ML for natural and physical scientists 2023 8

NNs and Deep Learning

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this slide deck:

https://slides.com/federicabianco/mlpns23_8

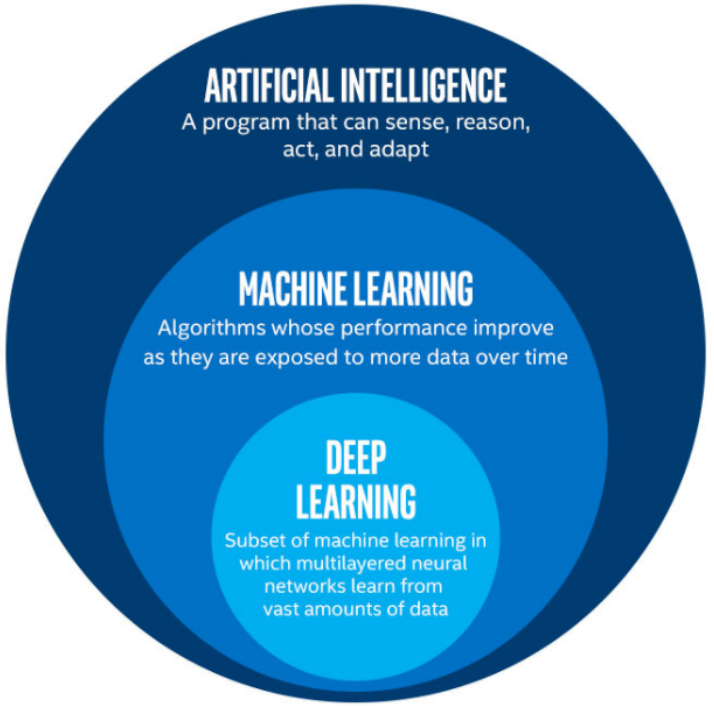
0

Recap

Machine Learning

Data driven models for exploration of structure, prediction that learn parameters from data.

General ML usage



used to:

- classify based on examples
- understand structure of feature space
- regression (classification with infinitely small classes)
    - understand which features are important in prediction (to get close to causality)

Machine Learning

Data driven models for exploration of structure, prediction that learn parameters from data.

unupervised ------

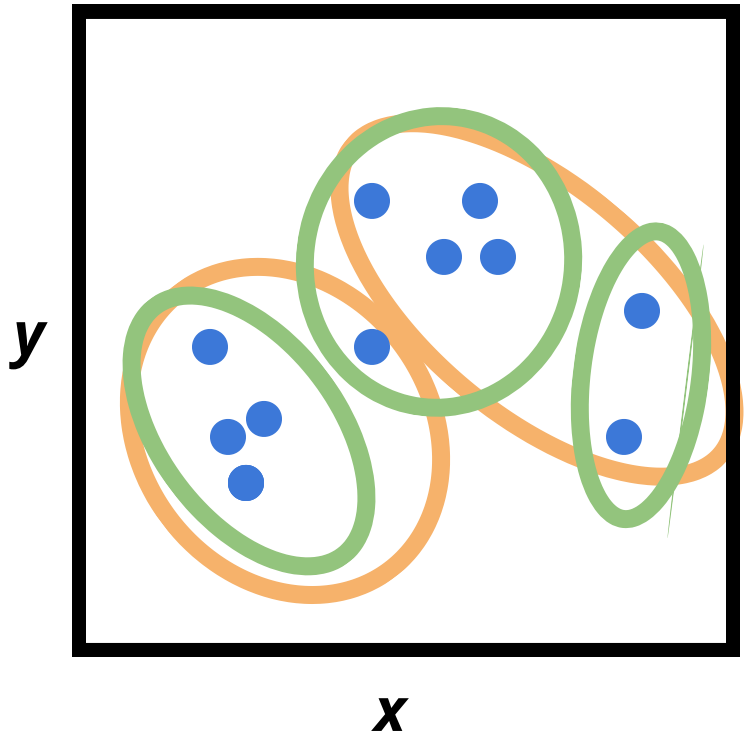
set up: All features known for all observations

Goal: explore structure in the data

- data compression

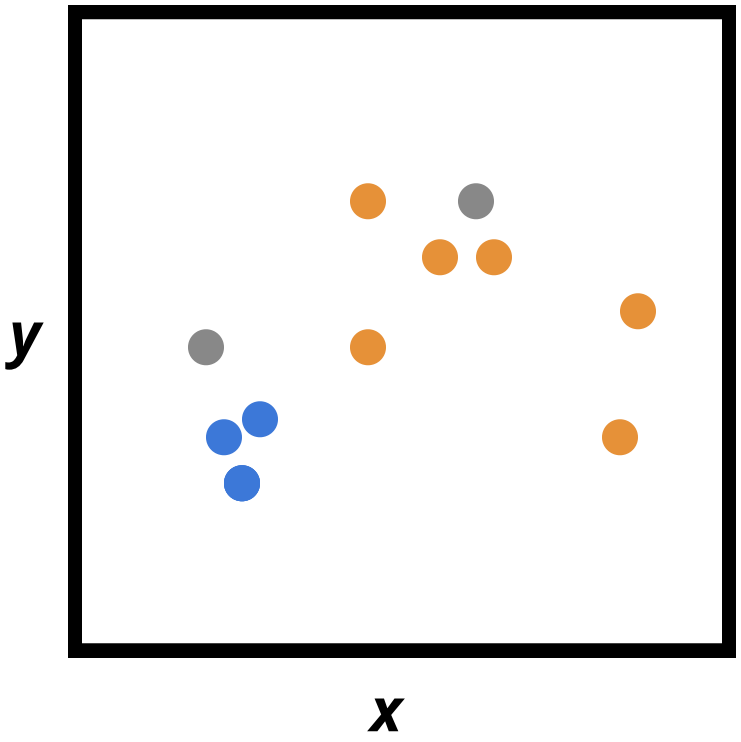
- understanding structure

Algorithms: ***Clustering, (...)***



Machine Learning

Data driven models for exploration of structure, prediction that learn parameters from data.



------ **supervised**

set up: All features known for a sunbset of the data; one feature cannot be observed for the rest of the data

Goal: predicting missing feature

- classification
- regression

Algorithms: ***regression, SVM, tree methods, k-nearest neighbors, neural networks, (...)***

Machine Learning

unupervised ------ **supervised**

set up: All features known for all observations

Goal: explore structure in the data

- data compression

- understanding structure

Algorithms: ***k-means clustering, agglomerative clustering, density based clustering, (...)***

set up: All features known for a sunbset of the data; one feature cannot be observed for the rest of the data

Goal: predicting missing feature

- classification

- regression

Algorithms: ***regression, SVM, tree methods, k-nearest neighbors, neural networks, (...)***

Machine Learning

Learning relies on the definition of a ***loss function***

model parameters are learned by calculating a loss function for diferent parameter sets and trying to minimize loss (or a target function and trying to maximize)

e.g.

$$\boldsymbol{L1} = |target - prediction|$$

Machine Learning

Learning relies on the definition of a ***loss function***

learning type	**loss / target**
unsupervised	intra-cluster variance / inter cluster distance
supervised	distance between prediction and truth

Machine Learning

The definition of a loss function requires the definition of *distance* or *similarity*

Machine Learning

The definition of a loss function requires the definition of *distance* or *similarity*

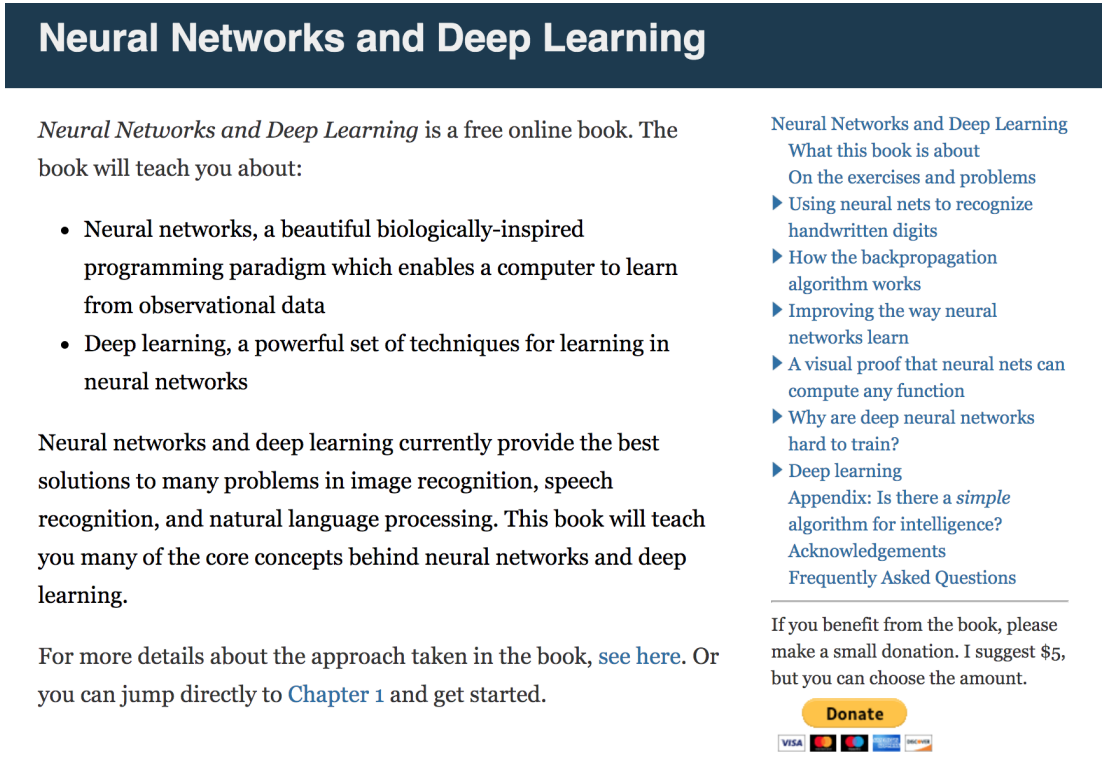
Minkowski distance

Jaccard similarity

Great circle distance

NN are a vast topics and we only have 2 weeks!

Some FREE references!



Neural Networks and Deep Learning

Neural Networks and Deep Learning is a free online book. The book will teach you about:

- Neural networks, a beautiful biologically-inspired programming paradigm which enables a computer to learn from observational data
- Deep learning, a powerful set of techniques for learning in neural networks

Neural networks and deep learning currently provide the best solutions to many problems in image recognition, speech recognition, and natural language processing. This book will teach you many of the core concepts behind neural networks and deep learning.

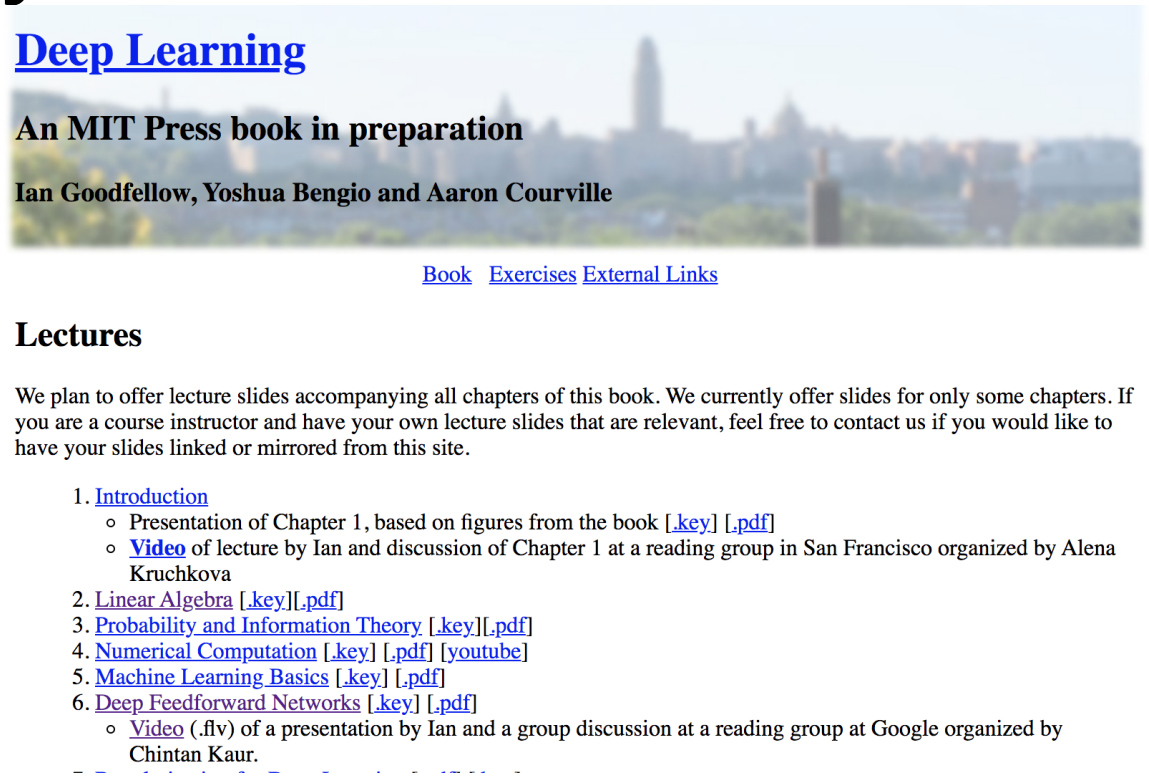
For more details about the approach taken in the book, see here. Or you can jump directly to Chapter 1 and get started.

Neural Networks and Deep Learning
- What this book is about
- On the exercises and problems
- Using neural nets to recognize handwritten digits
- How the backpropagation algorithm works
- Improving the way neural networks learn
- A visual proof that neural nets can compute any function
- Why are deep neural networks hard to train?
- Deep learning

Appendix: Is there a *simple* algorithm for intelligence?
Acknowledgements
Frequently Asked Questions

If you benefit from the book, please make a small donation. I suggest $5, but you can choose the amount.

Donate



Deep Learning

An MIT Press book in preparation

Ian Goodfellow, Yoshua Bengio and Aaron Courville

Book Exercises External Links

Lectures

We plan to offer lecture slides accompanying all chapters of this book. We currently offer slides for only some chapters. If you are a course instructor and have your own lecture slides that are relevant, feel free to contact us if you would like to have your slides linked or mirrored from this site.

1. Introduction
   - Presentation of Chapter 1, based on figures from the book [.key] [.pdf]
   - **Video** of lecture by Ian and discussion of Chapter 1 at a reading group in San Francisco organized by Alena Kruchkova
2. Linear Algebra [.key][.pdf]
3. Probability and Information Theory [.key][.pdf]
4. Numerical Computation [.key] [.pdf] [youtube]
5. Machine Learning Basics [.key] [.pdf]
6. Deep Feedforward Networks [.key] [.pdf]
   - Video (.flv) of a presentation by Ian and a group discussion at a reading group at Google organized by Chintan Kaur.

http://neuralnetworksanddeeplearning.com/index.html

michael nielsen

better pedagogical approach, more basic, more clear

https://www.deeplearningbook.org/

ian goodfellow

mathematical approach, more advanced, unfinished

NN: 1 Neural Networks

NN:1 Neural Networks origins

M-P Neuron McCulloch & Pitts 1943

A LOGICAL CALCULUS OF THE IDEAS IMMANENT IN NERVOUS ACTIVITY

WARREN S. MCCULLOCH and WALTER H. PITTS

Because of the "all-or-none" character of nervous activity, neural events and the relations among them can be treated by means of propositional logic. It is found that the behavior of every net can be described in these terms, with the addition of more complicated logical means for nets containing circles; and that for any logical expression satisfying certain conditions, one can find a net behaving in the fashion it describes. It is shown that many particular choices among possible neurophysiological assumptions are equivalent, in the sense that for every net behaving under one assumption, there exists another net which behaves under the other and gives the same results, although perhaps not in the same time. Various applications of the calculus are discussed.

1943

THE THEORY: NETS WITHOUT CIRCLES

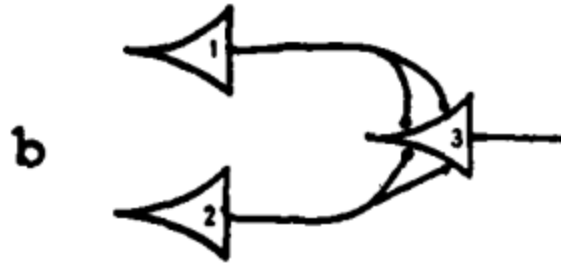
We shall make the following physical assumptions for our calculus.

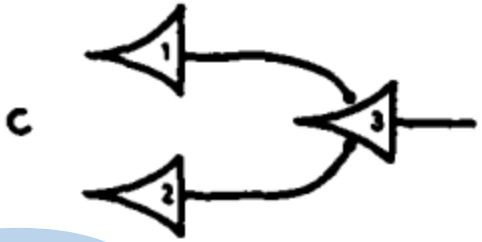
1. The activity of the neuron is an "all-or-none" process.

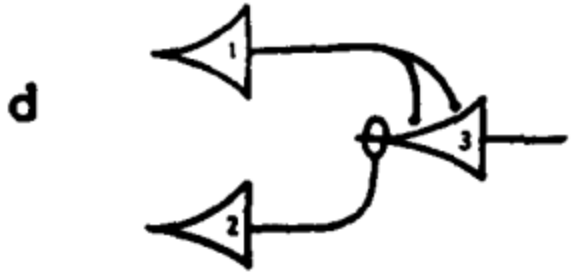
5. The structure of the net does not change with time.

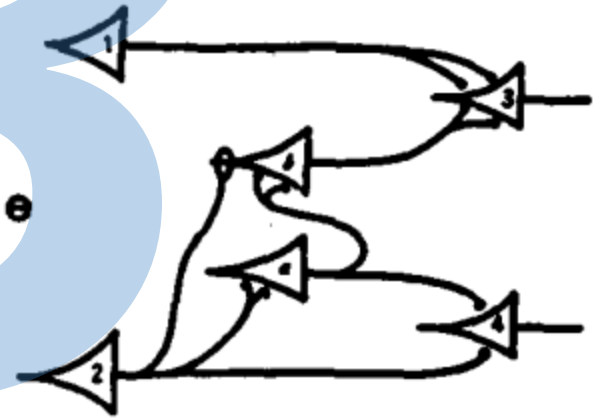
M-P Neuron McCulloch & Pitts 1943

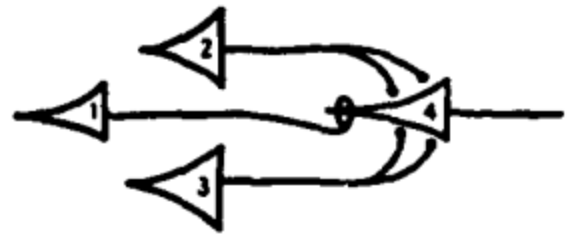
A Logical Calculus of Ideas Immanent in Nervous Activity



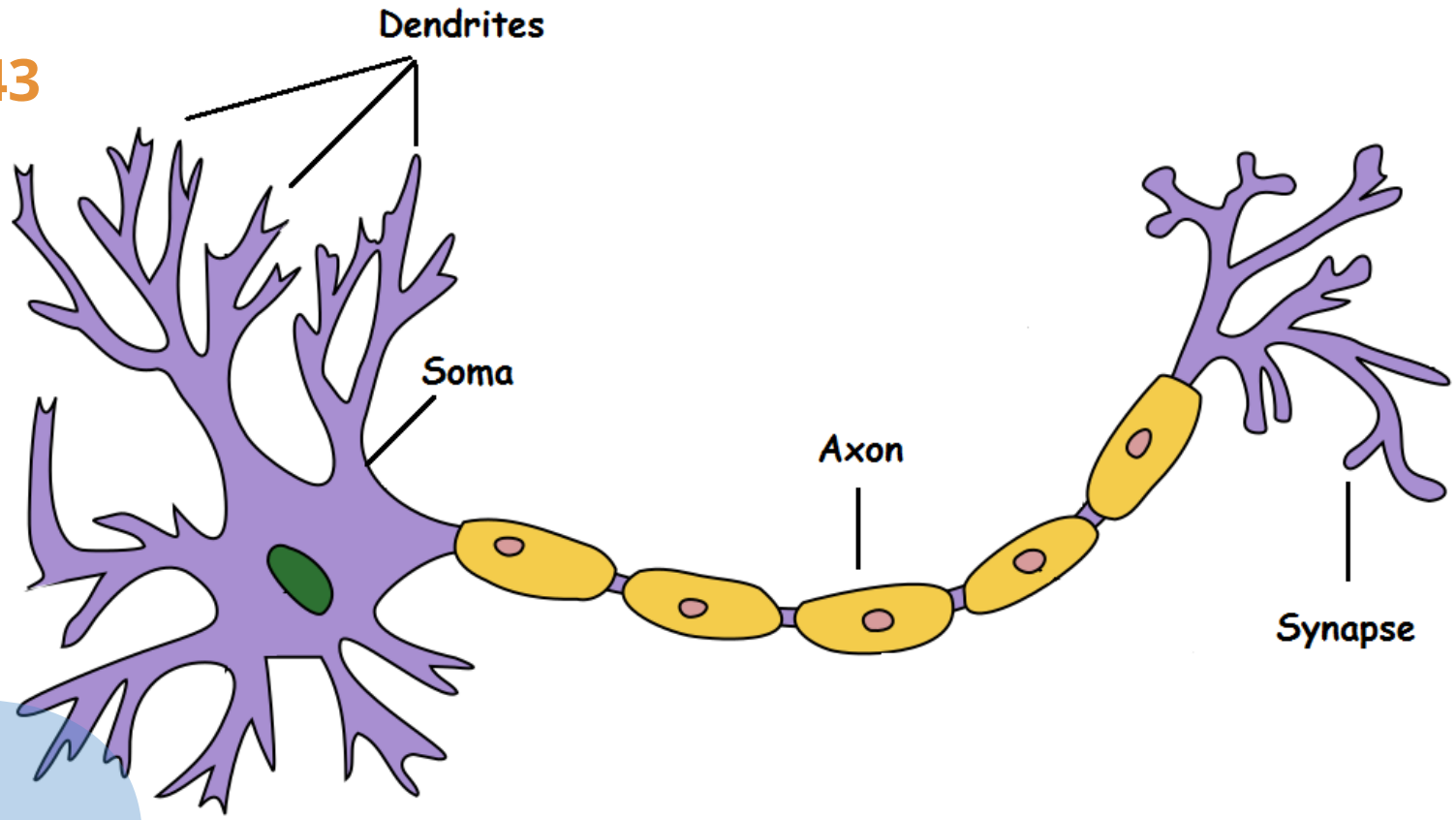




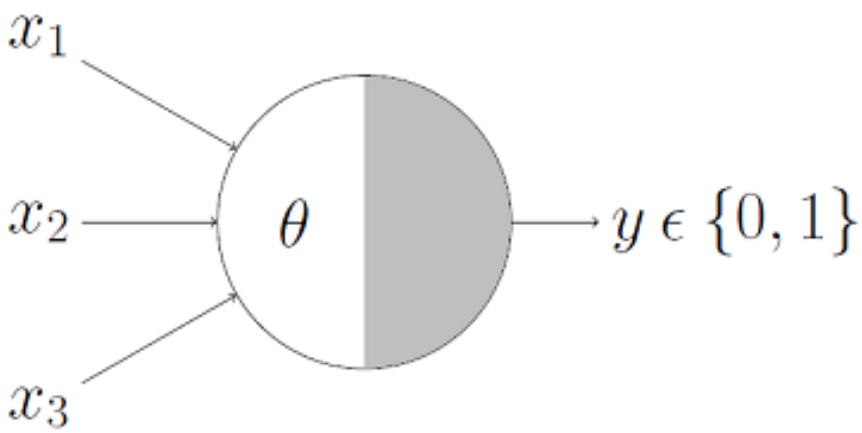




M-P Neuron

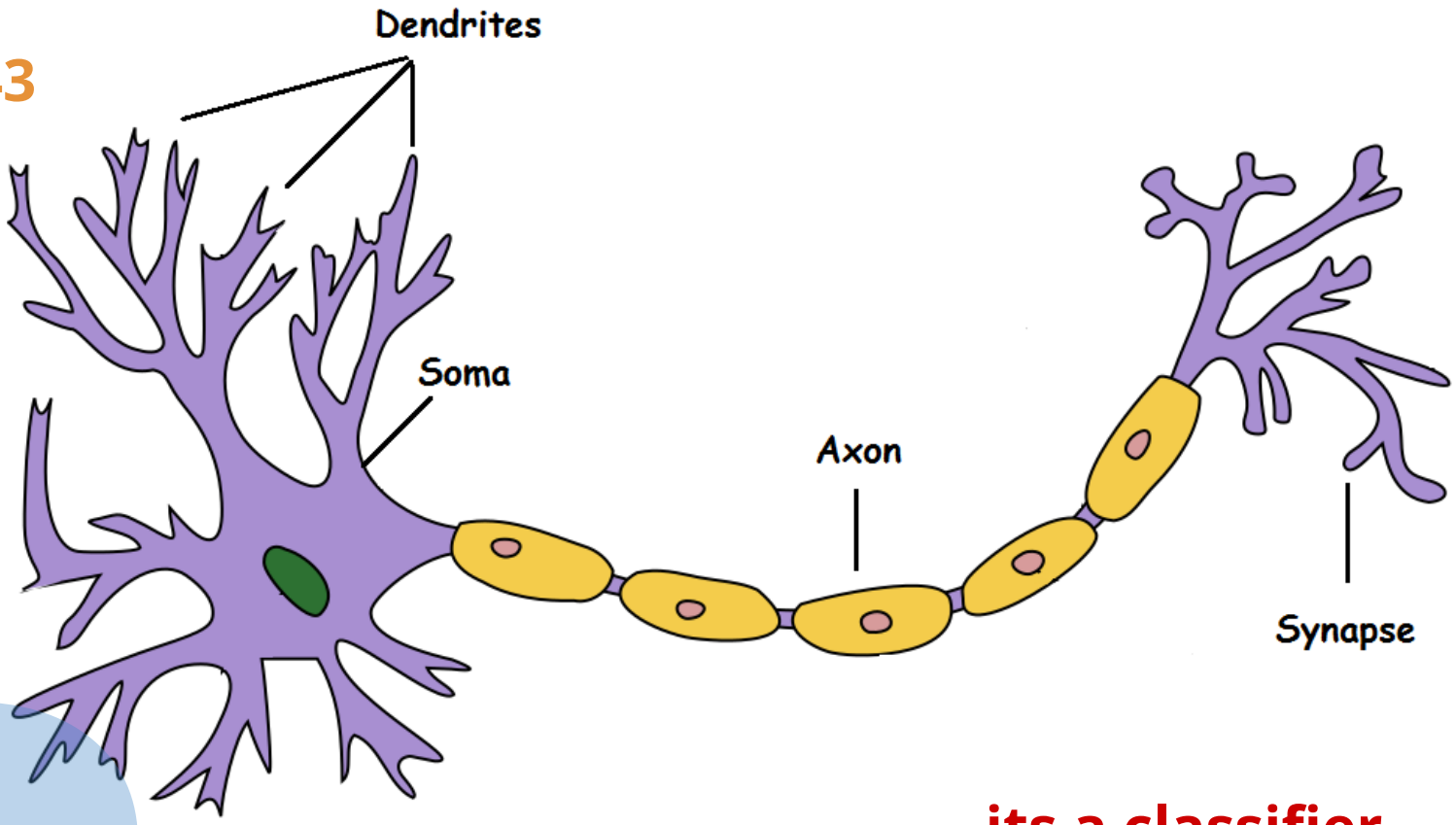


1943



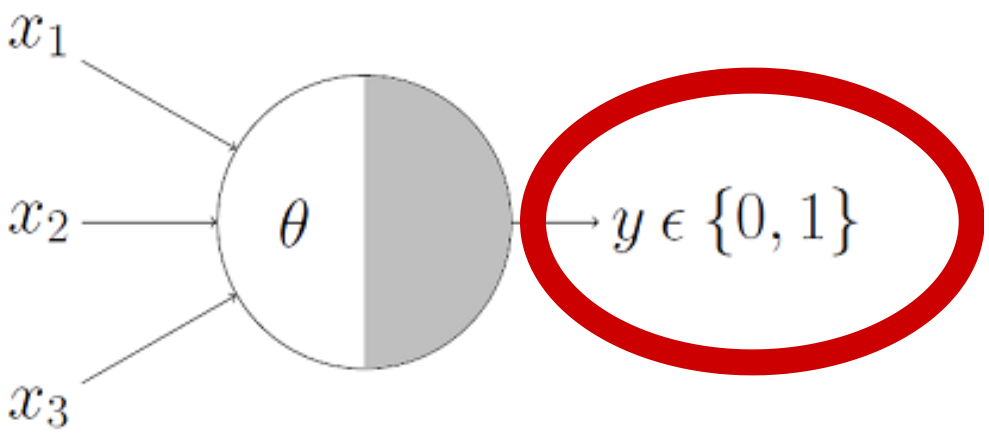
M-P Neuron McCulloch & Pitts 1943

M-P Neuron



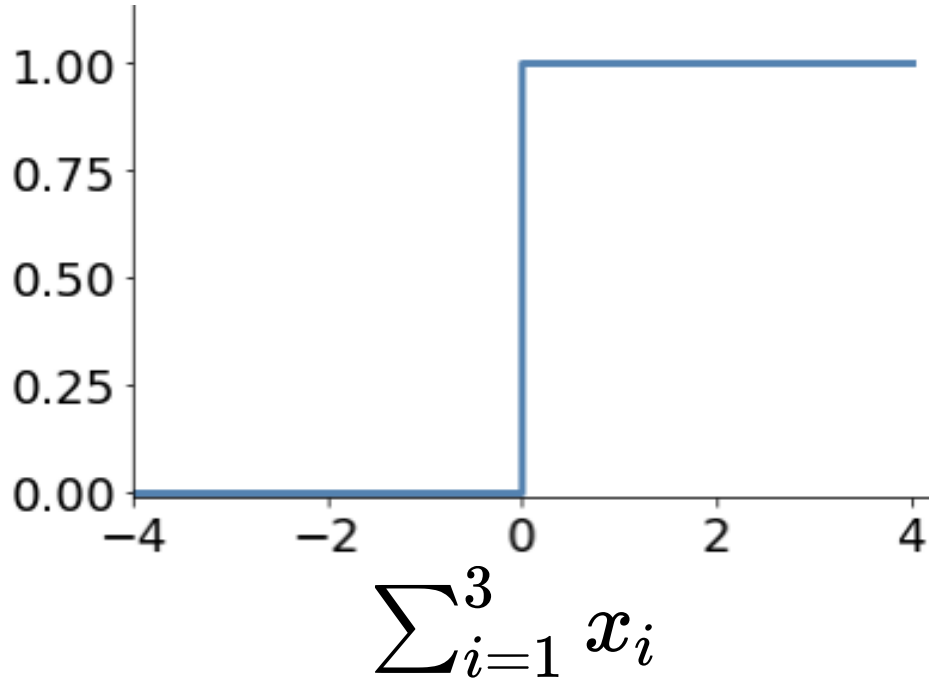
1943

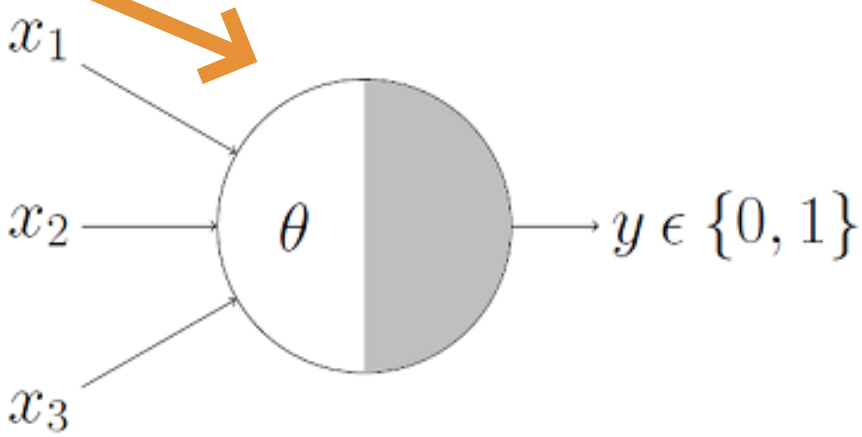
its a classifier



M-P Neuron

$$1 \text{ if } \sum_{i=1}^{3} x_i \geq \theta \text{ else } 0$$





M-P Neuron McCulloch & Pitts 1943

$$1 \text{ if } \sum_{i=1}^{3} x_i \geq \theta \text{ else } 0$$

1943

if x_i is Bool (True/False)

what value of θ corresponds to logical *AND*?

