http://bit.ly/idl2018

#DLUPC

Day 4 Lecture 2

Reinforcement & Unsupervised Learning

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UPC

Motivation

Yann Lecun's Black Forest cake

- "Pure" Reinforcement Learning (cherry)
  - The machine predicts a scalar reward given once in a while.
  - **A few bits for some samples**
- Supervised Learning (icing)
  - The machine predicts a category or a few numbers for each input
  - Predicting human-supplied data
  - **10→10,000 bits per sample**
- Unsupervised/Predictive Learning (cake)
  - The machine predicts any part of its input for any observed part.
  - Predicts future frames in videos
  - **Millions of bits per sample**

- (Yes, I know, this picture is slightly offensive to RL folks. But I'll make it up)

Motivation

We can categorize three types of learning procedures:

1. Supervised Learning:

   $$\mathbf{y} = f(\mathbf{x})$$

2. Unsupervised Learning:

   $$f(\mathbf{x})$$

3. Reinforcement Learning (RL):

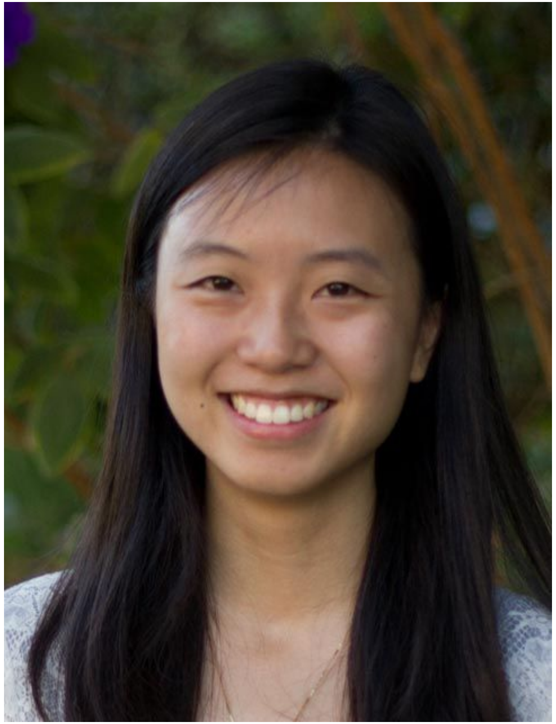
   $$\mathbf{y} = f(\mathbf{x})$$

   $$\mathbf{z}$$

Acknowledegments

Bellver M, Giró-i-Nieto X, Marqués F, Torres J. [Hierarchical Object Detection with Deep Reinforcement Learning](). In Deep Reinforcement Learning Workshop, NIPS 2016. 2016.

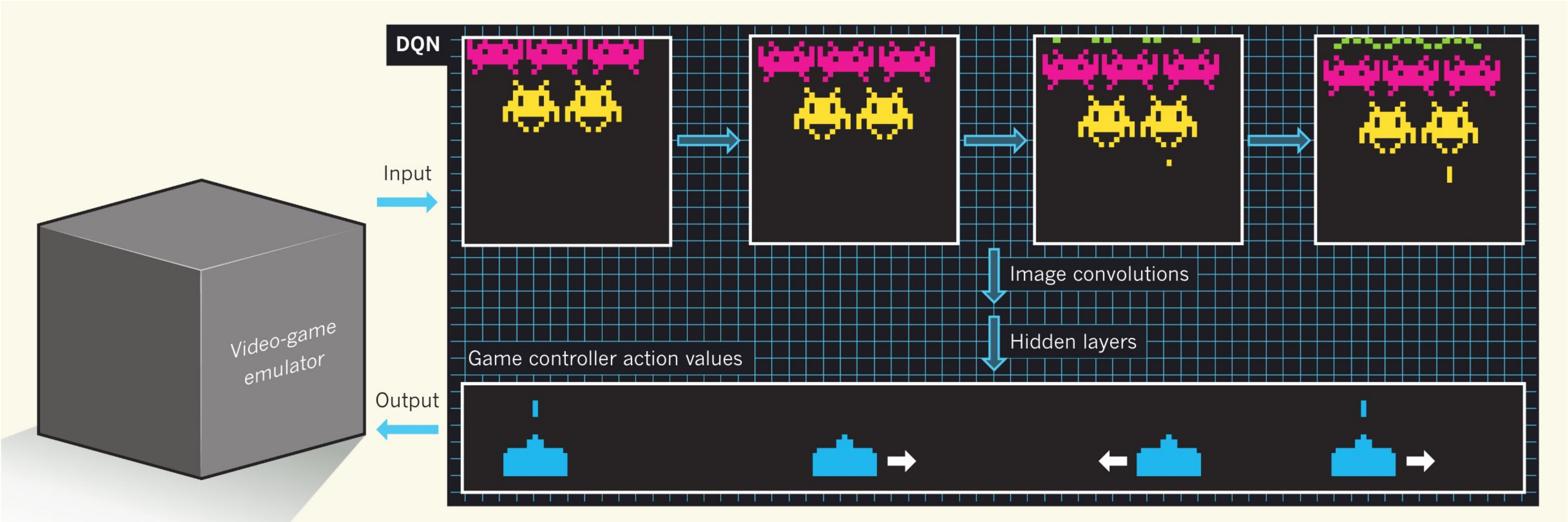
Acknowledegments



Serena Yeung, "Deep Reinforcement Learning". Stanford University CS231n, 2017.

Mnih, Volodymyr, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, and Martin Riedmiller. "Playing atari with deep reinforcement learning." arXiv preprint arXiv:1312.5602 (2013).

Motivation



Bernhard Schölkkopf, [“Learning to see and act”]() Nature 2015.

Motivation

Google DeepMind

Artificial intelligence (AI)

Google buys UK artificial intelligence startup Deepmind for £400m

Google makes its biggest EU purchase yet with the technology that aims to make computers think like humans

Samuel Gibbs

Monday 27 January 2014 13.23 GMT

This article is **2 years old**

1046 186

https://www.theguardian.com/technology/2014/jan/27/google-acquires-uk-artificial-intelligence-startup-deepmind

Motivation

AlphaGo

Google DeepMind

Silver, D., Huang, A., Maddison, C.J., Guez, A., Sifre, L., Van Den Driessche, G., Schrittwieser, J., Antonoglou, I., Panneershelvam, V., Lanctot, M. and Dieleman, S., 2016. Mastering the game of Go with deep neural networks and tree search. *Nature*, *529*(7587), pp.484-489

Motivation

Greg Kohs, "AlphaGo" (2017)

Motivation

Vinyals, O., Ewalds, T., Bartunov, S., Georgiev, P., Vezhnevets, A.S., Yeo, M., Makhzani, A., Küttler, H., Agapiou, J., Schrittwieser, J. and Quan, J., 2017. [Starcraft II: A new challenge for reinforcement learning](). arXiv preprint arXiv:1708.04782. [[Press release]]()

