Deep Reinforcement Learning

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RoboCup Soccer

Objective of the RoboCup Federation:

"By the middle of the 21st century, a team of fully autonomous humanoid robot soccer players shall win a soccer game, complying with the official rules of FIFA, against the winner of the most recent World Cup."

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[RoboCup Nao video[1]]

1. `https://www.youtube.com/watch?v=b6Zu5fLUa3c`

Half Field Offense (KLS2007)

[Video of task[1]]

1. http://www.cs.utexas.edu/~AustinVilla/sim/halffieldoffense/

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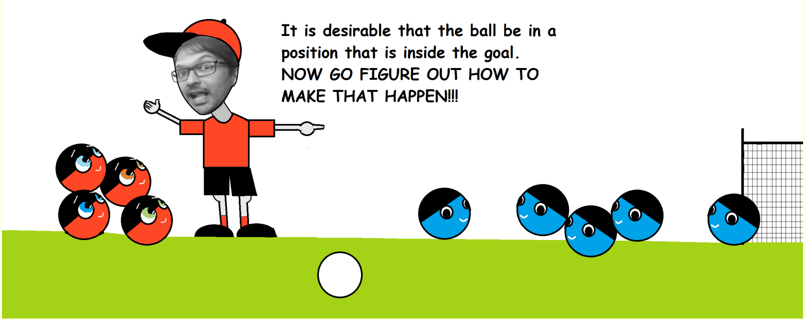
Training



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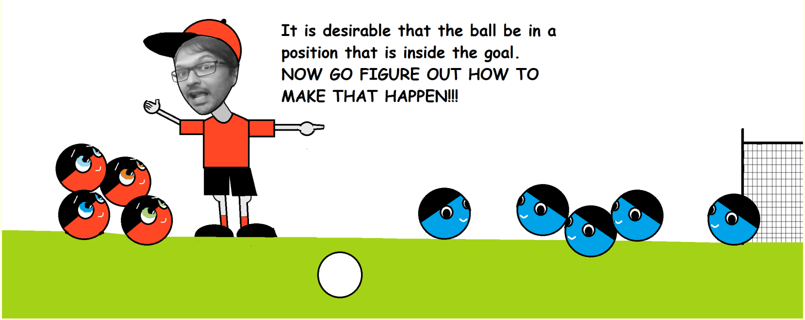

[Video of task after training[2]]

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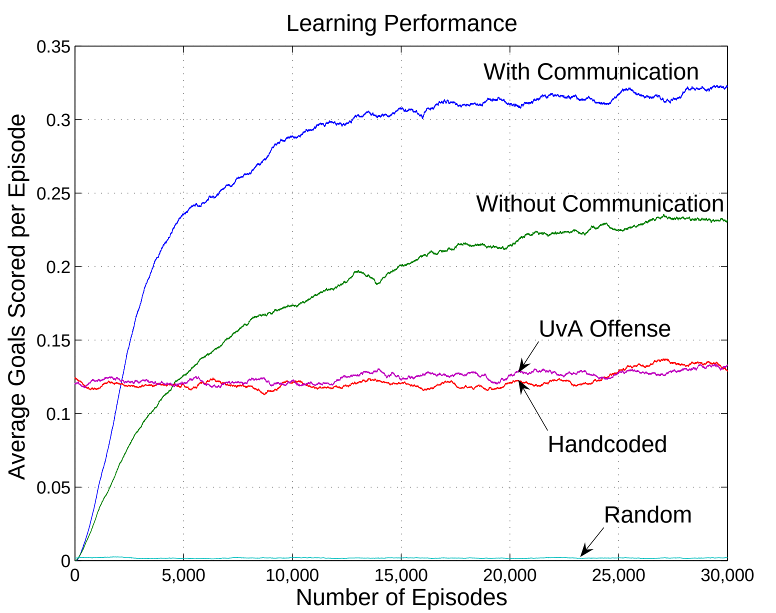


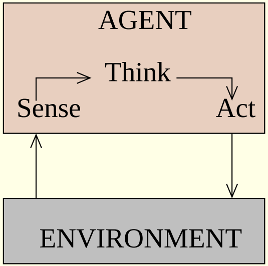
Overview

1. Reinforcement Learning
2. Neural Networks and Deep Learning
3. Deep Reinforcement Learning

Learning to Act Purposefully

Answer: Reinforcement Learning (RL).