The perceptron algorithm : 1958, Frank Rosenblatt

Perceptron

Psychological Review
Vol. 65, No. 6, 1958

THE PERCEPTRON: A PROBABILISTIC MODEL FOR INFORMATION STORAGE AND ORGANIZATION IN THE BRAIN[1]

F. ROSENBLATT

Cornell Aeronautical Laboratory

If we are eventually to understand the capability of higher organisms for perceptual recognition, generalization, recall, and thinking, we must first have answers to three fundamental questions:

1. How is information about the physical world sensed, or detected, by the biological system?
2. In what form is information stored, or remembered?
3. How does information contained in storage, or in memory, influence recognition and behavior?

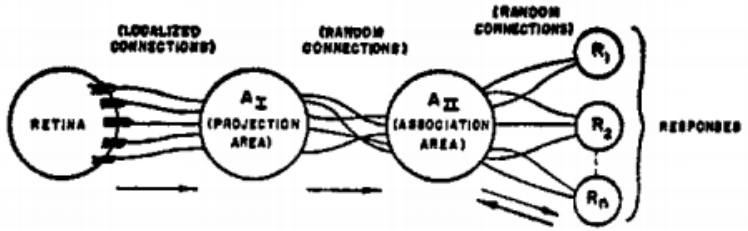


FIG. 1. Organization of a perceptron.

The perceptron algorithm : 1958, Frank Rosenblatt

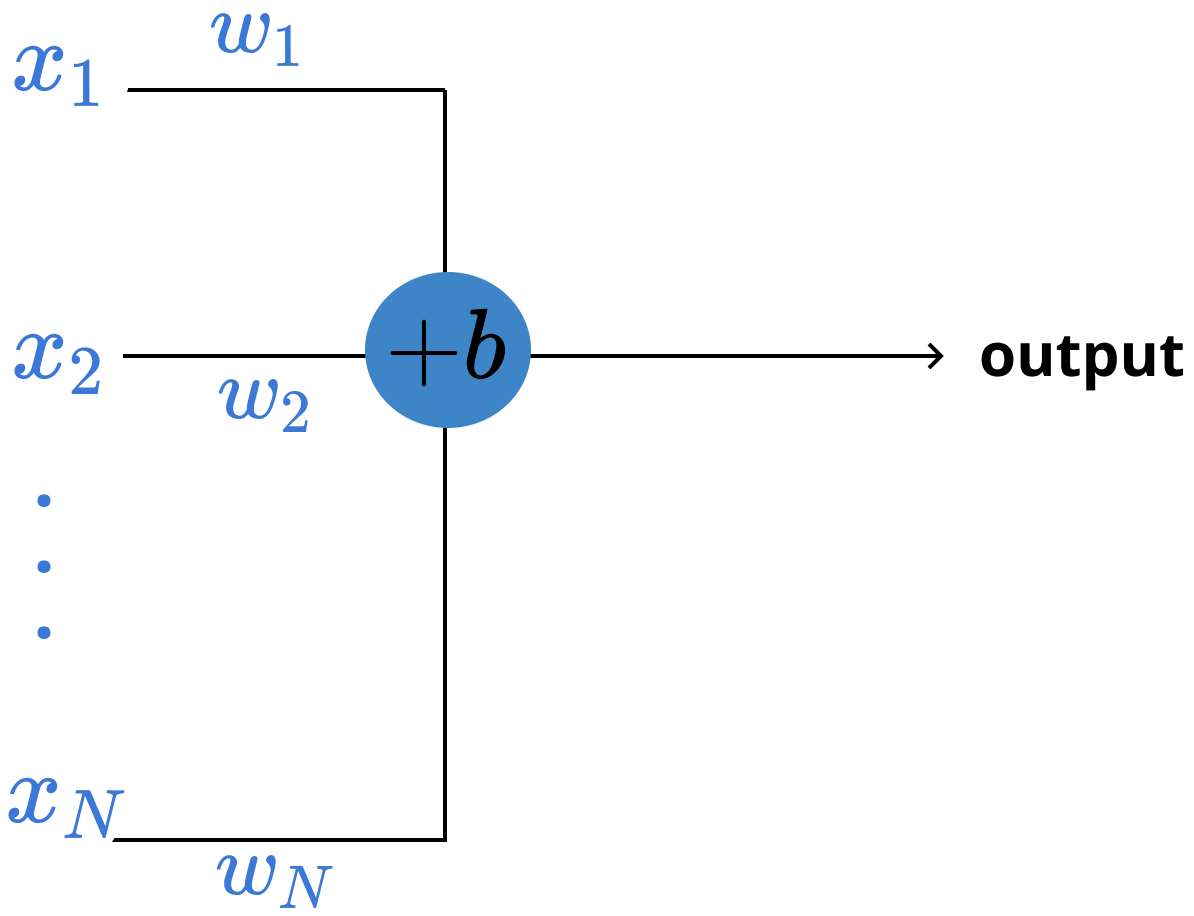
Perceptron

linear regression: w_i weights

b bias

$$1 \text{ if } \sum_{i=1}^{N} w_i x_i \geq \theta \text{ else } 0$$

1958

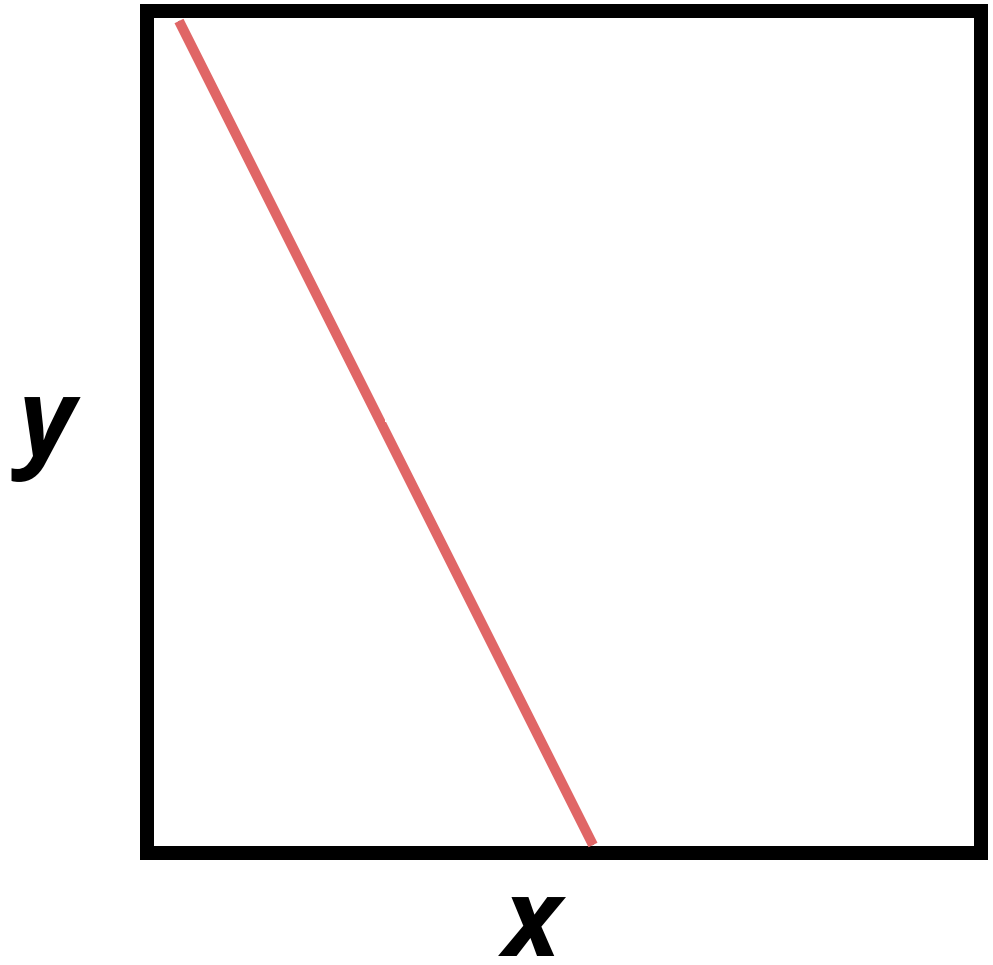


The perceptron algorithm : 1958, Frank Rosenblatt

Perceptrons are ***linear classifiers:*** makes its predictions based on a linear predictor function

combining a set of weights (=parameters) with the feature vector.

$$y = \sum_i w_i x_i + b$$



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The perceptron algorithm : 1958, Frank Rosenblatt

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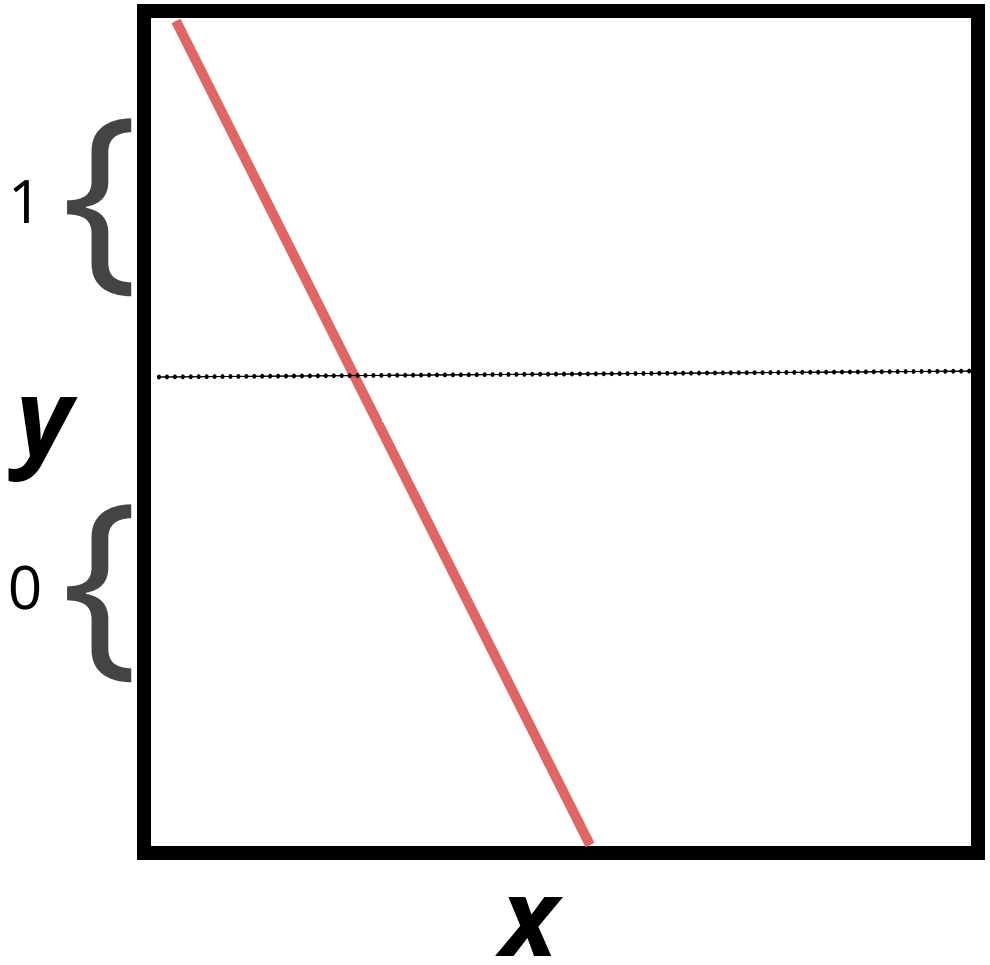


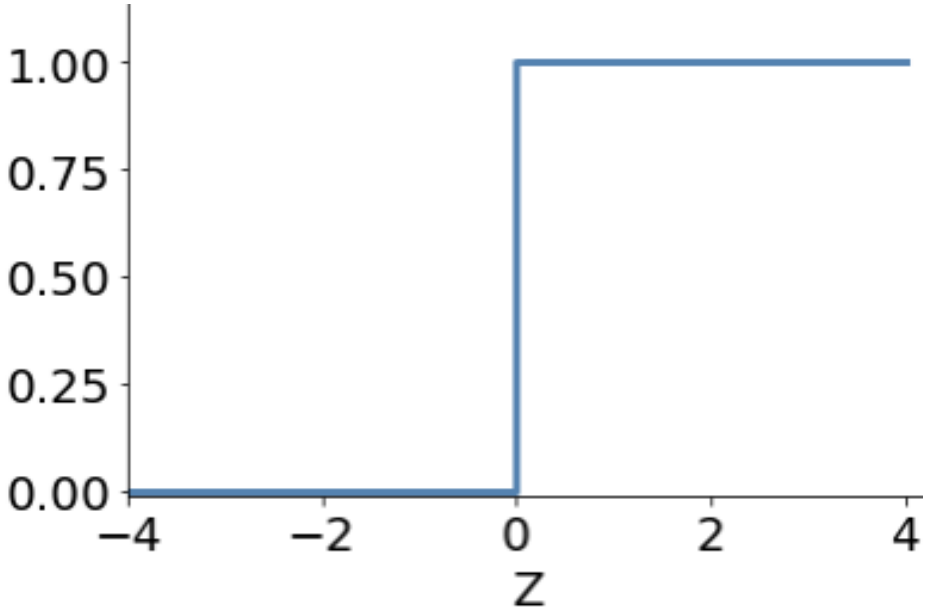
1958

The perceptron algorithm : 1958, Frank Rosenblatt

Perceptrons are ***linear classifiers:*** makes its predictions based on a linear predictor function

combining a set of weights (=parameters) with the feature vector.

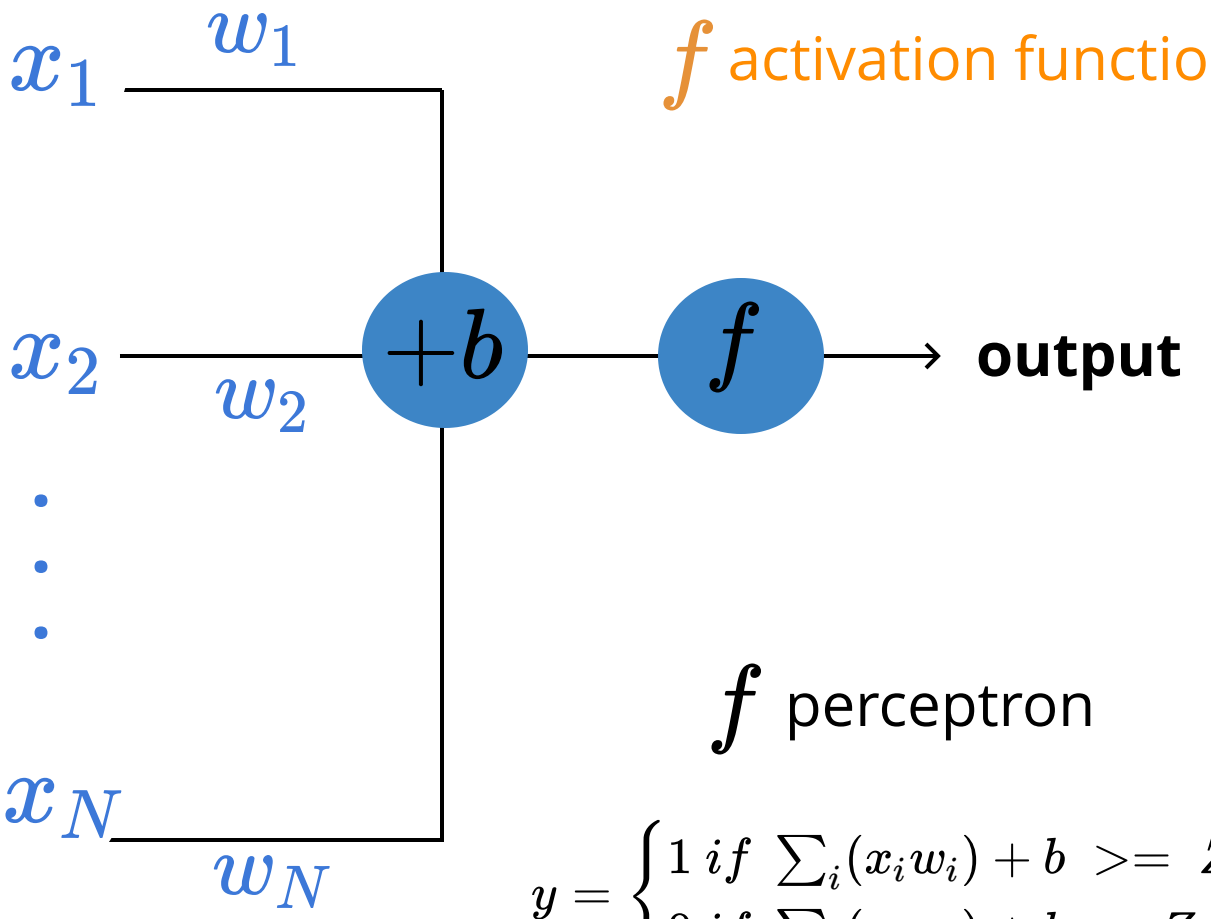
$$y = f(\sum_i w_i x_i + b)$$



w_i weights

b bias

f activation function



f perceptron

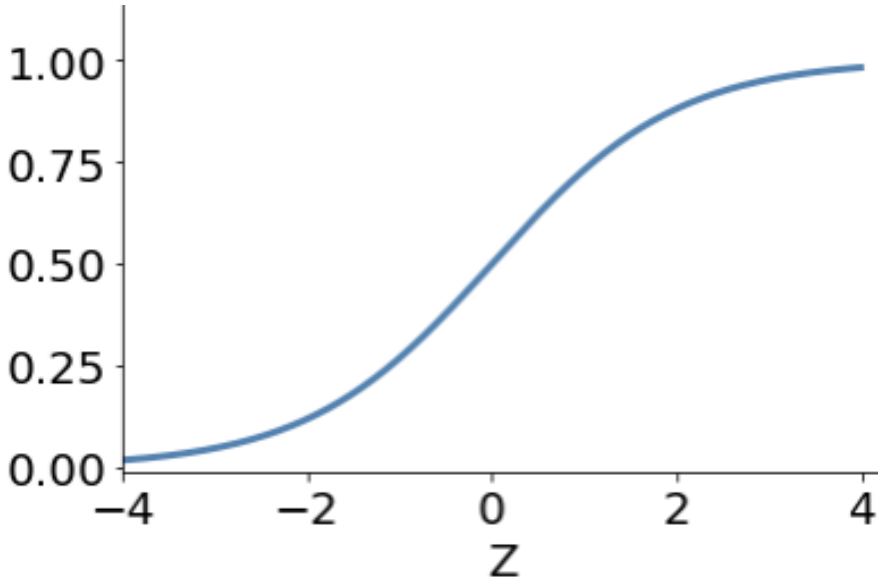
$$y = \begin{cases} 1 \; if \; \sum_i (x_i w_i) + b >= Z \\ 0 \; if \; \sum_i (x_i w_i) + b < Z \end{cases}$$

The perceptron algorithm : 1958, Frank Rosenblatt

Perceptrons are ***linear classifiers:*** makes its predictions based on a linear predictor function

combining a set of weights (=parameters) with the feature vector.

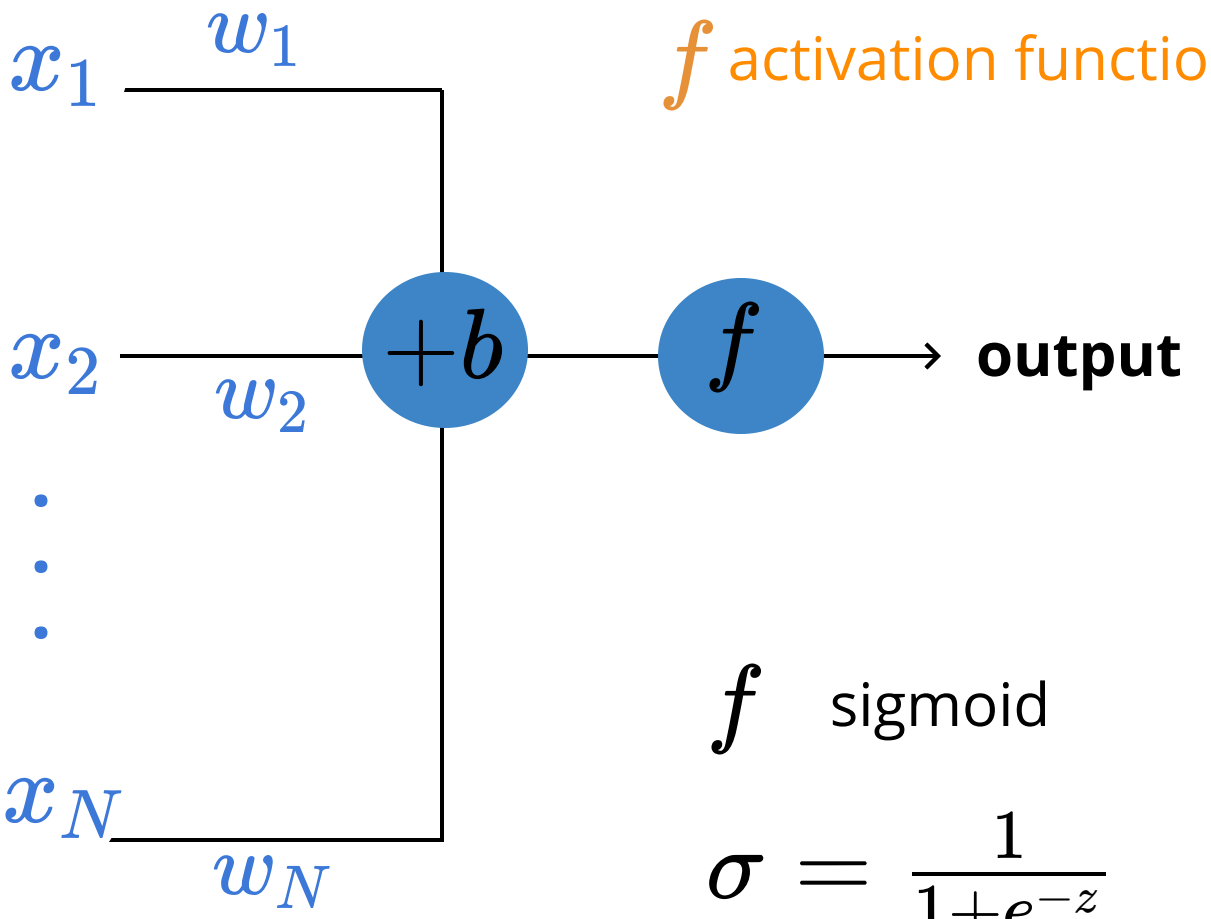
$$y = f\left(\sum_i w_i x_i + b\right)$$



w_i weights

b bias

f activation function

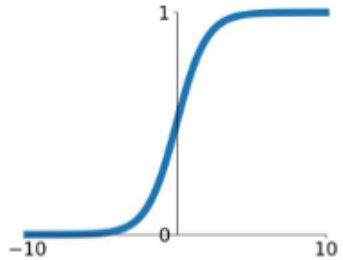


f sigmoid

$$\sigma = \frac{1}{1+e^{-z}}$$

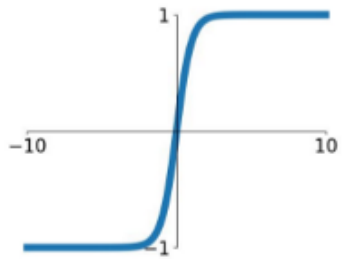
Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



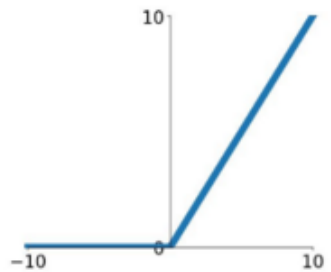
tanh

$$\tanh(x)$$



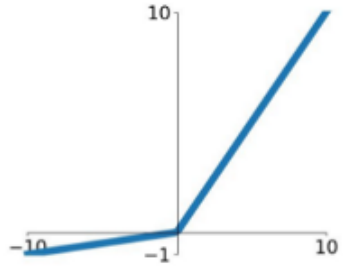
ReLU

$$\max(0, x)$$



Leaky ReLU

$$\max(0.1x, x)$$

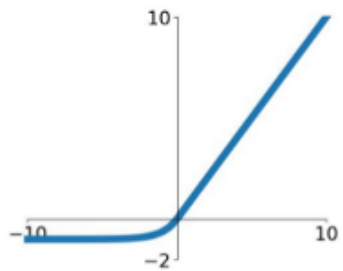


Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



The perceptron algorithm : 1958, Frank Rosenblatt

Perceptron

NEW NAVY DEVICE LEARNS BY DOING

Psychologis Shows Embryo of Computer Designed to Read anc Grow Wiser

WASHINGTON, July 7 (UPI)—The Navy revealed the embryo of an electronic computer today that it expects will be able to walk, talk, see, write, reproduce itself and be conscious of its existence.

The embryo—the Weather Bureau's $2,000,000 "704" computer—learned to differentiate between right and left after fifty attempts in the Navy's demonstration for newsmen.

The service said it would use this principle to build the first of its Perceptron thinking machines that will be able to read and write. It is expected to be finished in about a year at a cost of $100,000.

Dr. Frank Rosenblatt, designer of the Perceptron, conducted the demonstration. He said the machine would be the first device to think as the human brain. As do human beings, Perceptron will make mistakes at first, but will grow wiser as it gains experience, he said.

Dr. Rosenlatt, a research psychologist at the Cornell Aeronautical Laboratory, Buffalo, said Perceptrons might be fired to the planets as mechanical space explorers.

Without Human Controls

The Navy said the perceptron would be the first non-living mechanism "capable of receiving, recognizing and identifying its surroundings without any human training or control."