Architecture

Figure: UCL Course on RL by David Silver

Architecture

Figure: UCL Course on RL by David Silver

Architecture

state (s_t)

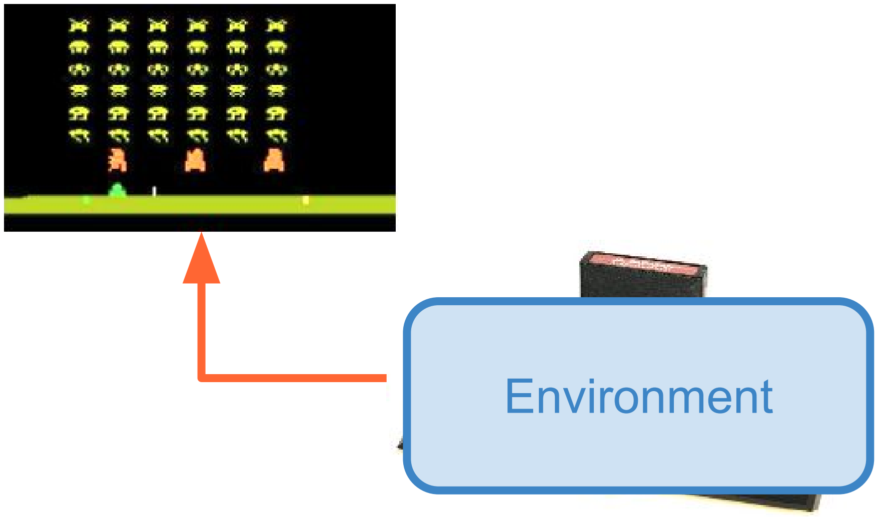


Figure: [UCL Course on RL by David Silver]

Architecture

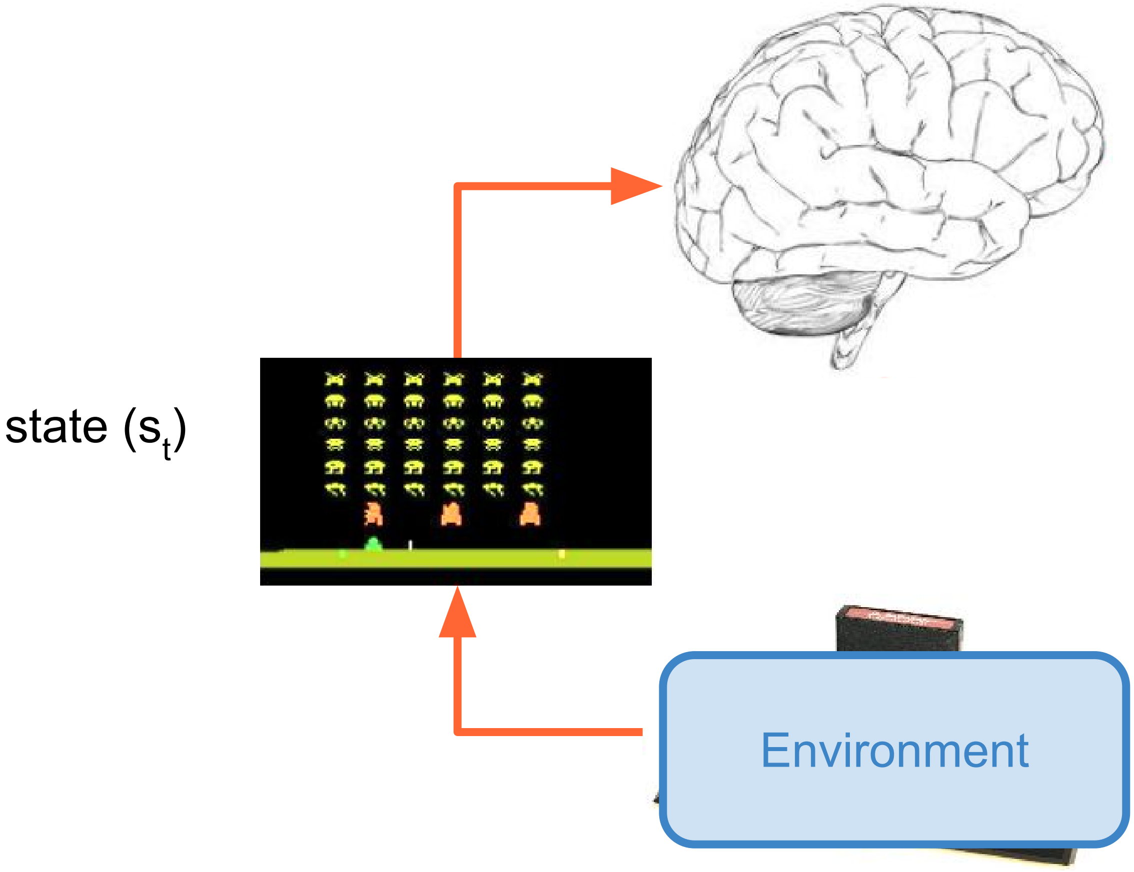
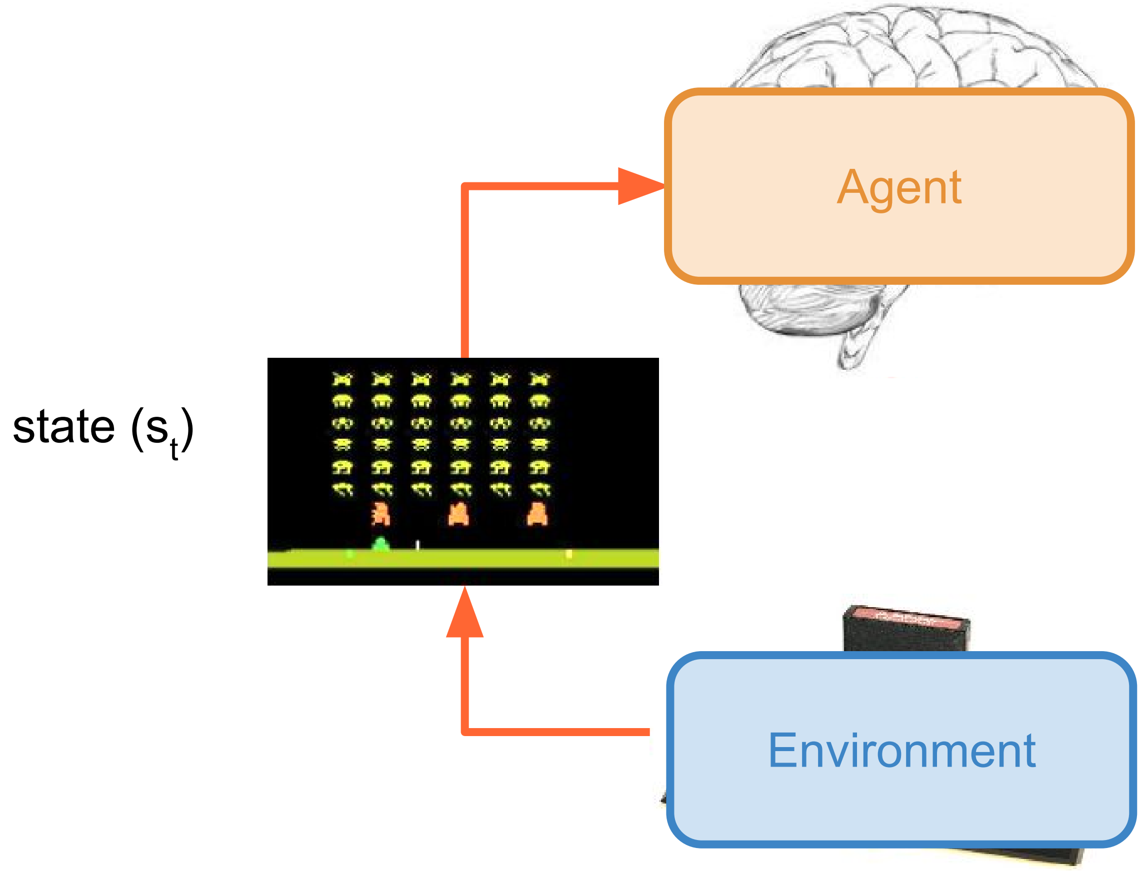