Learning to Act Purposefully



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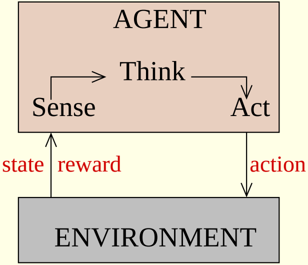

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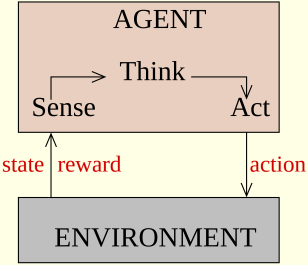
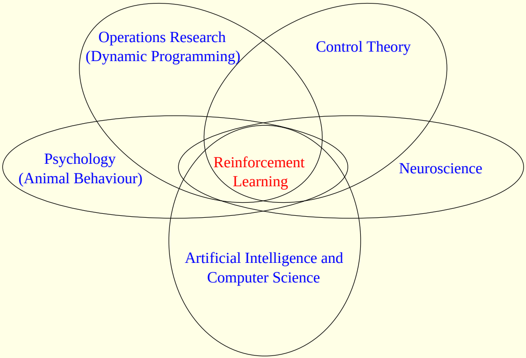


Question: How must an agent in an *unknown* environment act so as to maximise its long-term reward?

Answer: Reinforcement Learning (RL).

Reinforcement Learning: Historical Foundations



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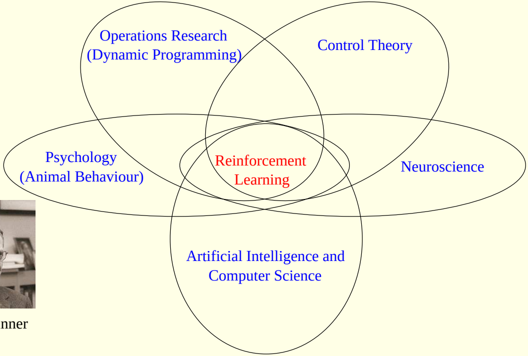
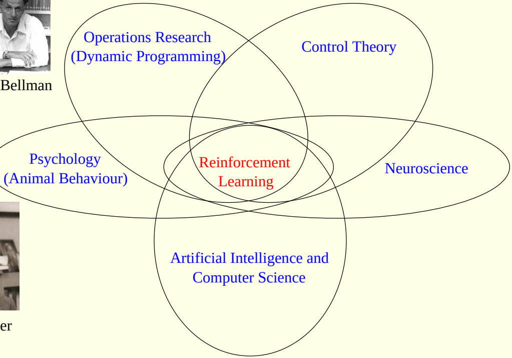


B. F. Skinner

Reinforcement Learning: Historical Foundations

R. E. Bellman

B. F. Skinner



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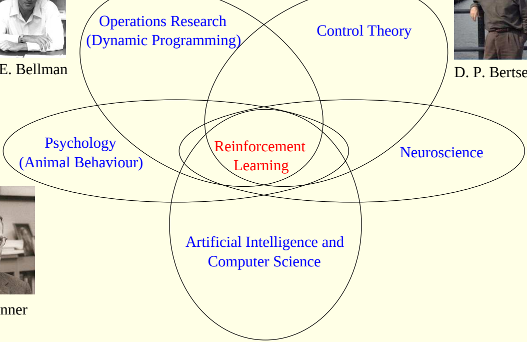
D. P. Bertsekas



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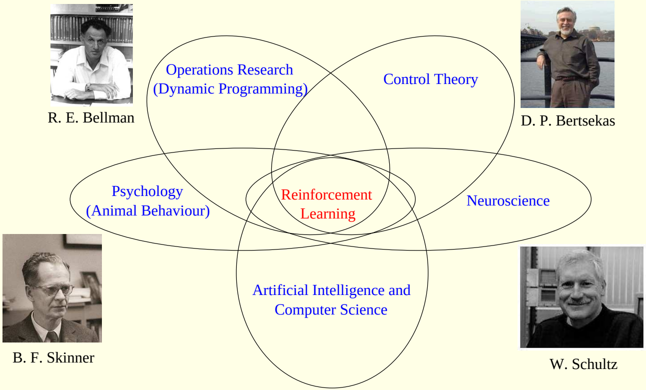