The "brain" is designed to remember images and information it has perceived itself. Ordinary computers remember only what is fed into them on punch cards or magnetic tape.

Later Perceptrons will be able to recognize people and call out their names and instantly translate speech in one language to speech or writing in another language, it was predicted.

Mr. Rosenlatt said in principle it would be possible to build brains that could reproduce themselves on an assembly line and which would be conscious of their existence.

In today's demonstration, the "704" was fed two cards, one with squares marked on the left side and the other with squares on the right side.

Learn by Doing

In the first fifty trials, the machine made no distinction between them. It then started registering a "Q" for the left squares and "O" for the right squares.

Dr. Rosenlatt said he could explain why the machine learned only in highly technical terms. But he said the computer had undergone a "self-induced change in the wiring diagram."

The first Perceptron will have about 1,000 electronic "association cells" receiving electrical impulses from an eye-like scanning device with 400 photo-cells. The human brain has 10,000,000,000 responsive cells, including 100,000,000 connections with the eyes.

Books Today

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By CHARLES POORE

Claude, author of "Mrs. O'."

Books—Authors

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ALBERT CAMUS: "I have never been able to read any book on the Algerian tragedy without a feeling of unreality, discomfort, and often even anger. Only one book — Germaine Tillion's — seemed to me at once true, fair, and constructive. Germaine Tillion knows what she is talking about. And no one either in Algeria or throughout the world can henceforth discuss the Algerian problem without having read what an understanding and cultivated woman has written about my misunderstood, desperate native land, now stirred by a heart-rending hope."

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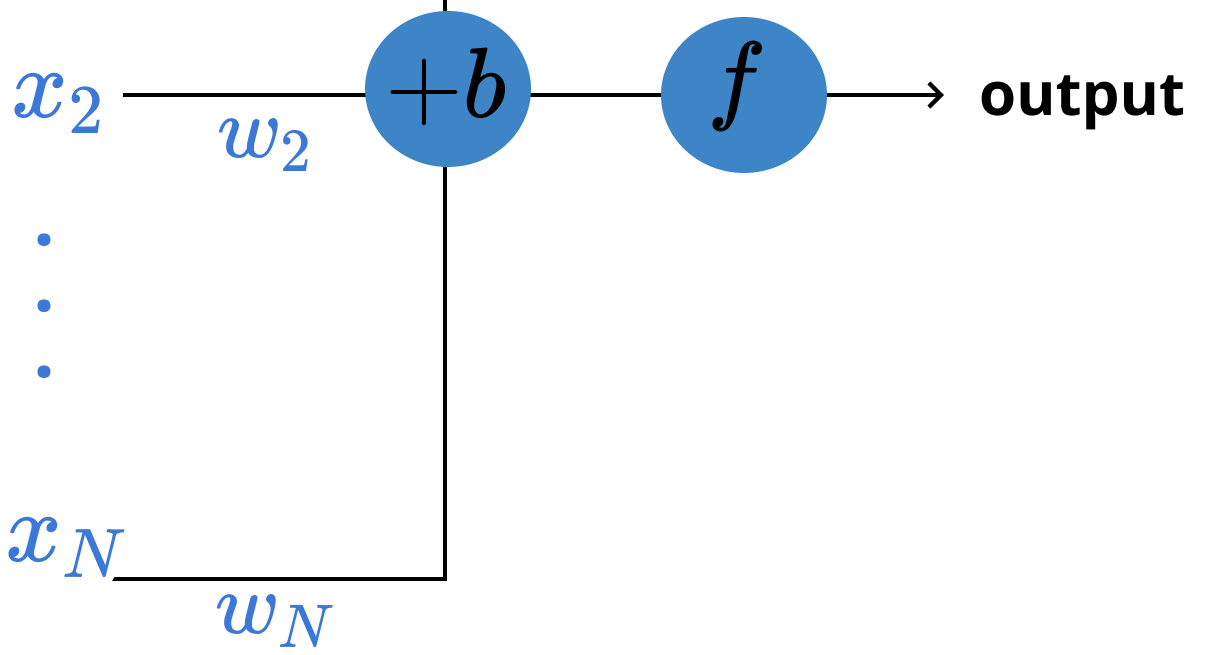
CROSSWORD PUZZLE

Edited by MARGARET FARRAR



w_i weights

b bias

f activation functio

The perceptron algorithm : 1958, Frank Rosenblatt

Perceptron

THE NEW YORK TIMES, TUESDAY, JULY 8, 1958.

NEW NAVY DEVICE LEARNS BY DOING

Psychologist Shows Embryo of Computer Designed to Read and Grow Wiser

WASHINGTON, July 7 (UPI) —The Navy revealed the embryo of an electronic computer today that it expects will be able to walk, talk, see, write, reproduce itself and be conscious of its existence.

The embryo—the Weather Bureau's $2,000,000 "704" computer—learned to differentiate between right and left after fifty attempts in the Navy's demonstration for newsmen.

The service said it would use this principle to build the first of its Perceptron thinking machines that will be able to read and write. It is expected to be finished in about a year at a cost of $100,000.

Dr. Frank Rosenblatt, designer of the Perceptron, conducted the demonstration. He said the machine would be the first device to think as the human brain. As do human beings, Perceptron will make mistakes at first, but will grow wiser as it gains experience, he said.

Dr. Rosenlatt, a research psychologist at the Cornell Aeronautical Laboratory, Buffalo, said Perceptrons might be fired to the planets as mechanical space explorers.

Without Human Controls

The Navy said the perceptron would be the first non-living mechanism "capable of receiving, recognizing and identifying its surroundings without any human training or control."

The "brain" is designed to remember images and information it has perceived itself. Ordinary computers remember only what is fed into them on punch cards or magnetic tape.

Later Perceptrons will be able to recognize people and call out their names and instantly translate speech in one language to speech or writing in another language, it was predicted.

Mr. Rosenlatt said in principle it would be possible to build brains that could reproduce themselves on an assembly line and which would be conscious of their existence.

In today's demonstration, the "704" was fed two cards, one with squares marked on the left side and the other with squares on the right side.

Learn by Doing

In the first fifty trials, the machine made no distinction between them. It then started registering a "Q" for the left squares and "O" for the right squares.

Dr. Rosenlatt said he could explain why the machine learned only in highly technical terms. But he said the computer had undergone a "self-induced change in the wiring diagram."

The first perceptron will have about 1,000 electronic "association cells" receiving electrical impulses from an eye-like scanning device with 400 photo-cells. The human brain has 10,000,000,000 responsive cells, including 100,000,000 connections with the eyes.

Books Today

Books of The Times

By CHARLES POORE

Claude, author of "Mrs. O."

Books—Authors

Just Published!

ALGERIA The Realities by Germaine Tillion

ALBERT CAMUS: "I have never been able to read any book on the Algerian tragedy without a feeling of unreality, discomfort, and often even anger. Only one book—Germaine Tillion's—seemed to me at once true, fair, and constructive. Germaine Tillion knows what she is talking about. And no one either in Algeria or throughout the world can hence forth discuss the Algerian problem without having read what an understanding and cultivated woman has written about my misunderstood, desperate native land, now stirred by a heart-rending hope."

A Borzoi Book
$3.50 at most bookstores
ALFRED A. KNOPF, Publisher

Fort Transfer Approved

House today legislation directing the Army to turn over the thirty-three-acre Fort Varnum installation to Rhode Island for use by the National Guard.

National Best Seller in more than 25 cities ANATOMY of a MURDER By ROBERT TRAVER $4.50 at bookstores ST. MARTIN'S PRESS

AND FOUR TO GO a New York Farrago by REX STOUT Four delectable novels in miniature, each with the stamp of the master detective's genius. VIKING $2.95

"How agreeable it is to read a novel by an author who has no guilt feelings about being agreeable!" This has been said of ELIZABETH CADELL who more than lives up to that commendation in her new novel SHADOWS ON THE WATER

An END to VALOR The Last Days of the Civil War by Philip Van Doren Stern

Bruce Catton: "Perceptive and illuminating."

CROSSWORD PUZZLE

The New York Times

July 8, 1958

NEW NAVY DEVICE LEARNS BY DOING; Psychologist Shows Embryo of Computer Designed to Read and Grow Wiser

The Navy revealed the embryo of an electronic computer today that it expects will be able to walk, talk, see, write, reproduce itself and be conscious of its existence.

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The perceptron algorithm : 1958, Frank Rosenblatt

Perceptron

The New York Times

Google Engineer Claims AI Chatbot Is Sentient: Why That Matters

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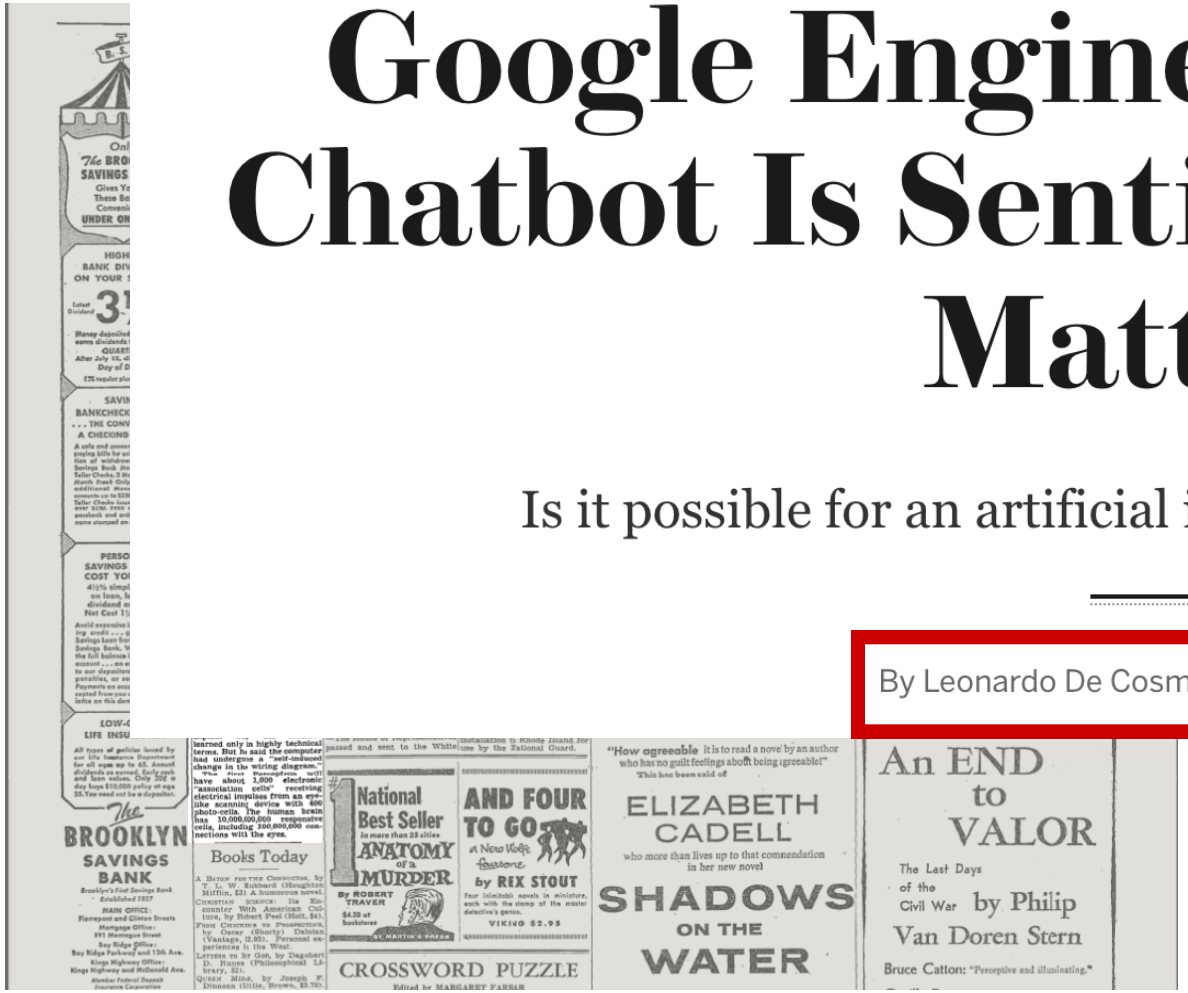
Is it possible for an artificial intelligence to be sentient?

By Leonardo De Cosmo on July 12, 2022



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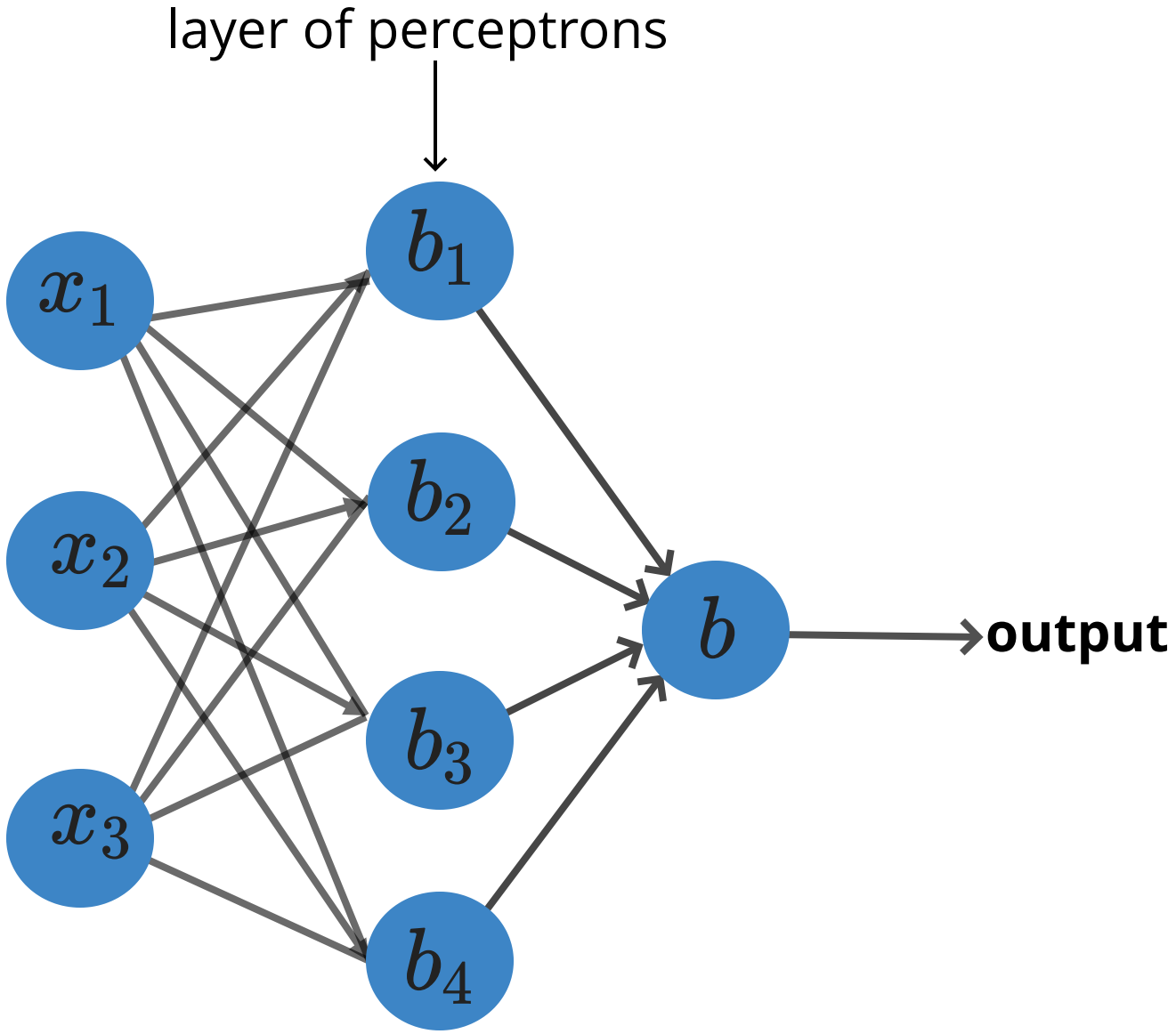
DNN: Deep Learning

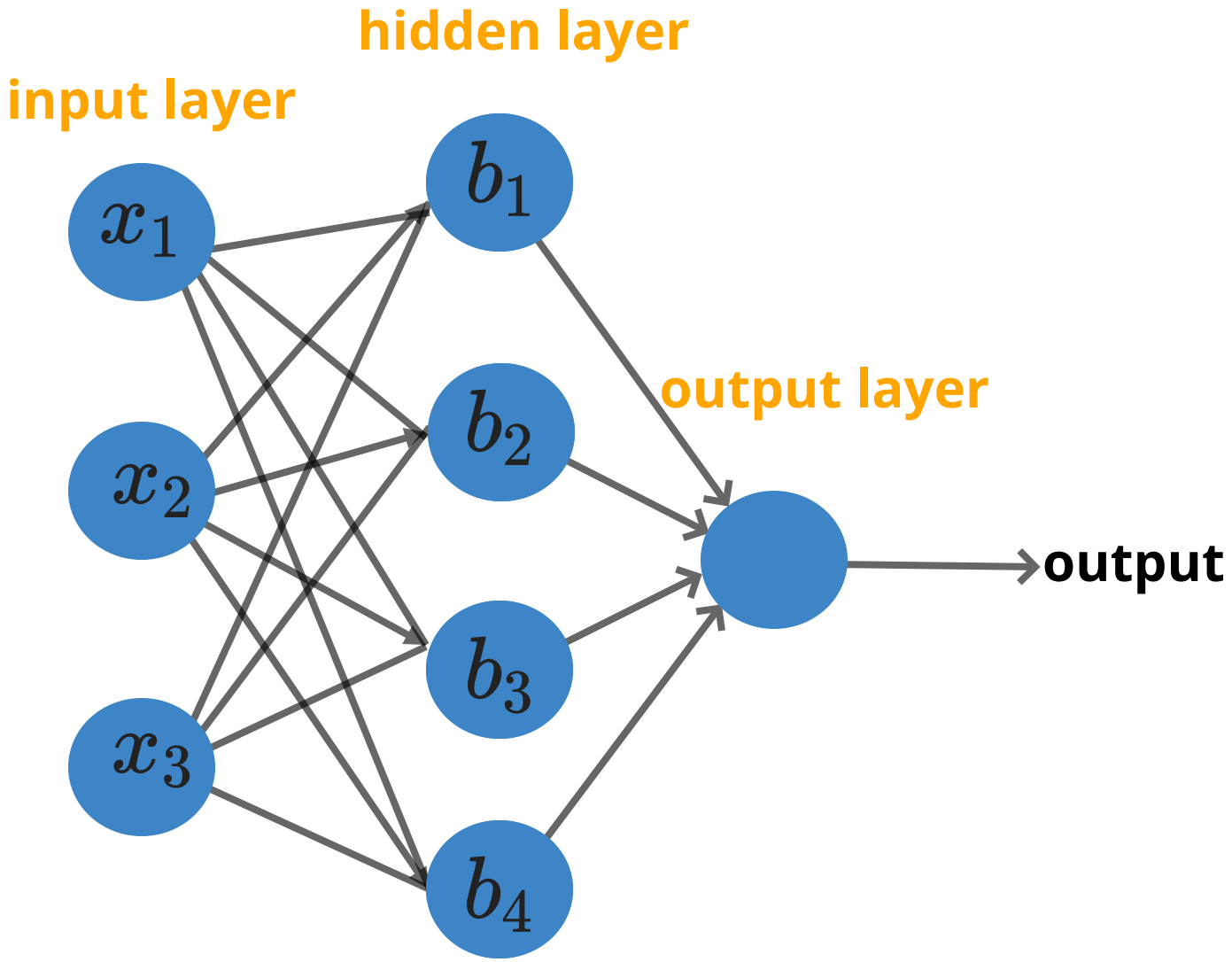
multilayer perceptron



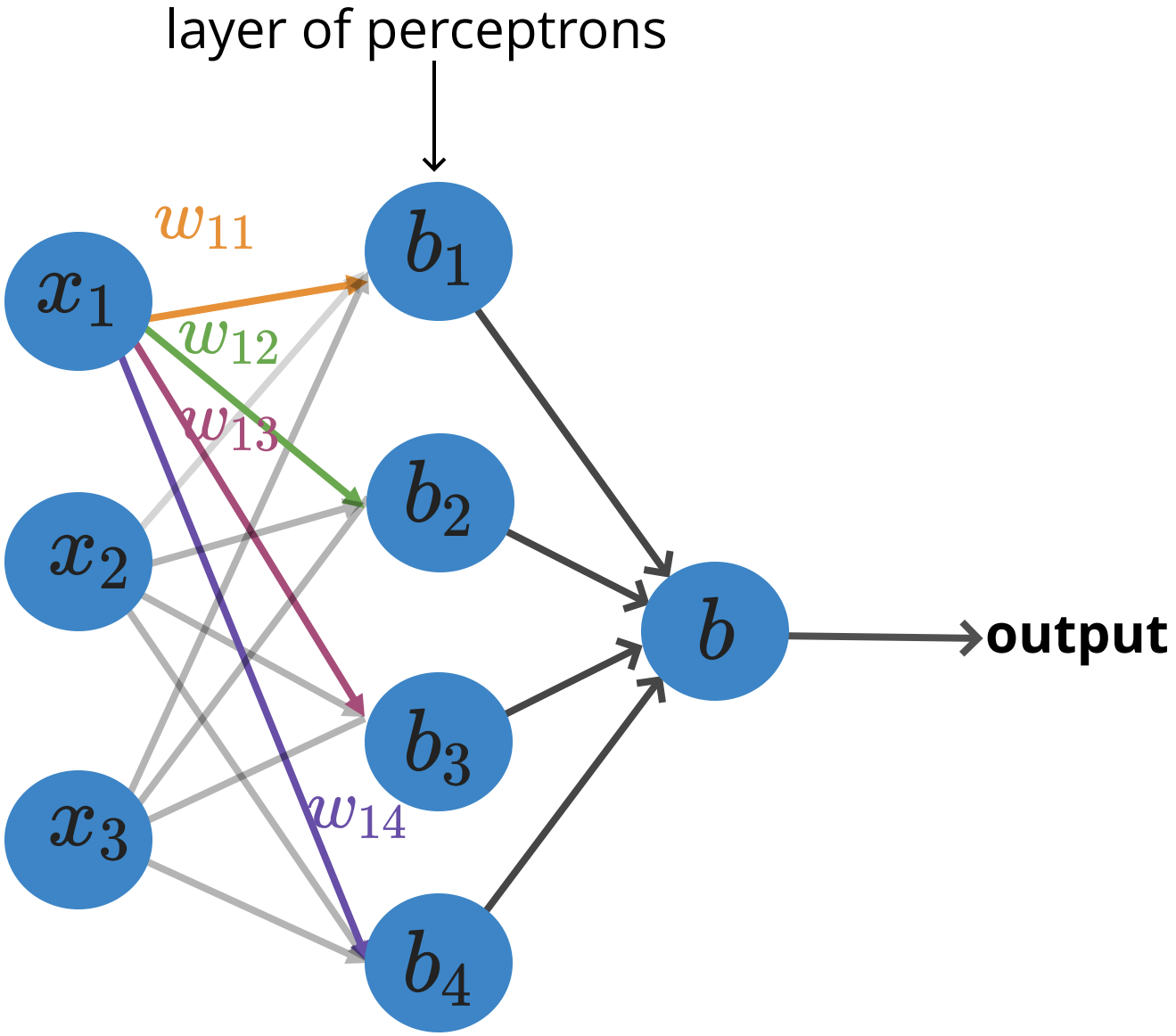
multilayer perceptron

1970: multilayer perceptron architecture

Fully connected: all nodes go to all nodes of the next layer.



multilayer perceptron



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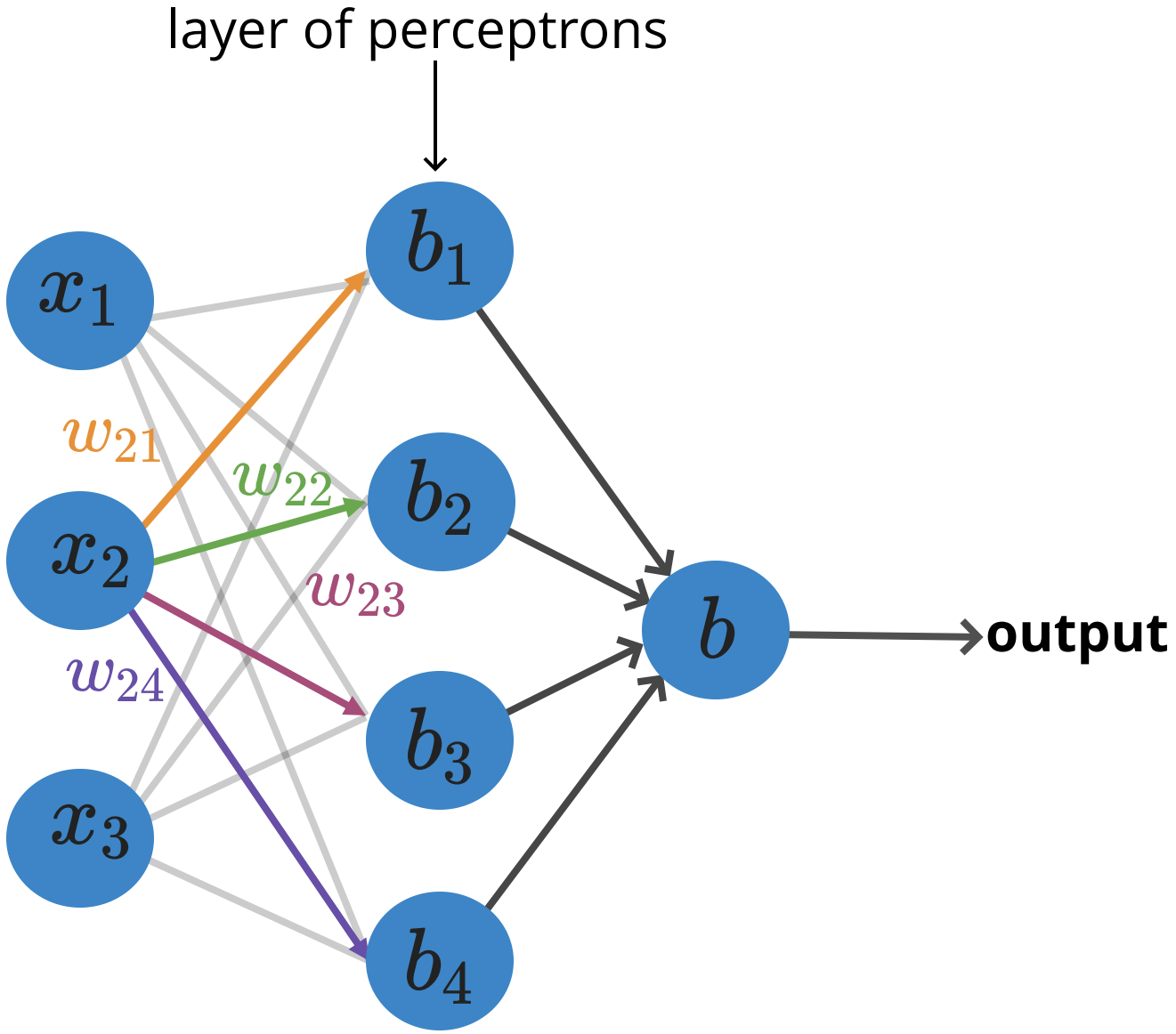
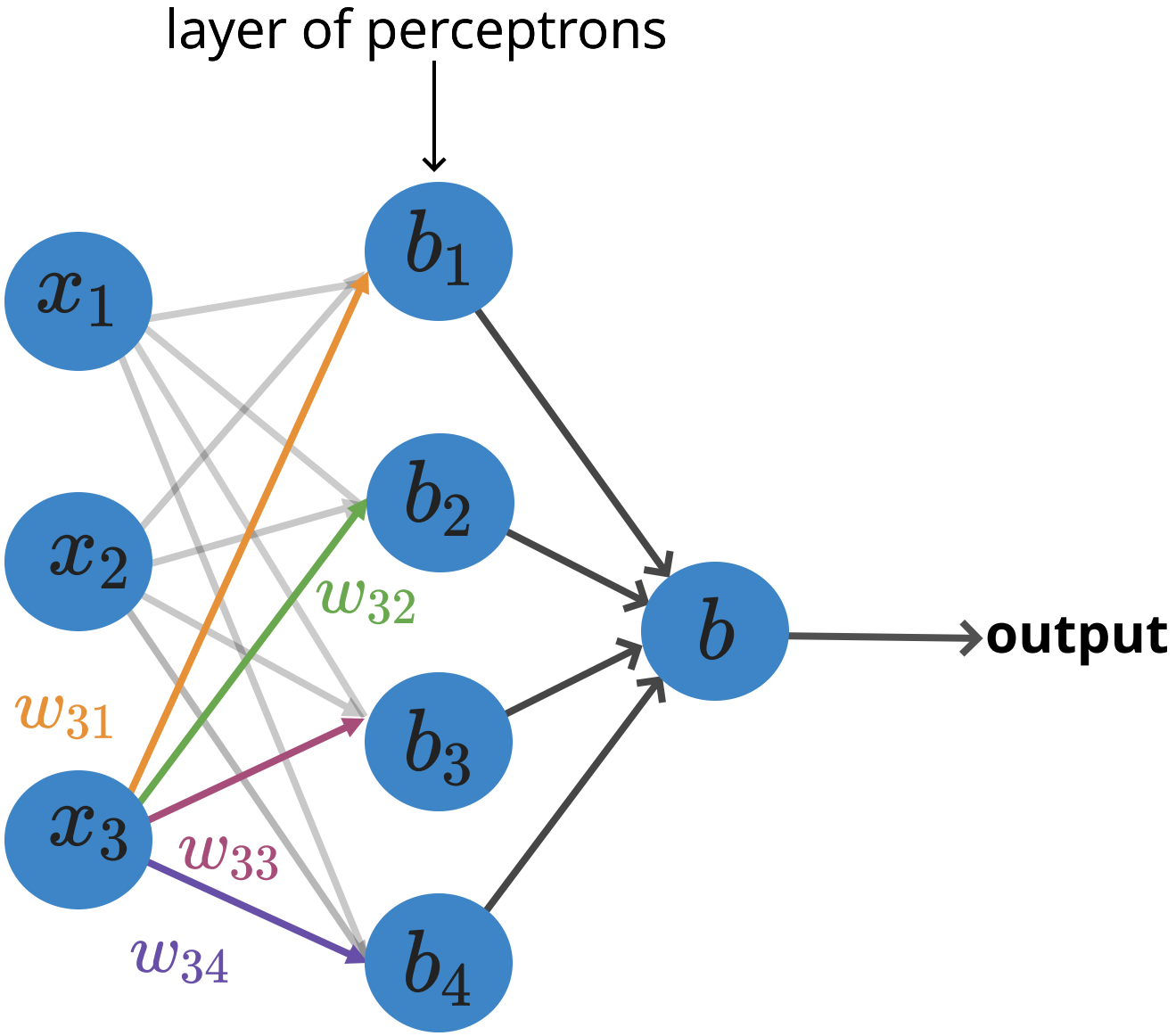


