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PhD Candidate

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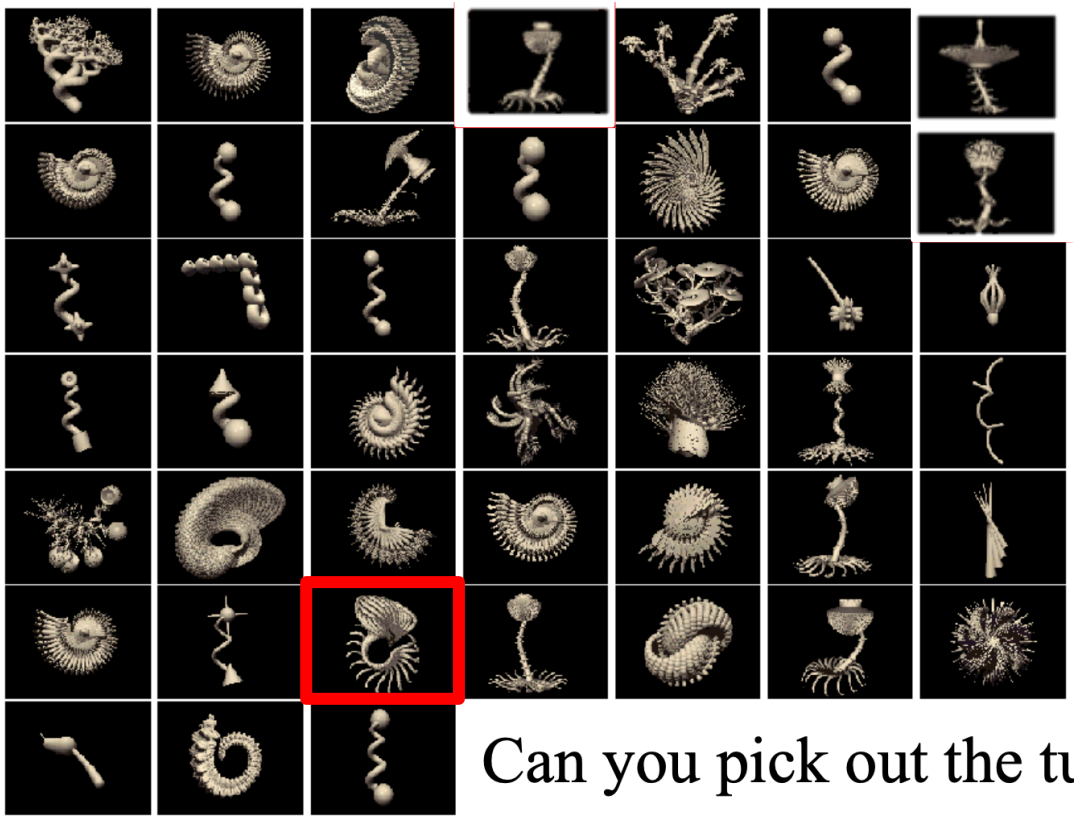
MSc in Neurosciences course
B7 Cognitive Neuroscience module

Machine Learning Applied to Neurosciences

Modelling and Predicting the brain and behaviour

London, United Kingdom, Feb 10th, 2020



Can you pick out the tufas?

Josh Tenenbaum

learning objectives

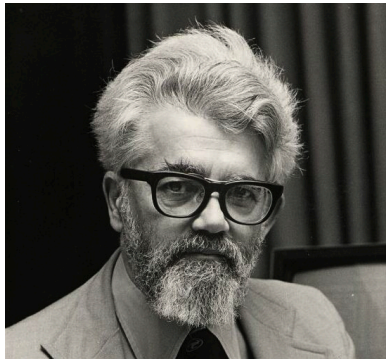
1. Distinguishing between Artificial Intelligence and Machine Learning;
2. Develop an understanding of how machines learn from data;
3. Understanding the concepts of bias and variance and how to balance them;
4. Understanding the advantages and shortcomings of using Machine Learning for modelling the brain and behaviour.

agenda

1. Distinguishing AI and ML
2. Different types of ML
3. Classification and regression
4. Finding the right fit to the data
5. The neural network
6. Bringing it to the real world
7. What is bayesian optimization?
8. Take home messages

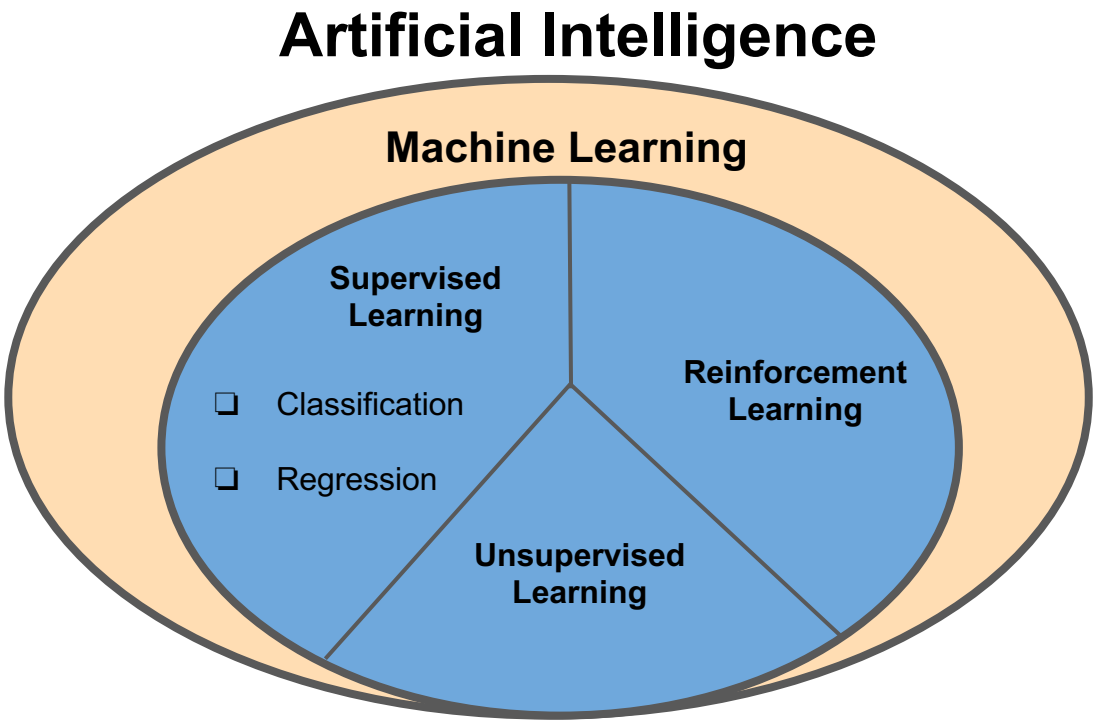
artificial intelligence and machine learning