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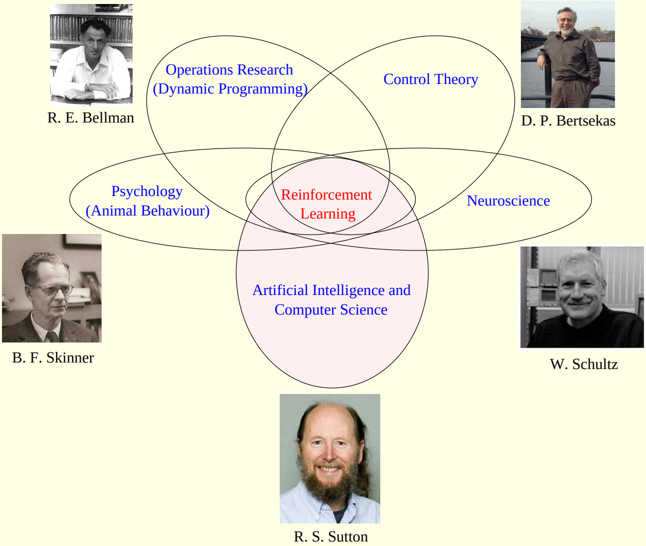

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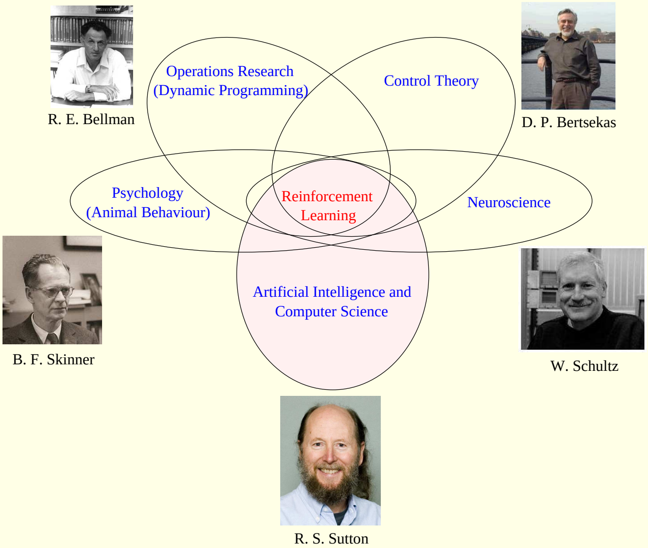

References: KLM1996, SB1998.

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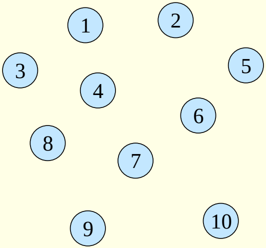

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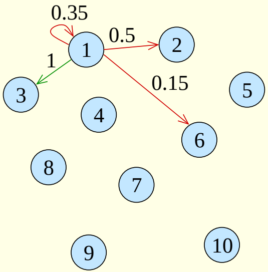

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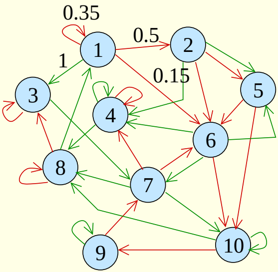

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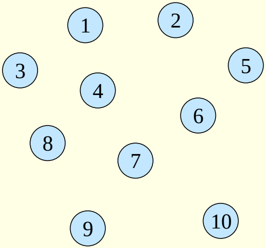

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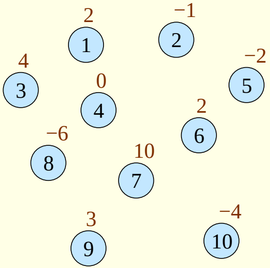

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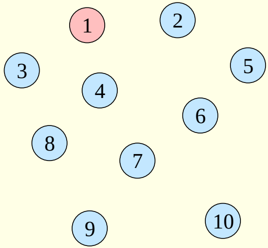

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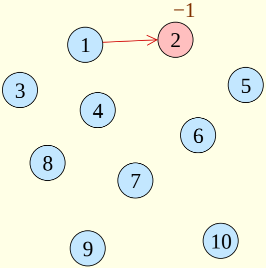

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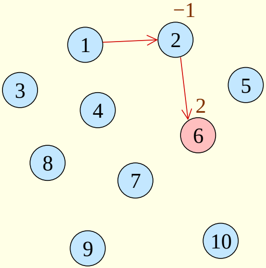