multilayer perceptron



multilayer perceptron

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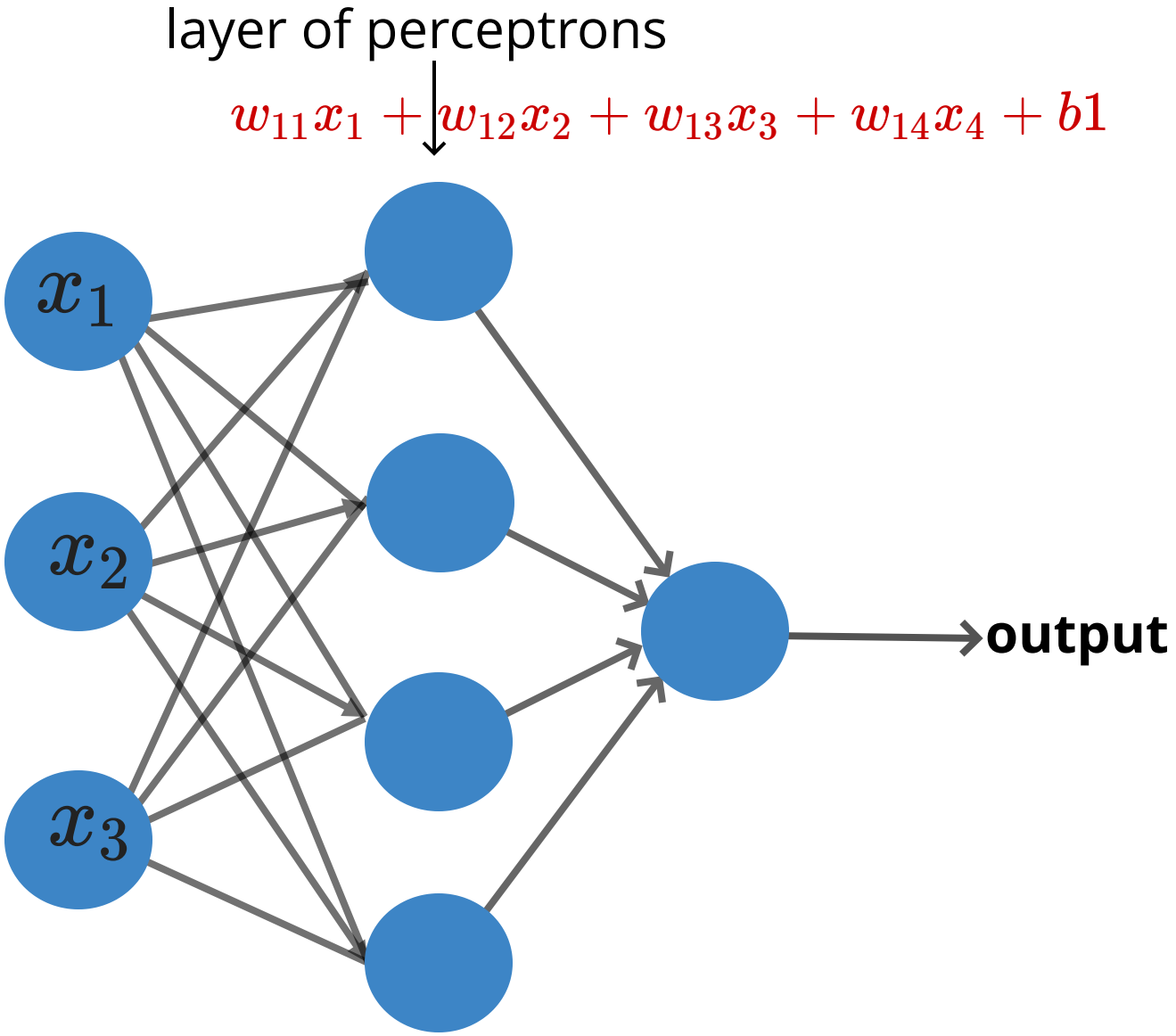


multilayer perceptron

Fully connected: all nodes go to all nodes of the next layer.

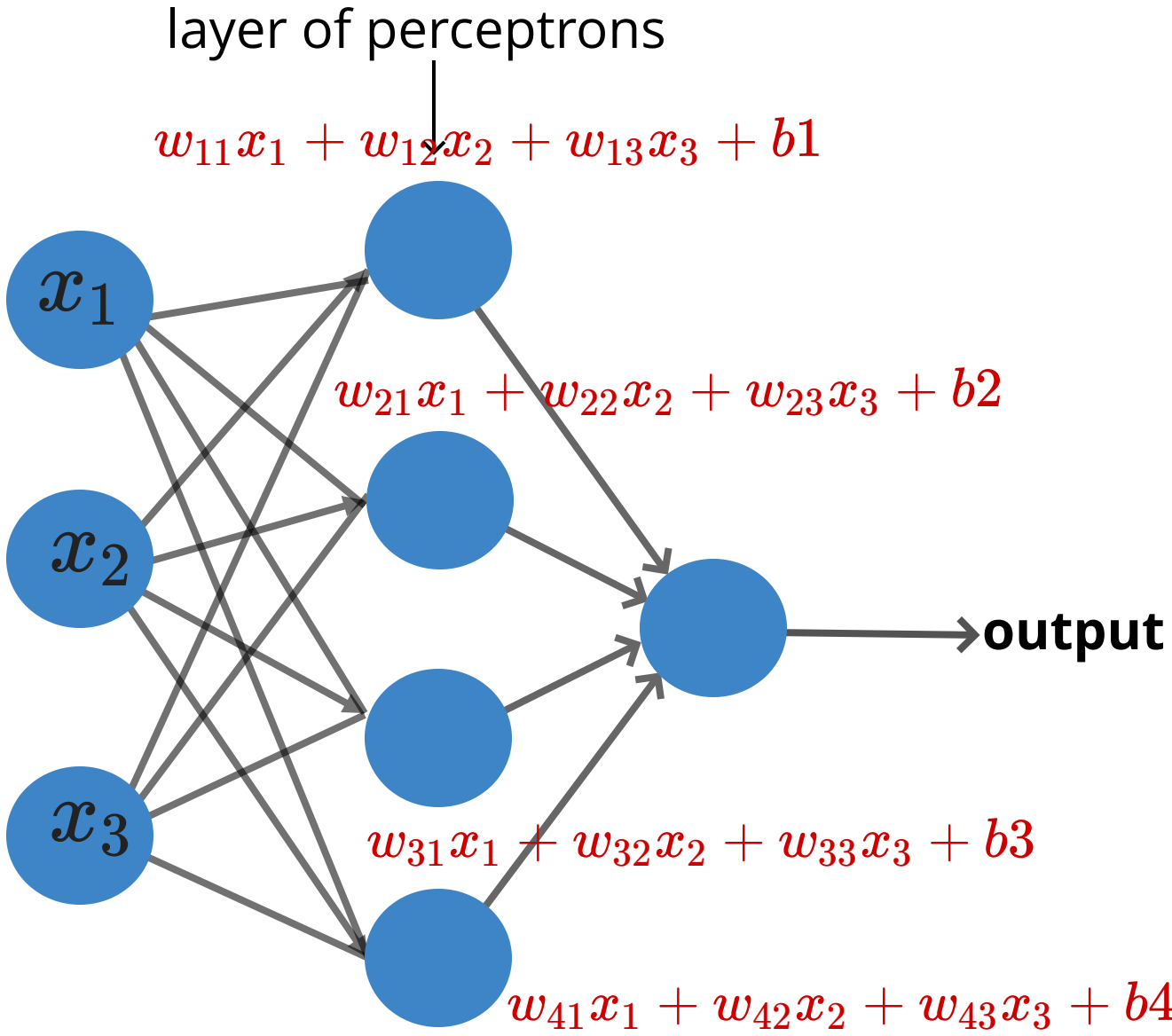
learned parameters

w: weight

sets the sensitivity of a neuron

b: bias:

up-down weights a neuron



multilayer perceptron

Fully connected: all nodes go to all nodes of the next layer.

f: activation function:

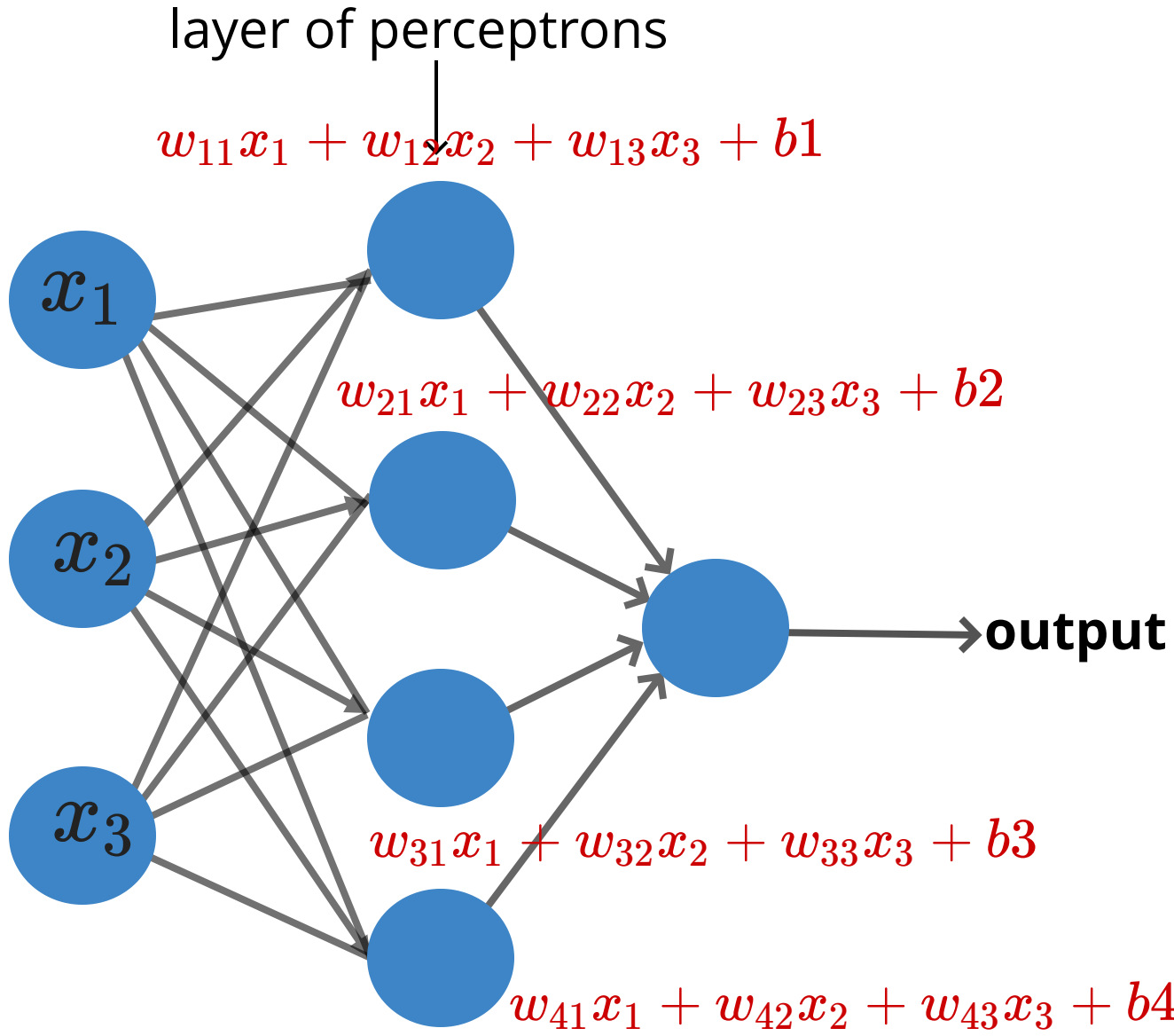
turns neurons on-off

w: weight

sets the sensitivity of a neuron

b: bias:

up-down weights a neuron



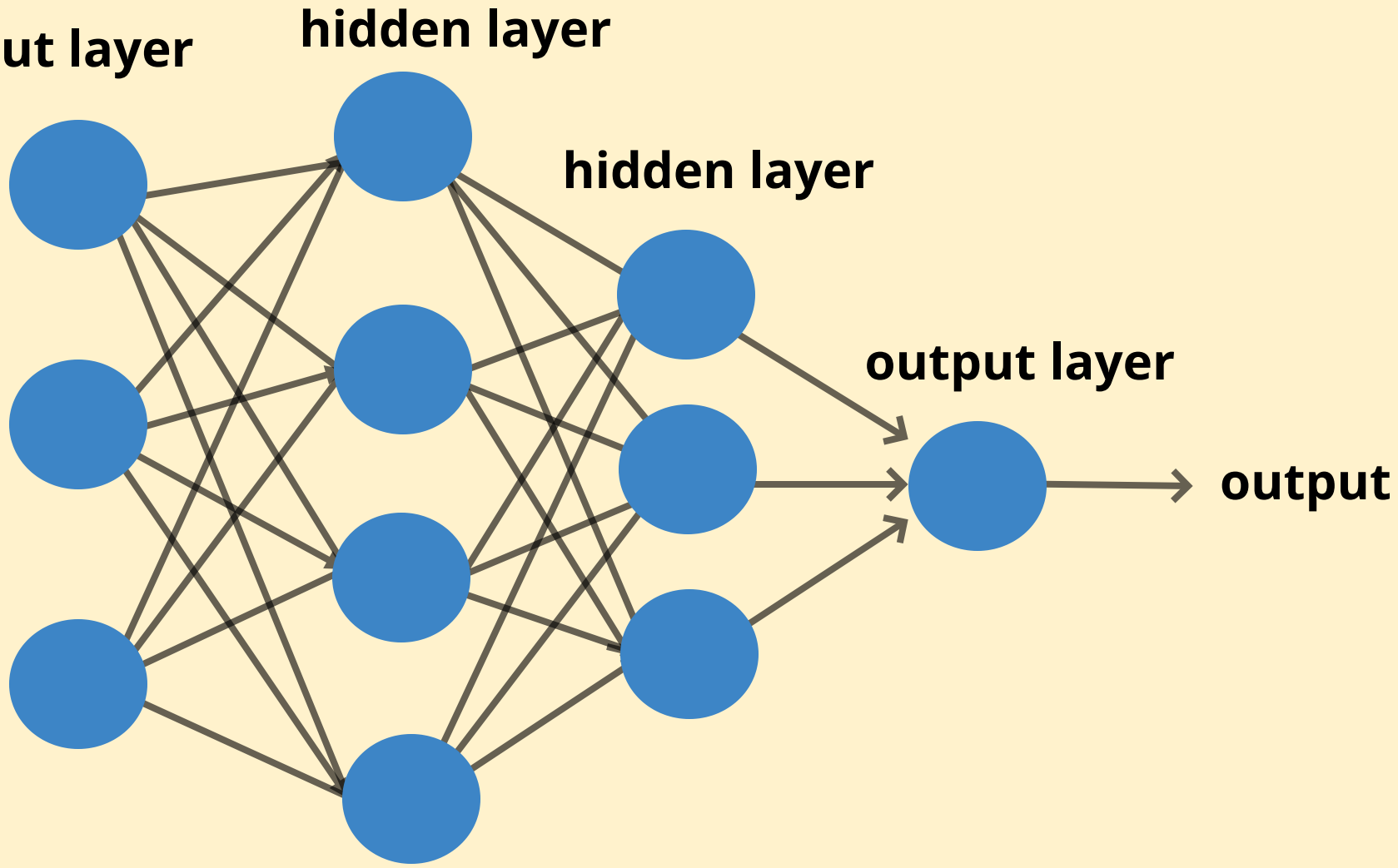
3

DNN:

hyperparameters of DNN

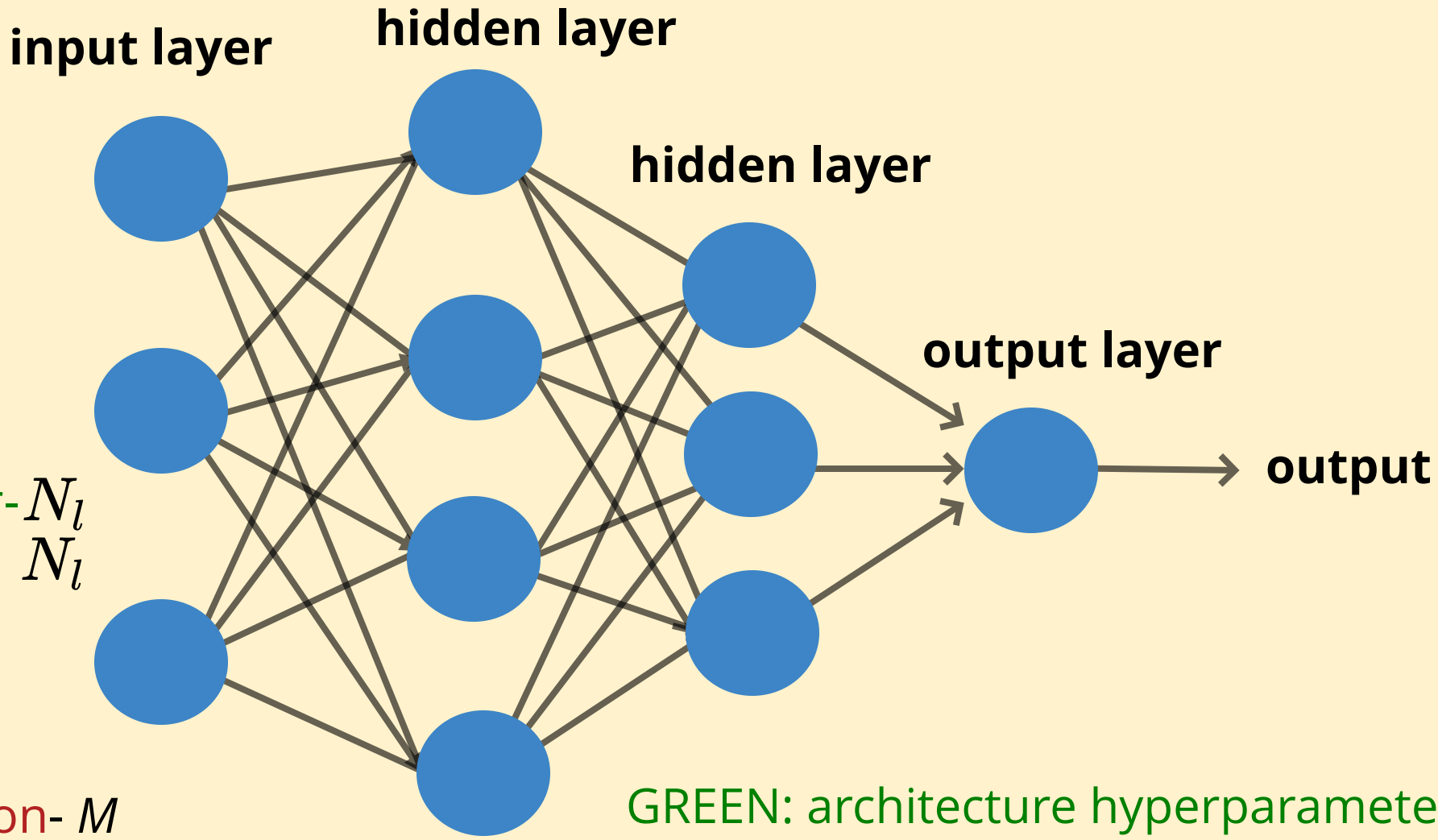
EXERCISE

how many parameters?



EXERCISE

how many hyperparameters?



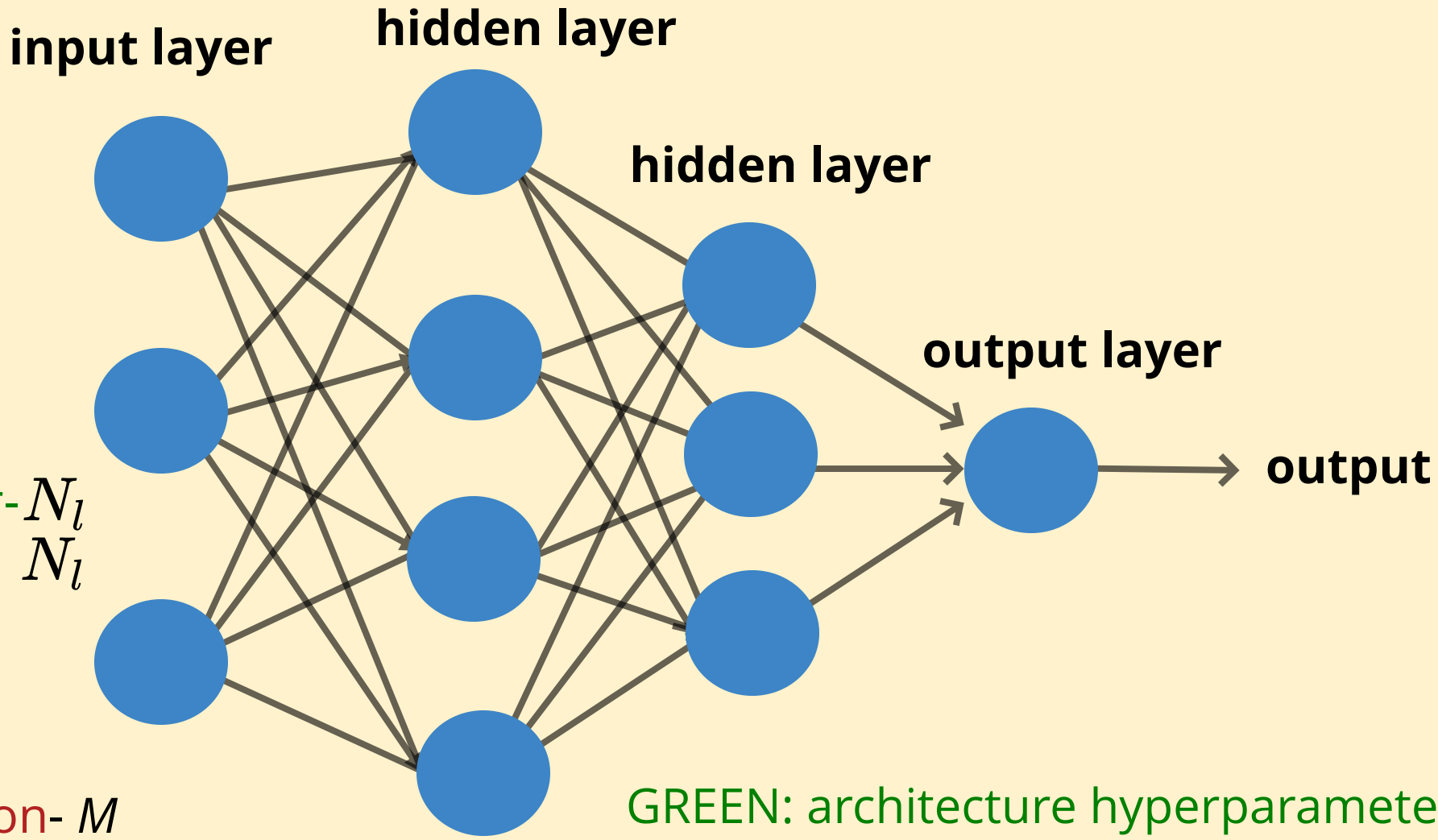
1. number of layers- *1*
2. number of neurons/layer- N_l
3. activation function/layer- N_l
4. layer connectivity- $N_l^{??}$
5. optimization metric - *1*
6. optimization method - *1*
7. parameters in optimization- *M*

GREEN: architecture hyperparamete

RED: training hyperparameters

EXERCISE

how many hyperparameters?



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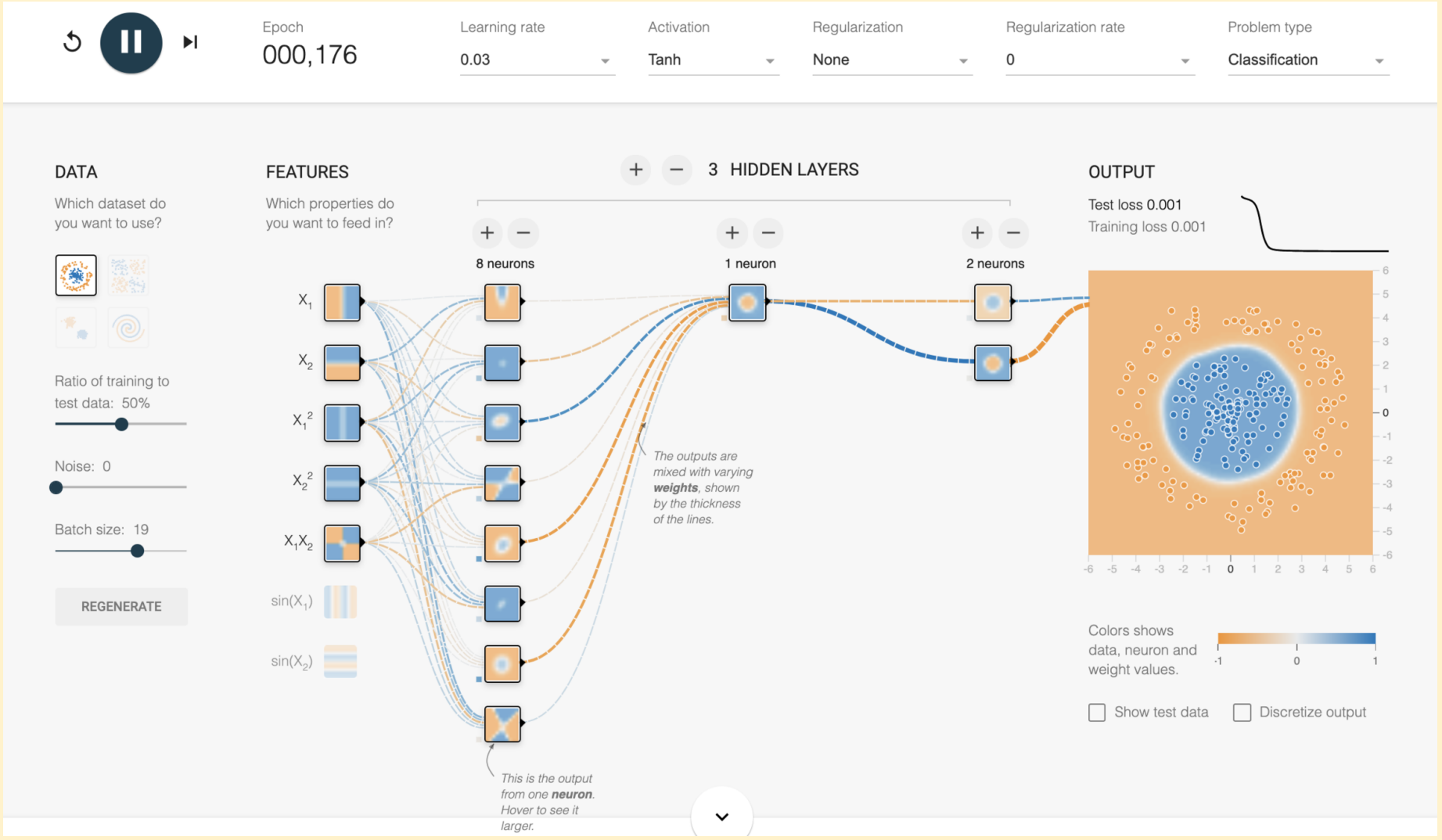
EXERCISE

http://playground.tensorflow.org/



4 DNN: *training DNN*

https://colab.research.google.com/drive/13c9uJ_fPGjszgsyEuYWafR2F4_n-IXeZ

deep neural net

1986: Deep Neural Nets

Fully connected: all nodes go to all nodes of the next layer.