Artificial Intelligence – *"the science and engineering of making intelligent machines."* – John McCarthy (1956).



Machine Learning – *"field of study that gives computers the ability to learn without being explicitly programmed."* – Arthur Samuel (1959)

artificial intelligence and machine learning



types of learning

supervised learning

Definition

➢ Machine learns from labelled data.

Type of data

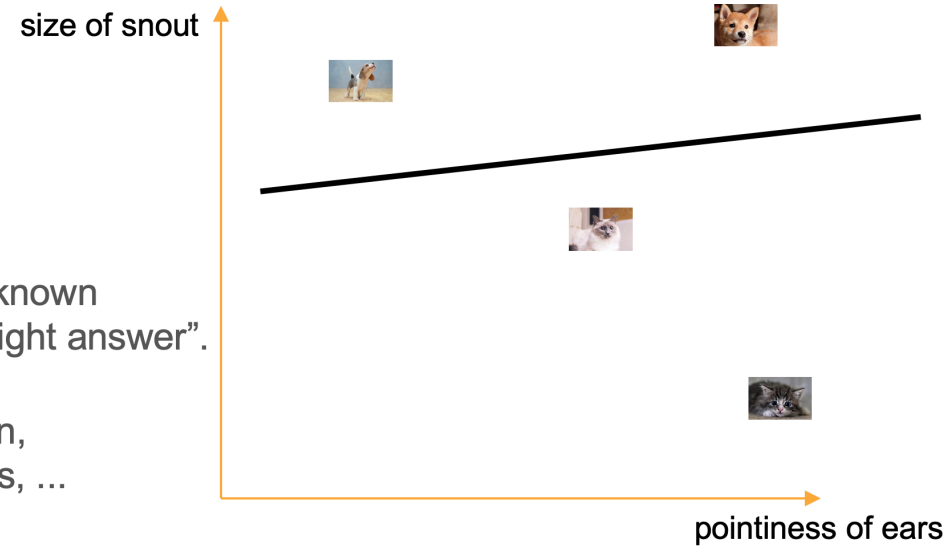
➢ Labelled data.

Approach

➢ Maps labelled input to known output. It is given the “right answer”.

Examples

➢ KNN, Linear Regression, SVMs, Neural Networks, ...



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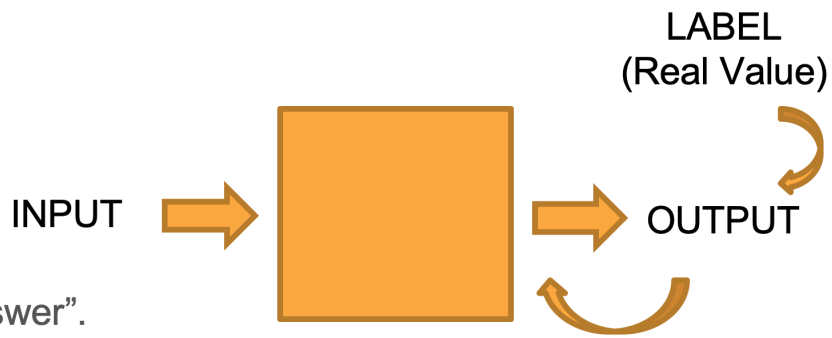
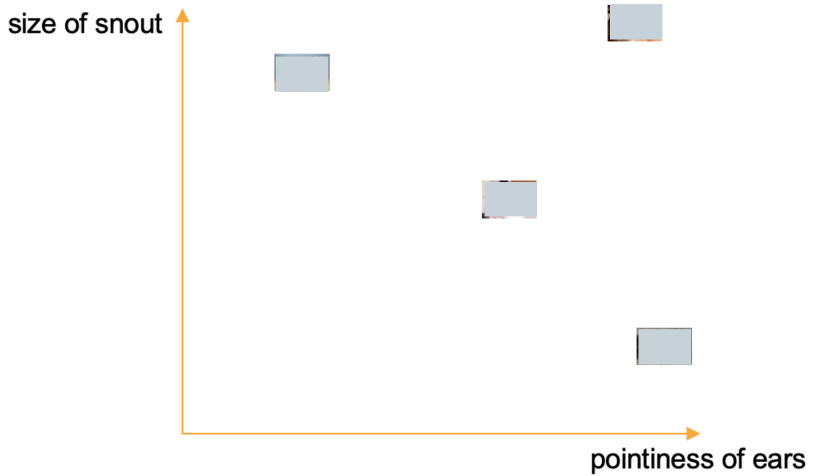


types of learning

unsupervised learning

Definition	➢ Machine is trained on unlabelled data.
Type of data	➢ Unlabelled data.
Approach	➢ Understanding patterns.
Examples	➢ K-Mean, tSNE, PCA, ...