Figure: [UCL Course on RL by David Silver]

Architecture



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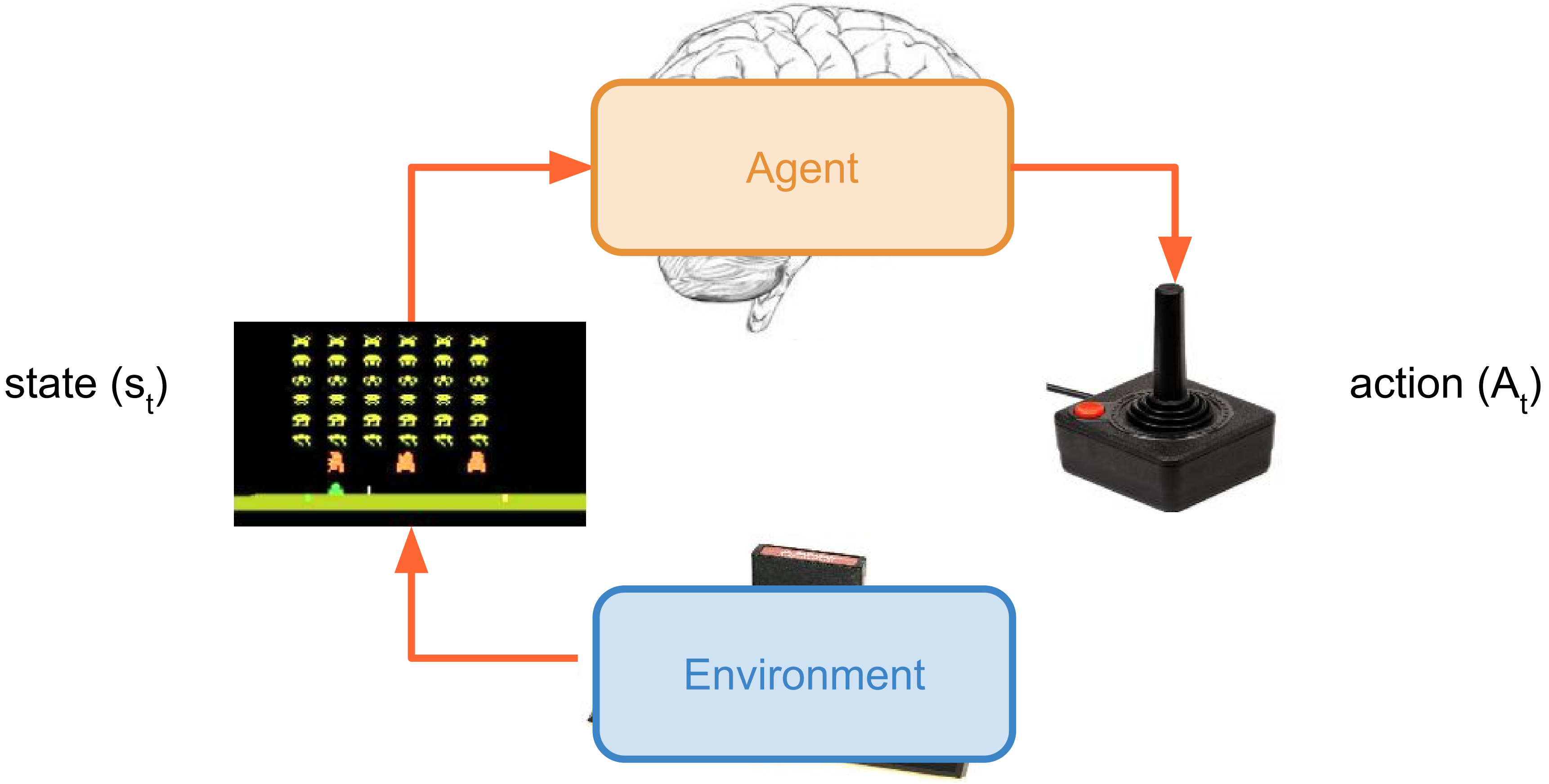

Figure: [UCL Course on RL by David Silver]

