Introduction to Machine Learning and Big Data

F. Sanfilippo [1]

[1] Department of Engineering Cybernetics, Norwegian University of Science and Technology, 7491 Trondheim, Norway,
filippo.sanfilippo@ntnu.no
http://filipposanfilippo.inspitivity.com/

Trial lecture at the Department of Computing, Mathematics and Physics,
Western Norway University of Applied Sciences, Norway, 2017

Høgskulen på Vestlandet

NTNU

About Me

Education:

- PhD in Engineering Cybernetics, Norwegian University of Science and Technology (NTNU), Norway
- MSc in Computer Science Engineering, University of Siena, Italy
- BSc degree in Computer Science Engineering, University of Catania, Italy

Mobility:

- Visiting Fellow, Technical Aspects of Multimodal Systems (TAMS), Department of Mathematics, Informatics and Natural Sciences, University of Hamburg, Hamburg, Germany
- Visiting Student, School of Computing and Intelligent Systems, University of Ulster, Londonderry, United Kingdom
- Granted with an Erasmus+ Staff Mobility for Teaching and Training project

Activities:

- Membership Development Officer for the IEEE Norway Section

Høgskulen på Vestlandet

NTNU

About Me

Current position:

- Filippo Sanfilippo, Postdoctoral Fellow at the Dept. of Eng. Cybernetics, Norwegian University of Science and Technology (NTNU), Trondheim, Norway

Current courses:

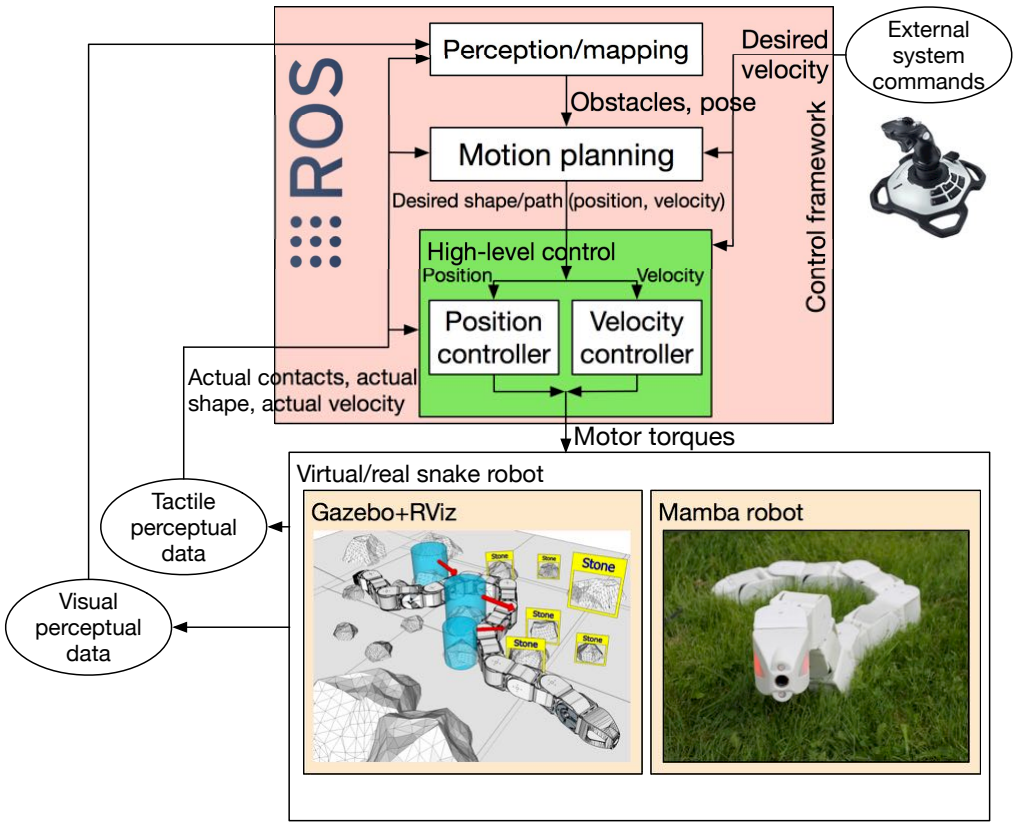
- TTK4235 - Embedded Systems (Lecturer)
- Experts in Teamwork - Snake robots (Supervisor)

Past courses:

- Real-time Computer Programming (Lecturer)
- Mechatronics, Robots and Deck Machines (Teaching Assistant)
- System Simulation in Matlab/Simulink (Lecturer)

Current research topic:

- "SNAKE - Control Strategies for Snake Robot Locomotion in Challenging Outdoor Environments", project number 240072, supported by the Research Council of Norway through the *Young research talents funding scheme*



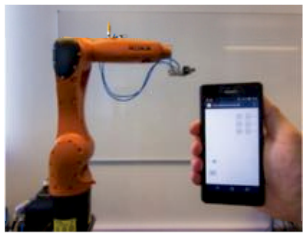
Research topics

Visualisation/Game Development

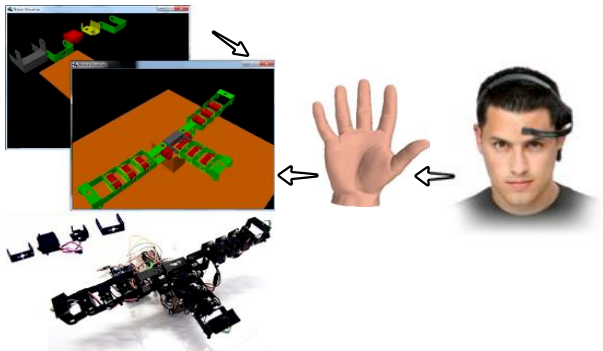
Augmented Reality/Virtual Reality

Micro-controllers, IoT, Maker Tech.