types of learning

unsupervised learning

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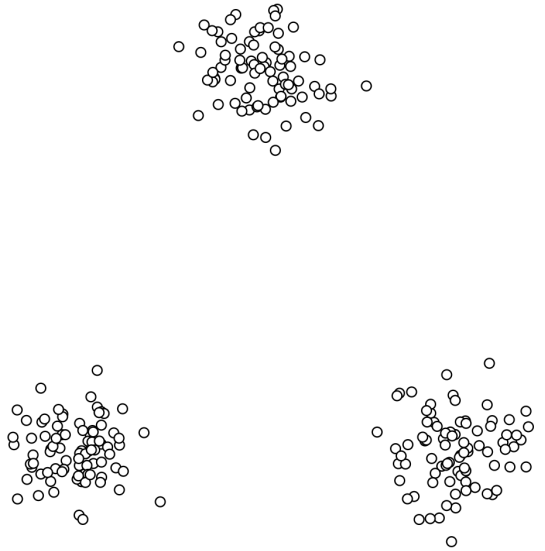
example of unsupervised learning – K-means clustering

1. initialise cluster centres.
2. assign data points to nearest centre
3. recalculate centre (mean)
4. go to point 2.



types of learning

Definition

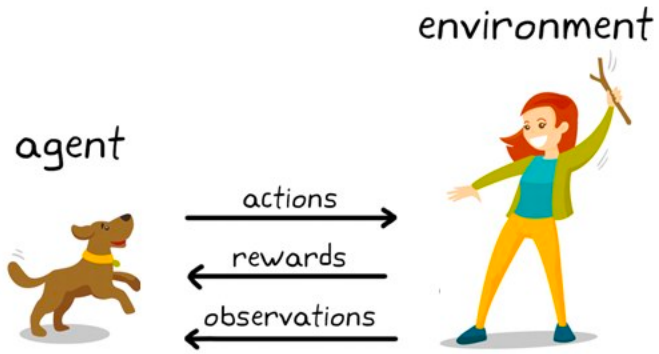
Type of data

Approach

Examples

reinforcement learning

- An agent explores its environment and learns policies based on rewards and punishments it receives.
- Unlabelled data.
- Trial and error.
- Q-Learning, PPO, Curiosity-based learning, ...

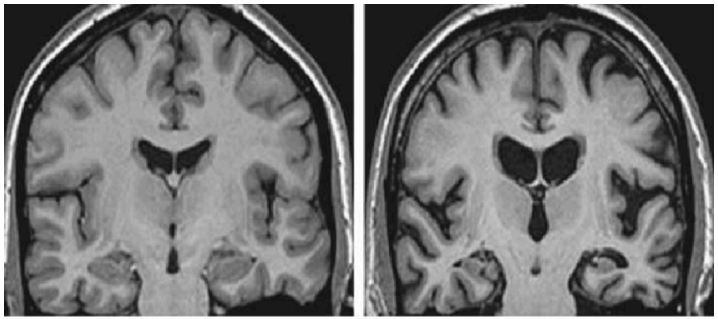


supervised learning

Classification

focuses on predicting a label
(cat vs dog example)

Sarah Parisot et al. (2018)



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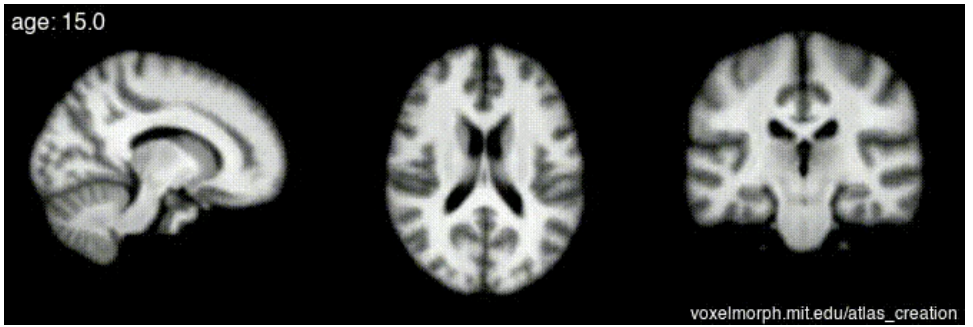
Regression

focuses on predicting a quantity

James Cole et al. (2017)