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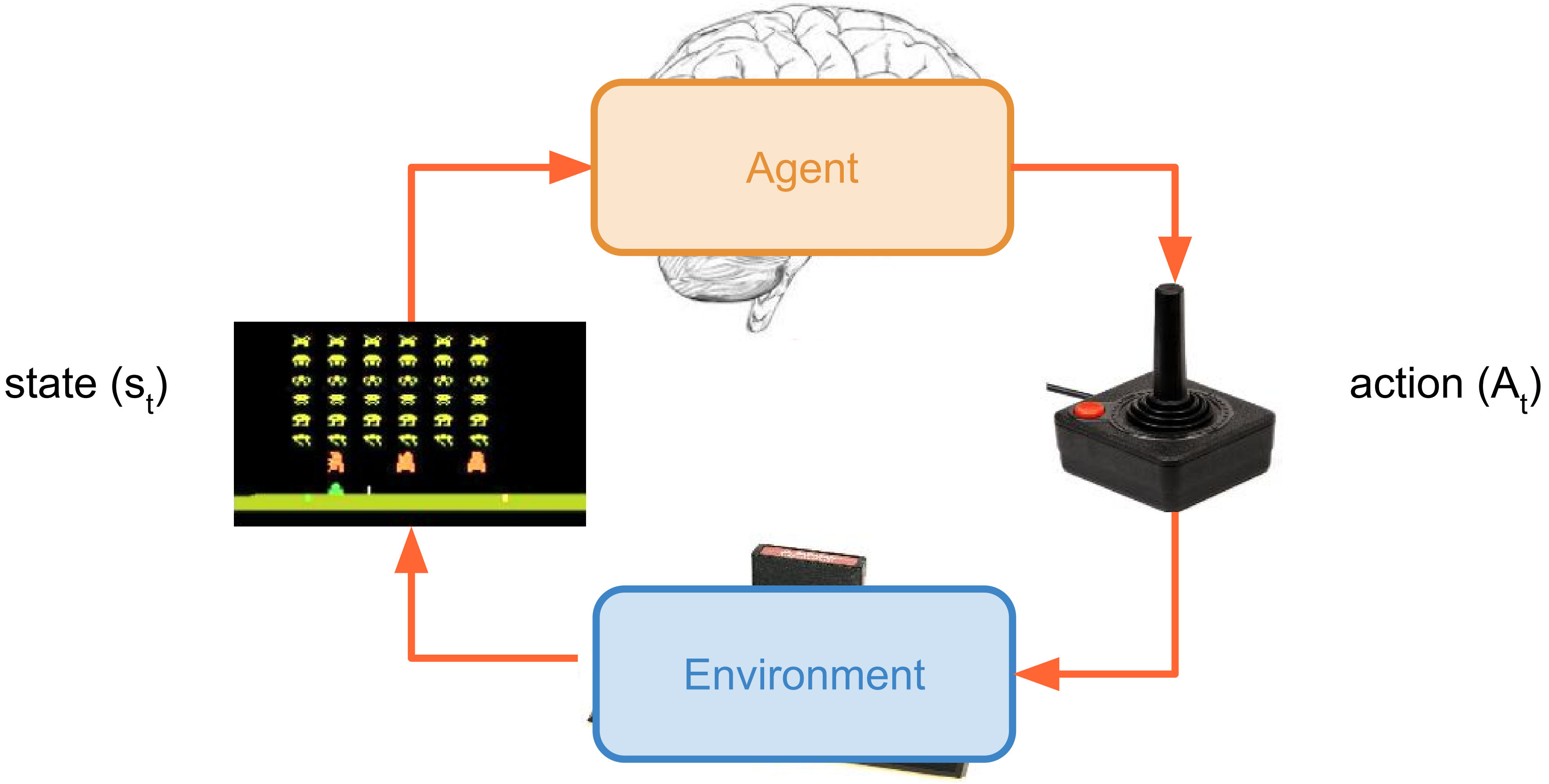


Figure: UCL Course on