Mobile Device

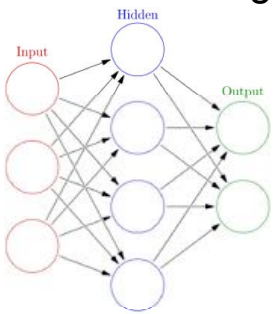


Software/Hardware Codesign



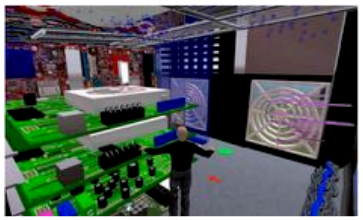
Real-time Systems

Artificial Intelligence



Safety-Critical Systems

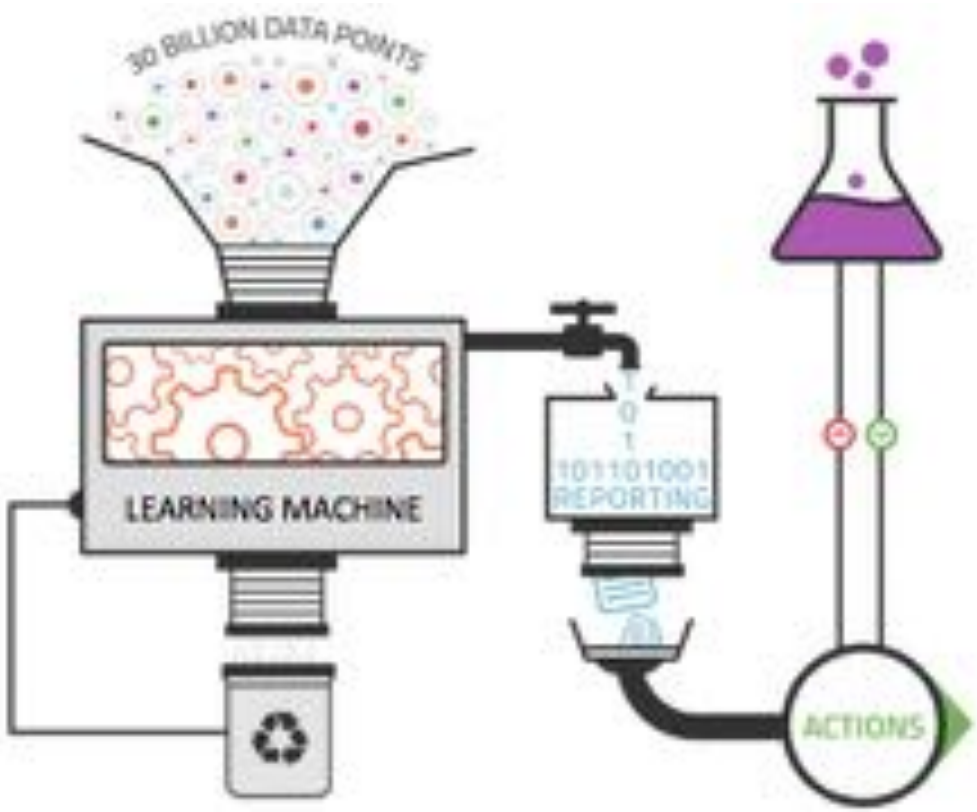
Education



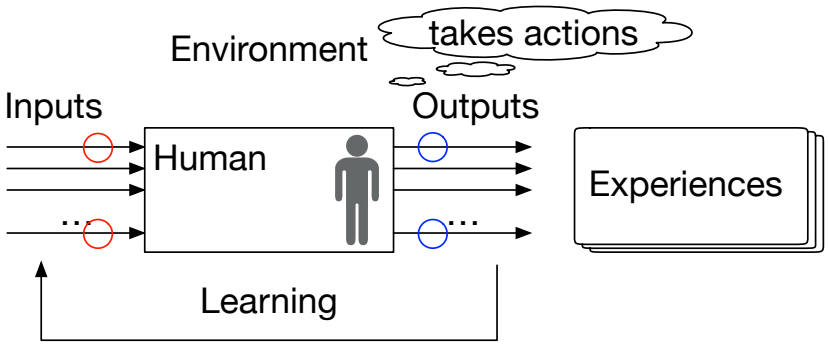
Introduction to Machine Learning and Big Data

Goals of this trial lecture:

- fundamental cocetps ("idea buckets") of ML and BD
- fundation for further learning about ML and BD
- spikes to further resources for self-learning about ML and BD



What is Machine Learning?



Learning:

- humans display intelligent behaviours by learning from experience
- remembering, adapting and generalising (this is what makes learning useful!)

What is Machine Learning?