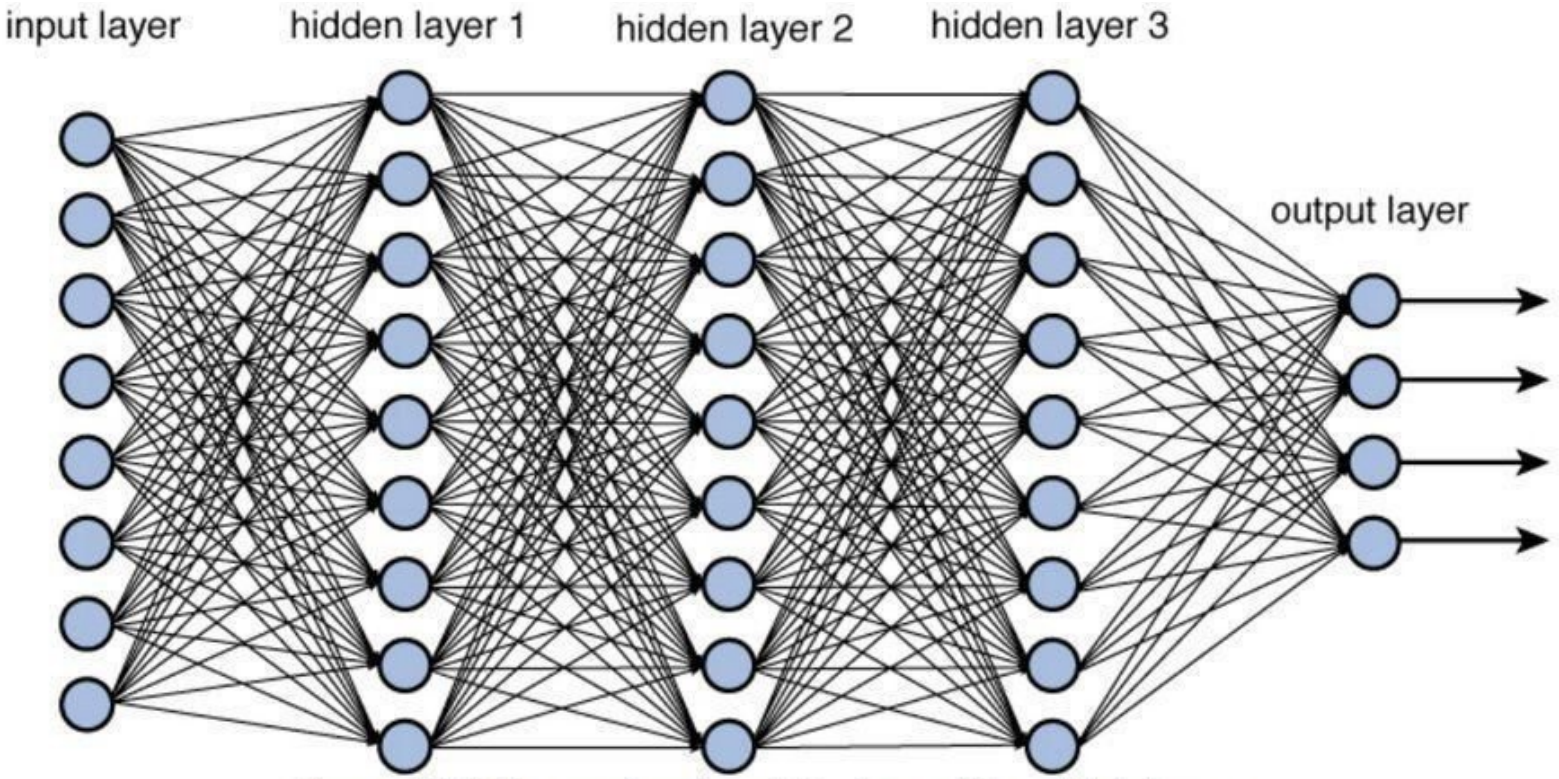


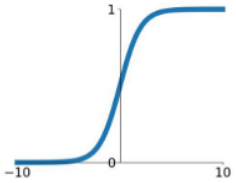
Figure 12.2 Deep network architecture with multiple layers.

f: activation function:

turns neurons on-off

Sigmoid

$\sigma(x) = \frac{1}{1+e^{-x}}$



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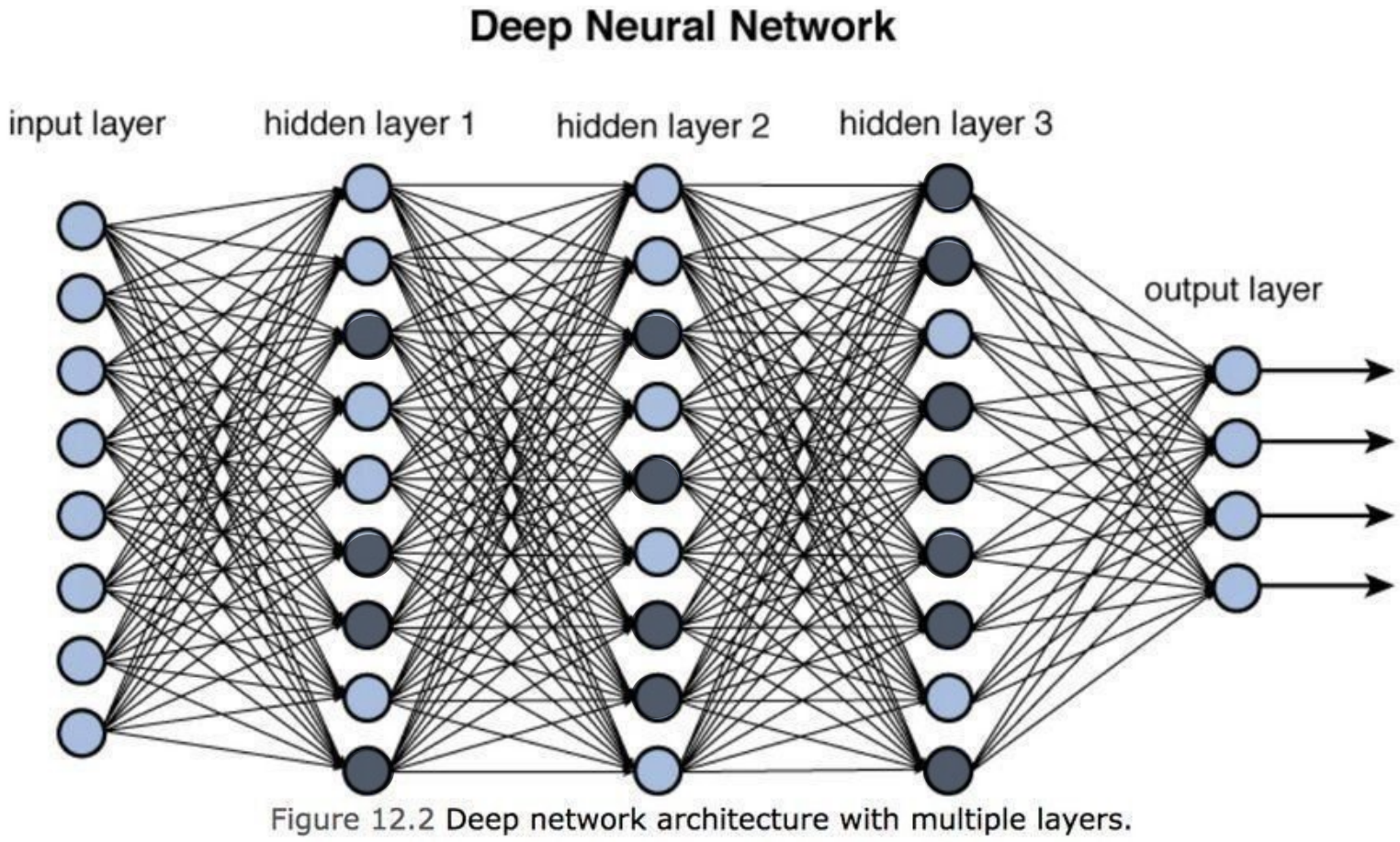


Figure 12.2 Deep network architecture with multiple layers.

In a CNN these layers would not be fully connected except the last one

$$\vec{y} = f_N(....(f_1(\vec{x}W_i + b_1...W_N + b_N)))$$

Seminal paper

Y. LeCun 1998

Gradient-Based Learning Applied to Document Recognition

Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner

Abstract—

Multilayer Neural Networks trained with the backpropagation algorithm constitute the best example of a successful Gradient-Based Learning technique. Given an appropriate network architecture, Gradient-Based Learning algorithms can be used to synthesize a complex decision surface that can classify high-dimensional patterns such as handwritten characters, with minimal preprocessing. This paper reviews various methods applied to handwritten character recognition and compares them on a standard handwritten digit recognition task. Convolutional Neural Networks, that are specifically designed to deal with the variability of 2D shapes, are shown to outperform all other techniques.

Real-life document recognition systems are composed of multiple modules including field extraction, segmentation, recognition, and language modeling. A new learning paradigm, called Graph Transformer Networks (GTN), allows such multi-module systems to be trained globally using Gradient-Based methods so as to minimize an overall performance measure.

Two systems for on-line handwriting recognition are described. Experiments demonstrate the advantage of global training, and the flexibility of Graph Transformer Networks.

A Graph Transformer Network for reading bank check is also described. It uses Convolutional Neural Network character recognizers combined with global training techniques to provides record accuracy on business and personal checks. It is deployed commercially and reads several million checks per day.

I. Introduction

Over the last several years, machine learning techniques, particularly when applied to neural networks, have played an increasingly important role in the design of pattern recognition systems. In fact, it could be argued that the availability of learning techniques has been a crucial factor in the recent success of pattern recognition applications such as continuous speech recognition and handwriting recognition.

The main message of this paper is that better pattern recognition systems can be built by relying more on automatic learning, and less on hand-designed heuristics. This is made possible by recent progress in machine learning and computer technology. Using character recognition as a case study, we show that hand-crafted feature extraction can be advantageously replaced by carefully designed learning machines that operate directly on pixel images. Using document understanding as a case study, we show that the traditional way of building recognition systems by manually integrating individually designed modules can be replaced by a unified and well-principled design paradigm, called *Graph Transformer Networks*, that allows training

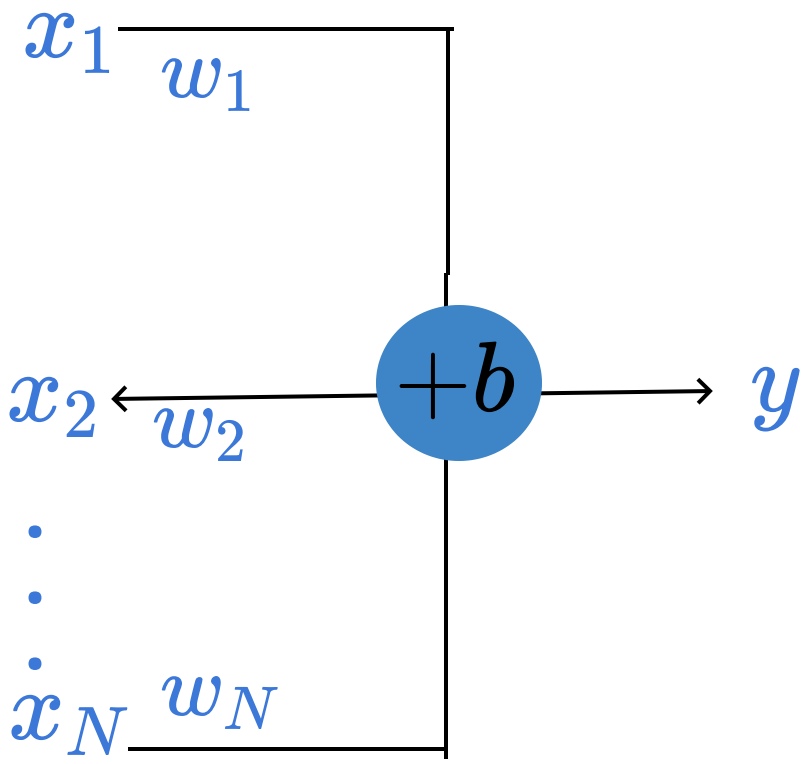
http://yann.lecun.com/exdb/publis/pdf/lecun-01a.pdf

back-propagation

y : prediction

Any linear model:

y$_{true}$: target



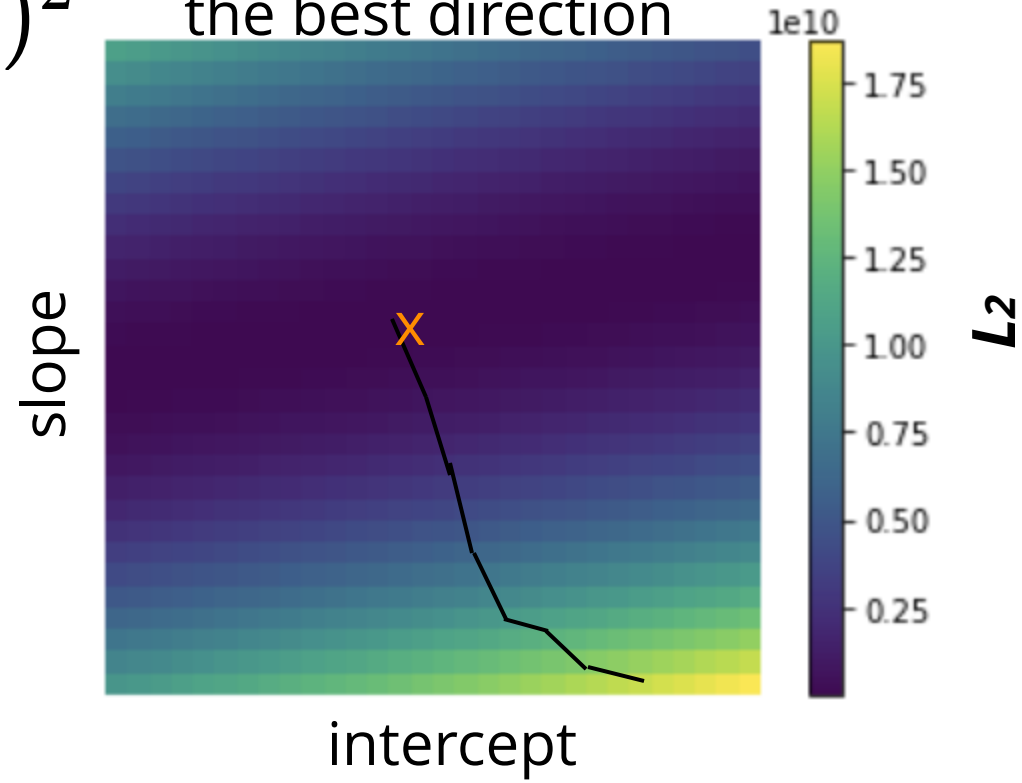
$$\vec{y} = \vec{x}W + b$$

Error: e.g.

$$L_2 = (y - y_{\text{true}})^2$$

Find the best parameters by finding the minimum of the L2 hyperplane

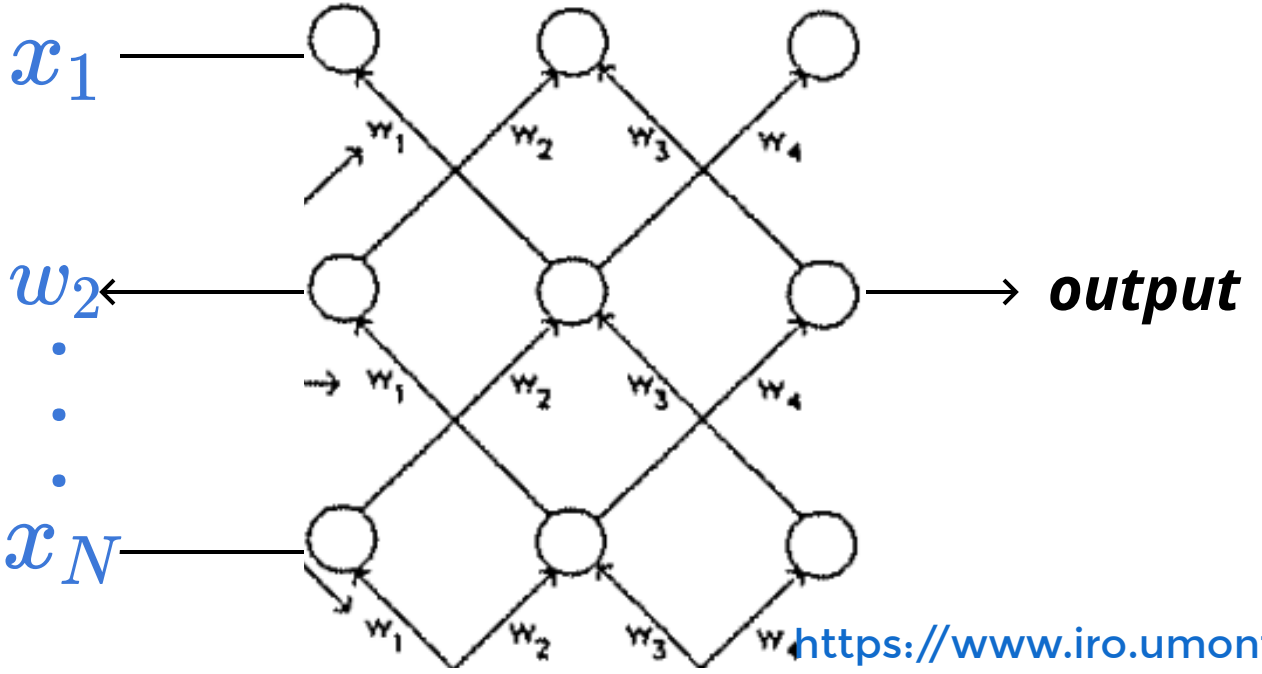
at every step look around and choose the best direction



back-propagation

how does linear descent look when you have a whole network structure with hundreds of weights and biases to optimize??

$$x_j = \sum_i y_i w_{ji} \qquad y_j = \frac{1}{1+e^{-x_j}}$$



nature

Learning representations by back-propagating errors

David E. Rumelhart, Geoffrey E. Hinton & Ronald J. Williams

Nature **323**, 533–536(1986) | Cite this article

22k Accesses | **7872** Citations | **167** Altmetric | Metrics

Abstract

We describe a new learning procedure, back-propagation, for networks of neurone-like units. The procedure repeatedly adjusts the weights of the connections in the network so as to minimize a measure of the difference between the actual output vector of the net and the desired output vector. As a result of the weight adjustments, internal 'hidden' units which are not part of the input or output come to represent important features of the task domain, and the regularities in the task are captured by the interactions of these units. The ability to create useful new features distinguishes back-propagation from earlier, simpler methods such as the perceptron-convergence procedure[1].

https://www.iro.umontreal.ca/~vincentp/ift3395/lectures/backprop_old.pdf

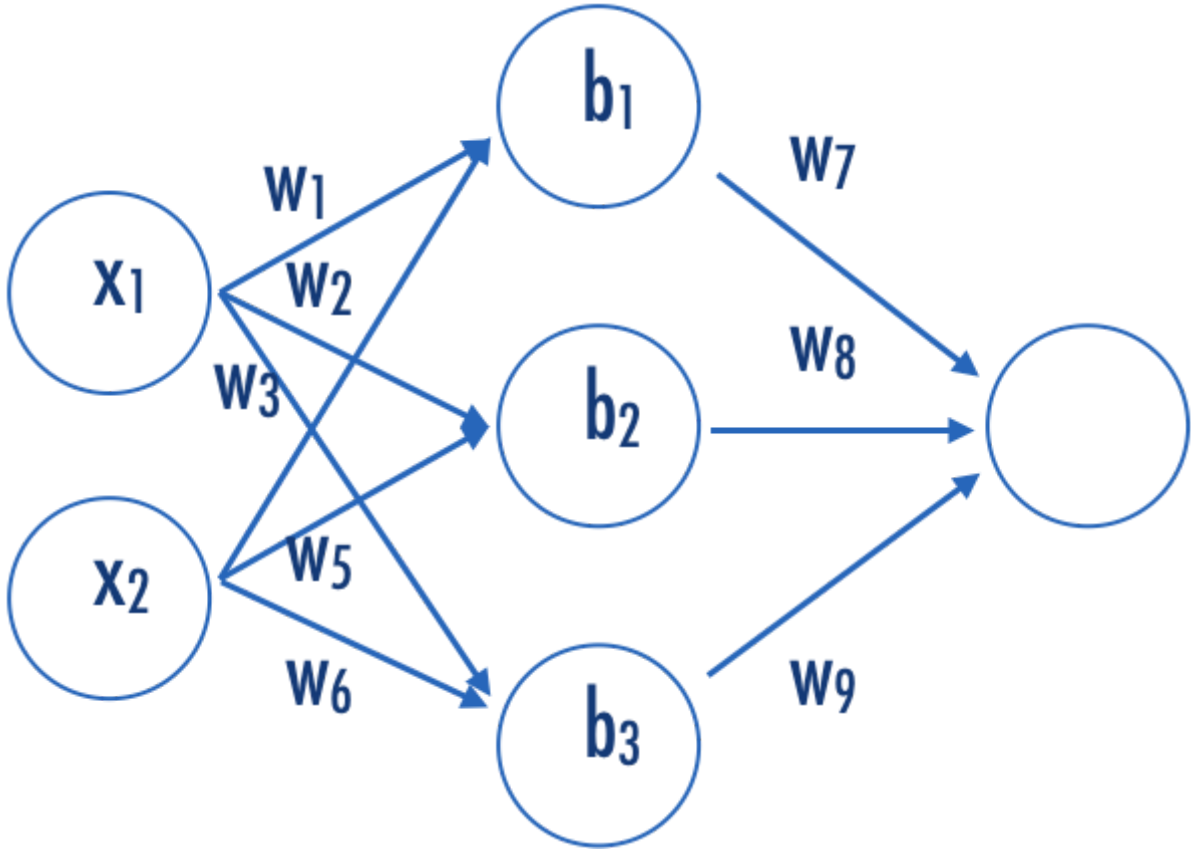
Training models with this many parameters requires a lot of care:

. defining the metric

. optimization schemes

. training/validation/testing sets

But just like our simple linear regression case, the fact that small changes in the parameters leads to small changes in the output for the right activation functions.



define a cost function, e.g.

$$C = \frac{1}{2}|y - a^L|^2 = \frac{1}{2}\sum_j (y_j - a_j^L)^2$$

$$\text{output} = \frac{1}{1+e^{-\frac{w_7}{1+e^{-w_1x_1-w_4x_2-b_1}}-\frac{w_8}{1+e^{-w_2x_1-w_5x_2-b_2}}-\frac{w_9}{1+e^{-w_3x_1-w_6x_2-b_3}}-b_4}}$$

$$\vec{y} = f_N(....(f_1(\vec{x}W_i + b_1 ... W_N + b_N)))$$

Training a DNN

Training models with this many parameters requires a lot of care:

. defining the metric

. optimization schemes

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But just like our simple linear regression case, the fact that small changes in the parameters leads to small changes in the output for the right activation functions.

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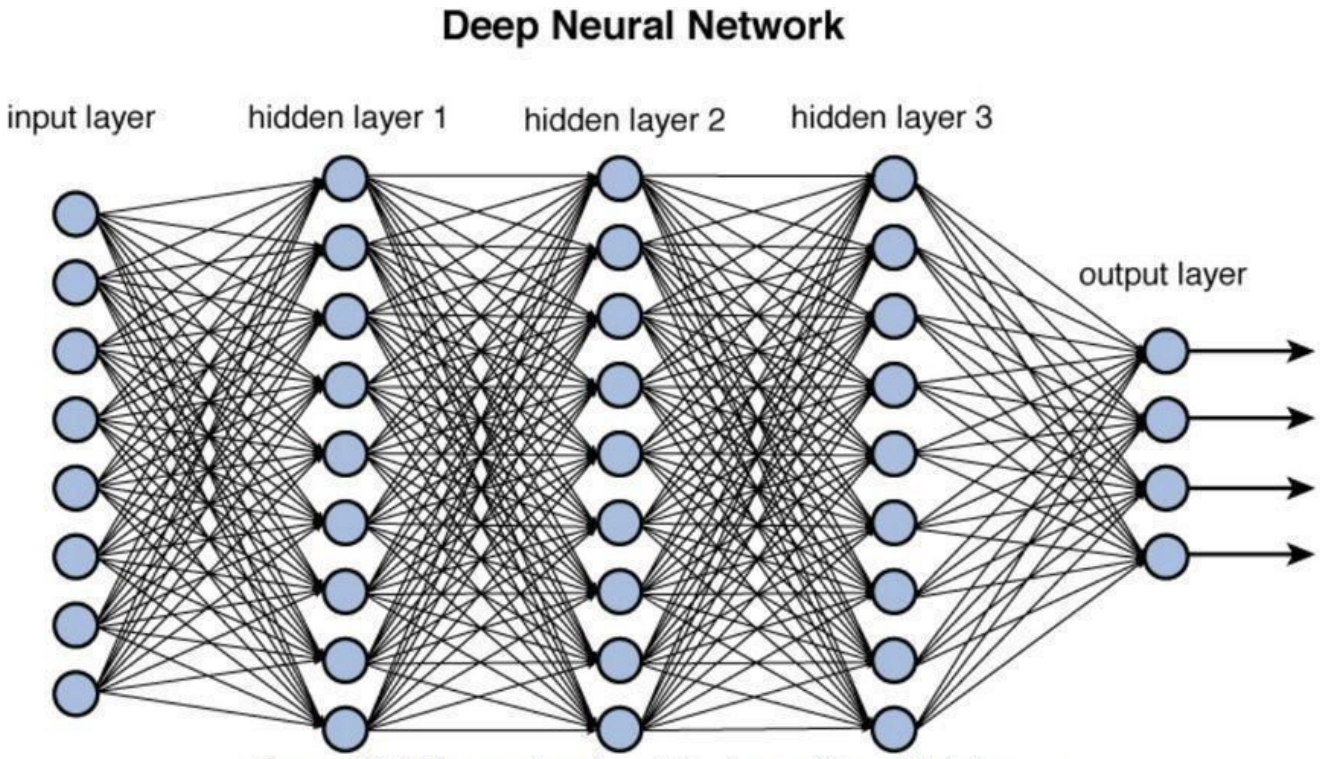

Figure 12.2 Deep network architecture with multiple layers.

feed data forward through network and calculate cost metric

for each layer, calculate effect of small changes on next layer

$$\vec{y} = f_N(....(f_1(\vec{x}W_i + b_1 ... W_N + b_N)))$$

Training a DNN

back-propagation

how does linear descent look when you have a whole network structure with hundreds of weights and biases to optimize??

think of applying just gradient to a function of a function... use:

1) partial derivatives, 2) chain rule

define a cost function, e.g. $C = \frac{1}{2}|y-a^L|^2 = \frac{1}{2}\sum_j (y_j - a_j^L)^2$

An equation for the error in the output layer, δ^L: The components of δ^L are given by

$$\delta^L_j = \frac{\partial C}{\partial a^L_j}\sigma'(z^L_j). \tag{BP1}$$

matrix-based form, as

$$\delta^L = \nabla_a C \odot \sigma'(z^L). \tag{BP1a}$$

Here, $\nabla_a C$ is defined to be a vector whose components are the partial derivatives $\partial C/\partial a^L_j$. You can think of $\nabla_a C$ as expressing the rate of change of C with respect to the output activations

The backpropagation equations provide us with a way of computing the gradient of the cost function. Let's explicitly write this out in the form of an algorithm:

1. **Input x:** Set the corresponding activation a^1 for the input layer.
2. **Feedforward:** For each $l = 2, 3, \ldots, L$ compute $z^l = w^l a^{l-1} + b^l$ and $a^l = \sigma(z^l)$.
3. **Output error δ^L:** Compute the vector $\delta^L = \nabla_a C \odot \sigma'(z^L)$.
4. **Backpropagate the error:** For each $l = L-1, L-2, \ldots, 2$ compute $\delta^l = ((w^{l+1})^T \delta^{l+1}) \odot \sigma'(z^l)$.
5. **Output:** The gradient of the cost function is given by $\frac{\partial C}{\partial w^l_{jk}} = a^{l-1}_k \delta^l_j$ and $\frac{\partial C}{\partial b^l_j} = \delta^l_j$.

Examining the algorithm you can see why it's called *back*propagation. We compute the error vectors δ^l backward, starting from the final layer. It may seem peculiar that we're going

http://neuralnetworksanddeeplearning.com/chap2.html

$$\vec{y} = f_N(....(f_1(\vec{x}W_i + b_1 ... W_N + b_N)))$$

Punch Line

Deep Neural Net are not
some fancy-pants
methods, they are just
linear models with a
bunch of parameters

Black Box?

Because they have many parameters they are difficult to "interpret" (no easy feature extraction)

that may be ok because they are prediction machines

Black Box?