RL by David Silver

Architecture

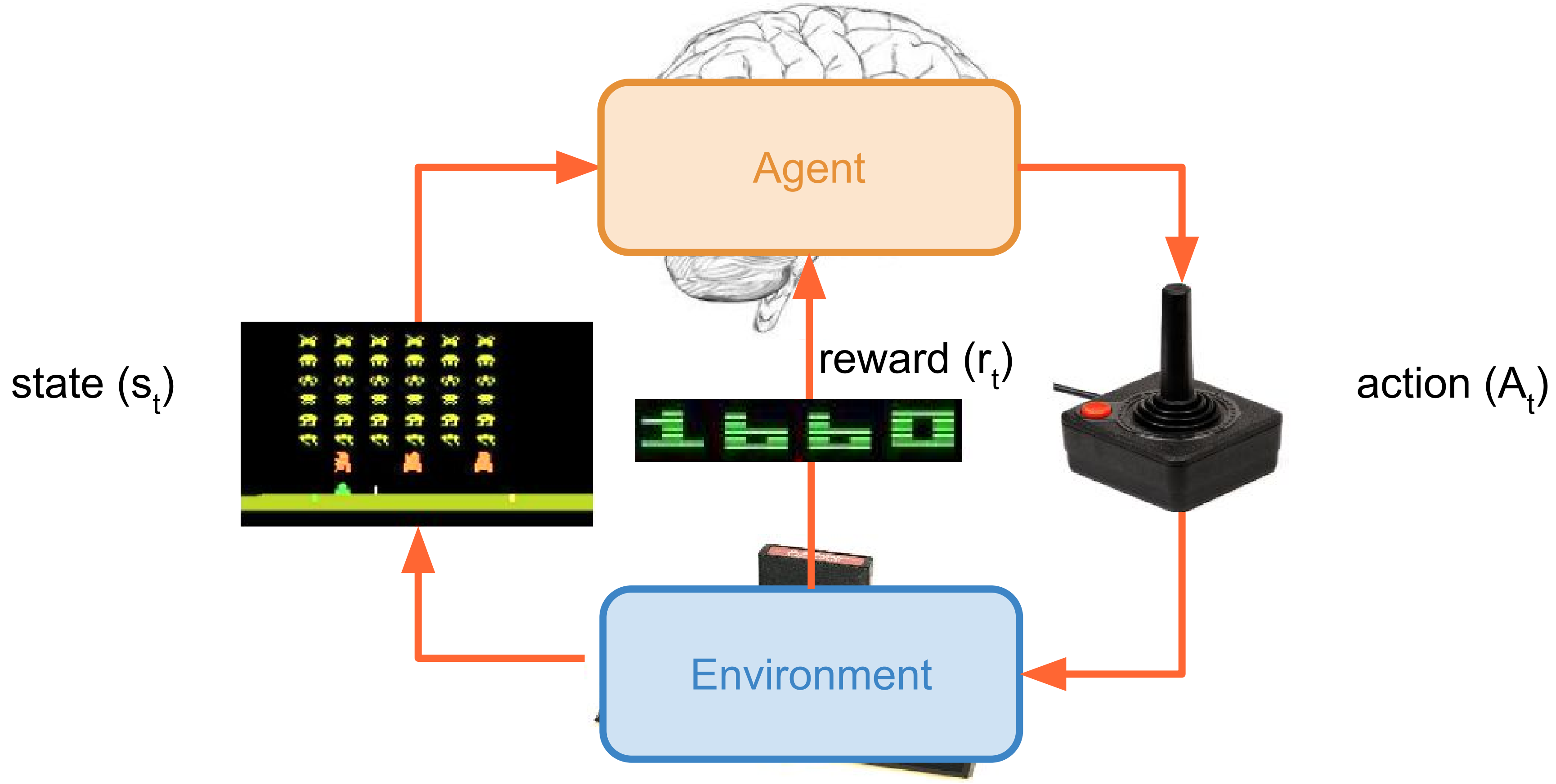
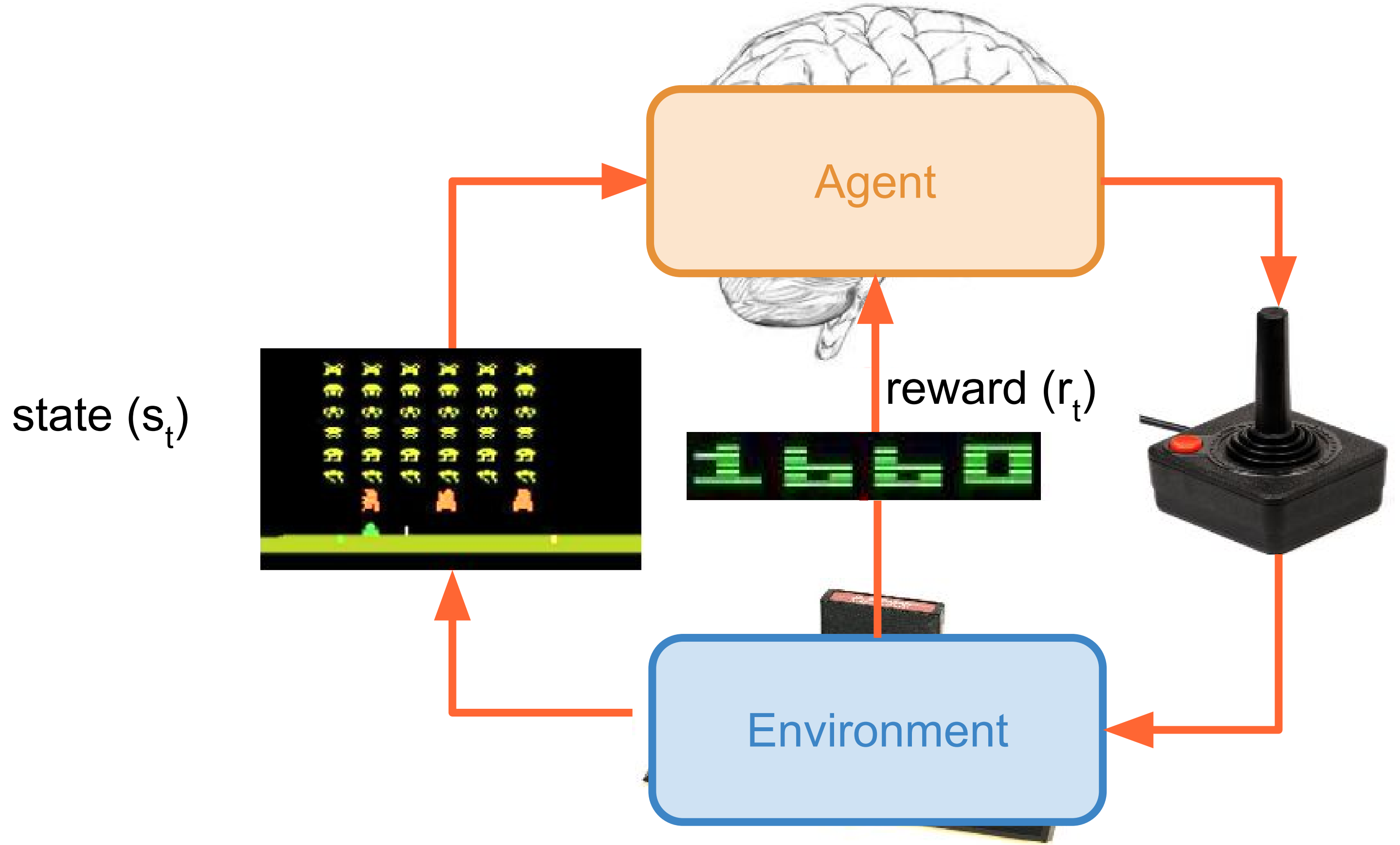