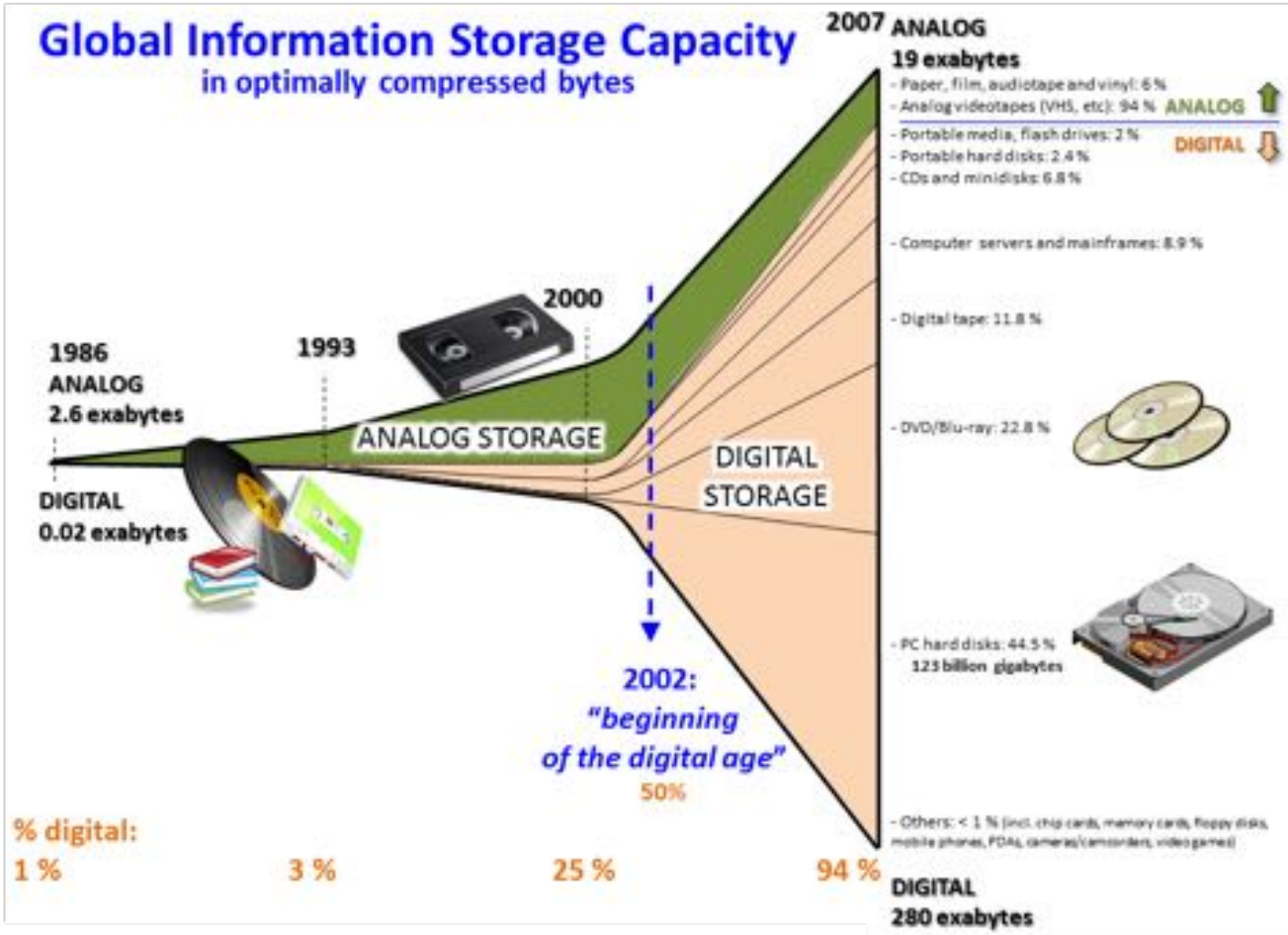
Machine Learning:

- Arthur Samuel (1959). "Field of study that gives computers the ability to learn without being explicitly programmed"
- The Samuel Checkers-playing Program appears to be the world's first self-learning program

[1]

[1] Arthur L Samuel. "Some studies in machine learning using the game of checkers". In: *IBM Journal of research and development* 44.1.2 (2000), pp. 206–226.

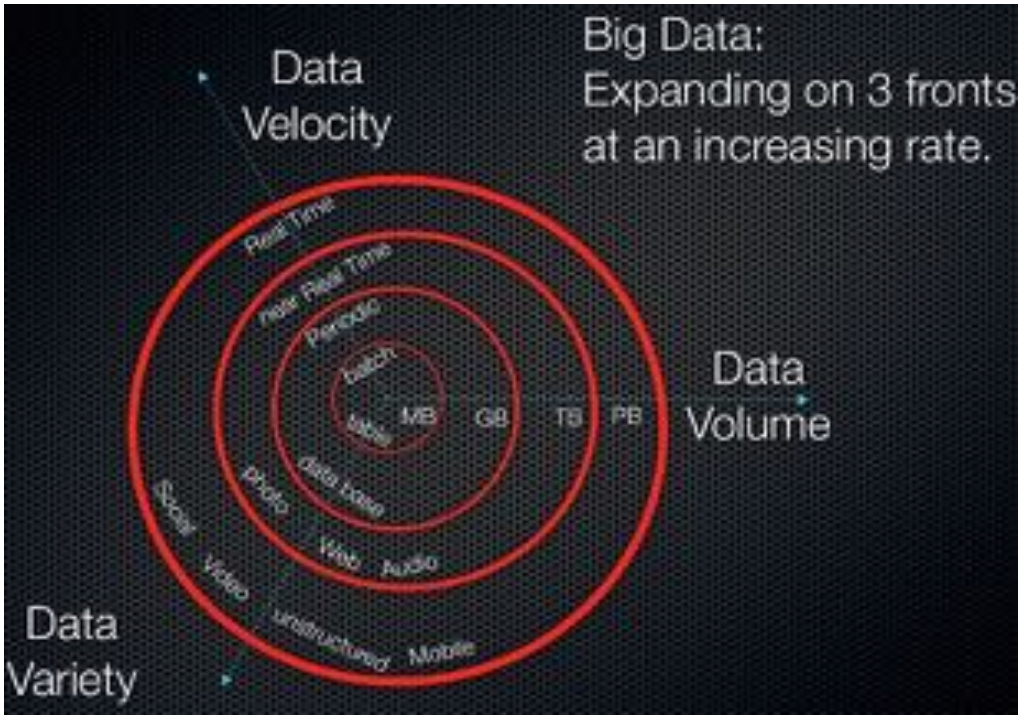
What is Big Data?



[2]

[2] Martin Hilbert and Priscila López. "The world's technological capacity to store, communicate, and compute information". In: *science* 332.6025 (2011), pp. 60–65.

What is Big Data?