$r_1 = -1.$

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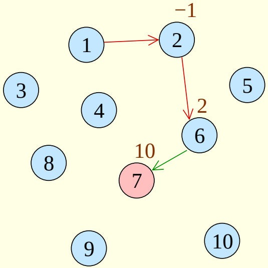

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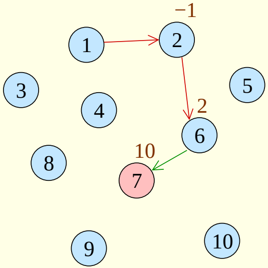

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How to take actions so as to maximise expected long-term reward

$$\mathbb{E}[r_1 + r_2 + r_3 + \ldots]?$$

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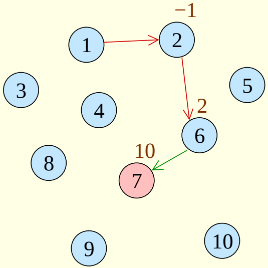

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How to take actions so as to maximise expected long-term reward

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[Note that there exists an (unknown) *optimal policy*.]

Q-Learning

- Keep a running estimate of the expected long-term reward obtained by taking each action from each state s, and acting *optimally* thereafter.

Q	red	green
1	-0.2	10
2	4.5	13
3	6	-8
4	0	0.2
5	-4.2	-4.2
6	1.2	1.6
7	10	6
8	4.8	9.9
9	5.0	-3.4
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- Update these estimates based on experience (s_t, a_t, r_t, s_{t+1}):

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha_t\{r_t + \max_a Q(s_{t+1}, a) - Q(s_t, a_t)\}.$$

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- Act greedily based on the estimates (exploit) most of the time, but still
- Make sure to explore each action enough times.

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- Make sure to explore each action enough times.

Q-learning will converge and induce an optimal policy (WD1992)!

Practice In Spite of the Theory!

Task	State Aliasing	State Space	Policy Representation (Number of features)
Backgammon (T1992)	Absent	Discrete	Neural network (198)
Job-shop scheduling (ZD1995)	Absent	Discrete	Neural network (20)
Tetris (BT1906)	Absent	Discrete	Linear (22)
Elevator dispatching (CB1996)	Present	Continuous	Neural network (46)
Acrobot control (S1996)	Absent	Continuous	Tile coding (4)
Dynamic channel allocation (SB1997)	Absent	Discrete	Linear (100's)
Active guidance of finless rocket (GM2003)	Present	Continuous	Neural network (14)
Fast quadrupedal locomotion (KS2004)	Present	Continuous	Parameterized policy (12)
Robot sensing strategy (KF2004)	Present	Continuous	Linear (36)
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Robot soccer keepaway (SSK2005)	Present	Continuous	Tile coding (13)
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Optimized trade execution (NFK2007)	Present	Discrete	Tabular (2-5)
Blimp control (RPHB2007)	Present	Continuous	Gaussian Process (2)
9 $\times$ 9 Go (SSM2007)	Absent	Discrete	Linear ($\approx$1.5 million)
Ms. Pac-Man (SL2007)	Absent	Discrete	Rule list (10)
Autonomic resource allocation (TJDB2007)	Present	Continuous	Neural network (2)
General game playing (FB2008)	Absent	Discrete	Tabular (part of state space)
Soccer opponent "hassling" (GRT2009)	Present	Continuous	Neural network (9)
Adaptive epilepsy treatment (GVAP2008)	Present	Continuous	Extremely rand. trees (114)
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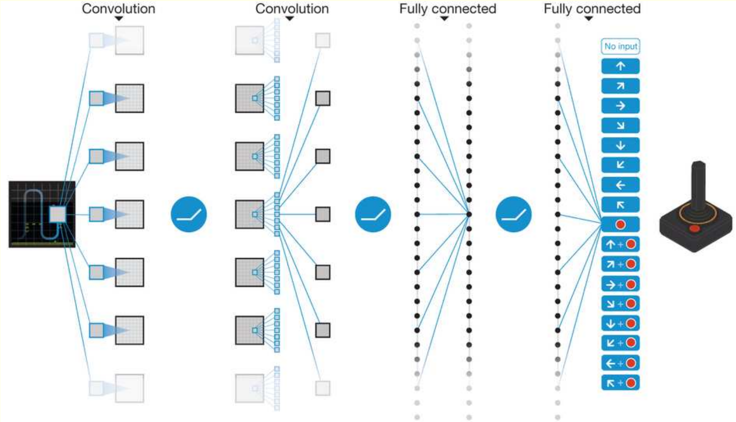
Perfect representations (fully observable, enumerable states) are impractical (K2011).