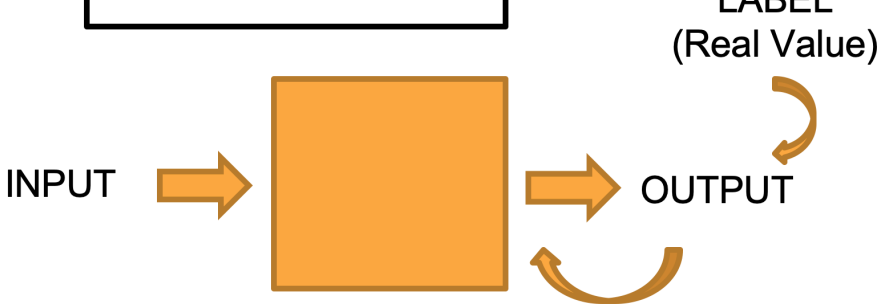


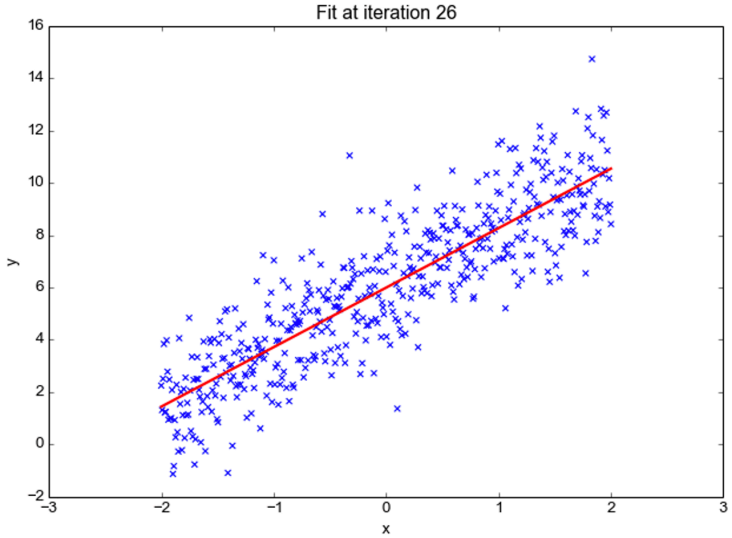
how do they learn?

univariate linear regression example

$$\hat{y} = m \times x + b$$

$$y = \hat{y} + e$$



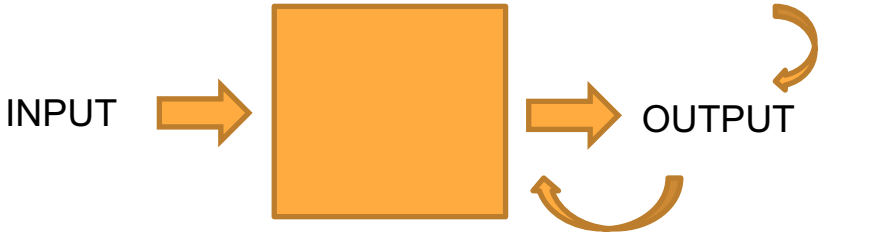


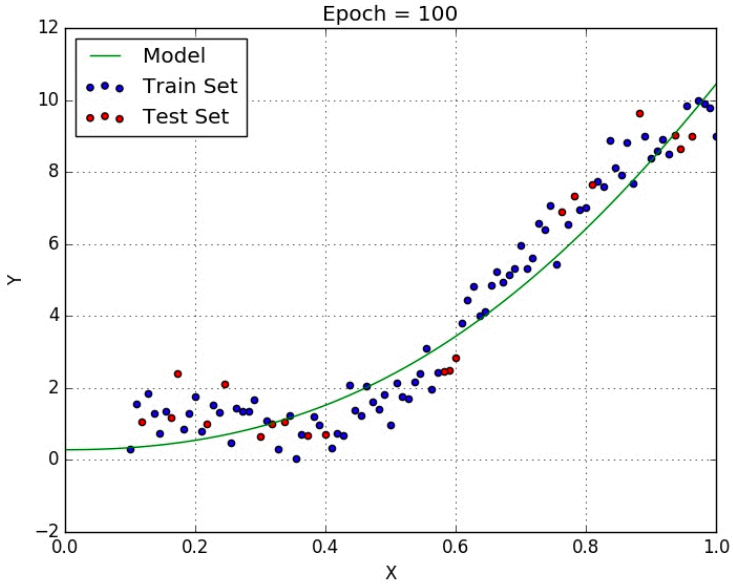
how do they learn?

univariate polynomial regression example

$$\hat{y} = m_1 \times x + m_2 \times x^2 + b$$

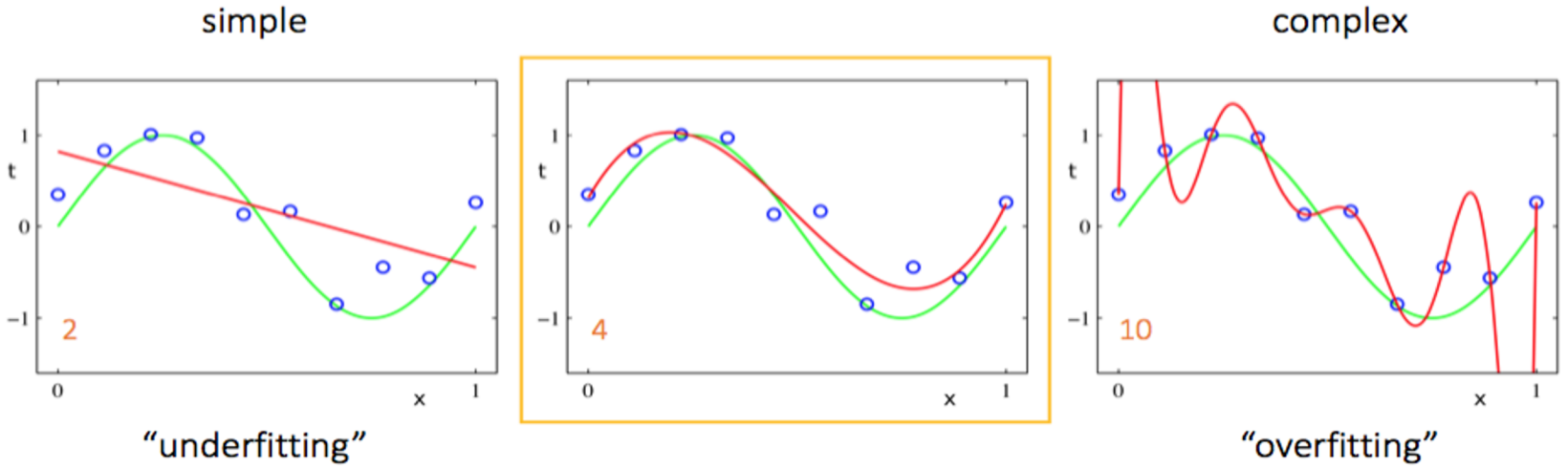
$$y = \hat{y} + e$$





underfitting vs overfitting

- **goal**: predict value of *t* for some new value of *x*
- three **models** of the data