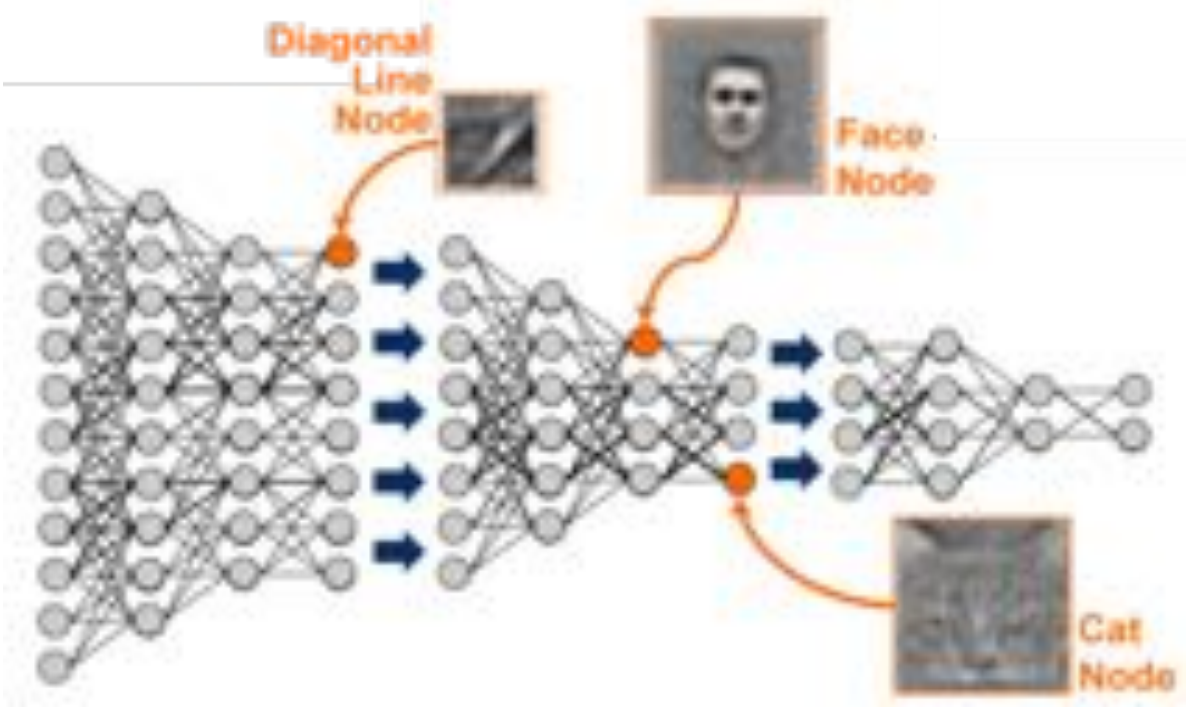
[3]

Big Data:

- high-volume, high-velocity and or high-variety information assets that demand cost-effective, innovative forms of information processing
- enable enhanced insight, decision making, and process automation

[3] John Gantz and David Reinsel. "The digital universe in 2020: Big data, bigger digital shadows, and biggest growth in the far east". In: *IDC iView: IDC Analyze the future* 2007.2012 (2012), pp. 1–16.

The huge potential of Machine Learning and Big Data



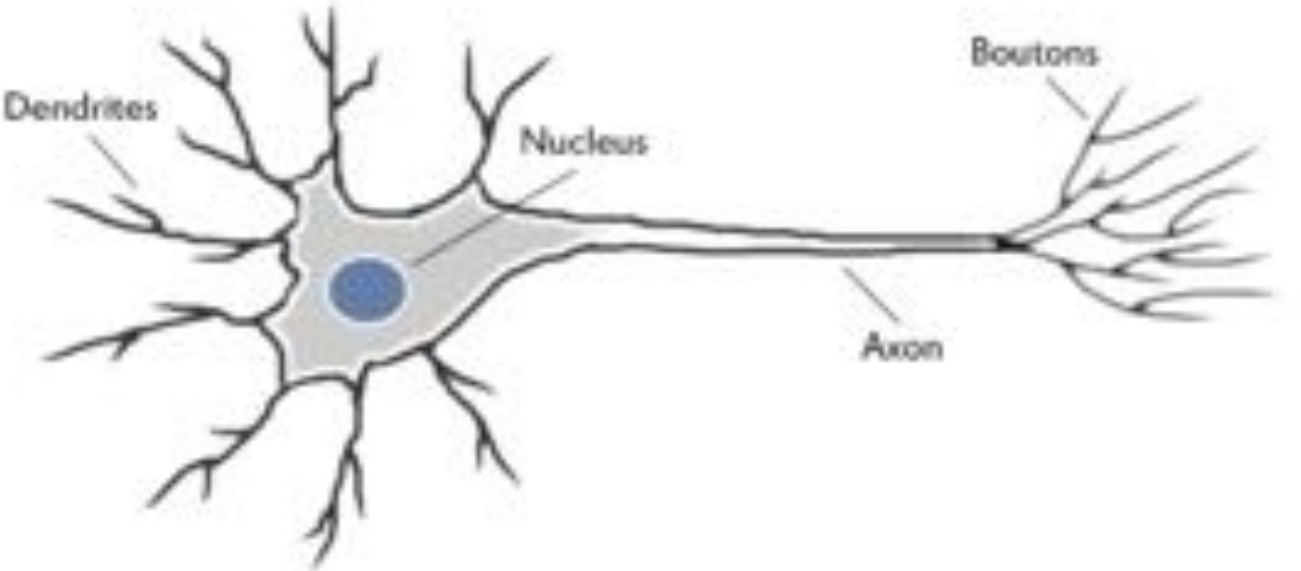
Google's artificial brain learns to find cats and faces:

- ANN, 1 billion connections, 16000 computers, browse YouTube for 3 days

[4]