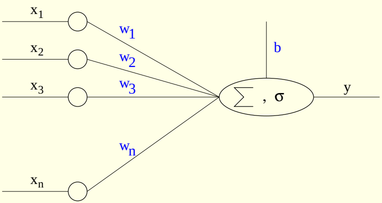
Typical Neural Network-based Representation of Q



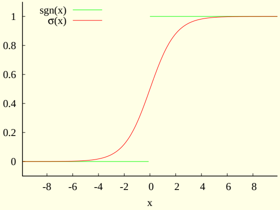
1. http://www.nature.com/nature/journal/v518/n7540/carousel/nature14236-f1.jpg

Overview

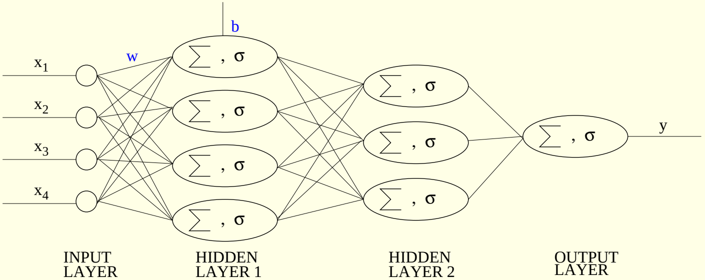
Artificial Neuron



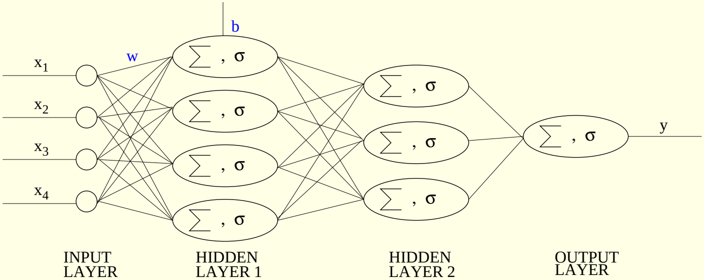
$$\sigma(x) \stackrel{\text{def}}{=} \frac{1}{1+\exp(-x)}.$$



Artificial Neural Networks



Artificial Neural Networks



Artificial neural networks are Universal Approximators.

For any function on a finite data set, there exists a single-hidden-layer neural network that fits it to an arbitrary degree of accuracy (HSW1989).

Backpropagation Algorithm (RHW1986)

We are given a training data set $\{(x^1, y^1), (x^2, y^2), \ldots, (x^D, y^D)\}$.

Let us start with some initial weights $\mathbf{w}$.

Backpropagation Algorithm (RHW1986)

We are given a training data set $\{(x^1, y^1), (x^2, y^2), \ldots, (x^D, y^D)\}$.

Let us start with some initial weights $\mathbf{w}$.

For each data point j,

the true label is y^j,

the prediction is $p^j(\mathbf{w})$; and

thus, the error is $(y^j - p^j(\mathbf{w}))^2$.

The aggregate error over the training data is $E(\mathbf{w}) = \sum_{j=1}^{D}(y^j - p^j(\mathbf{w}))^2$.

We move a step in the direction minimising error:

$\mathbf{w} \leftarrow \mathbf{w} - \alpha \nabla_{\mathbf{w}} E(\mathbf{w})$,

and iterate until convergence.

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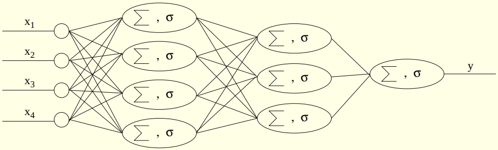
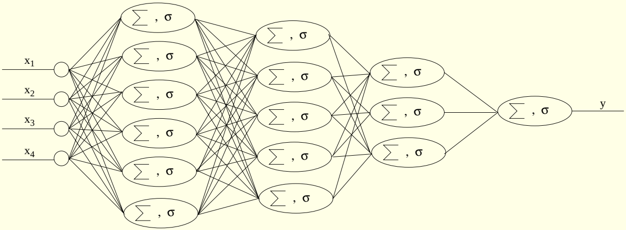
For a given neural network, $\nabla_{\mathbf{w}} E(\mathbf{w})$ can be easily computed.
Backpropagation will converge to a local minimum.