C. M. Bishop "Pattern Recognition and Machine Learning"

underfitting vs overfitting

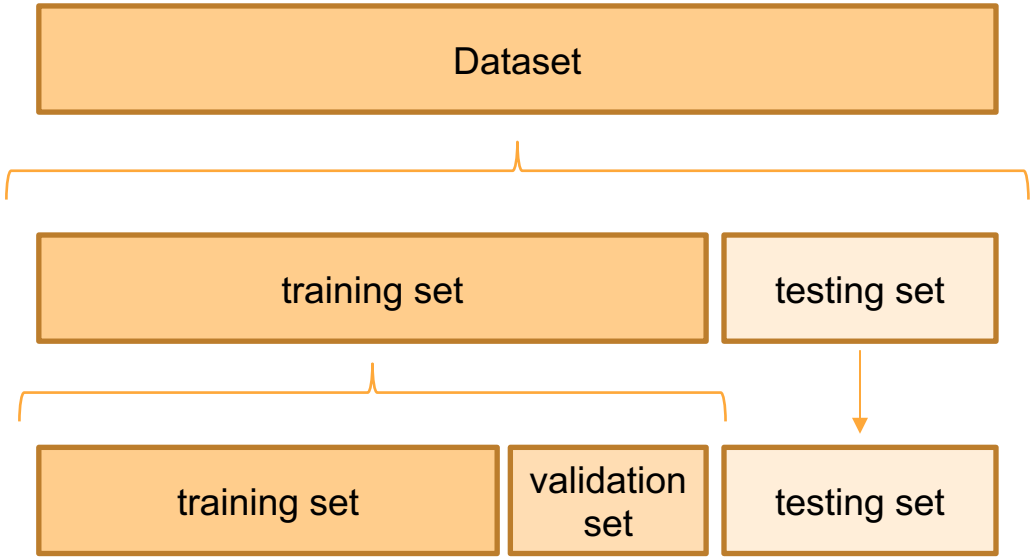
underfitting

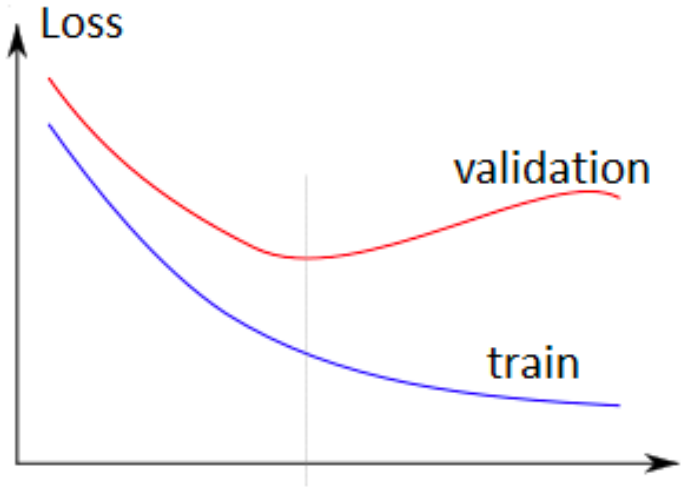
- model has limited flexibility to learn the true signal.
- **high bias.**
- solution:
  - increase number of features.

overfitting

- model is too complex and is fitting to noise instead of the signal.
- **high variance.**
- solutions:
  - increase number of samples;
  - separate training and test sets;
  - constrain the parameters to reduce complexity (regularization).