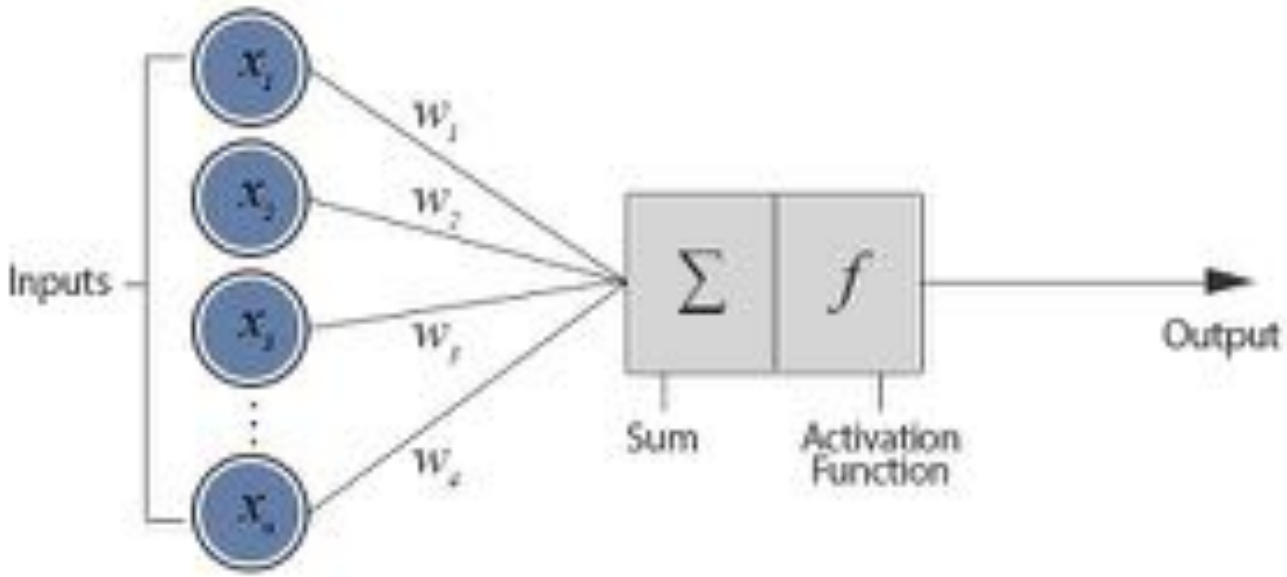
[4] Quoc V Le. "Building high-level features using large scale unsupervised learning". In: *Acoustics, Speech and Signal Processing (ICASSP), 2013 IEEE International Conference on*. IEEE. 2013, pp. 8595–8598.

ANN biological inspiration

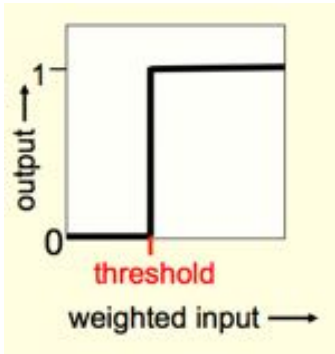


- One hundred billion (100,000,000,000) neurons inside the human brain each with about one thousand synaptic connections
- It's effectively the way in which these synapses are wired that give our brains the ability to process information the way they do.

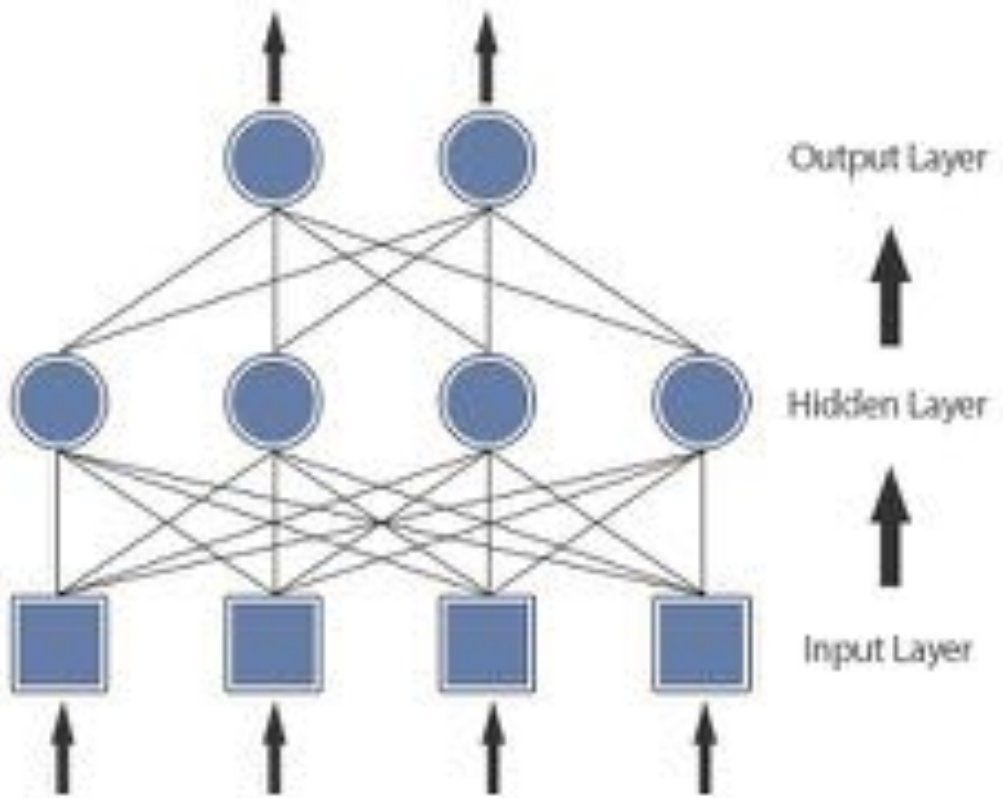
Modeling artificial neurons: perceptrons




```
x1  = 0.6        //Input 1
x2  = 1.0        //Input 2

w1 = 0.5         //Weight 1
w2 = 0.8         //Weight 2

Threshold = 1.0

x1w1 + x2w2 = (0.6 x 0.5) + (1 x 0.8) = 1.1
```