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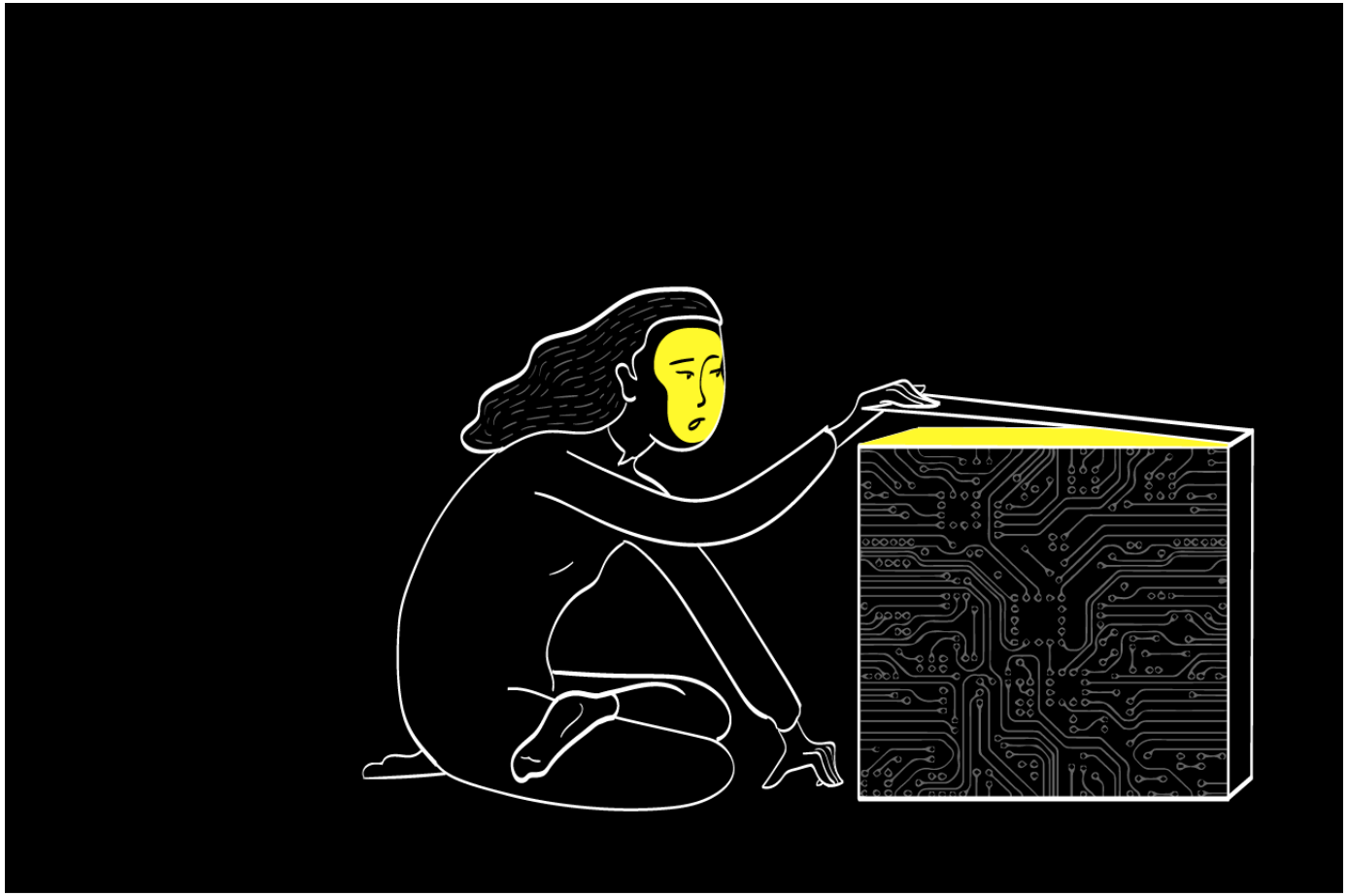
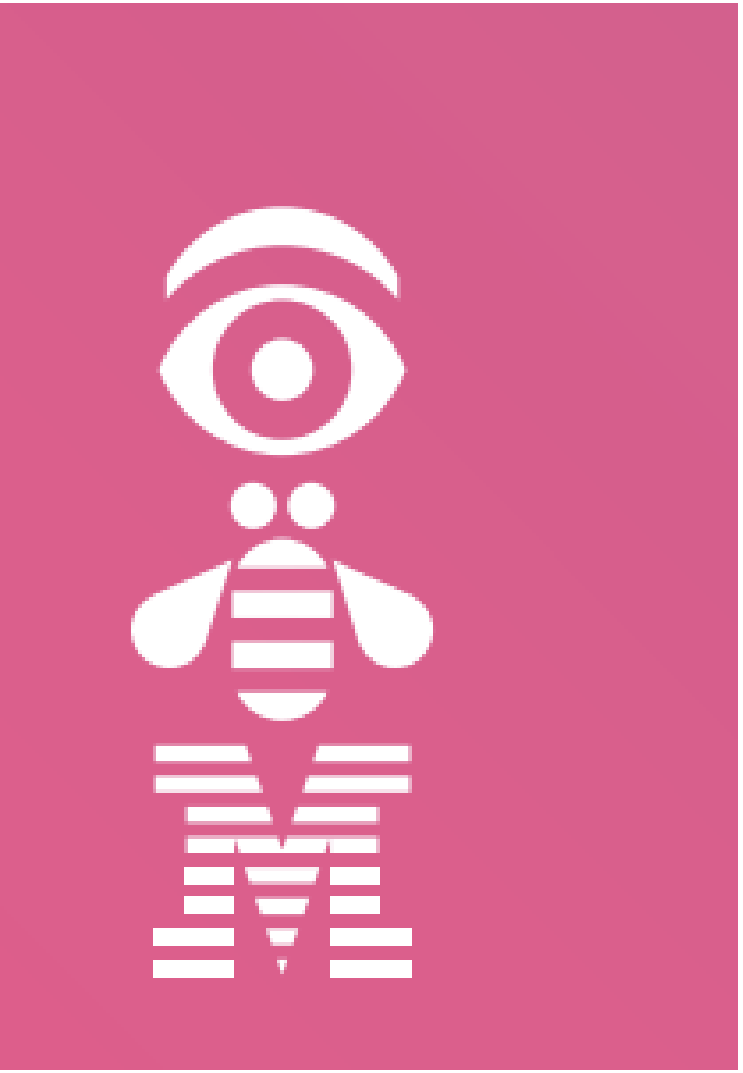
Epistemic transparency

Accountability: who is responsible if an algorithm does harm

Right to explanation: the scope of a general "right to explanation" is a matter of ongoing debate



tration by Hanne Morstad



Everyday Ethics for Artificial Intelligence

Five Areas of Ethical Focus

Accountability
Value Alignment
Explainability
Fairness
User Data Rights

algorithmic transparency

strictly policy issues:

proprietary algorithms + audability

technical + policy issues:

data access and redress + data provenance

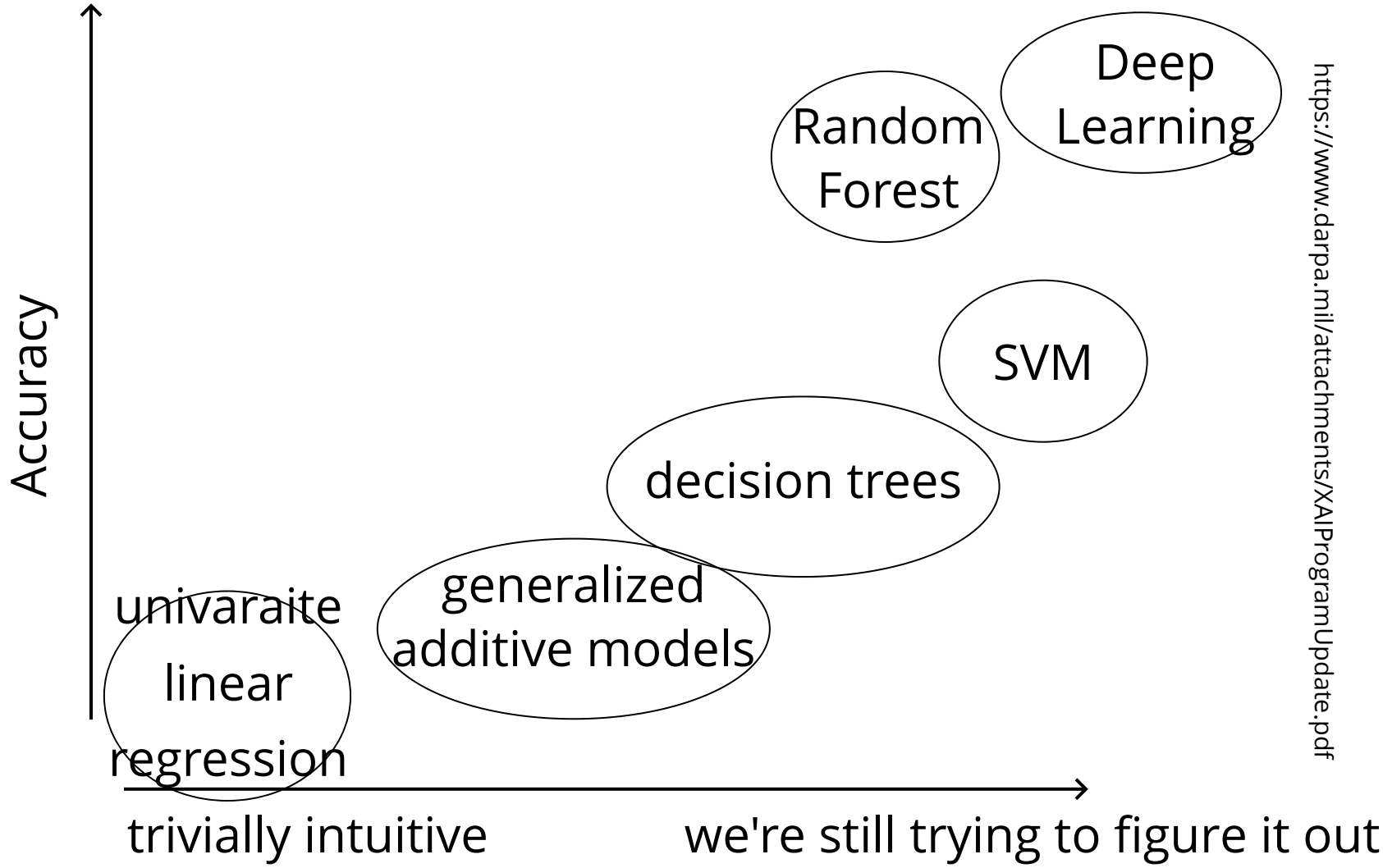
Principles for Algorithmic Transparency and Accountability

1. **Awareness:** Owners, designers, builders, users, and other stakeholders of analytic systems should be aware of the possible biases involved in their design, implementation, and use and the potential harm that biases can cause to individuals and society.
2. **Access and Redress:** Regulators should encourage the adoption of mechanisms that enable questioning and redress for individuals and groups that are adversely affected by algorithmically informed decisions.
3. **Accountability:** Institutions should be held responsible for decisions made by the algorithms that they use, even if it is not feasible to explain in detail how the algorithms produce their results.
4. **Explanation:** Systems and institutions that use algorithmic decision-making are encouraged to produce explanations regarding both the procedures followed by the algorithm and the specific decisions that are made. This is particularly important in public policy contexts.
5. **Data Provenance:** A description of the way in which the training data was collected should be maintained by the builders of the algorithms, accompanied by an exploration of the potential biases induced by the human or algorithmic data-gathering process. Public scrutiny of the data provides maximum opportunity for corrections. However, concerns over privacy, protecting trade secrets, or revelation of analytics that might allow malicious actors to game the system can justify restricting access to qualified and authorized individuals.
6. **Auditability:** Models, algorithms, data, and decisions should be recorded so that they can be audited in cases where harm is suspected.
7. **Validation and Testing:** Institutions should use rigorous methods to validate their models and document those methods and results. In particular, they should routinely perform tests to assess and determine whether the model generates discriminatory harm. Institutions are encouraged to make the results of such tests public.

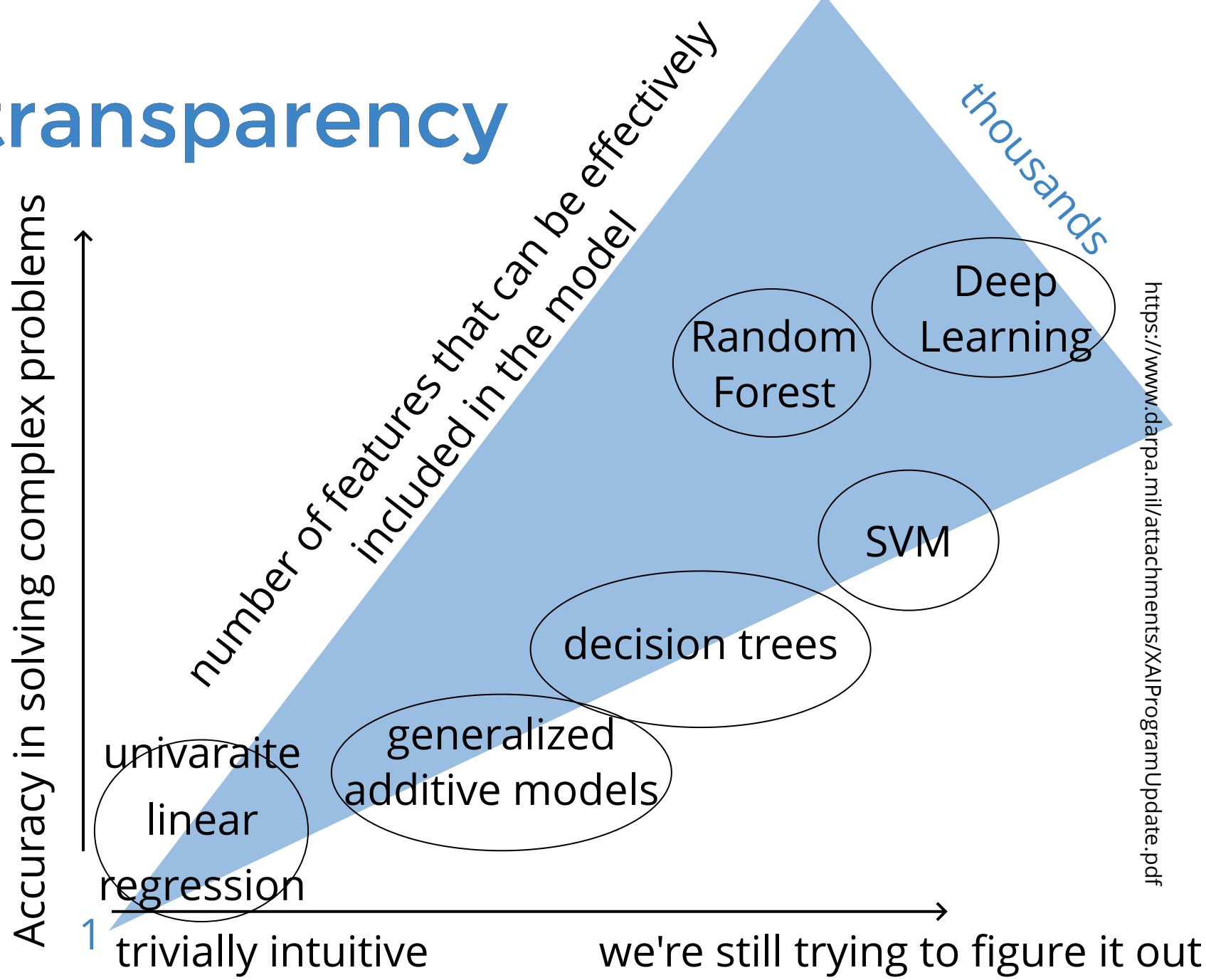
Source: https://www.acm.org/binaries/content/assets/public-policy/2017_usacm_statement_algorithms.pdf

https://www.americanscientist.org/article/a-peek-at-proprietary-algorithms

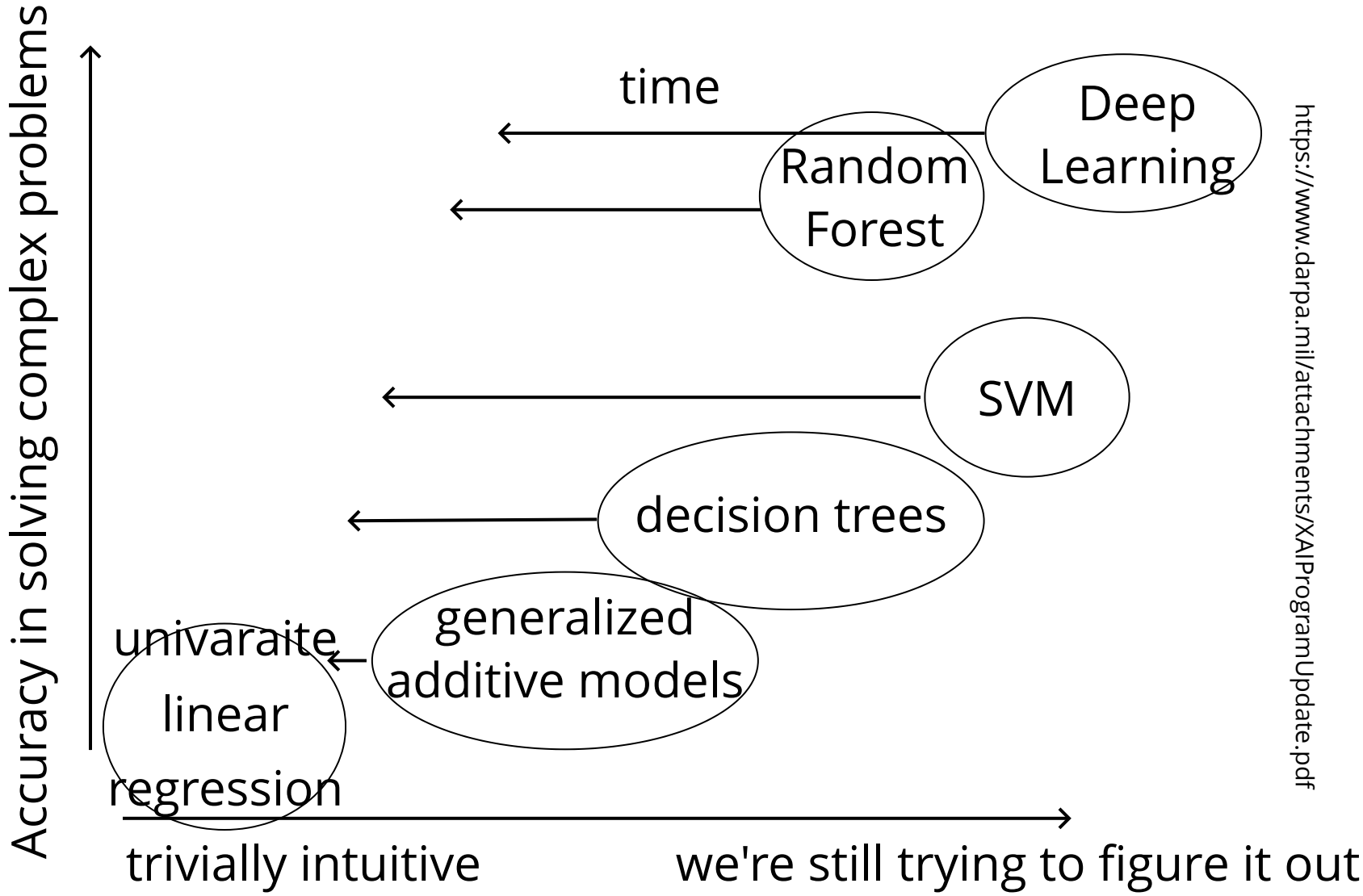
algorithmic transparency



algorithmic transparency



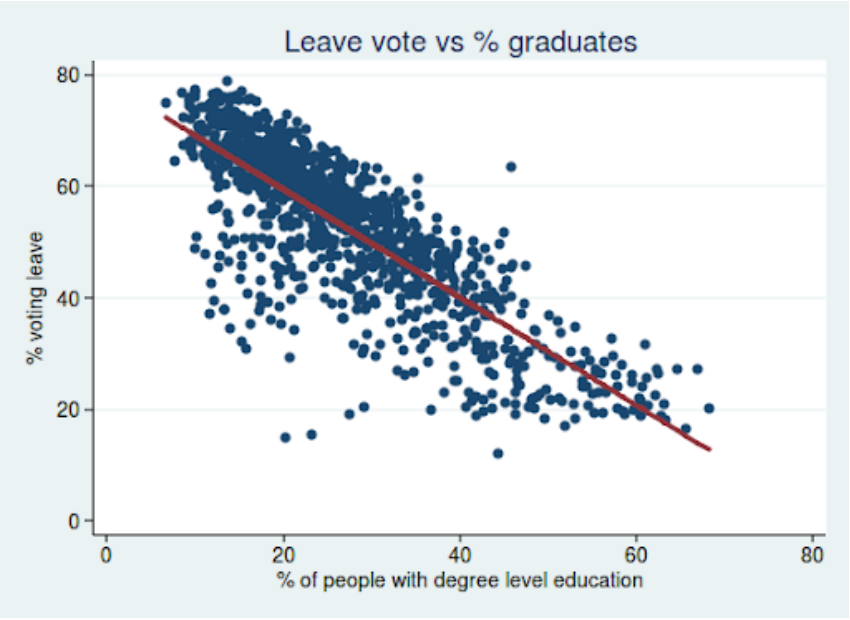
algorithmic transparency



algorithmic transparency

1

Machine learning: any method that learns parameters from the data



http://www.statsguy.co.uk/brexit-voting-and-education/

2

The transparency of an algorithm is proportional to its complexity *and* the complexity of the data space

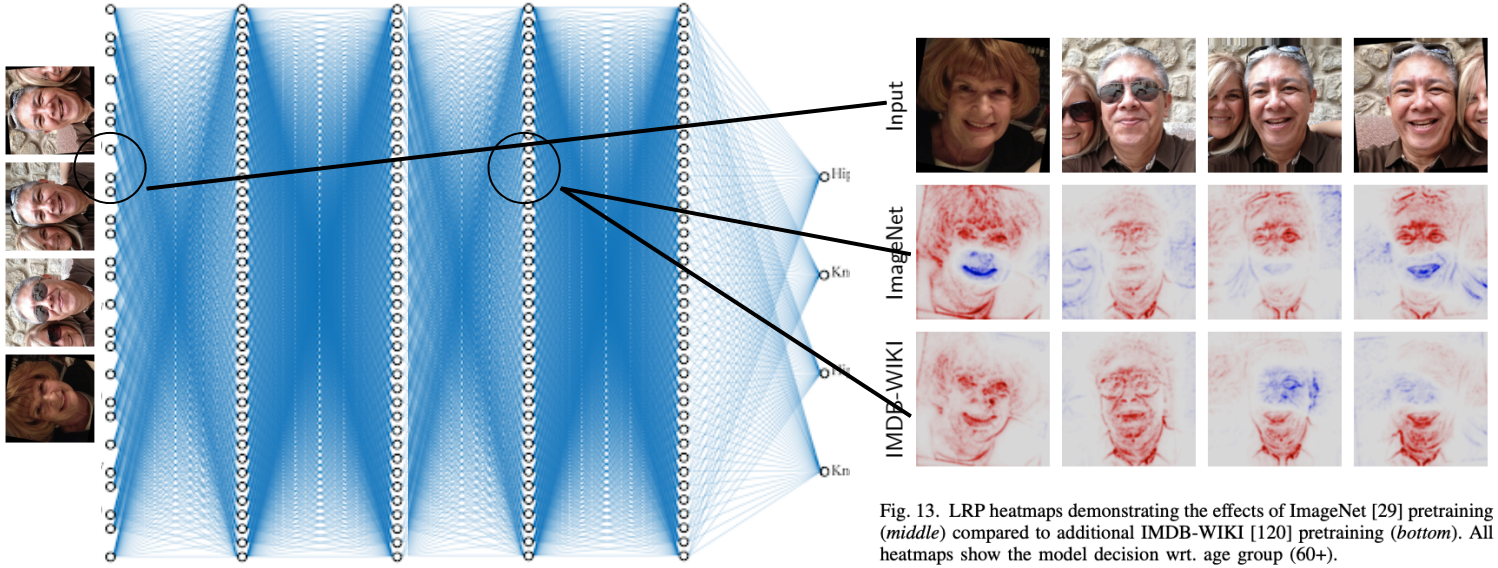


Fig. 13. LRP heatmaps demonstrating the effects of ImageNet [29] pretraining (*middle*) compared to additional IMDB-WIKI [120] pretraining (*bottom*). All heatmaps show the model decision wrt. age group (60+).

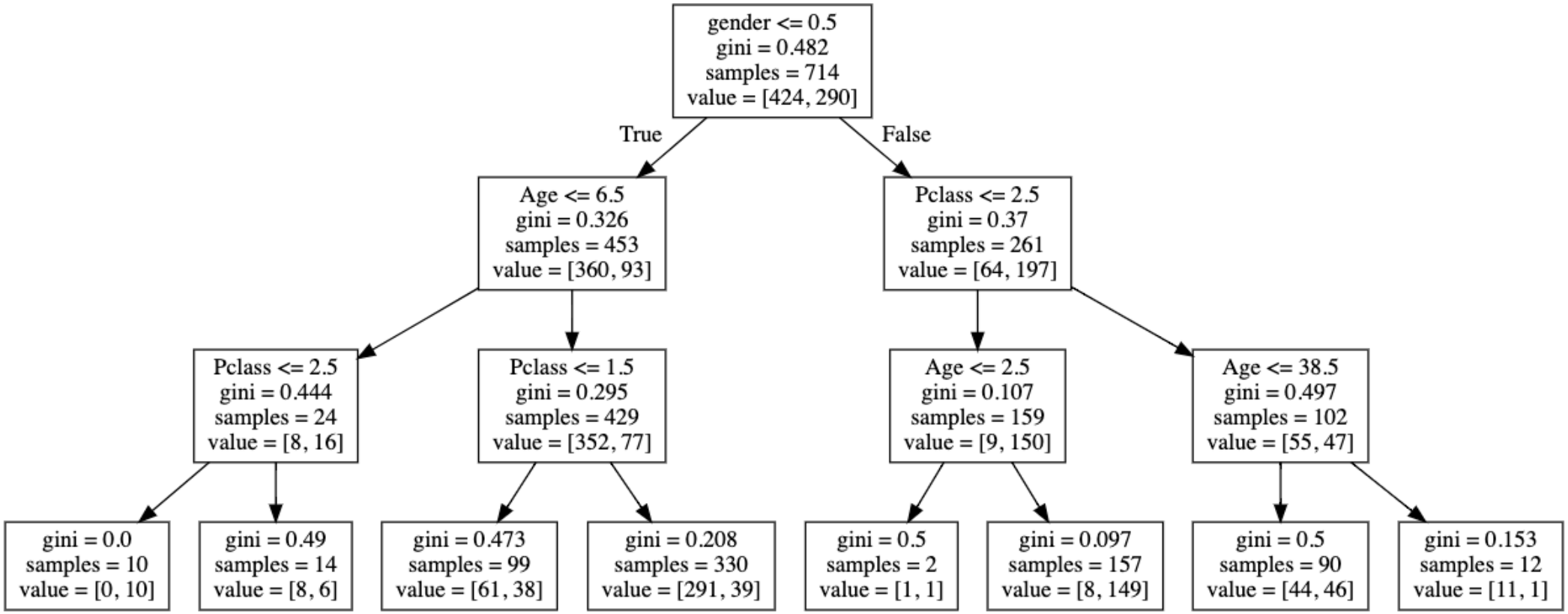
3

The transparency of an algorithm is limited by our own ability and preparedness to interpret it

Toward Interpretable Machine Learning, Samek+2003

algorithmic transparency

A single tree model



accountability

- can scientists be held responsible?
- should whoever commissions be responsible?
- is nobody responsible under the premise that decisions are *objective*? -> are they objective?, what does objective mean?, how can we objectively measure objectivity

Italian Scientists Sentenced to 6 Years for Earthquake Statements

A year-long trial about downplayed risks from a 2009 quake came to a close with the verdict, which alarmed Earth scientists worldwide

https://www.scientificamerican.com/article/italian-scientists-get/

accountability

Robert Williams, a 43-year-old father who resides in the Detroit suburb of Farmington Hills, was arrested in early January on charges that he stole watches from Shinola, a trendy accessories store in the city. Detroit Police used facial recognition software on the store's surveillance camera footage and wrongfully identified him as the thief.

