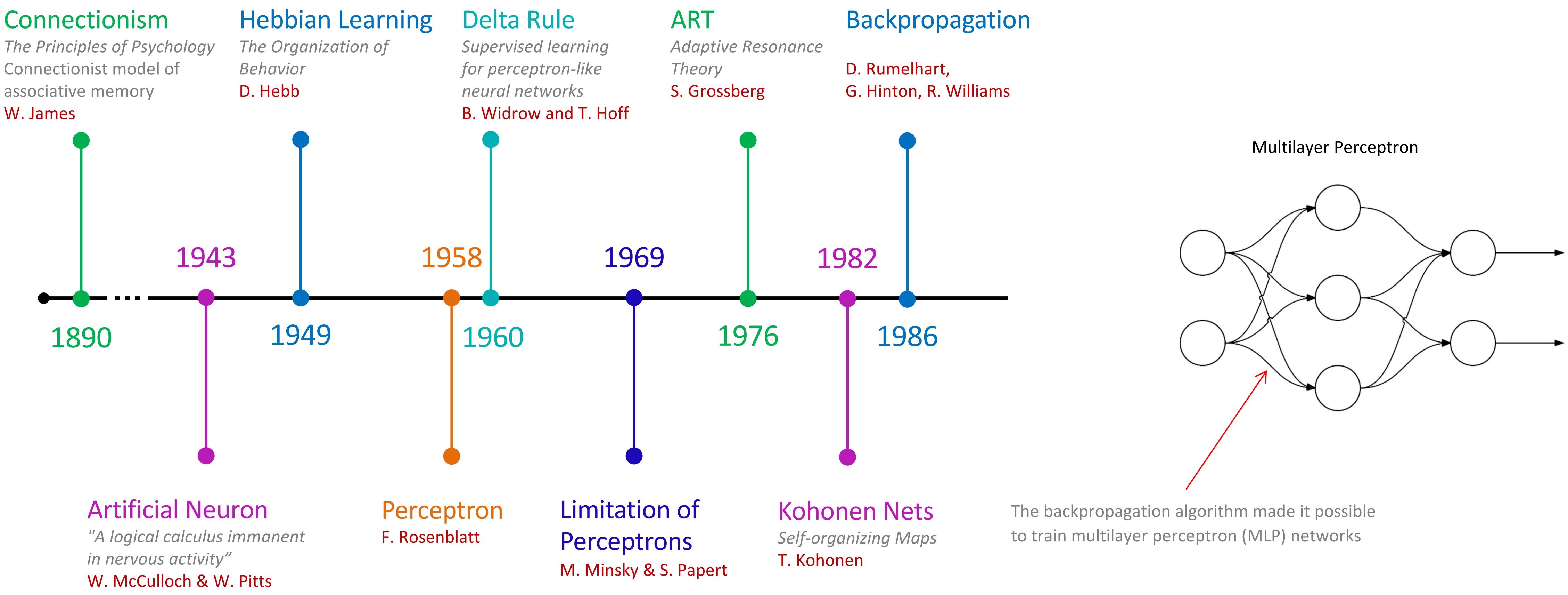
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Multilayer Perceptron
The backpropagation algorithm made it possible to train multilayer perceptron (MLP) networks

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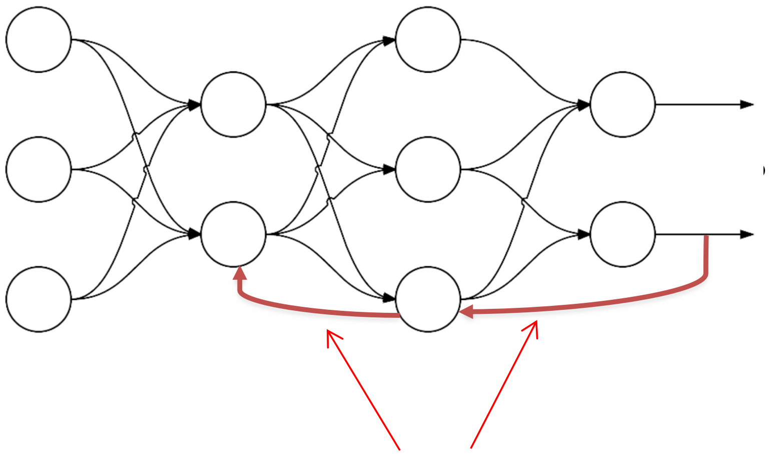