Figure: [UCL Course on RL by David Silver]

Architecture



Reward is given to the agent delayed with respect to previous states and actions !

Figure: [UCL Course on RL by David Silver]

Architecture

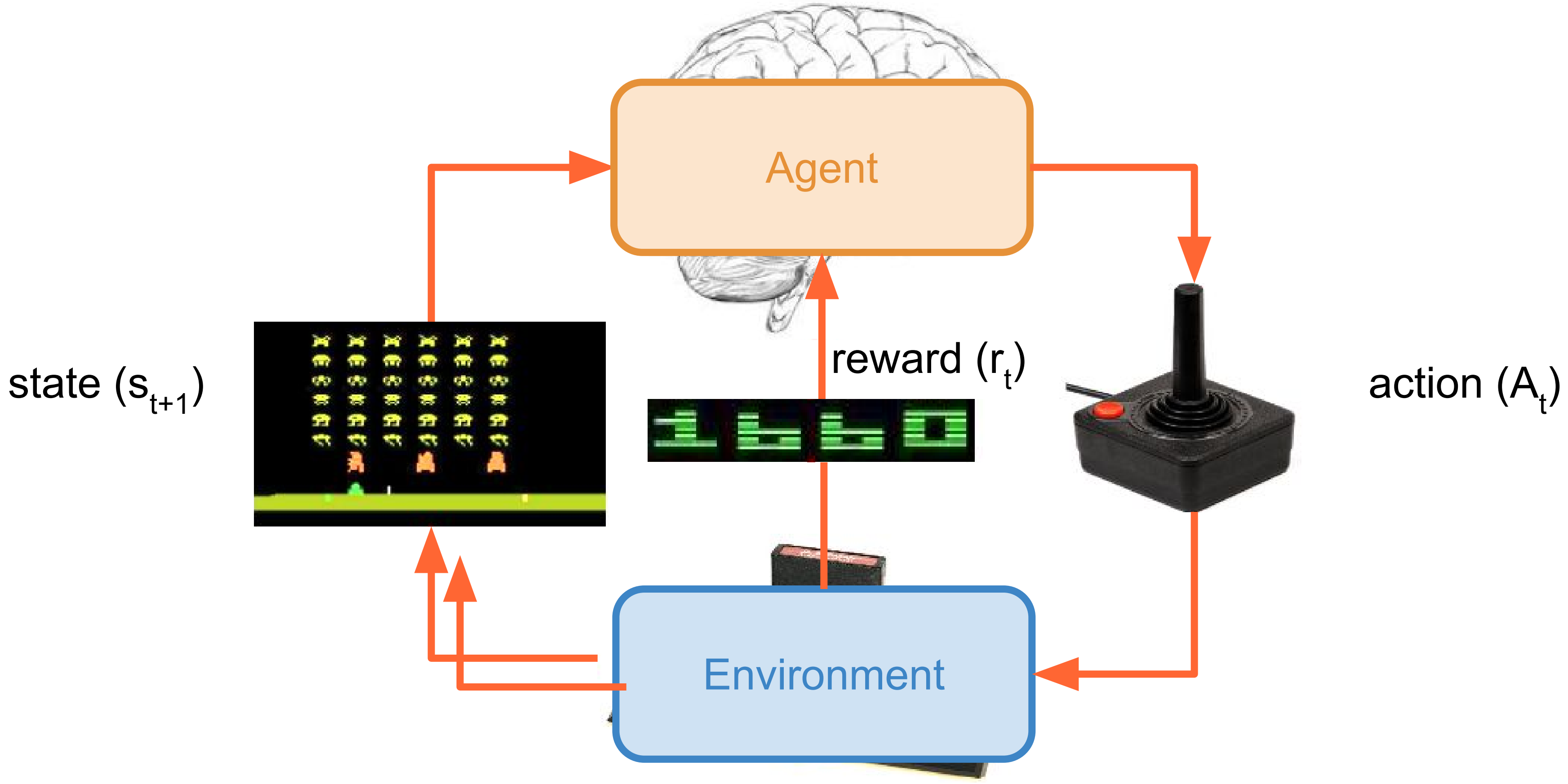


Figure: UCL Course on RL by David Silver

Architecture

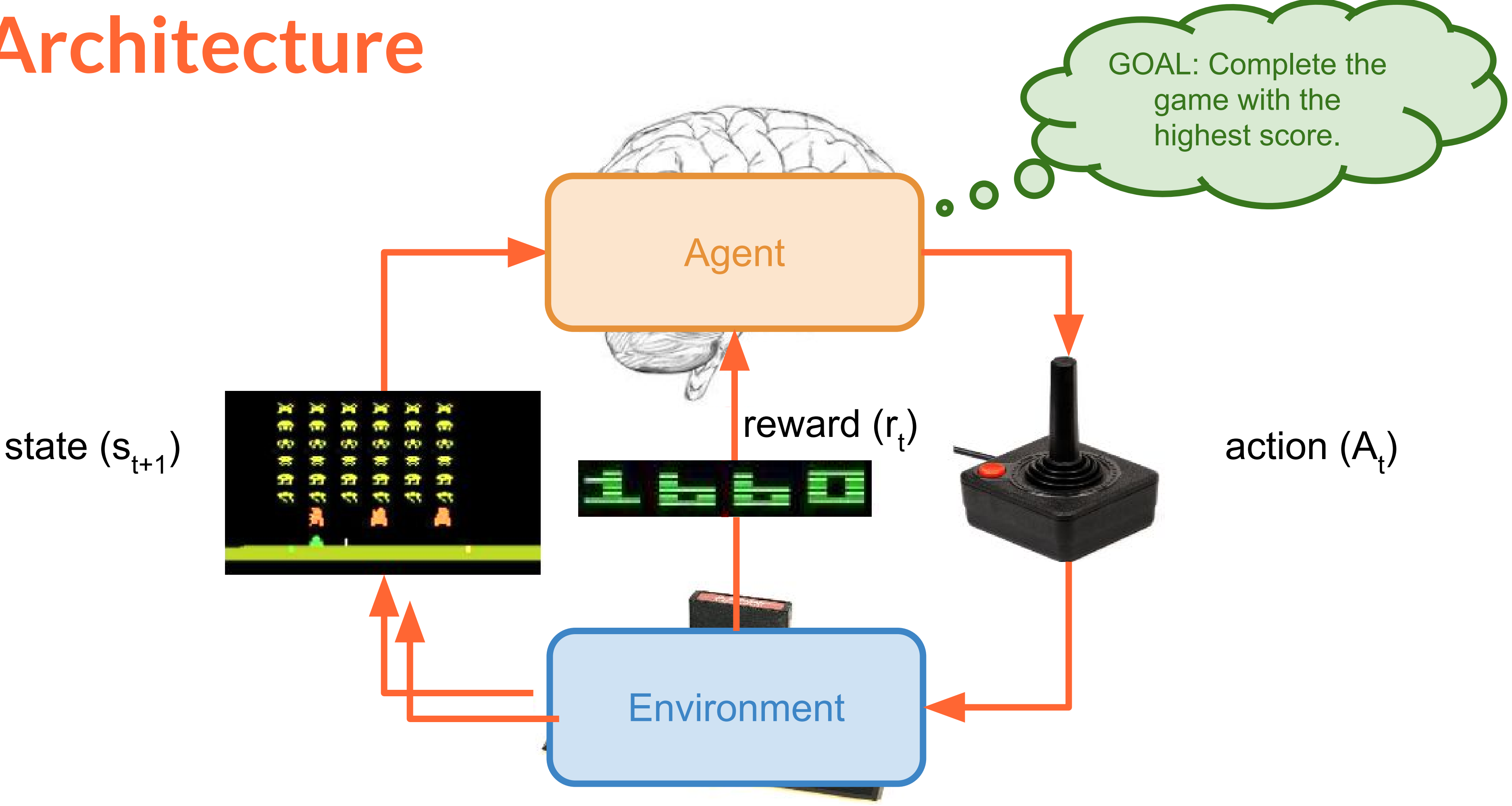


Figure: [UCL Course on RL by David Silver]