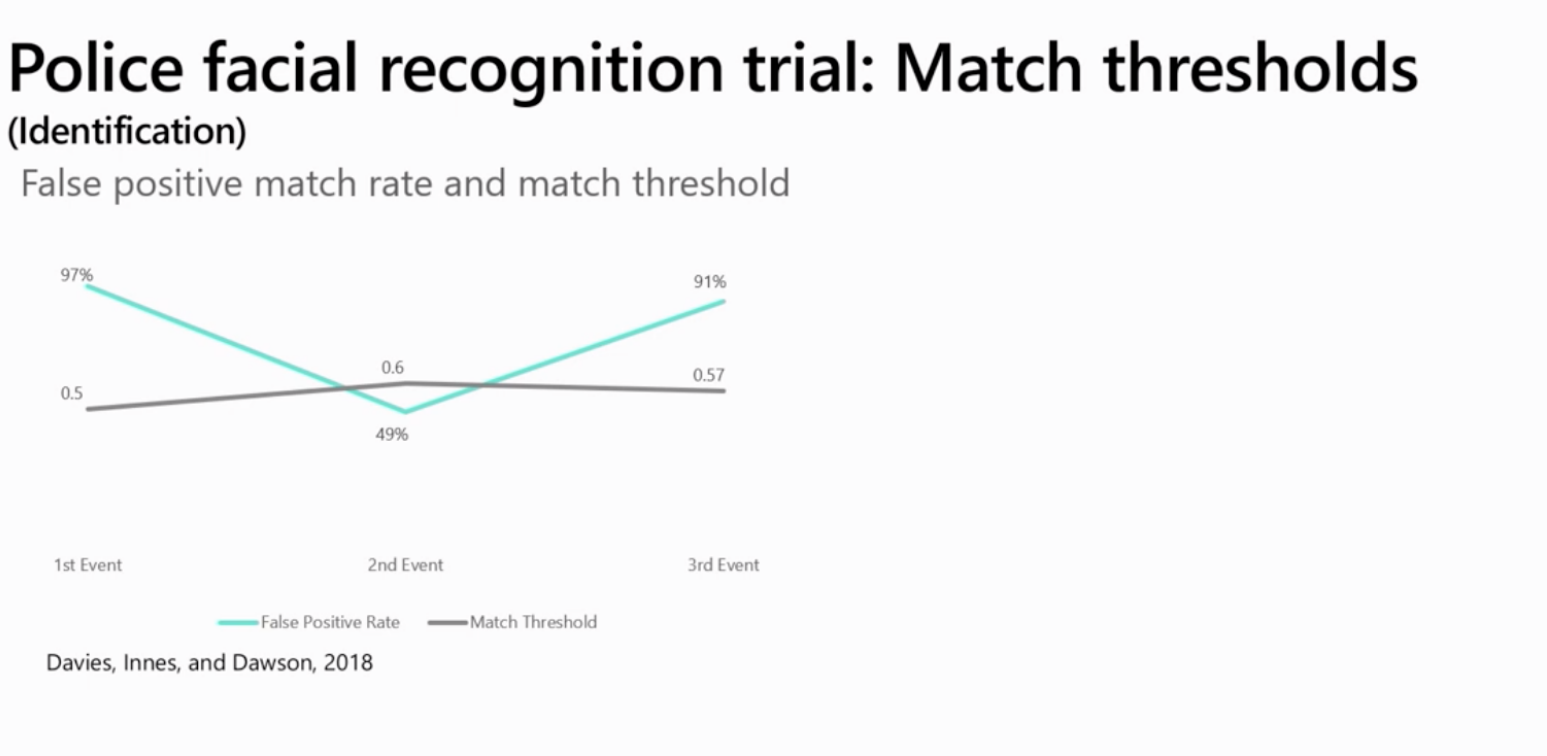
Robert Williams has sued Detroit Police after a false facial recognition match led to him being wrongfully identified and subsequently arrested as a shoplifting suspect. (ACLU)

In a press release, the ACLU wrote, "Mr. Williams' experience was the first case of wrongful arrest due to facial recognition technology to come to light in the United States."

accountability

FR returns a ***probabilistic*** result

a threshold is chosen to turn it into a T/F match for decision making



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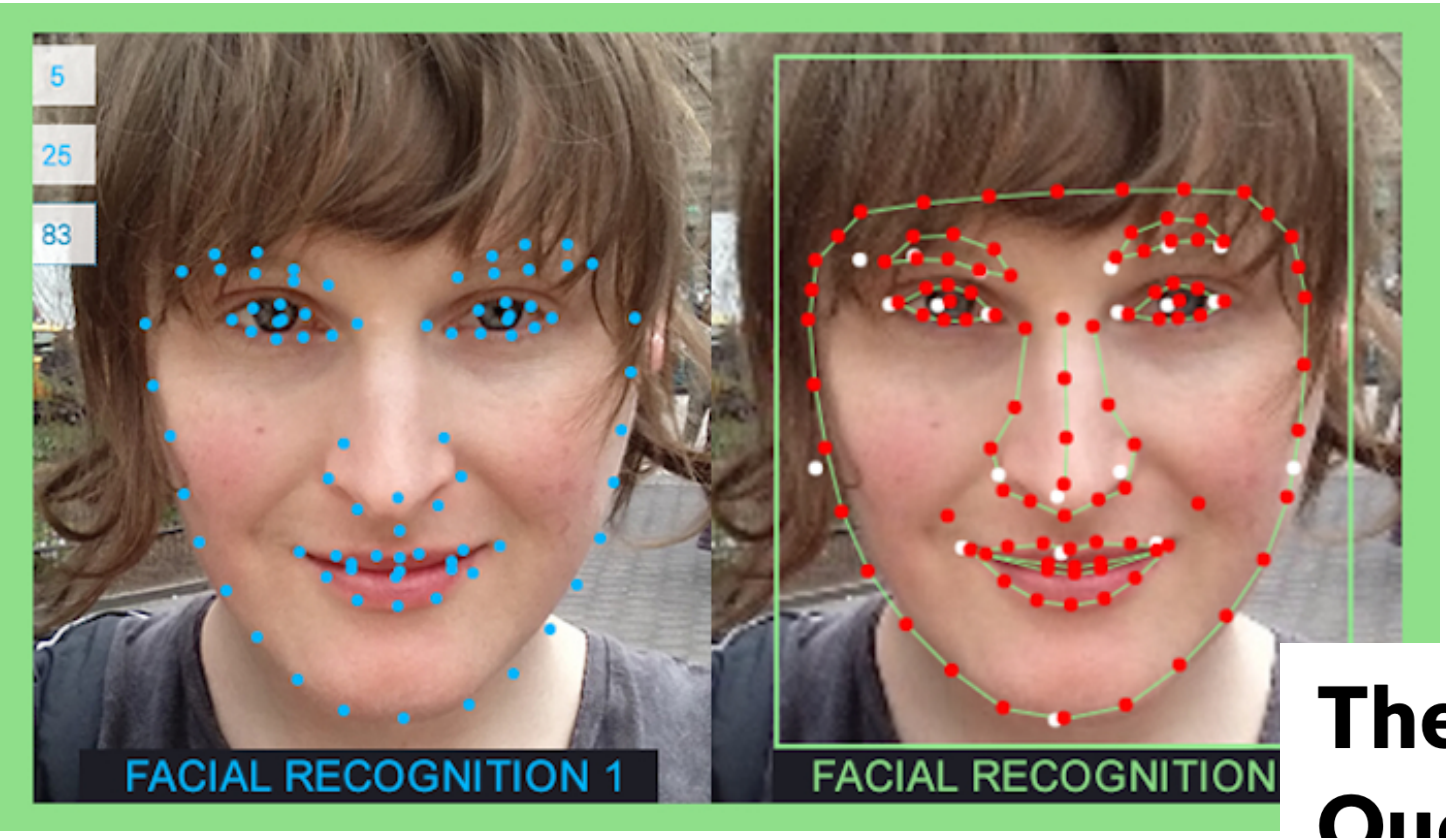
Who is responsible for setting the threshold?

unethical applications of FR



https://modelviewculture.com/pieces/the-hidden-dangers-of-ai-for-queer-and-trans-people

The Hidden Dangers of AI for Queer and Trans People

The more we discuss the dangers of training AI on only small sets of data and narrow ideas about identity, the better prepared we will be for the future.

unethical applications of FR

Table 2 Compare results of proposed solution and current solution

results							
Sample Images	Proposed Solution (Haar Cascades) Eyes and Mouth				Current Solution (Sobel Edge Detection Eyes)		
	Output	Detected Emotion	Accuracy (%)	Processing Time(sec)	Output	Accuracy (%)	Processing Time(sec)
Group 1							
		Sad	80.5	138		79	142
		Disgust	89.2	113		89	115
		Fear	84.3	158		83	164
		Anger	87	113.5		82	118
		Disgust	81	115.5		80	119
		Fear	79	155.5		75	161
		Happy	90	115		89	122
		Sad	75	131		72	143
		Surprise	89.8	165		87	172

An Emotion Recognition Model Based on Facial Recognition in Virtual Learning Environment

D. Yang [a], Abeer Alsadoon [a], P.W.C. Prasad [a] ✉, A.K. Singh [b], A. Elchouemi [c]

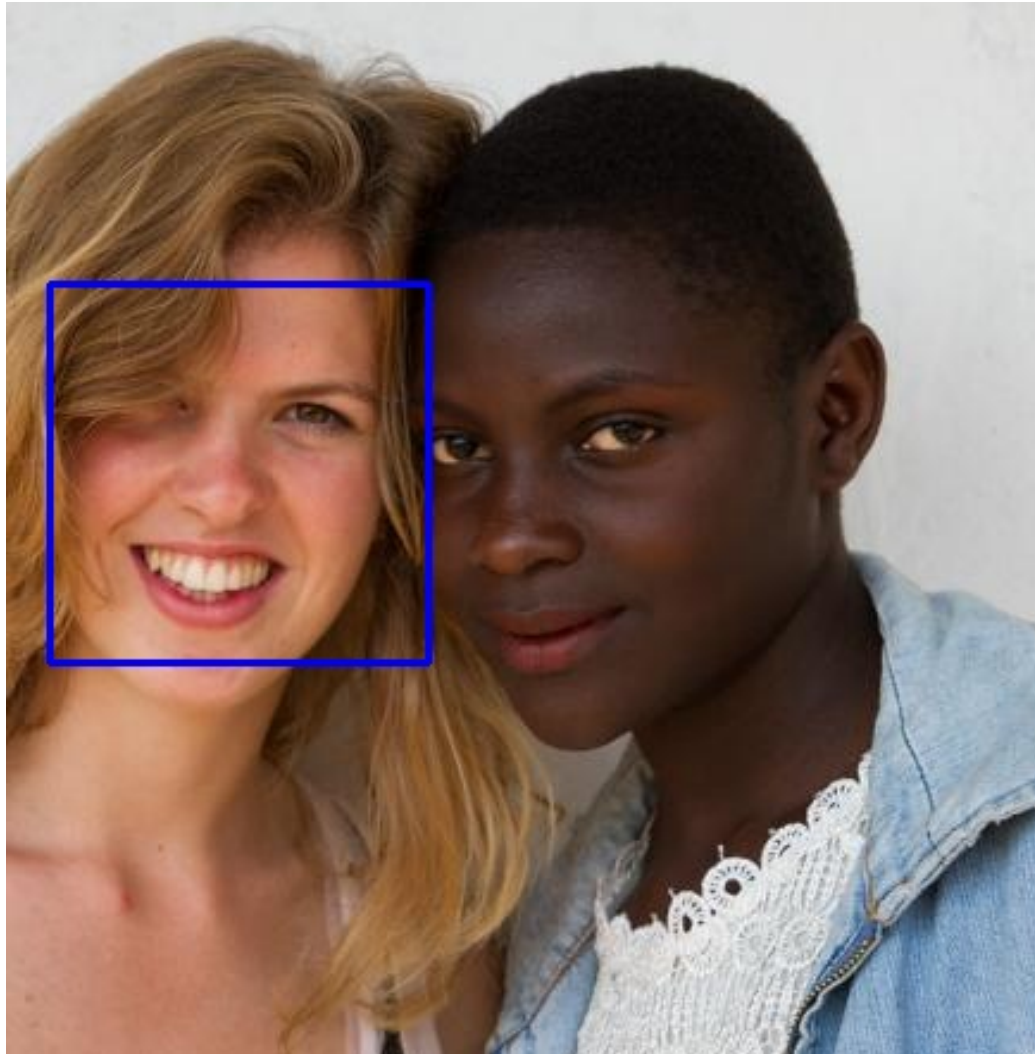
Show more

unethical applications of FR

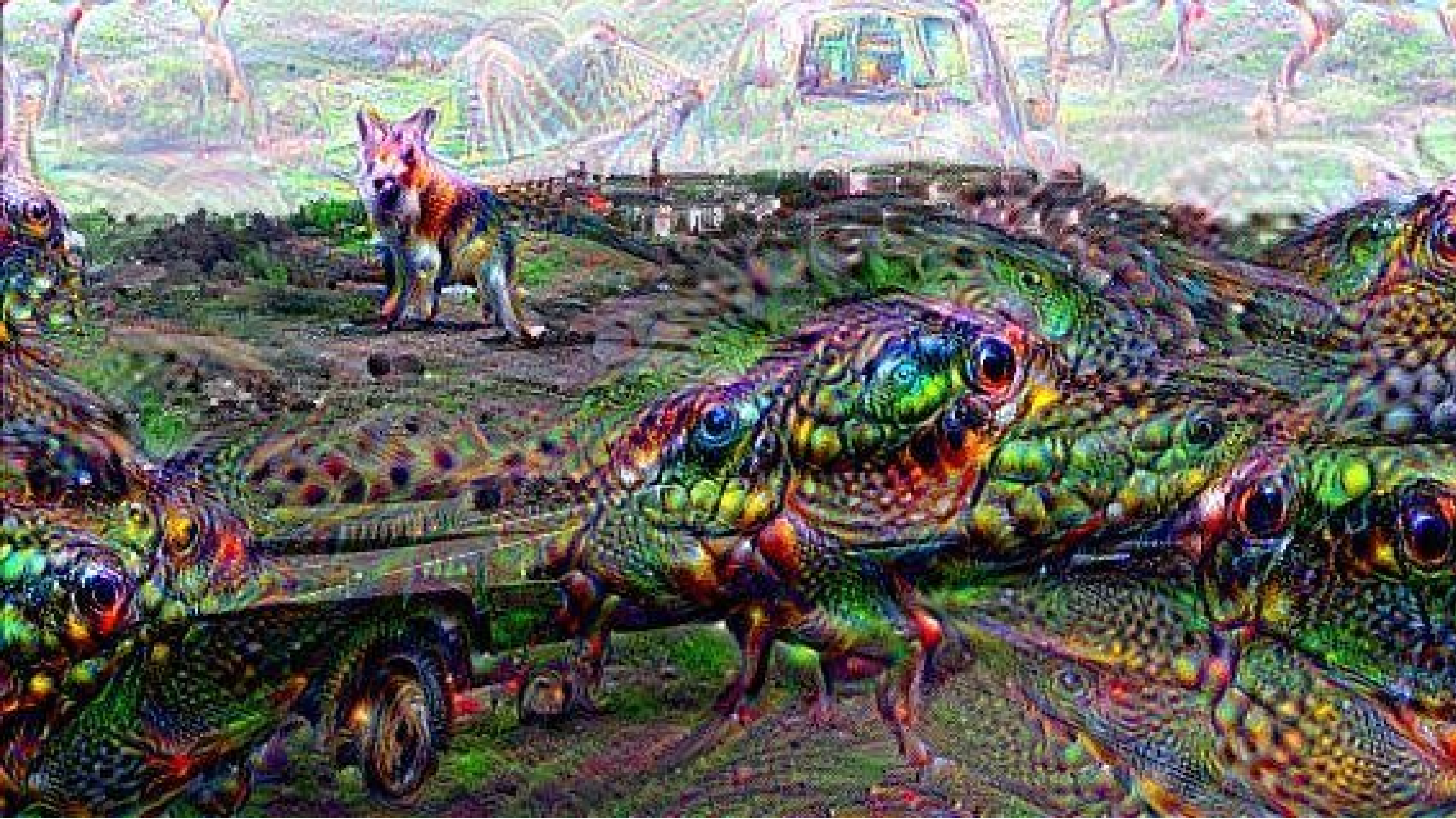
Proctorio Is Using Racist Algorithms to Detect Faces

A student researcher has reverse-engineered the controversial exam software—and discovered a tool infamous for failing to recognize non-white faces.

https://www.vice.com/en/article/g5gxg3/proctorio-is-using-racist-algorithms-to-detect-faces




deep dreams



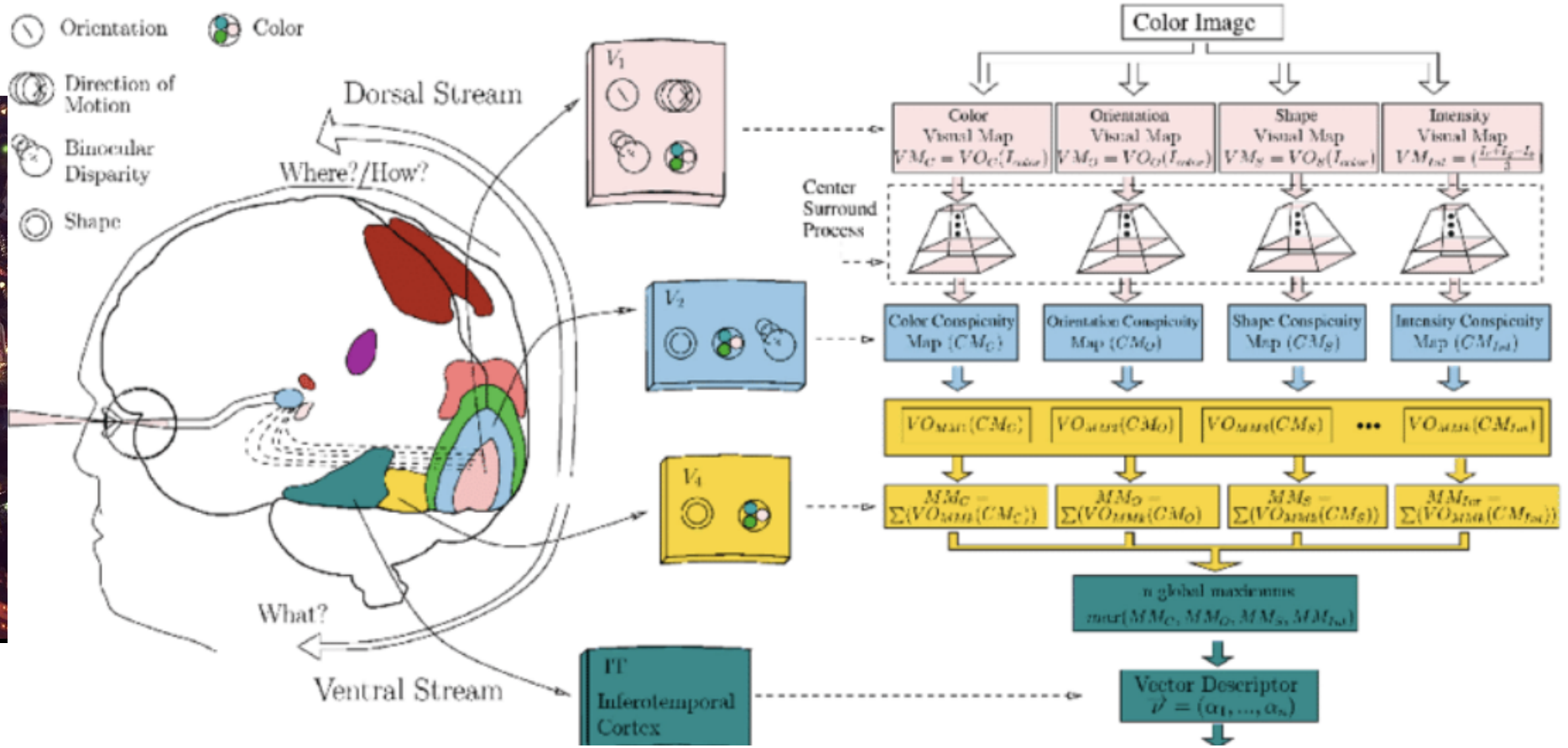
what is happening in DeepDream?

Deep Dream (DD) is a google software, a pre-trained NN (originally created on the Cafe architecture, now imported on many other platforms including tensorflow).

The high level idea relies on training a convolutional NN to recognize common objects, e.g. dogs, cats, cars, in images. As the network learns to recognize those objects is developes its layers to pick out "features" of the NN, like lines at a cetrain orientations, circles, etc.

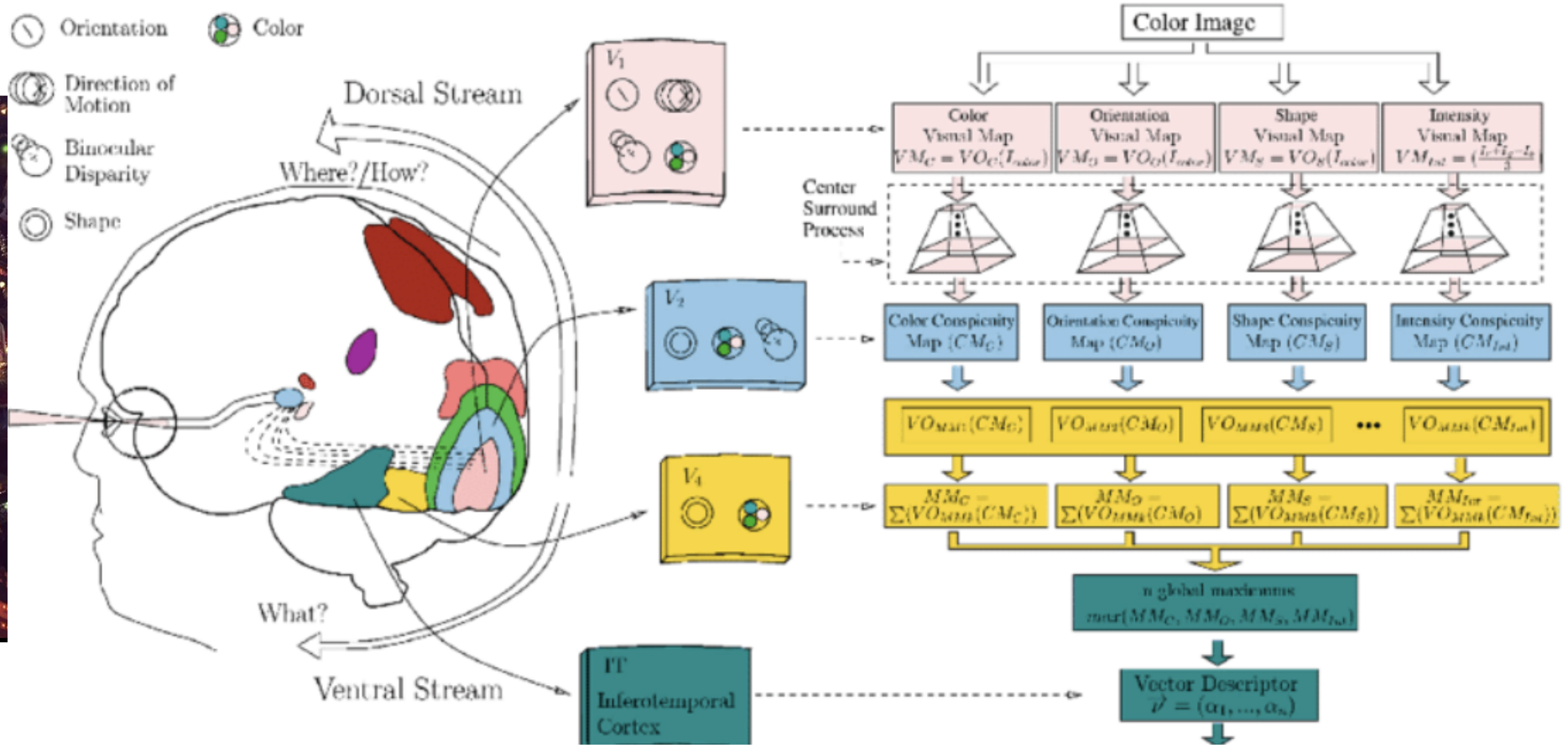
The DD software runs this NN on an image you give it, and it loops on some layers, thus "manifesting" the things it knows how to recognize in the image.

@akumadog



Brain Programming and the Random Search in Object Categorization Olague et al 2017

The visual cortex learns hierarchically: first detects simple features, then more complex features and ensembles of features



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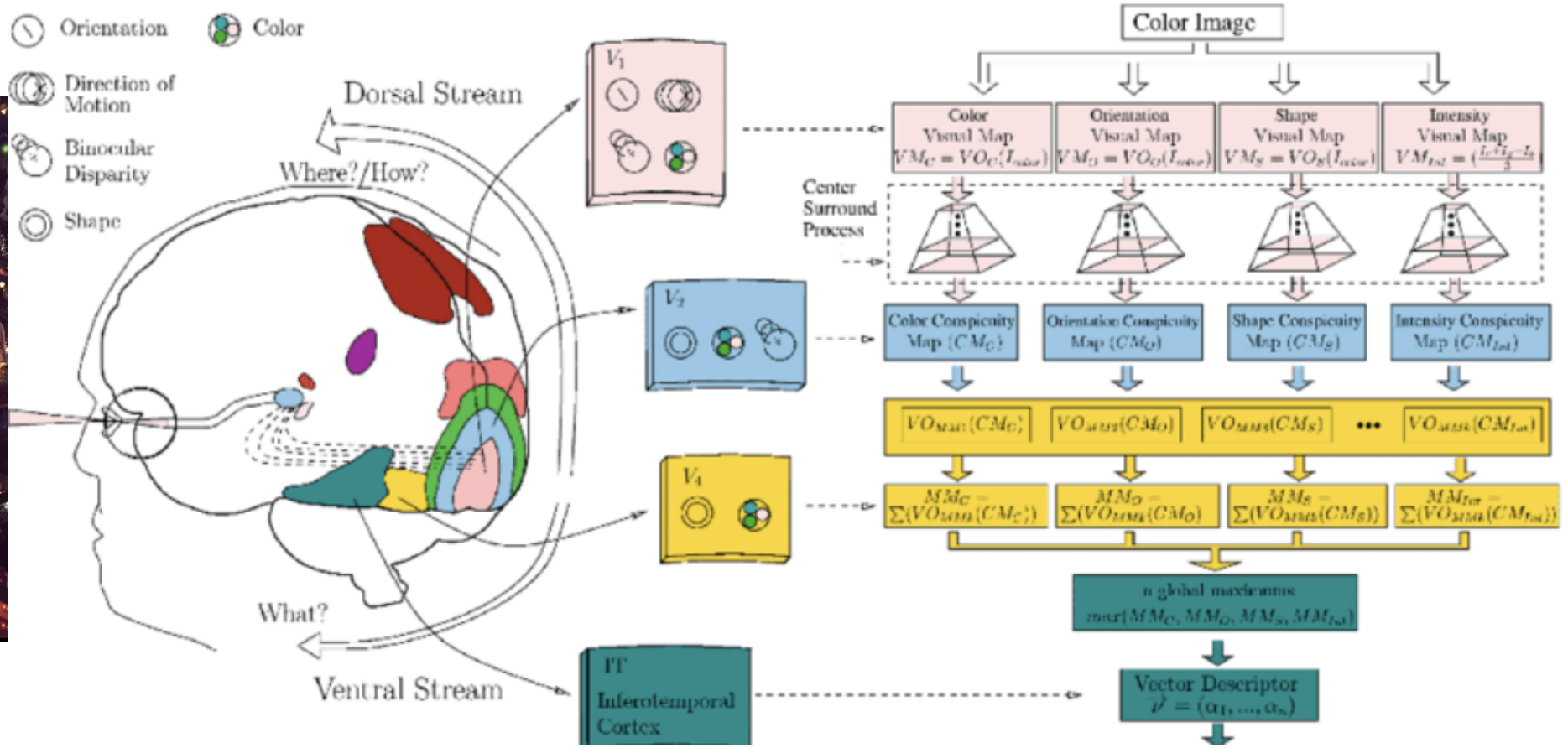