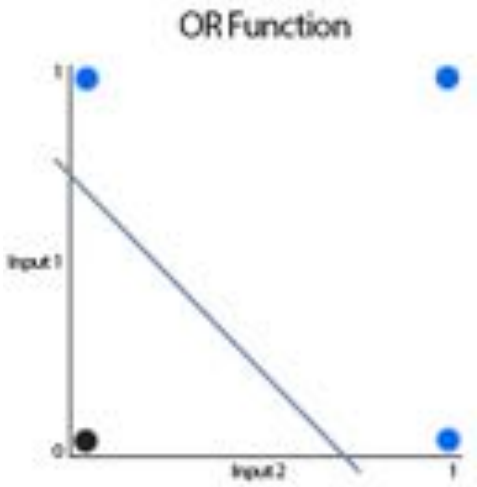
Implementing Artificial Neural Networks

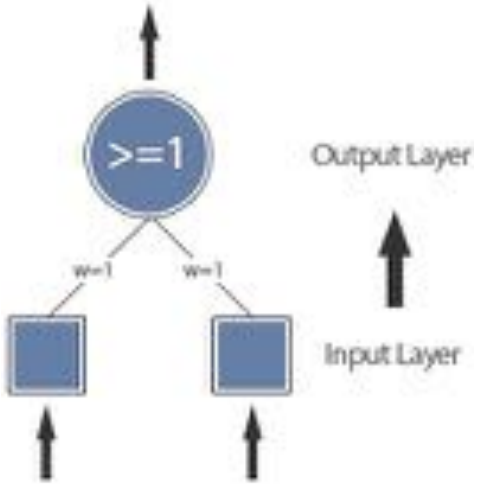


- feedforward network: the signals are passed through the layers of the neural network in a single direction
- These aren't the only type of neural network though. There are also feedback networks where their architecture allows signals to travel in both directions

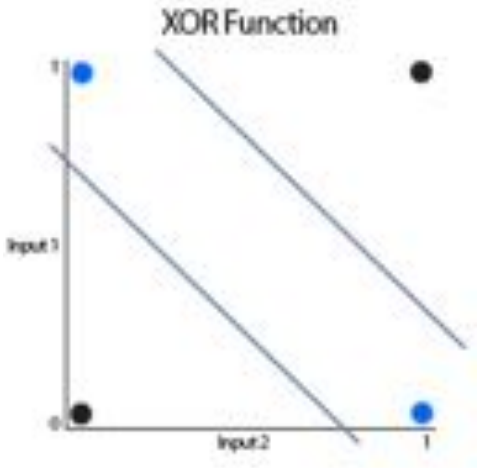
Linear separability and multi layer perceptron

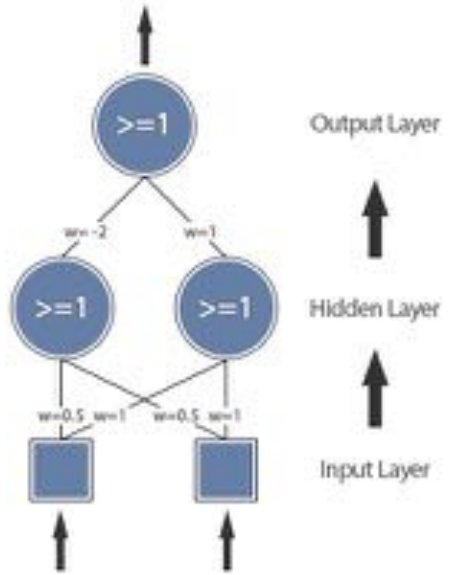
OR		
0	0	0
0	1	1
1	0	1
1	1	1





XOR		
0	0	0
0	1	1
1	0	1
1	1	0





The perceptron learning rule

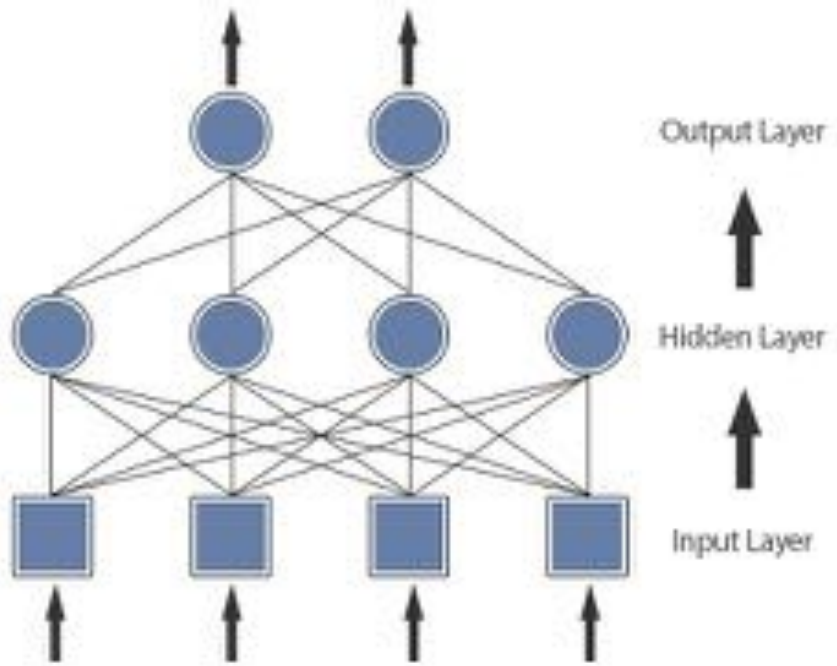
$$o = f(\sum_{i=1}^{n} x_i w_i), \quad (1)$$