Expressiveness and Learnability

Small network



Large network



Is a larger network always better?

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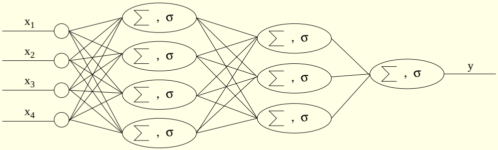

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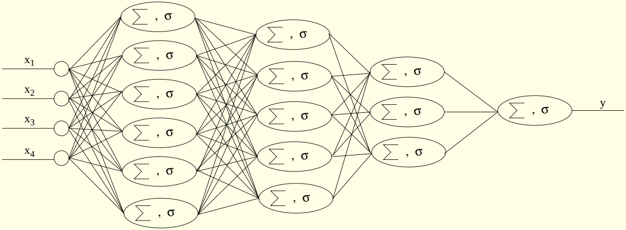
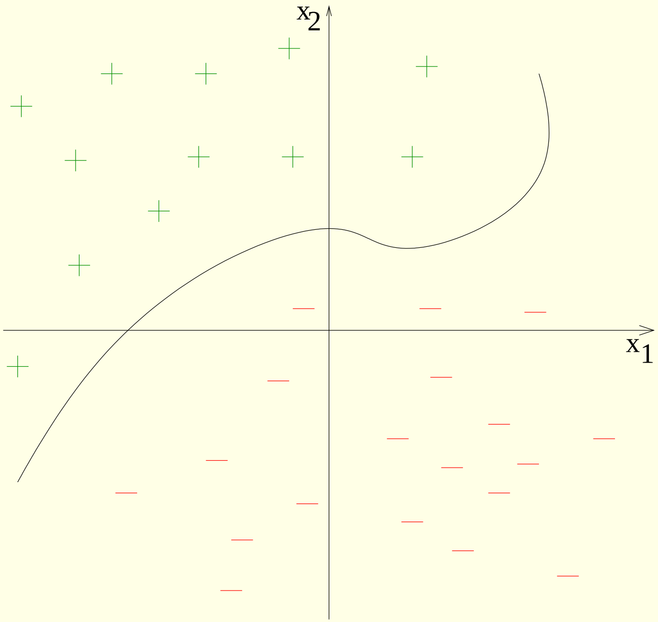


Is a larger network always better?

No!

Expressiveness and Learnability: Overfitting



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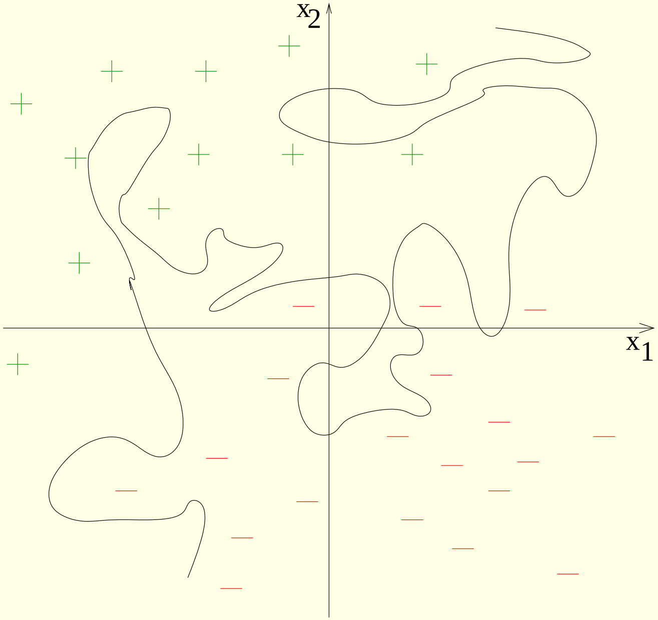
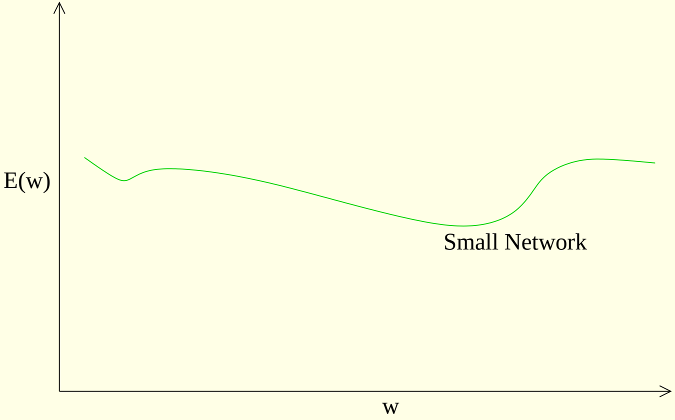