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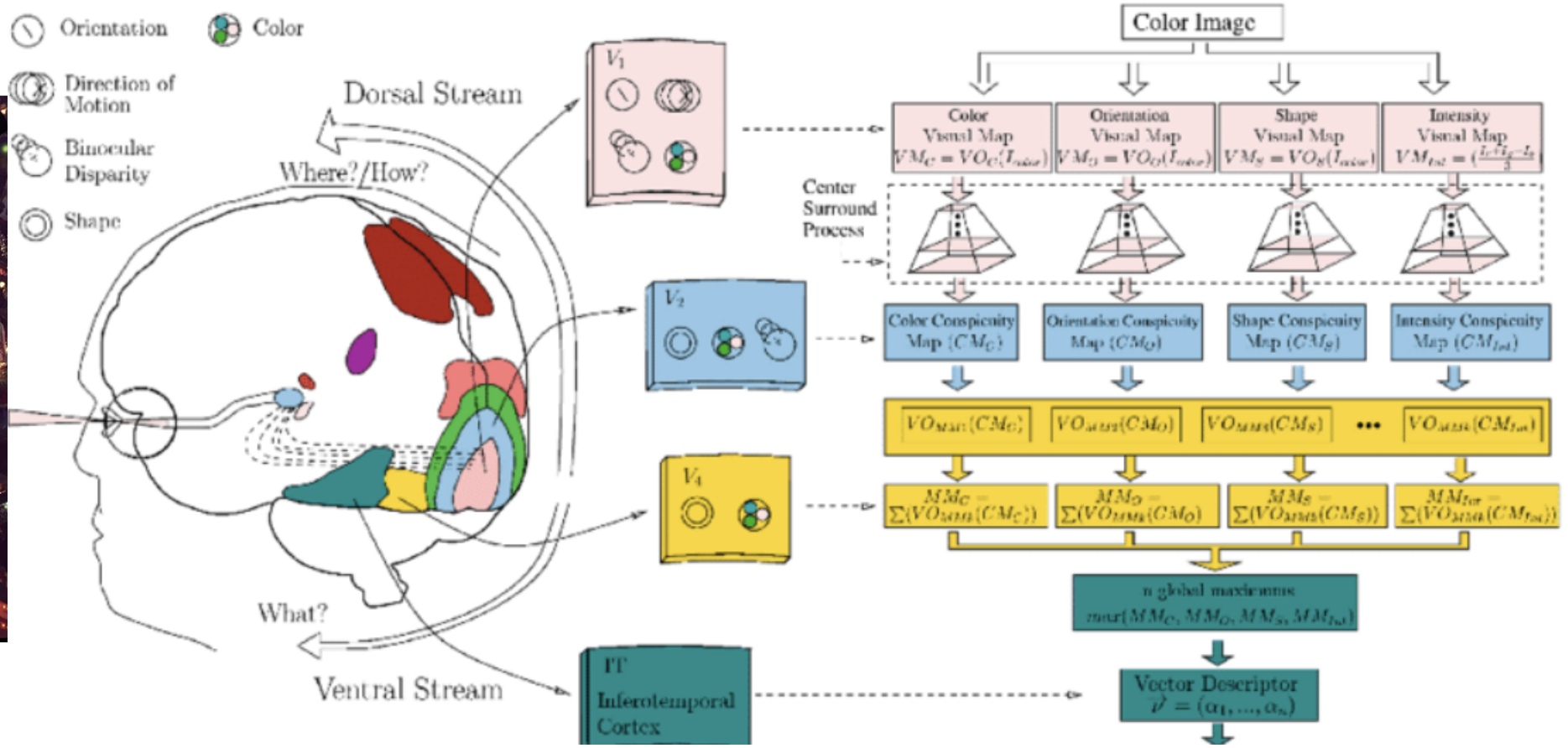

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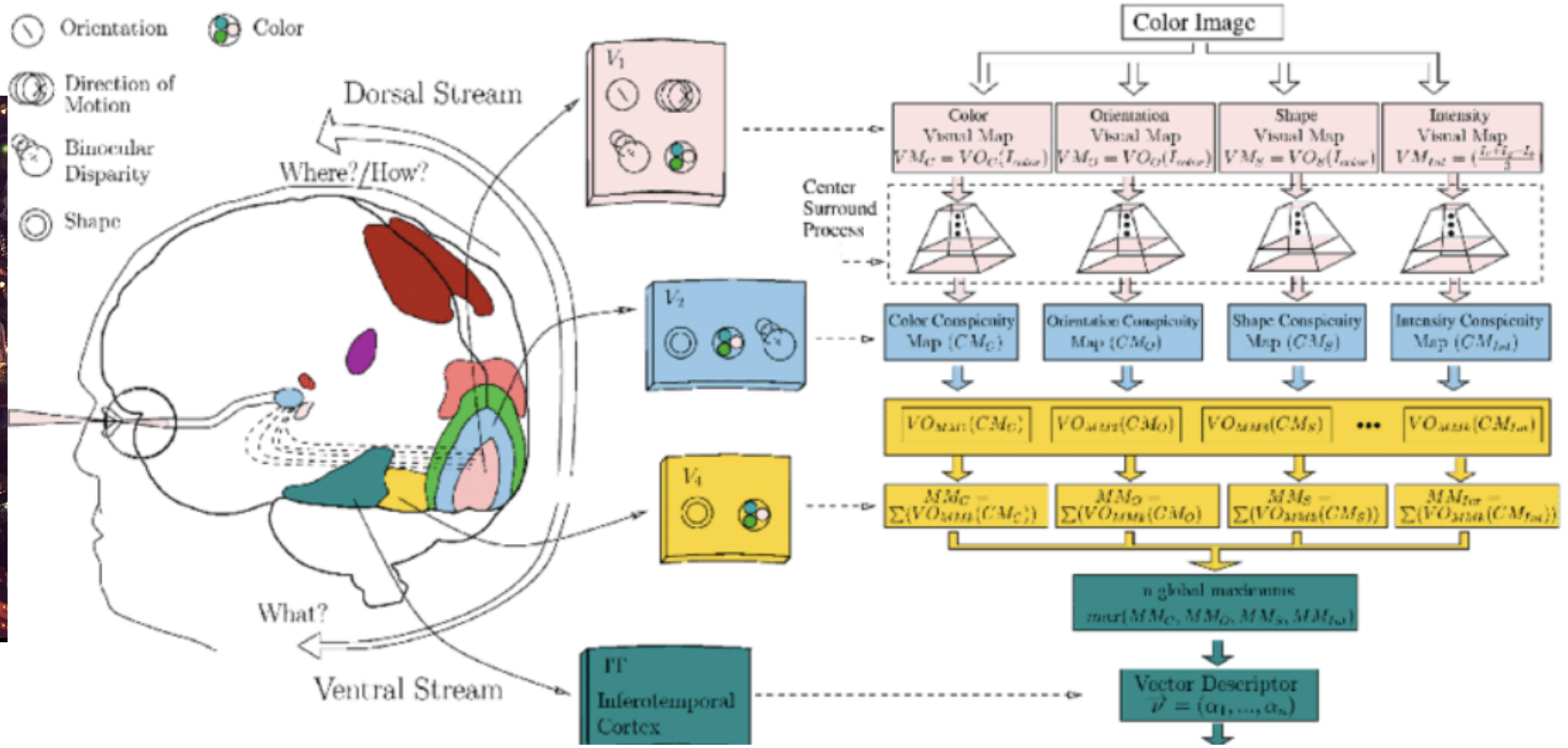

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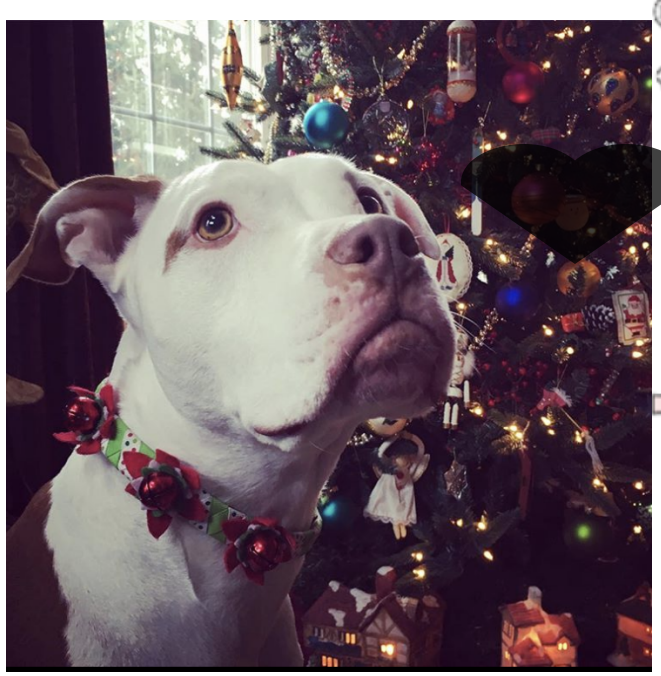

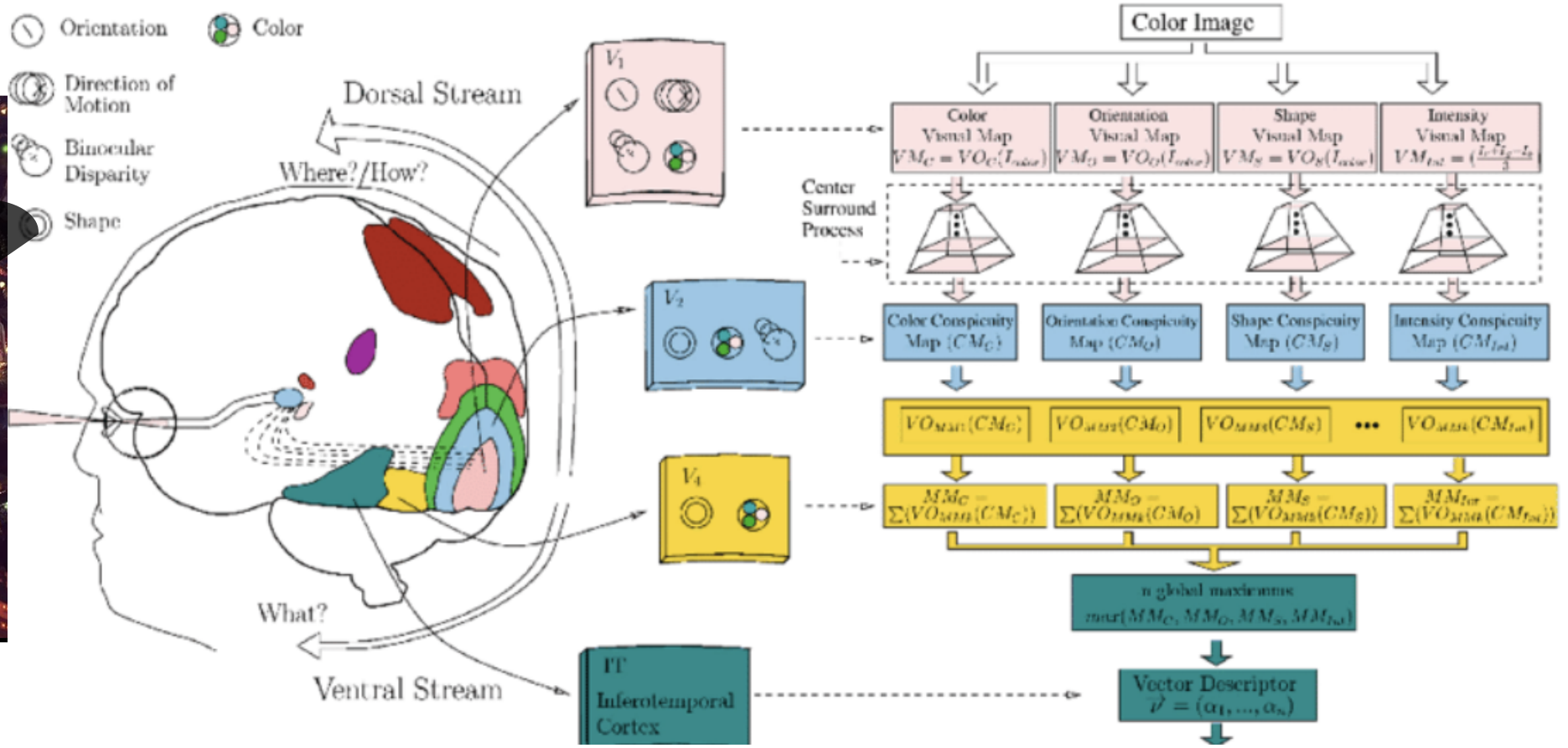

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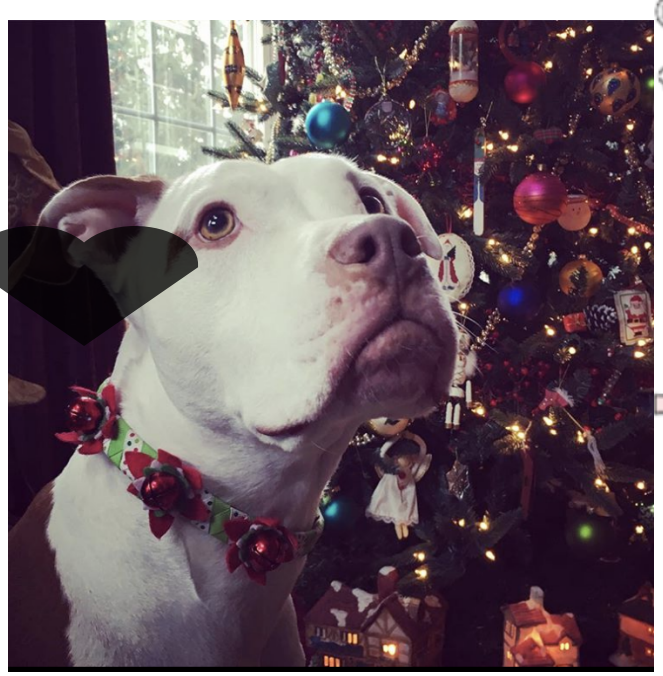

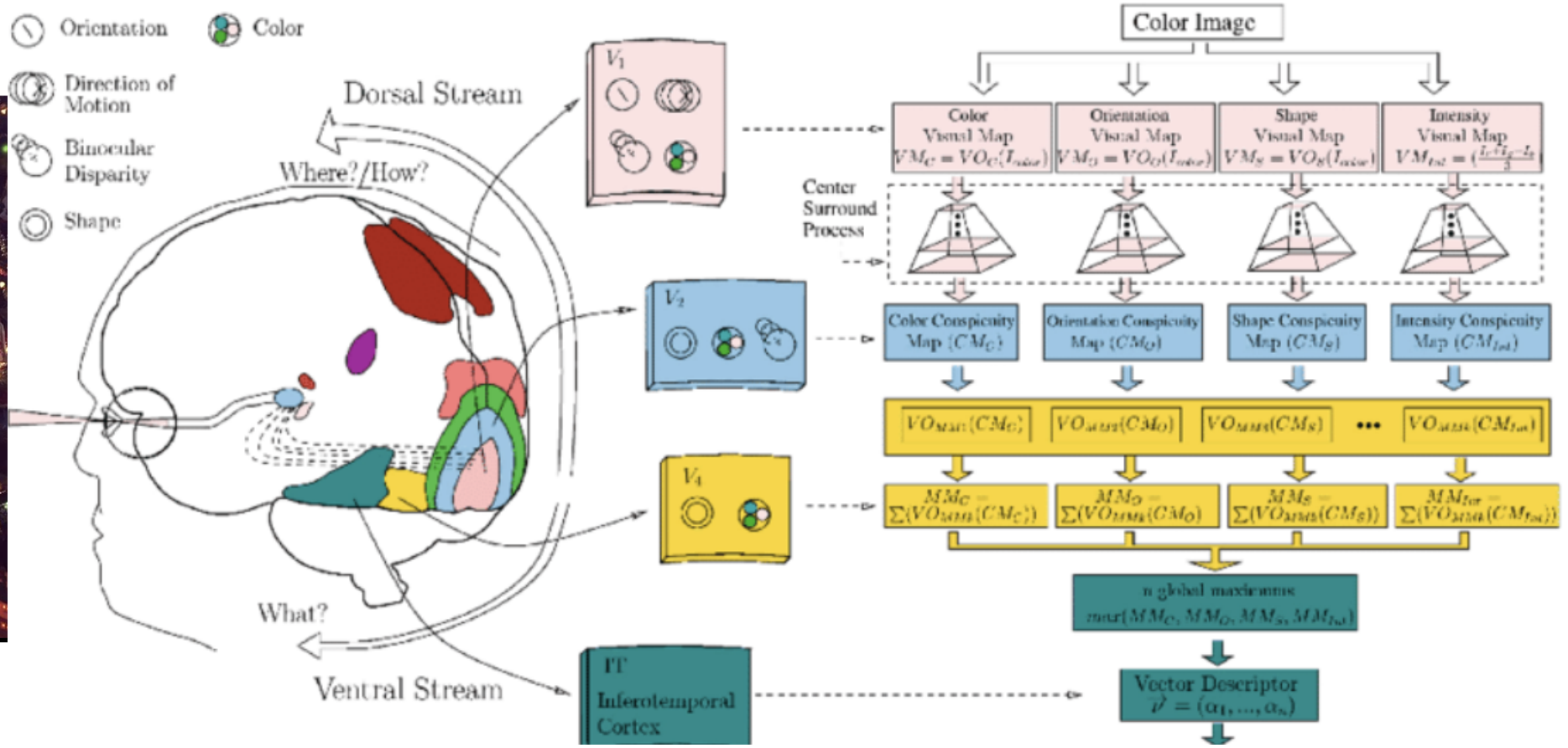

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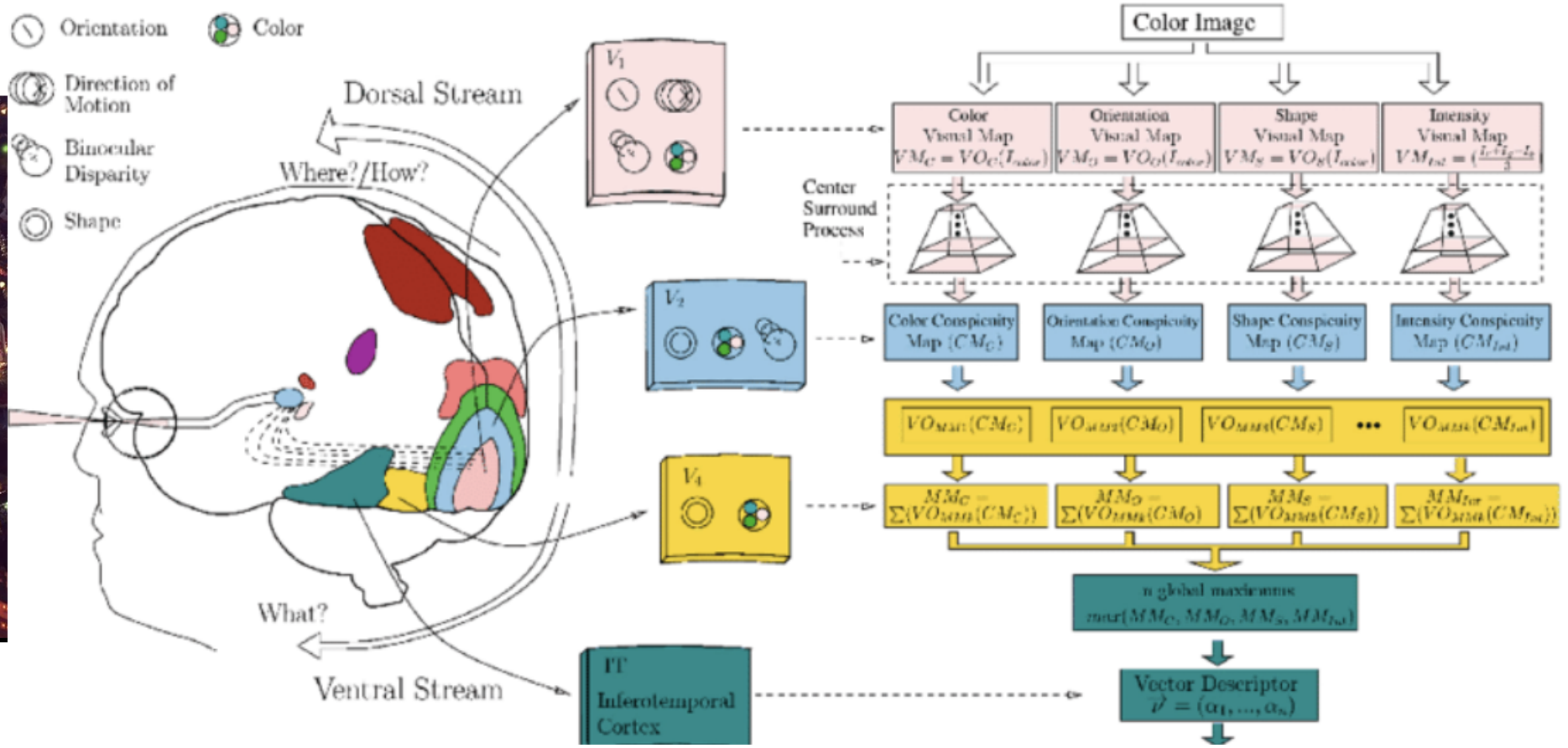

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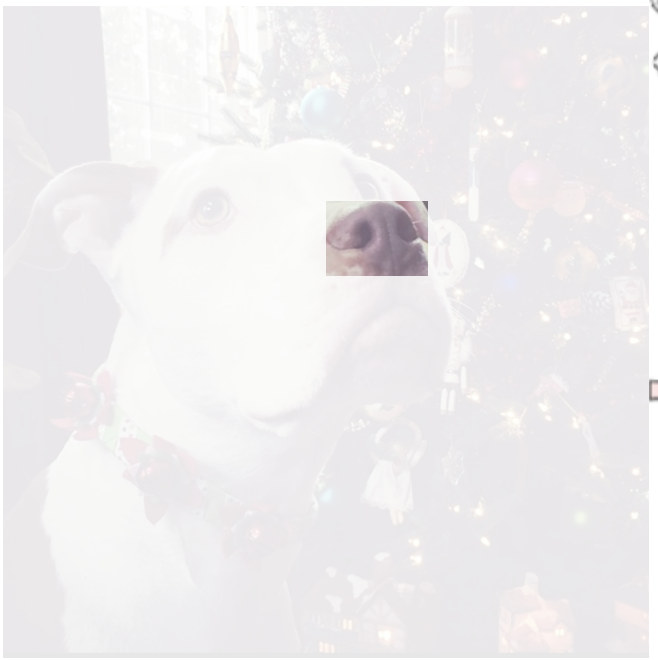

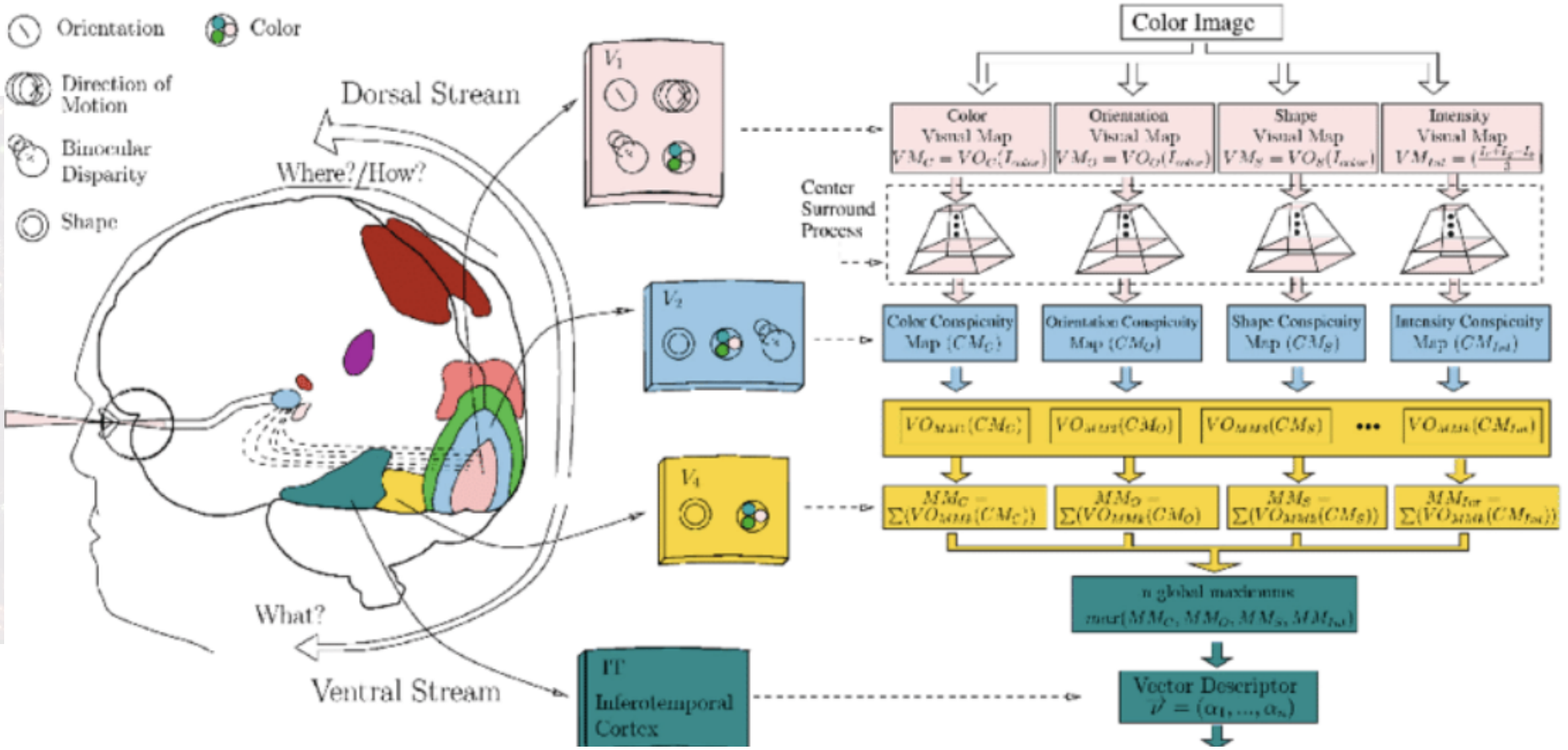

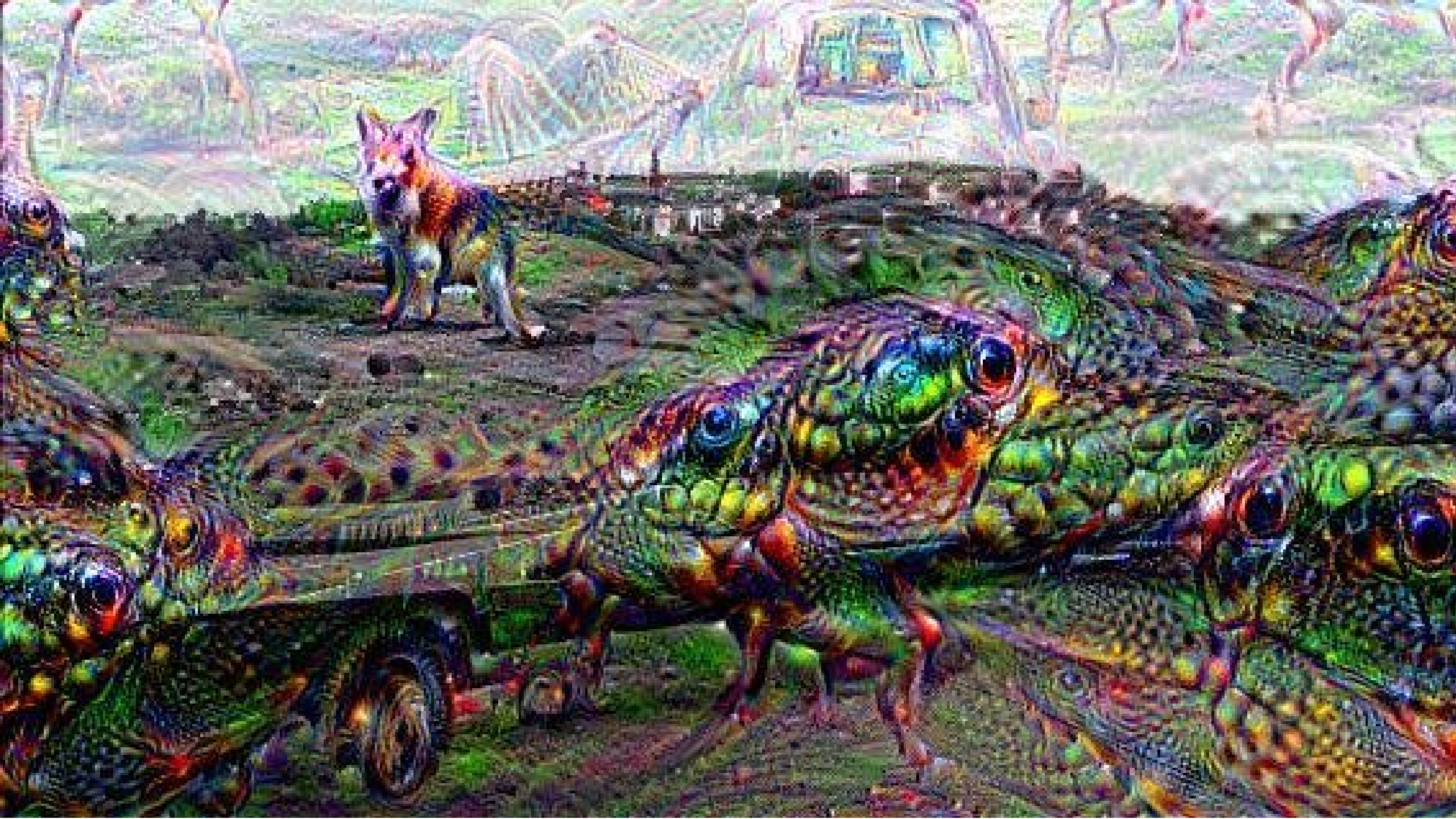

Gradient Descent

https://ml-cheatsheet.readthedocs.io/en/latest/gradient_descent.html

Neural Network and Deep Learning

an excellent and free book on NN and DL

http://neuralnetworksanddeeplearning.com/index.html

History of NN

https://cs.stanford.edu/people/eroberts/courses/soco/projects/neural-networks/History/history2.html

Inceptionism: Going Deeper into Neural Networks

Wednesday, June 17, 2015

https://ai.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html

https://github.com/fedhere/PUS2020_FBianco/blob/master/HW13/Instructions_PUS2020_deepdream.ipynb

homework