Recurrent neural networks have output connections that feed back into the inputs

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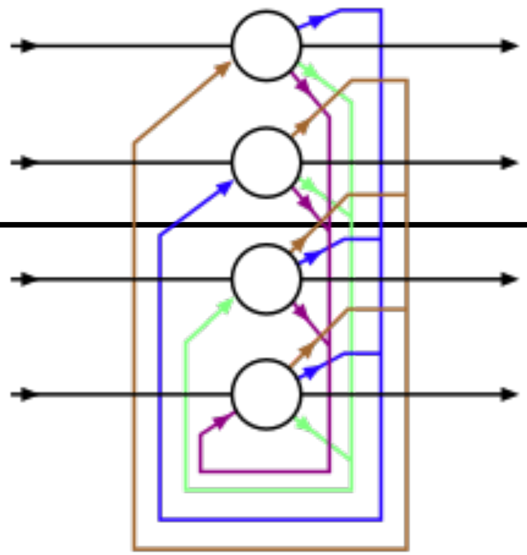
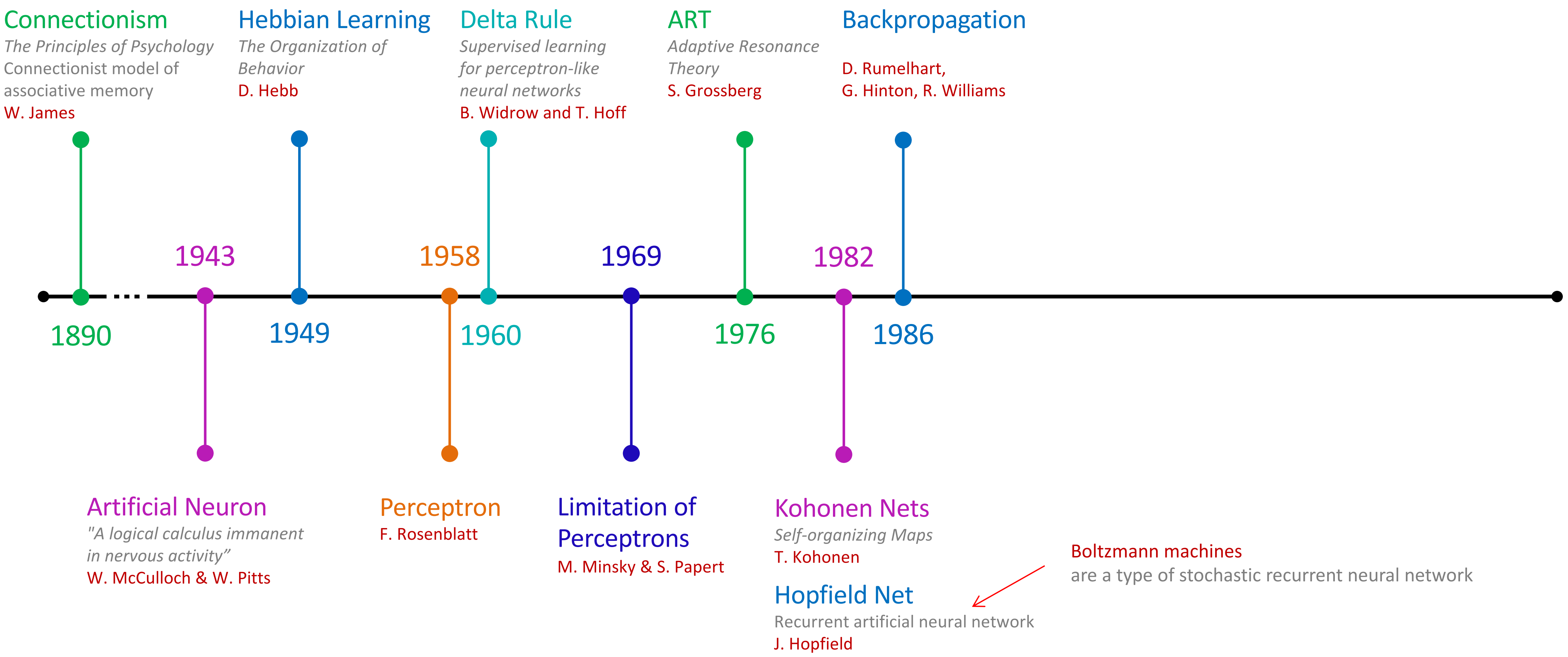
Hopfield Net
Recurrent artificial neural network
J. Hopfield

1986 — Backpropagation
D. Rumelhart,
G. Hinton, R. Williams

Hopfield net with four units



https://en.wikipedia.org/wiki/Hopfield_network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Recurrent artificial neural network
J. Hopfield
Boltzmann machines
are a type of stochastic recurrent neural network