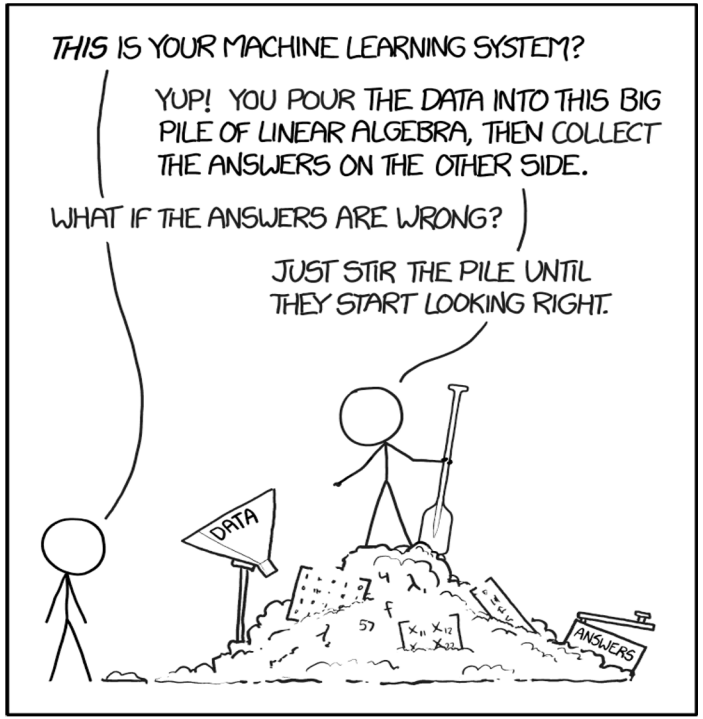
train, validation and test set





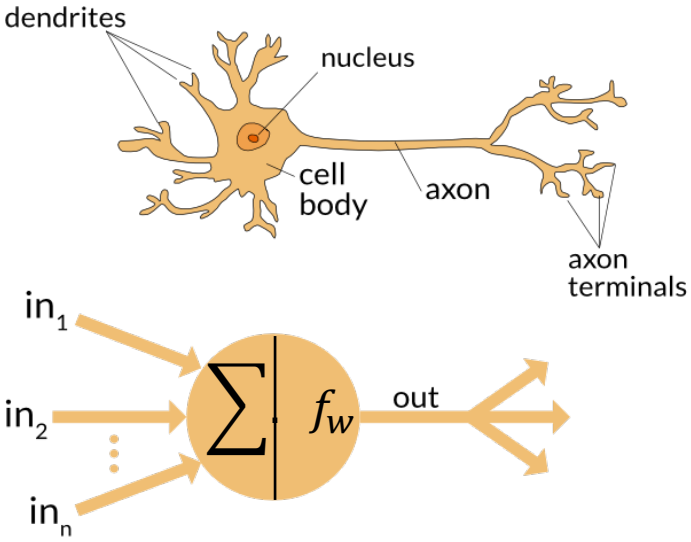
garbage in garbage out

- machine learning algorithms are good at pattern recognition.
- errors in the dataset might make the algorithm to pick up on non-existing patterns.



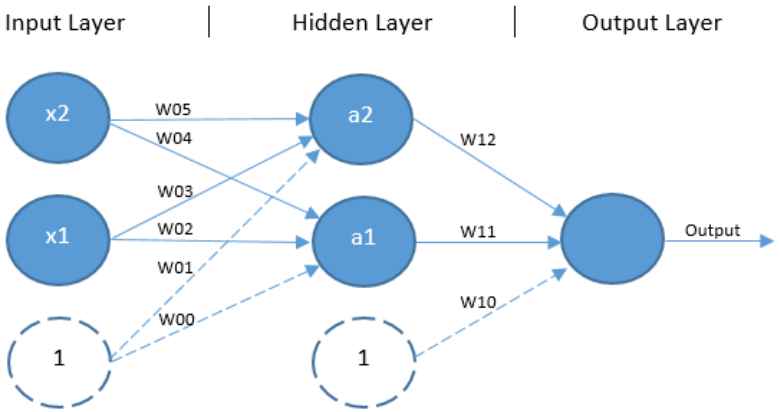
xkcd.com

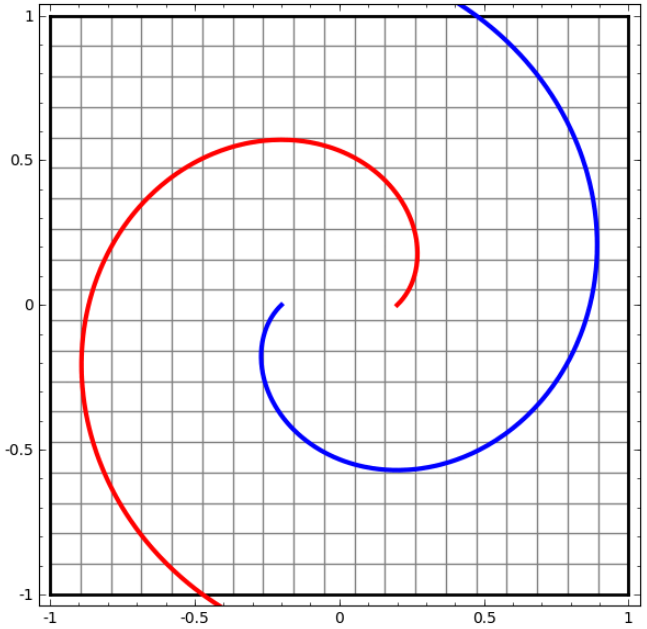
neural networks – the perceptron



- created in 1958 by Frank Rosenblatt, an American psychologist.
- inspired by the neuron's processing of information.
- they weren't able to solve some simple data problems

neural networks – the multilayer perceptron





predicting neurological and psychiatric disorders

ALZHEIMER'S DISEASE DIAGNOSTICS BY A DEEPLY SUPERVISED ADAPTABLE 3D CONVOLUTIONAL NETWORK

Ehsan Hosseini-Asl[1], Georgy Gimel'farb[2], Ayman El-Baz[3], for the Alzheimer's Disease Neuroimaging Initiative*

[1]Electrical and Computer Engineering Department, University of Louisville, Louisville, KY, USA.
[2]Department of Computer Science, University of Auckland, Auckland, New Zealand.
[3]Bioengineering Department, University of Louisville, Louisville, KY, USA.

Alzheimer's accuracy: 97.6%
AD = 70
HC = 70

Fully Connected Cascade Artificial Neural Network Architecture for Attention Deficit Hyperactivity Disorder Classification From Functional Magnetic Resonance Imaging Data

Publisher: IEEE

4 Author(s) Gopikrishna Deshpande ; Peng Wang ; D. Rangaprakash ; Bogdan Wilamowski **View All Authors**

ADHD's accuracy: 90.0%
HC = 744
ADHD = 260

predicting neurological and psychiatric disorders

Schizophrenia accuracy: 91%
SZ = 198
HC = 191

Deep learning for neuroimaging: a validation study

Sergey M. Plis[1*], Devon R. Hjelm[2], Ruslan Salakhutdinov[3], Elena A. Allen[1,4], Henry J. Bockholt[5], Jeffrey D. Long[6,7], Hans J. Johnson[6,8], Jane S. Paulsen[6,9,10], Jessica A. Turner[11] and Vince D. Calhoun[1,2,12]

[1]The Mind Research Network, Albuquerque, NM, USA

n= 1188
Divided patients into 4 neurophysiological subtypes.