$$E = t - o, \quad (2)$$

$$\Delta w_i = rEx_i, \quad (3)$$

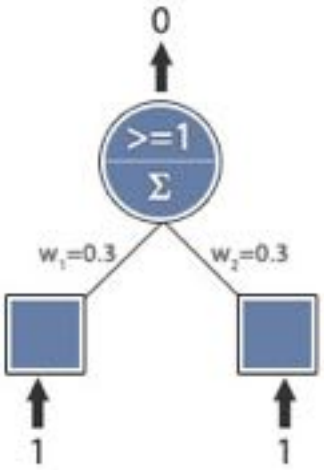
$$\Delta w_i = r(t - o)x_i, \quad (4)$$

$$w_i(t + 1) = w_i(t) + \Delta w_i, \quad (5)$$

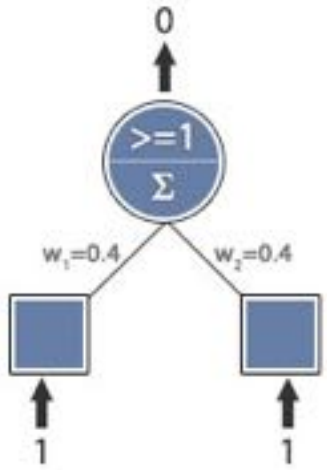


If the learning rate is too high the perceptron can jump too far and miss the solution, if it's too low, it can take an unreasonably long time to train.

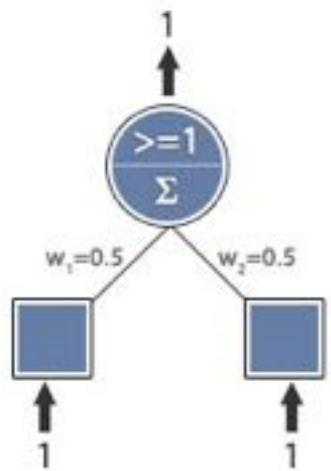
AND function example




```
r = 0.1
t = 1
o =  0
E = 1

//Weight Update
wi = r E x + wi
w1 = 0.1 * 1 * 1 + w1
w2 = 0.1 * 1 * 1 + w2

//New Weights
w1 = 0.4
w2 = 0.4
```

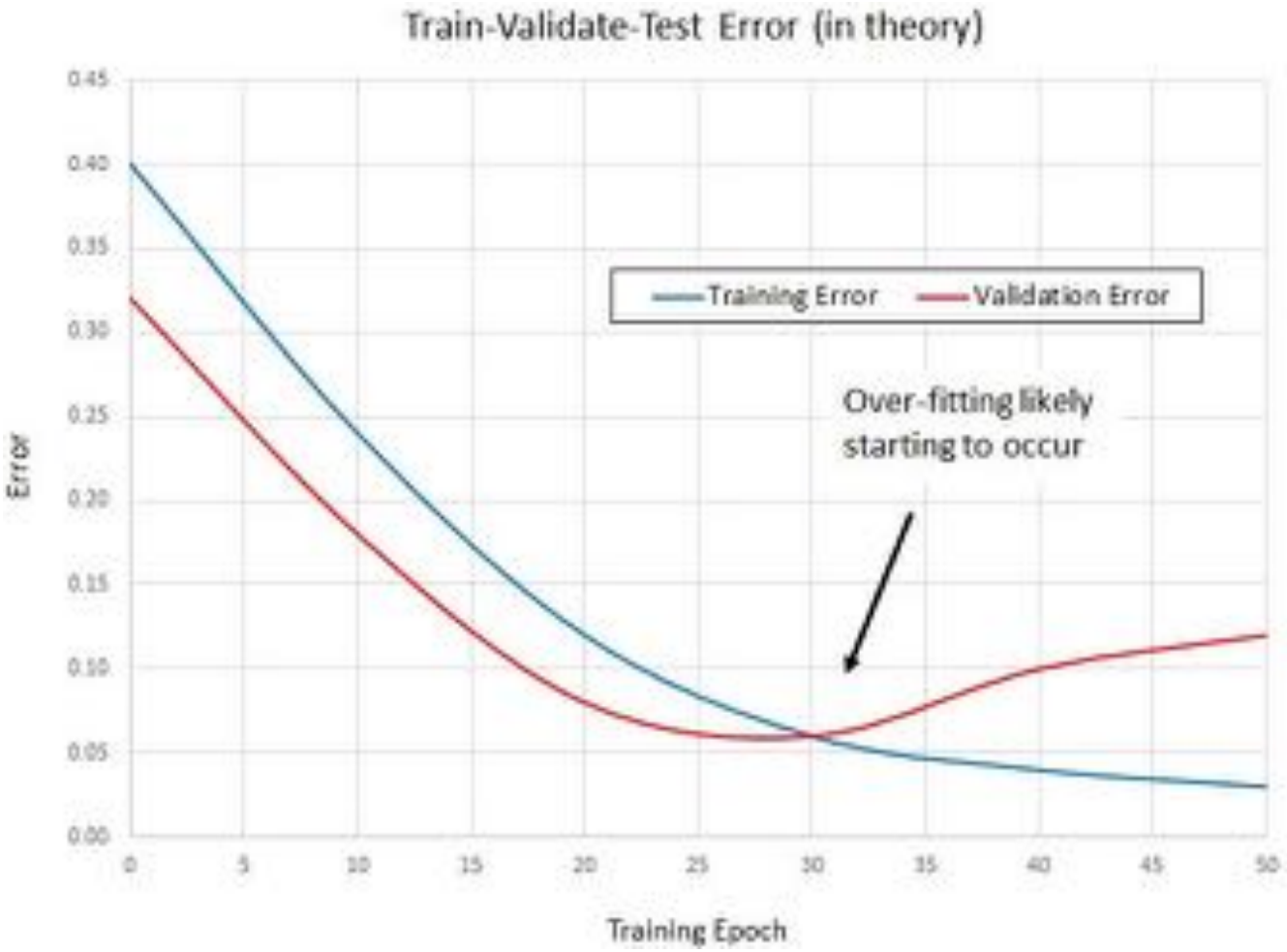



```
r = 0.1
t = 1
o =  0
E = 1

//Weight Update
wi = r E x + wi
w1 = 0.1 * 1 * 1 + w1
w2 = 0.1 * 1 * 1 + w2

//New Weights:
w1 = 0.5
w2 = 0.5
```




```
r = 0.1
t = 1
o =  1
E = 0

//No error
```