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1986 — **Backpropagation**
D. Rumelhart,
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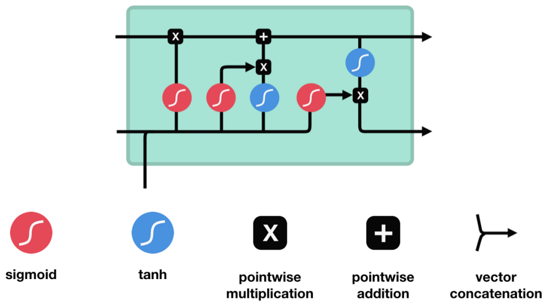
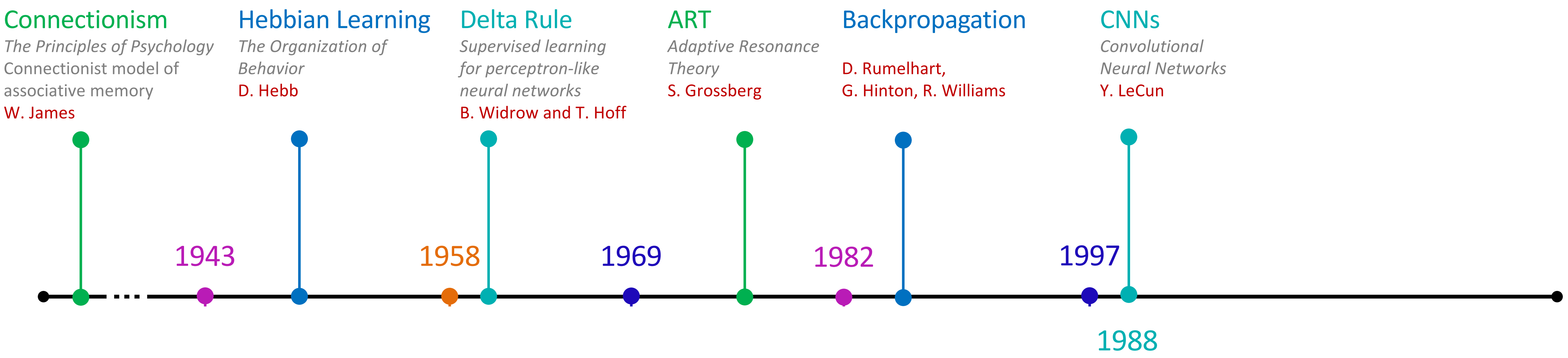
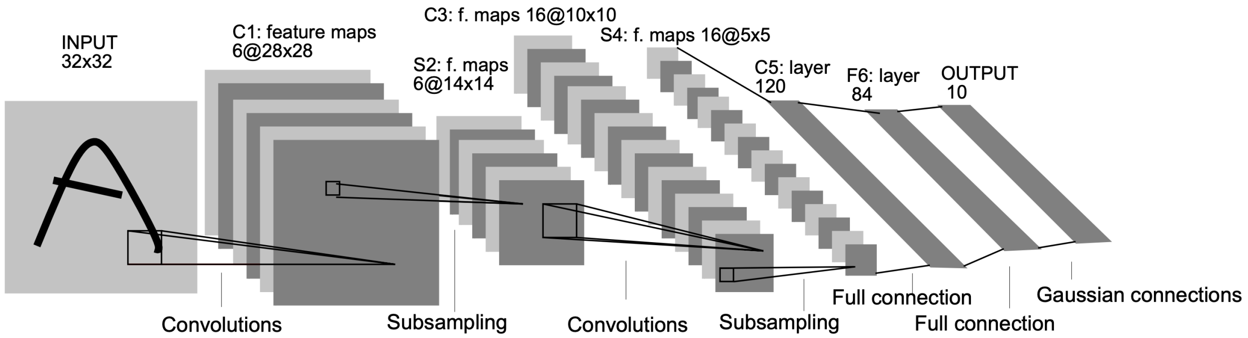
1997 — **LSTM**
Long short-term memory
S. Hochreiter & J. Schmidhuber

LSTM (Long short-term memory) is a form of recurrent neural network that can select which information is relevant to remember or forget when processing a sequence of data or time-varying information



https://towardsdatascience.com/illustrated-guide-to-lstms-and-gru-s-a-step-by-step-explanation-44e9eb85bf21





LeCun Y, Bottou L, Bengio Y, Haffner P (1998) Gradient-based learning applied to document recognition. Proceedings of the IEEE 86(11):2278–2324

A convolutional neural network is similar in principle to a multi-layer perceptron but they have many more layers which learn the features required to do the task instead of having to hand-craft them.

They map from the input space to the output space, and, consequently, are often called end-to-end systems

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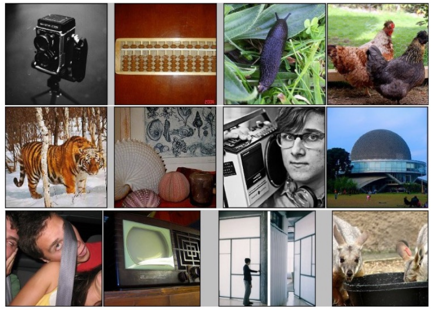
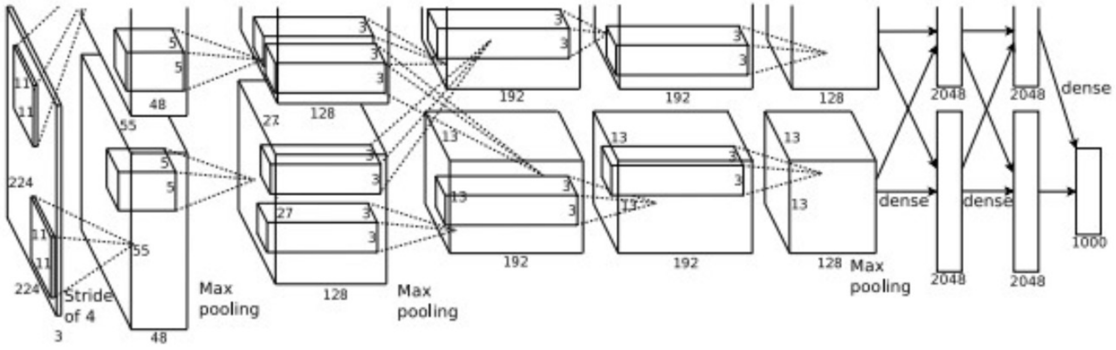
CNNs
Convolutional Neural Networks
Y. LeCun