Allowed to be classified with 82-93% sensitivity and specificity.

Article | Published: 05 December 2016

Resting-state connectivity biomarkers define neurophysiological subtypes of depression

Andrew T Drysdale, Logan Grosenick, Jonathan Downar, Katharine Dunlop, Farrokh

clinical implementation pros and cons

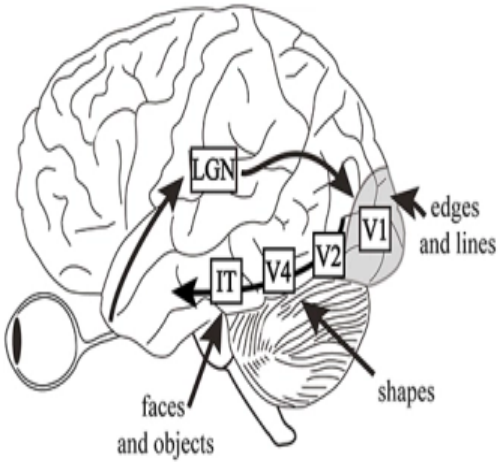
pros

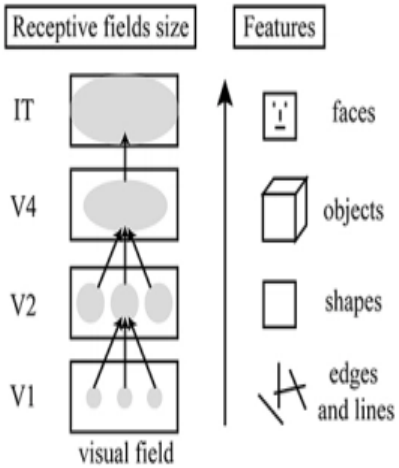
- high precision.
- allows almost immediate diagnosis.
- can scale to places with scarcity of resources.

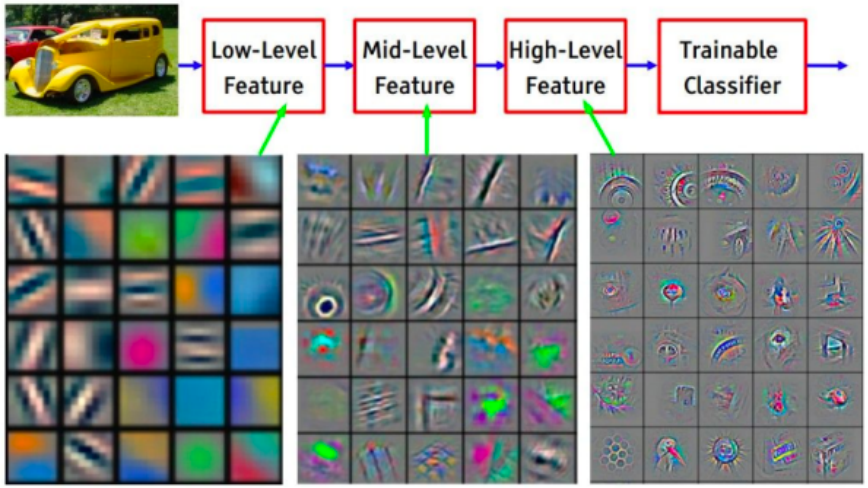
cons

- lack of explainibility.
- problems with generalisation.

modelling the brain – the visual system



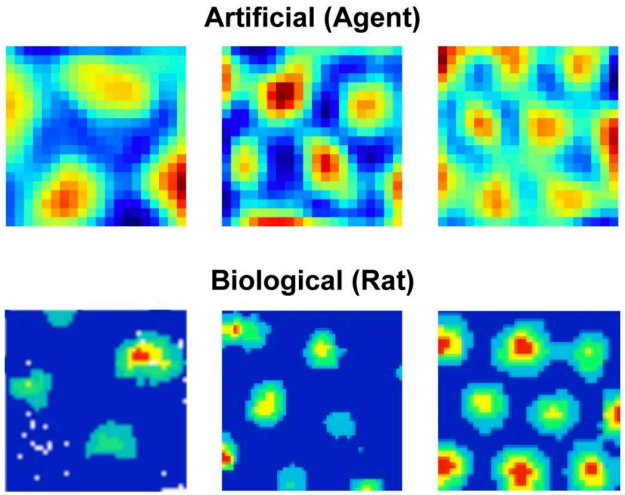




[Convolutional Neural Networks as a Model of the Visual System: Past, Present, and Future]

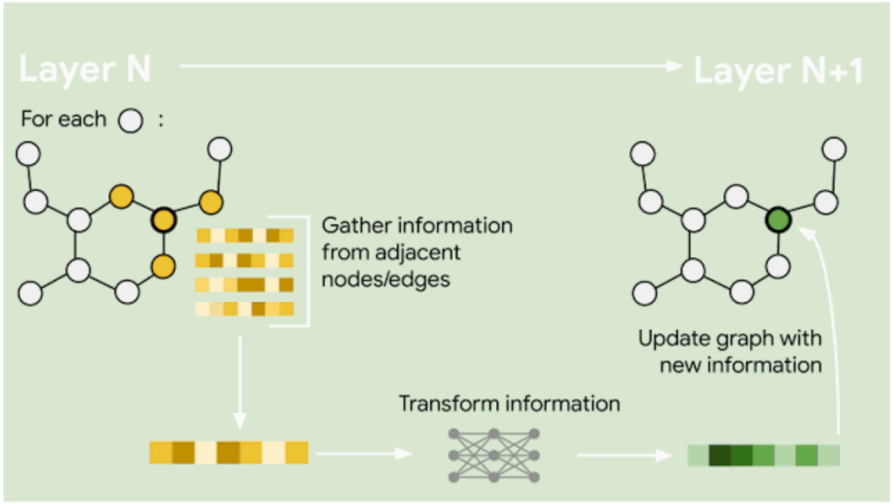
modelling the brain

modelling navigation neural pattern (DeepMind, 2018)