Expressiveness and Learnability: Initialisation



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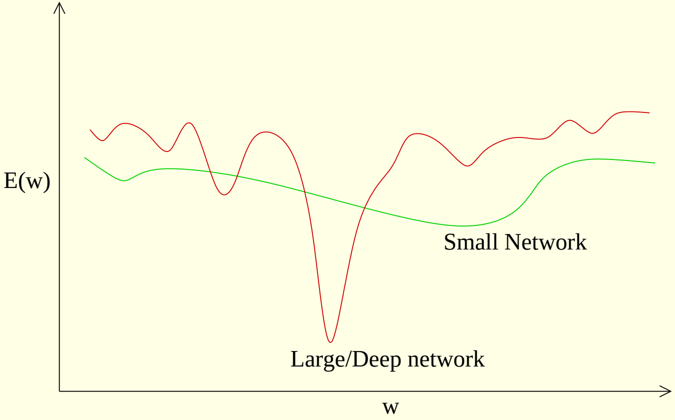
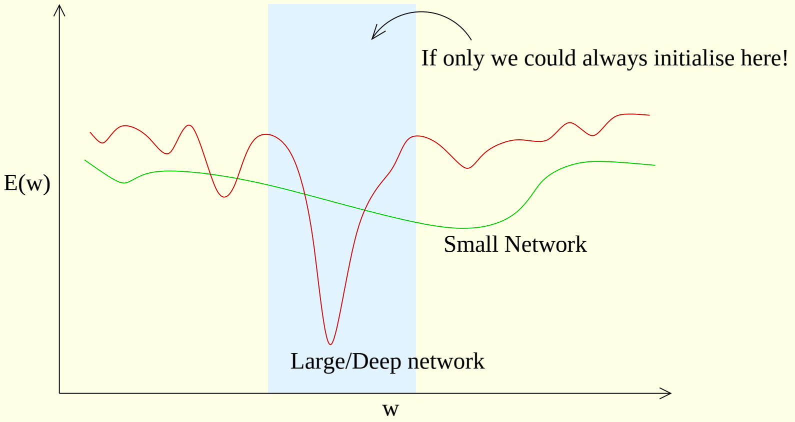
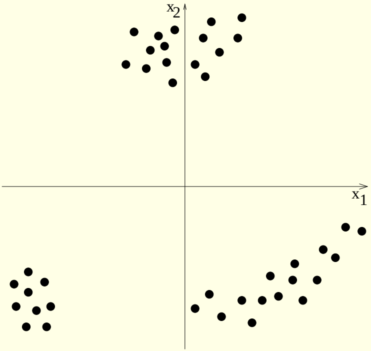


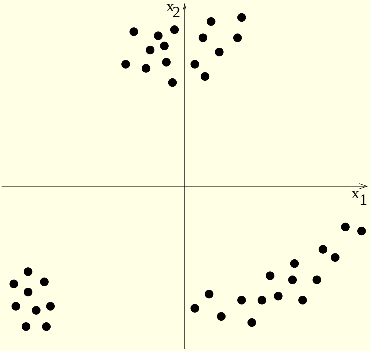
Expressiveness and Learnability: Initialisation



Deep Learning



Deep Learning

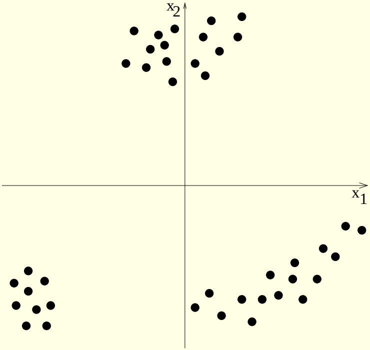


Preprocessing: Learn the distribution of the data (without seeing labels).

Deep Belief Networks: learned greedily, one layer at a time (HOT2006).

Subsequently apply backpropagation.