1943 · 1958 · 1969 · 1982 · 1997 · 2012

IMAGENET

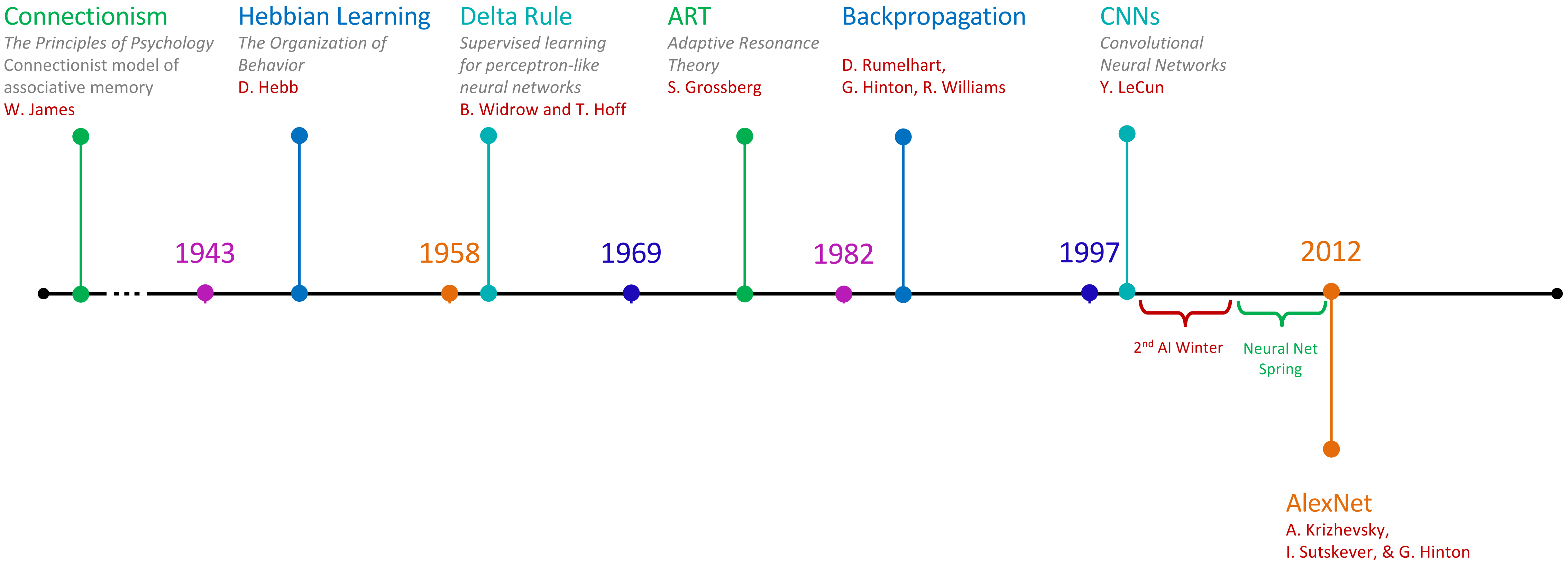


1.2 million training images for 1000 classes



AlexNet
A. Krizhevsky,
I. Sutskever, & G. Hinton

Krizhevsky A, Sutskever I, Hinton G (2012) Imagenet classification with deep convolutional neural networks. In: Pereira F, Burges CJC, Bottou L, Weinberger KQ (eds) Advances in Neural Information Processing Systems, vol 25.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2nd AI Winter
Neural Net Spring
AlexNet
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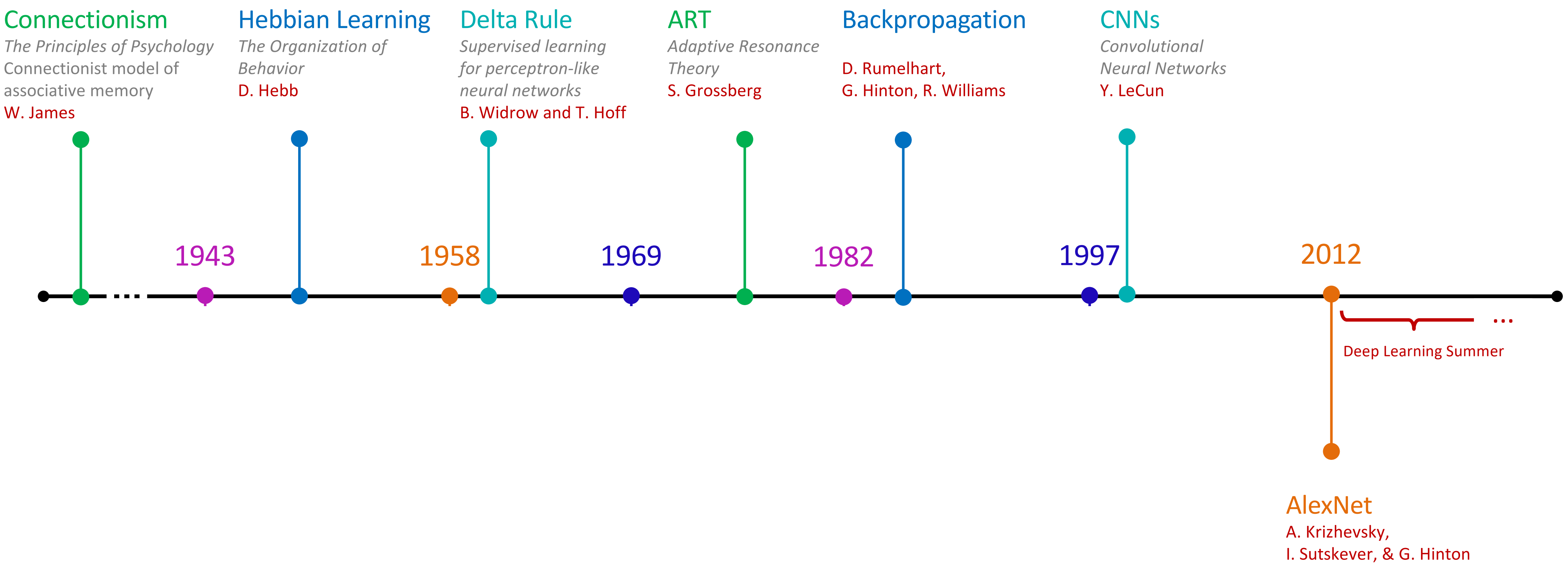
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Much deeper neural networks

... 1943 1958 1969 1982 1997 2012 ...