Architecture

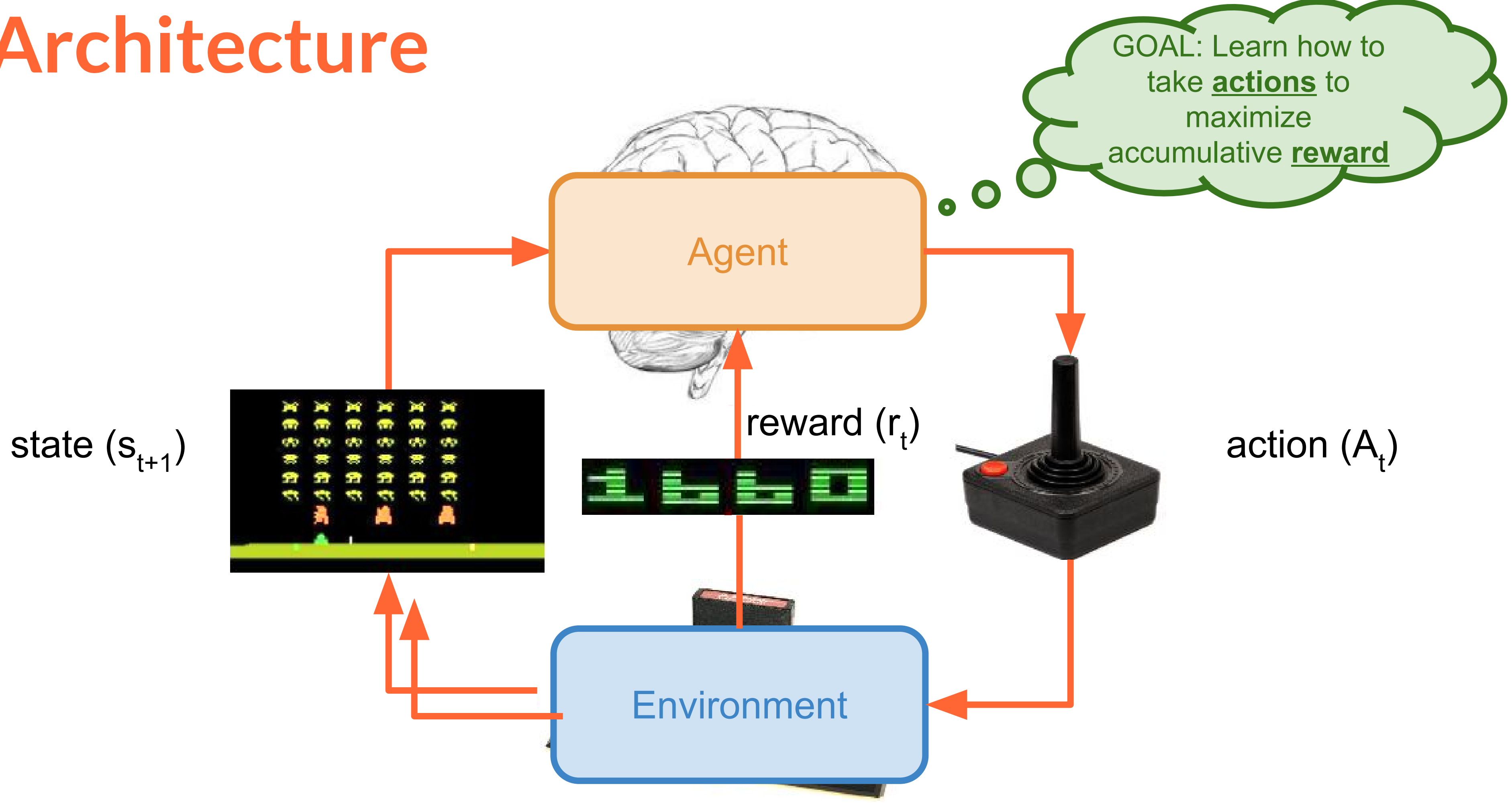


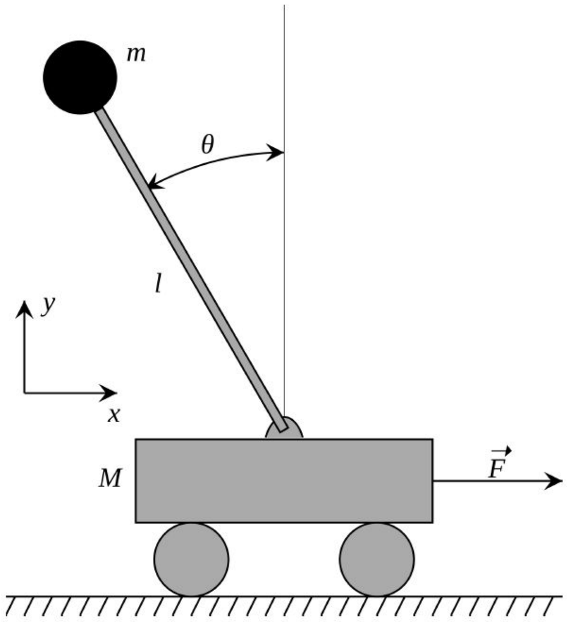
Figure: [UCL Course on RL by David Silver]()

Architecture

Other problems that can be formulated with a RL architecture.

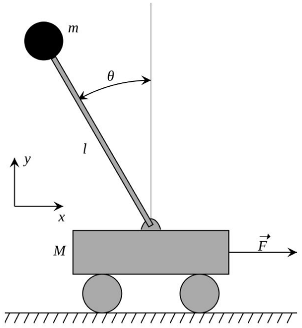
Cart-Pole Problem

<u>Objective</u>: Balance a pole on top of a movable car



Slide credit: [Serena Yeung](), ["Deep Reinforcement Learning"](). [Stanford University CS231n](), 2017.

Architecture



Agent

state (s_t)

Angle
Angular speed
Position
Horizontal velocity

reward (r_t)

1 at each time step if the pole is upright

Horizontal force applied in the car

action (A_t)

Environment

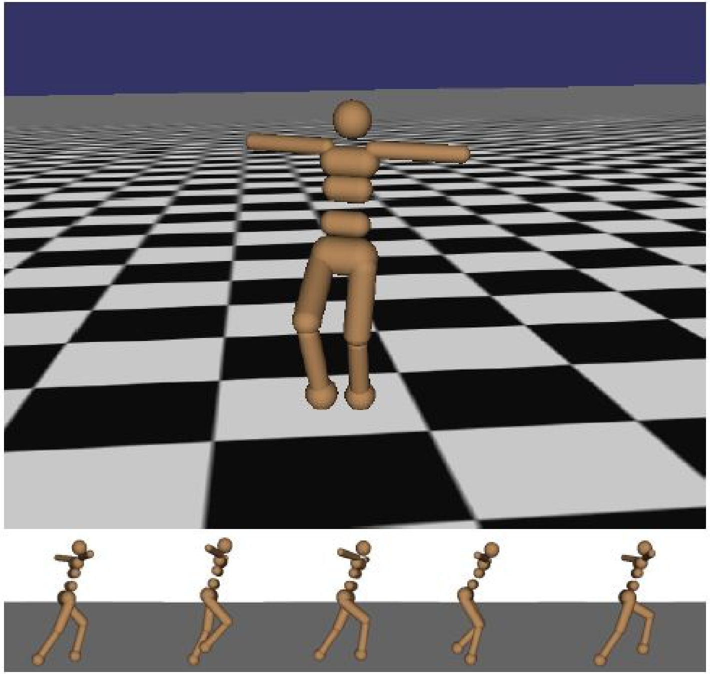
Slide concept: Serena Yeung, "Deep Reinforcement Learning". Stanford University CS231n, 2017.

Architecture

Other problems that can be formulated with a RL architecture.