Deep Learning



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Deep Belief Networks: learned greedily, one layer at a time (HOT2006).

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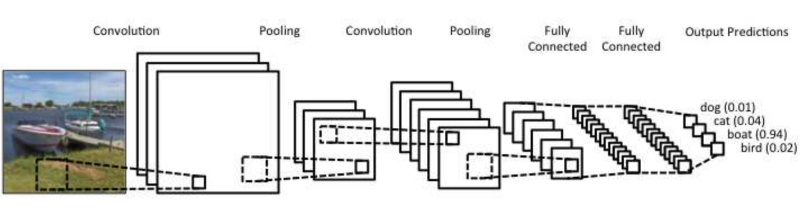
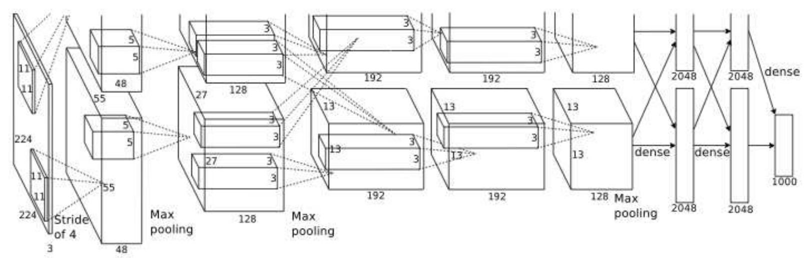
Aided by astronomical growth in data sizes and computational power.

Specifically successful in domains such as vision and speech.

Convolutional Neural Networks





253,440–186,624–64,896–64,896–43,264 –4096–4096–1000 network (KSH 2012).

1. https://www.clarifai.com/static/img_ours/cnn.png
2. http://mappingignorance.org/fx/media/2013/04/Deep-learning-4.png

Overview

ATARI 2600 Games (MKSRVBGRFOPBSAKKWLH2015)

[Breakout video[1]]

1. http://www.nature.com/nature/journal/v518/n7540/extref/nature14236-sv2.mov

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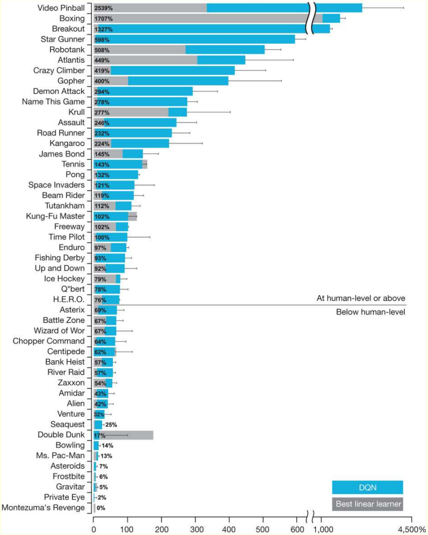

1. `http://www.nature.com/nature/journal/v518/n7540/extref/nature14236-sv2.mov`

AlphaGo (SHMGSDSAPLDGNKSLLKGH2016)

March 2016: DeepMind's program beats Go champion Lee Sedol 4-1.

1. http://www.kurzweilai.net/images/AlphaGo-vs.-Sedol.jpg

AlphaGo (SHMGSDSAPLDGNKSLLKGH2016)

1. `http://static1.uk.businessinsider.com/image/56e0373052bcd05b008b5217-810-602/screen%20shot%202016-03-09%20at%2014.png`

Learning Algorithm

1. Represent action value function Q as a neural network.

2. Gather data (on the simulator) by taking ϵ-greedy actions w.r.t. Q:
   $(s_1, a_1, r_1, s_2, a_2, r_2, s_3, a_3, r_3, \ldots s_D, a_D, r_D, s_{D+1})$.

3. Train the network such that $Q(s_t, a_t) \approx r_t + \max_a Q(s_{t+1}, a)$.
   Go to 2.

Learning Algorithm

1. Represent action value function Q as a neural network.
   AlphaGo: Use both a policy network and an action value network.

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   AlphaGo: Use Monte Carlo Tree Search for action selection

3. Train the network such that $Q(s_t, a_t) \approx r_t + \max_a Q(s_{t+1}, a)$.
   Go to 2.

AlphaGo: Trained using self-play.

References

(For references on slide 9, see Kalyanakrishnan's thesis (K2011).)

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Rich history, at confluence of several fields of study, firm foundation.

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Thank you!