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Deep neural networks have been applied successfully in many challenging applications.

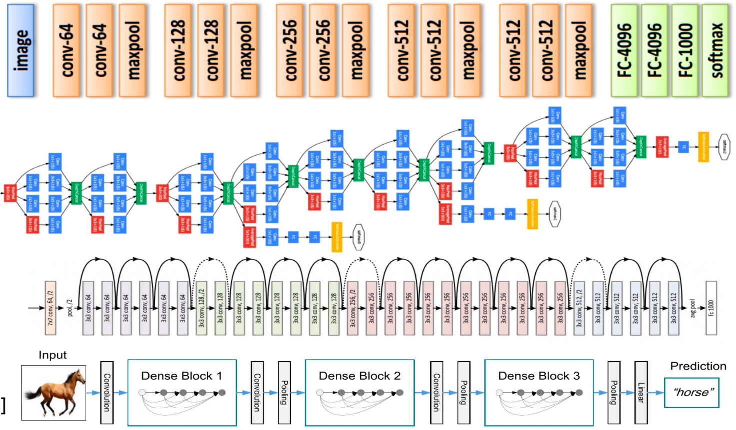
The network have 17, 19, 22 or many more layers.

VGG
[Simonyan 2013]

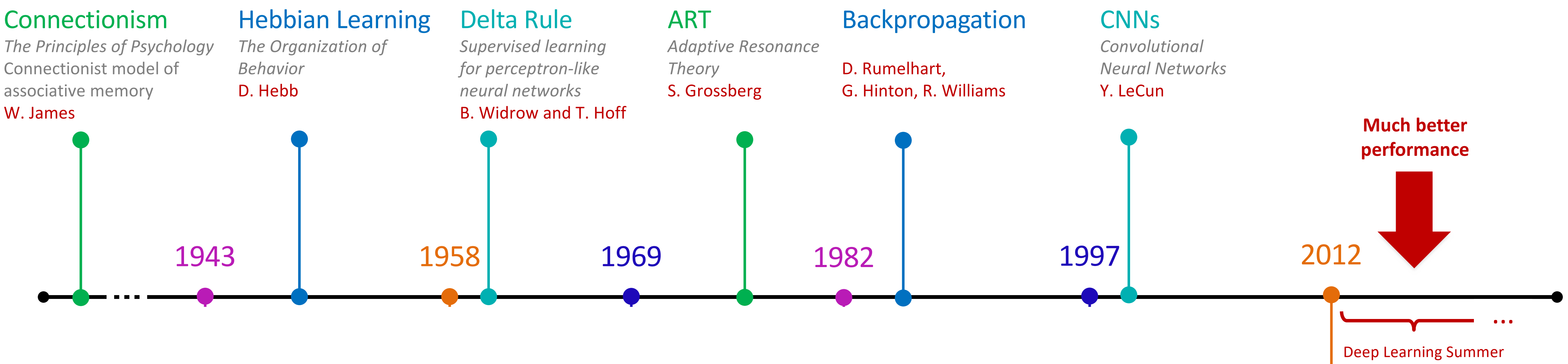
GoogLeNet
Szegedy 2014]

ResNet
[He et al. 2015]

DenseNet
[Huang et al 2017]



Y. LeCun, Deep Learning Hardware: Past, Present, & Future, ISSCC 2019
https://drive.google.com/file/d/17w443t_5Atnwnu-iOrHKUPFik1pThyhx/view



Significant improvement in performance through the use of

- Specialized layers in deep neural networks (e.g., pooling),
- More advanced learning techniques (e.g., batch normalization and dropout),
- Techniques to overcome the problem of vanishing gradients (where the error terms become too small to produce an improvement in network performance as they are propagated back in a deep network)
- Better understanding of how to adjust the system hyper-parameters during training to improve performance.

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Y. LeCun

Significant progress in computer vision

1943 · 1958 · 1969 · 1982 · 1997 · 2012 ...

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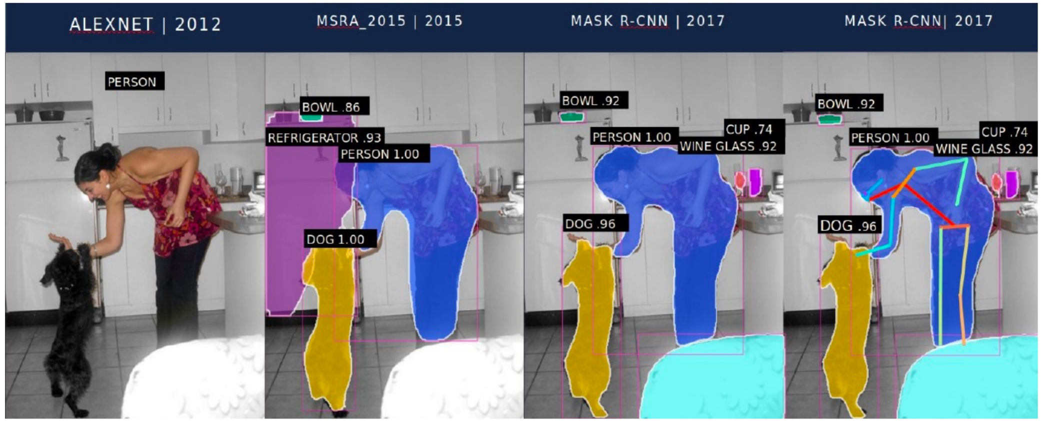
CNNs and regional CNNs (RCNNs) achieve very impressive performance in image recognition, object detection and localization, face detection, face recognition, and object tracking