Neural Network Train-Validate-Test Stopping



- the data is split into three sets: a training set (typically 60 percent of the data), a validation set (20 percent) and a test set (20 percent)

An architecture for different models of maritime cranes and robotic arms

[5–8]

---

[5] Filippo Sanfilippo et al. "A mapping approach for controlling different maritime cranes and robots using ANN". In: *Proc. of the IEEE International Conference on Mechatronics and Automation (ICMA)*. 2014, pp. 594–599.

[6] Filippo Sanfilippo et al. "A Universal Control Architecture for Maritime Cranes and Robots Using Genetic Algorithms as a Possible Mapping Approach". In: *Proc. of the IEEE International Conference on Robotics and Biomimetics (ROBIO), Shenzhen, China*. 2013, pp. 322–327.

[7] Filippo Sanfilippo et al. "Integrated flexible maritime crane architecture for the offshore simulation centre AS (OSC): A flexible framework for alternative maritime crane control algorithms". In: *IEEE Journal of Oceanic Engineering* 41.2 (2016), pp. 450–461.

[8] Filippo Sanfilippo et al. "A Benchmarking Framework for Control Methods of Maritime Cranes Based on the Functional Mockup Interface". In: *IEEE Journal of Oceanic Engineering* (2017).

Conclusion

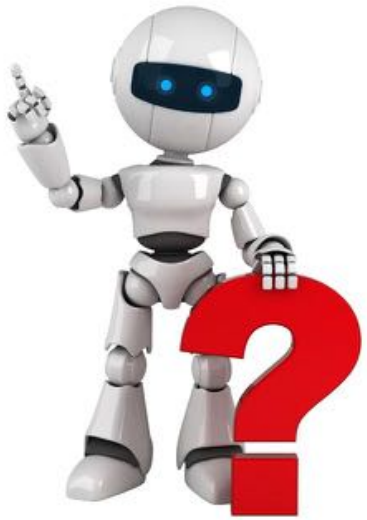
Huge potential for ML and BD:

- intelligent decision making systems
- prediction methods
- applications (social networks, biology, life sciences datasets)
- swarm Intelligence
- BD Cybernetics, from a large number of sensor channels into smart data

[9]

[9] Cui-Ru Wang, Chun-Lei Zhou, and Jian-Wei Ma. "Machine learning and cybernetics". In: *Proceedings of 2005 International Conference on An improved artificial fish-swarm algorithm and its application in feed-forward neural networks*. Vol. 5. Springer. 2003, pp. 2890–2894.

Thank you for your attention



ML and BD useful resources:

- `http://playground.tensorflow.org/`, a Neural Network right in your browser
- `https://www.tensorflow.org/`, an open-source software library for Machine Intelligence

Contact:

- F. Sanfilippo, Department of Engineering Cybernetics, Norwegian University of Science and Technology, 7491 Trondheim, Norway, filippo.sanfilippo@ntnu.no.

Høgskulen på Vestlandet

NTNU

References

[1] Arthur L Samuel. "Some studies in machine learning using the game of checkers". In: *IBM Journal of research and development* 44.1.2 (2000), pp. 206–226.

[2] Martin Hilbert and Priscila López. "The world's technological capacity to store, communicate, and compute information". In: *science* 332.6025 (2011), pp. 60–65.

[3] John Gantz and David Reinsel. "The digital universe in 2020: Big data, bigger digital shadows, and biggest growth in the far east". In: *IDC iView: IDC Analyze the future* 2007.2012 (2012), pp. 1–16.

[4] Quoc V Le. "Building high-level features using large scale unsupervised learning". In: *Acoustics, Speech and Signal Processing (ICASSP), 2013 IEEE International Conference on*. IEEE. 2013, pp. 8595–8598.

[5] Filippo Sanfilippo et al. "A mapping approach for controlling different maritime cranes and robots using ANN". In: *Proc. of the IEEE International Conference on Mechatronics and Automation (ICMA)*. 2014, pp. 594–599.

[6] Filippo Sanfilippo et al. "A Universal Control Architecture for Maritime Cranes and Robots Using Genetic Algorithms as a Possible Mapping Approach". In: *Proc. of the IEEE International Conference on Robotics and Biomimetics (ROBIO), Shenzhen, China*. 2013, pp. 322–327.

References (contd.)

[7] Filippo Sanfilippo et al. "Integrated flexible maritime crane architecture for the offshore simulation centre AS (OSC): A flexible framework for alternative maritime crane control algorithms". In: *IEEE Journal of Oceanic Engineering* 41.2 (2016), pp. 450–461.

[8] Filippo Sanfilippo et al. "A Benchmarking Framework for Control Methods of Maritime Cranes Based on the Functional Mockup Interface". In: *IEEE Journal of Oceanic Engineering* (2017).

[9] Cui-Ru Wang, Chun-Lei Zhou, and Jian-Wei Ma. "Machine learning and cybernetics". In: *Proceedings of 2005 International Conference on An improved artificial fish-swarm algorithm and its application in feed-forward neural networks*. Vol. 5. Springer. 2003, pp. 2890–2894.