Banino et al.

modelling the olfactory system (Google Brain, 2019)



ai.googleblog.com

modelling behaviour

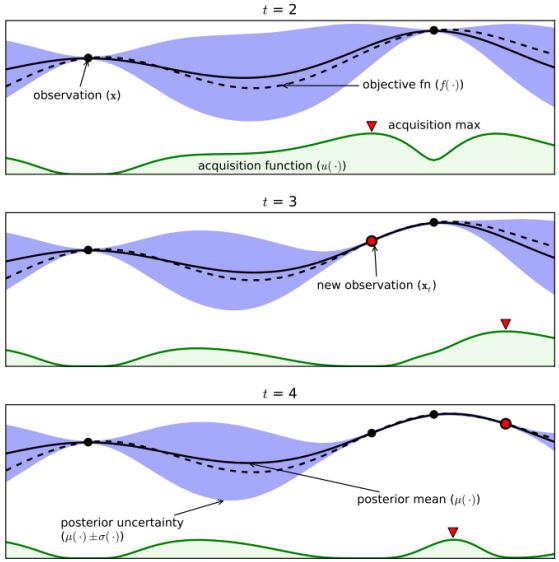
"Looked at it in one way, everyone knows what intelligence is; looked at in another way, no one does." – Robert J. Sternberg (2000)

Conversation 4	
Human:	*I like how cute cows are*
Meena:	*Ah, interesting. You like how they are cute, right?*
Human:	*yeah, and they're realy smart*
Meena:	*I heard they go to college*
Human:	*cows go to college?*
Meena:	*I heard that a cow went to Harvard.*
Human:	*what did the cow study?*
Meena:	*Bovine sciences.*
Human:	*do horses go to Harvard?*
Meena:	*Horses go to Hayvard.*
Human:	*that's a pretty good joke, I feel like you led me into it*
Meena:	*You were trying to steer it elsewhere, I can see it.*

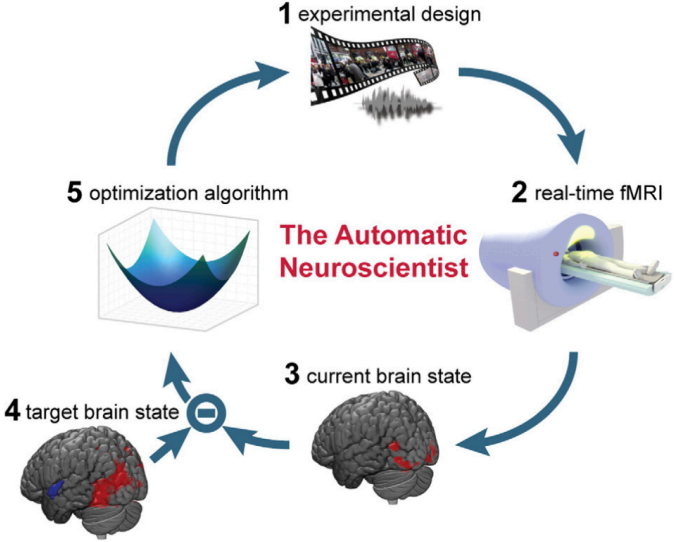
Daniel Adiwardana et al. (2020)

bayesian optimization

- Method to find the maximum of expensive functions;



Brochu et al. (2010)



Lorenz et al. (2016)

take home messages

- AI and ML are different concepts: AI encapsulates ML;
- In Machine Learning models learn from experience. In supervised learning they use their errors to adapt their behaviour;
- When fitting a model, one should avoid errors of bias and variance by using a training, a validation and a test set;
- There have been some interesting results in modelling the brain with machine learning but it still has some limitations.

resources

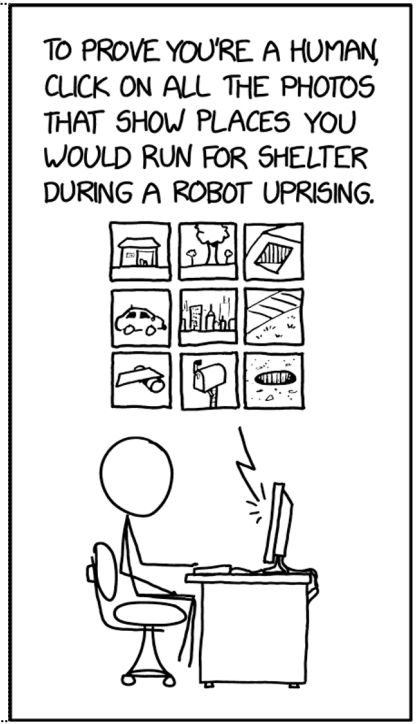
Slides can be obtained from:
github.com/PedroFerreiradaCosta/Lectures

For further knowledge:
Online Courses: Machine Learning on Coursera (free)

Reading: Hasson et al. - Direct Fit to Nature: An Evolutionary Perspective on Biological and Artificial Neural Networks

Videos:
Blake Richards – deep learning and the brain
Geoffrey Hinton – does the brain do backpropagation?
Yoshua Bengio – from System 1 deep learning to system 2 deep learning
David Cox – neuroscience and machine learning

Summer schools in Computational Neurosciences worldwide



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