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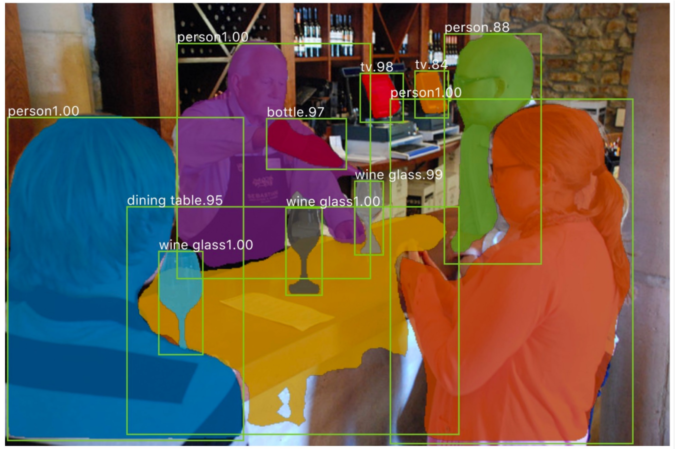

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Significant progress in natural language processing

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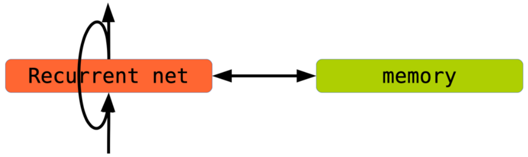
New forms of recurrent neural networks are very successful solving problems that involve sequences of states, e.g., in natural language, by using new recurrent elements, e.g., long short-term memory (LSTM) and gated recurrent units (GRU).



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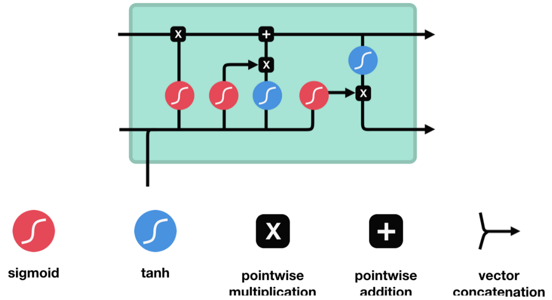

https://towardsdatascience.com/illustrated-guide-to-lstms-and-gru-s-a-step-by-step-explanation-44e9eb85bf21

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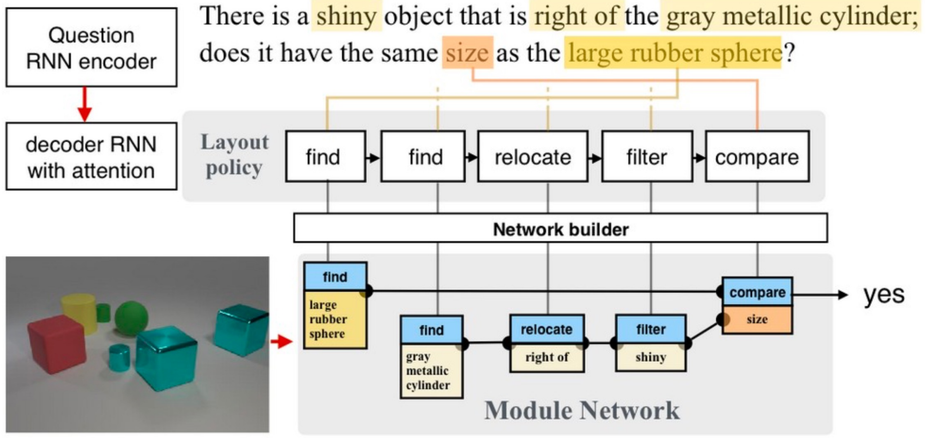
Modern architectures successfully combine the power of deep CNNs and LSTMs to address problems that involve both images and language, e.g. automatic image annotation and captioning, image retrieval and synthesis base on linguistic description



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GANs
Generative Adversarial Networks

1943 1958 1969 1982 1997 2012

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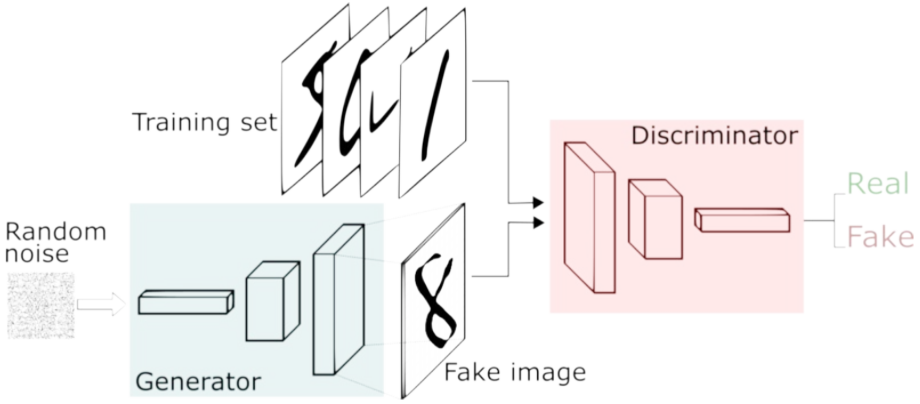
Generative adversarial networks, or GANs, which work as actor-critic systems, has provided the means for two learning networks to learn from each other and thereby improve the performance of both



https://www.freecodecamp.org/news/an-intuitive-introduction-to-generative-adversarial-networks-gans-7a2264a81394

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AlexNet
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Yielding remarkable results in image synthesis, among many other applications.

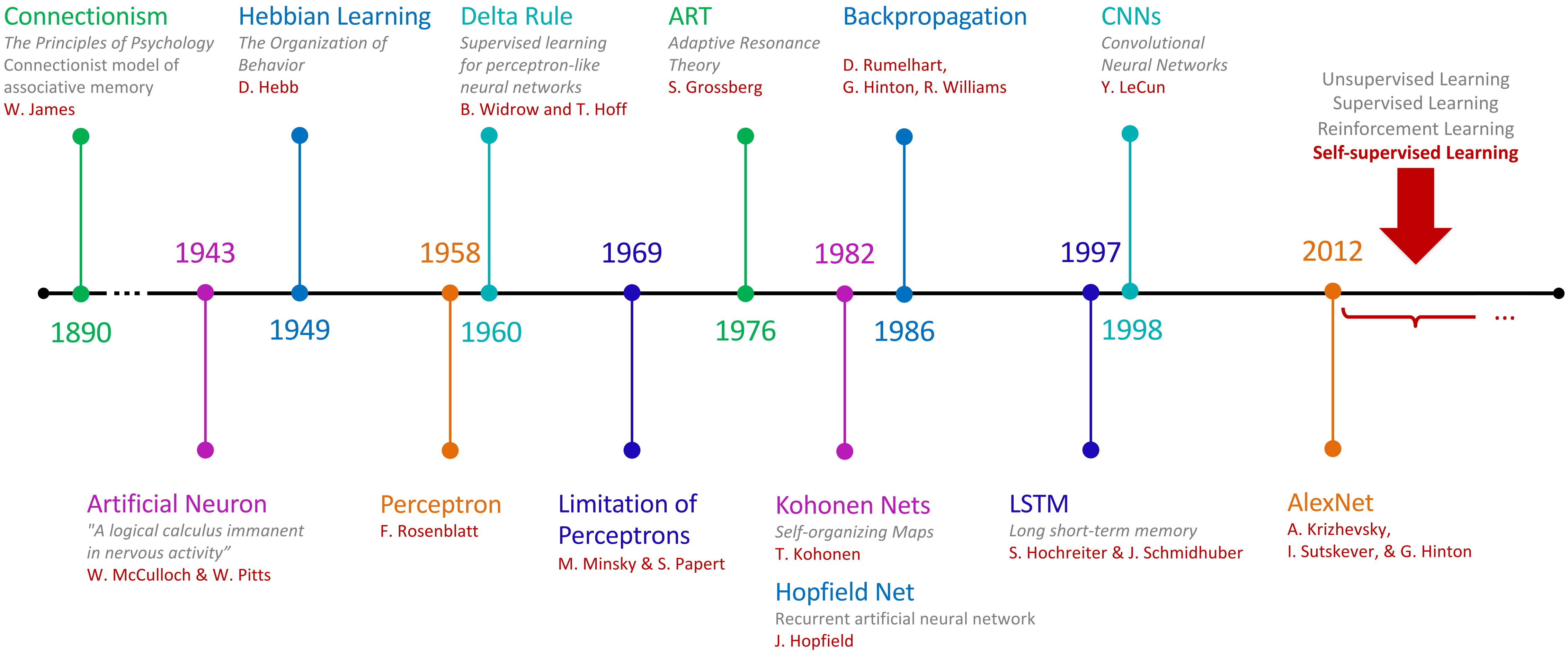

DCGAN
11/2015


EBGAN-PT
9/2016


BEGAN
3/2017
128 × 128


Progressive GAN
10/2017
1024 x 1024

https://jonathan-hui.medium.com/gan-a-comprehensive-review-into-the-gangsters-of-gans-part-1-95ff52455672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1890
Artificial Neuron
"A logical calculus immanent in nervous activity"
W. McCulloch & W. Pitts
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Perceptron
F. Rosenblatt
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Self-organizing Maps
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Unsupervised Learning
Supervised Learning
Reinforcement Learning
Self-supervised Learning
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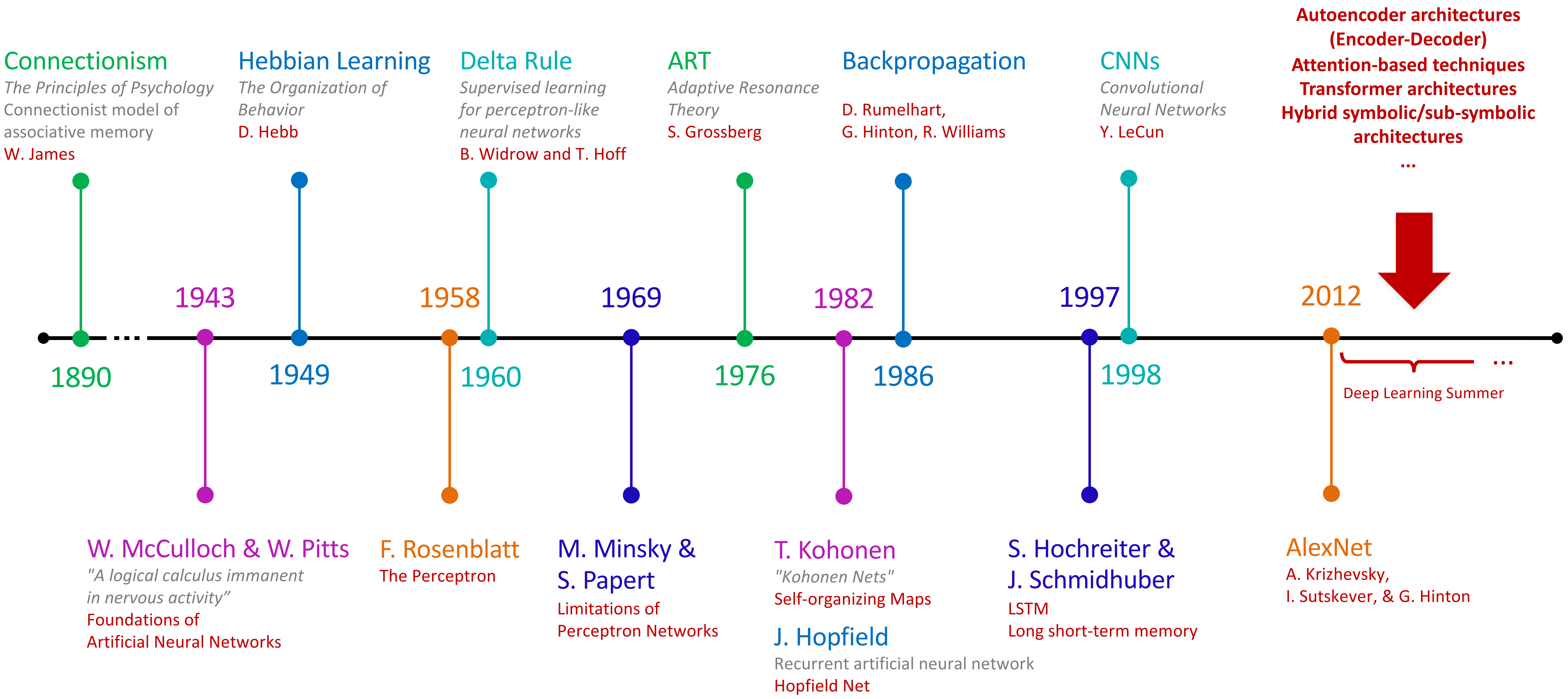
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Attention-based techniques
Transformer architectures
Hybrid symbolic/sub-symbolic architectures
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Limitations of Perceptron Networks
T. Kohonen
"Kohonen Nets"
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Recurrent artificial neural network
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Autoencoder architectures (Encoder-Decoder)
Attention-based techniques
Transformer architectures
Hybrid symbolic/sub-symbolic architectures
...

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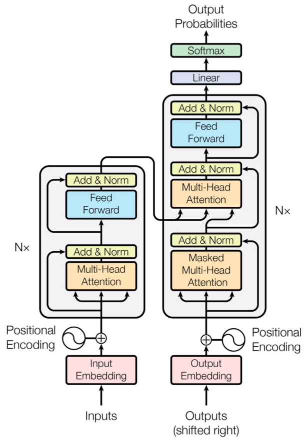
The Transformer, introduced by Google in 2017, has been particularly influential in recent years. It replaces recurrence with attention mechanisms, allowing for significantly more parallelization than other models such as recurrent neural networks



(Vaswani et al., 2017)

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BERT
Bidirectional Encoder Representations from Transformers

GPT-3
Generative Pre-trained Transformer

LaMDA 2
Language Model for Dialogue Applications

Generative Pre-trained Transformer (GPT) architectures, e.g., GPT-3, trained on trillions of words with ~175 billion machine learning parameters, are capable of generating natural language text that is often indistinguishable from that generated by humans

A robot wrote this entire article. Are you scared yet, human?

GPT-3

We asked GPT-3, OpenAI's powerful new language generator, to write an essay for us from scratch. The assignment? To convince us robots come in peace

- For more about GPT-3 and how this essay was written and edited, please read our editor's note below

https://www.theguardian.com/commentisfree/2020/sep/08/robot-wrote-this-article-gpt-3

Natural Language Processing

Foundation Models

BERT
Bidirectional Encoder Representations from Transformers

GPT-3
Generative Pre-trained Transformer

LaMDA 2
Language Model for Dialogue Applications

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DALL-E 2
from Salvador Dali, the painter, and WALL-E, the animated robot

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AlexNet
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DALL-E 2 is transformer-based system developed by OpenAI to generate highly-realistic digital images based on natural language descriptions of the desired content.

This image was generated from the text "An astronaut riding a horse in a photorealistic style".

https://openai.com/dall-e-2/

Lecture Summary

1. Connectionist AI has its roots in early work in psychology and associative memory

2. Connectionist AI is typically implemented using artificial neural networks

3. Although limited at first, artificial neural networks for the basis of modern high-performance deep machine learning

4. These modern artificial networks achieve their performance by using

    - Many layers of processing
    - Very large training data sets, and
    - Very powerful GPU-based computers during the training phase

Recommended Reading

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Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., and Polosukhin, I. (2017). Attention is all you need. Advances in Neural Information Processing Systems, NIPS 2017, Vol. 20.