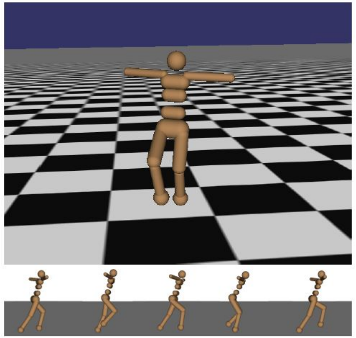
Robot Locomotion

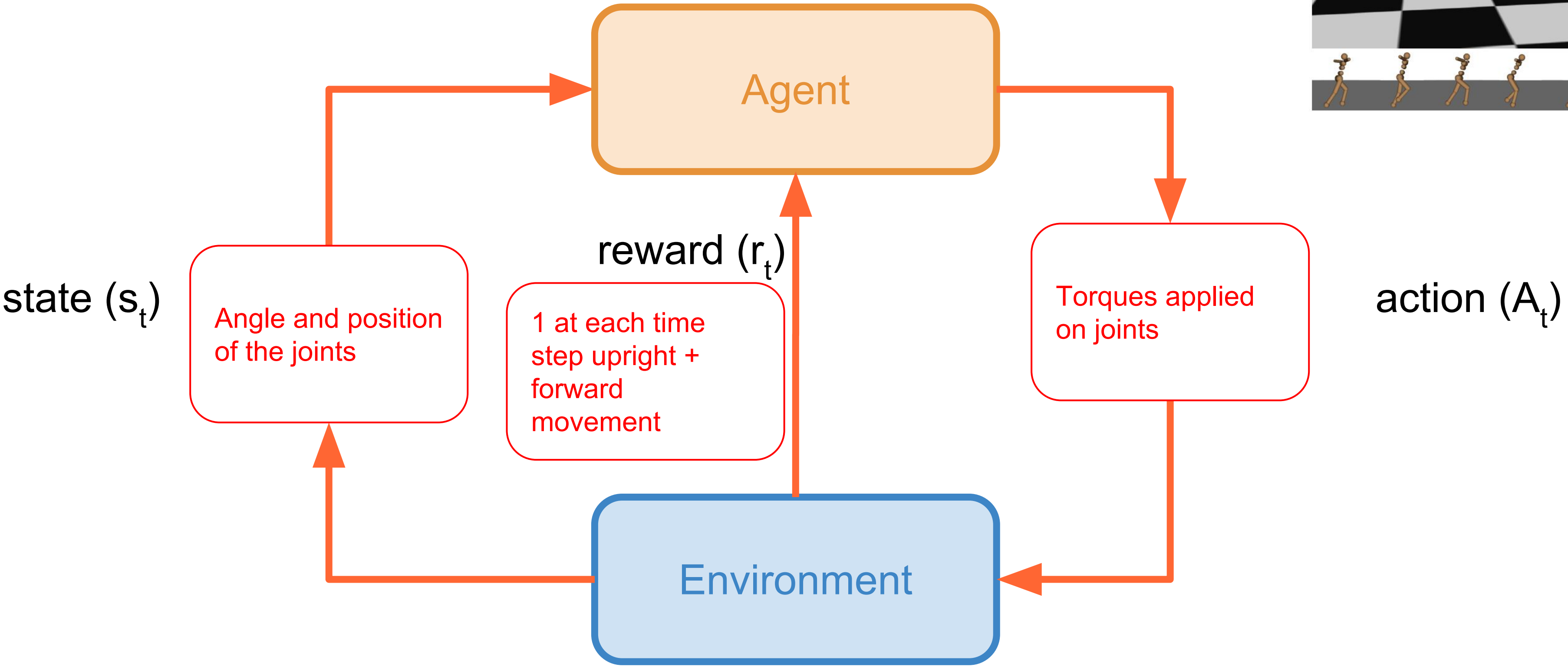
Objective: Make the robot move forward



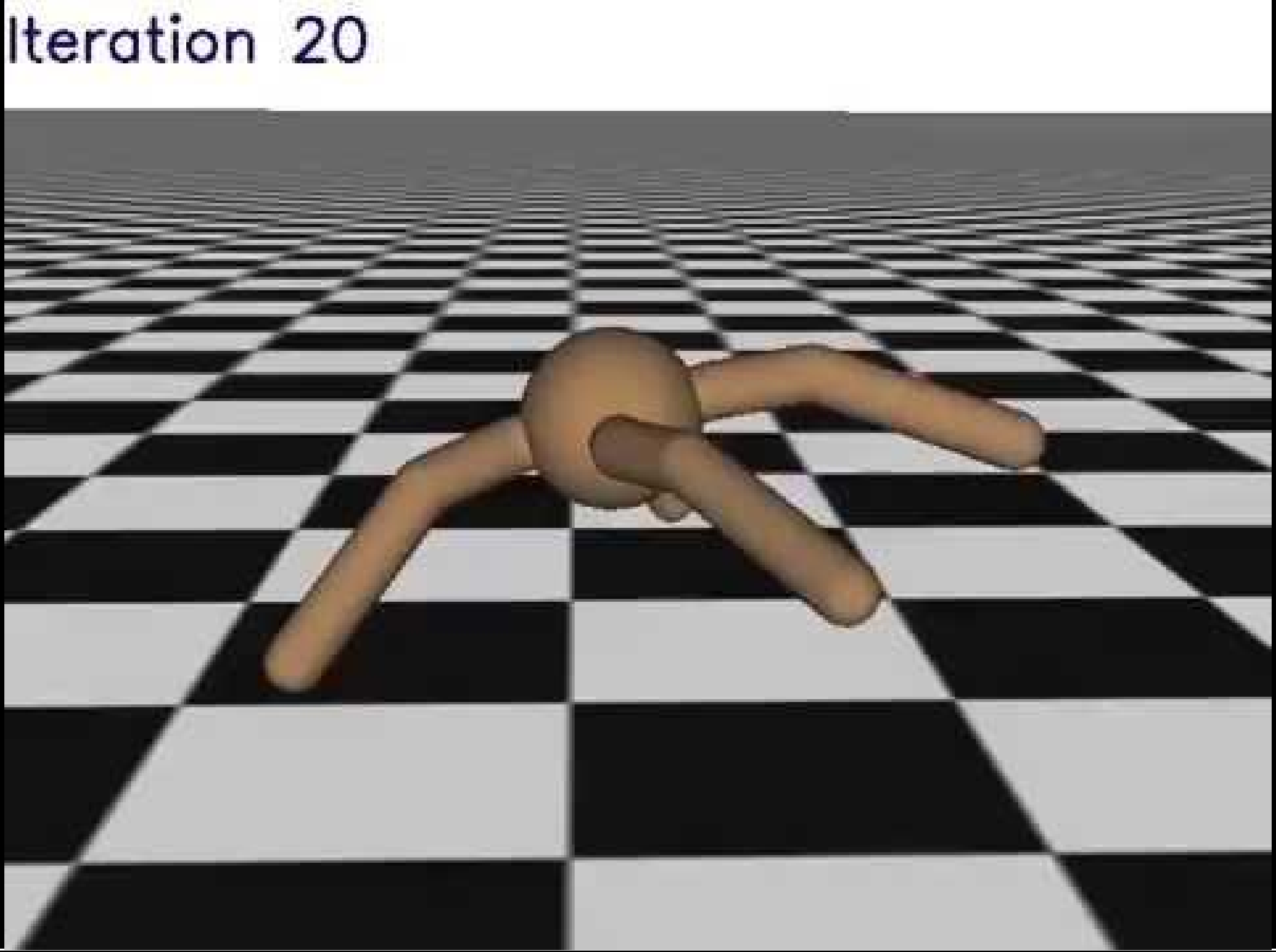
Schulman, John, Philipp Moritz, Sergey Levine, Michael Jordan, and Pieter Abbeel. "High-dimensional continuous control using generalized advantage estimation." ICLR 2016 [project page]

Architecture



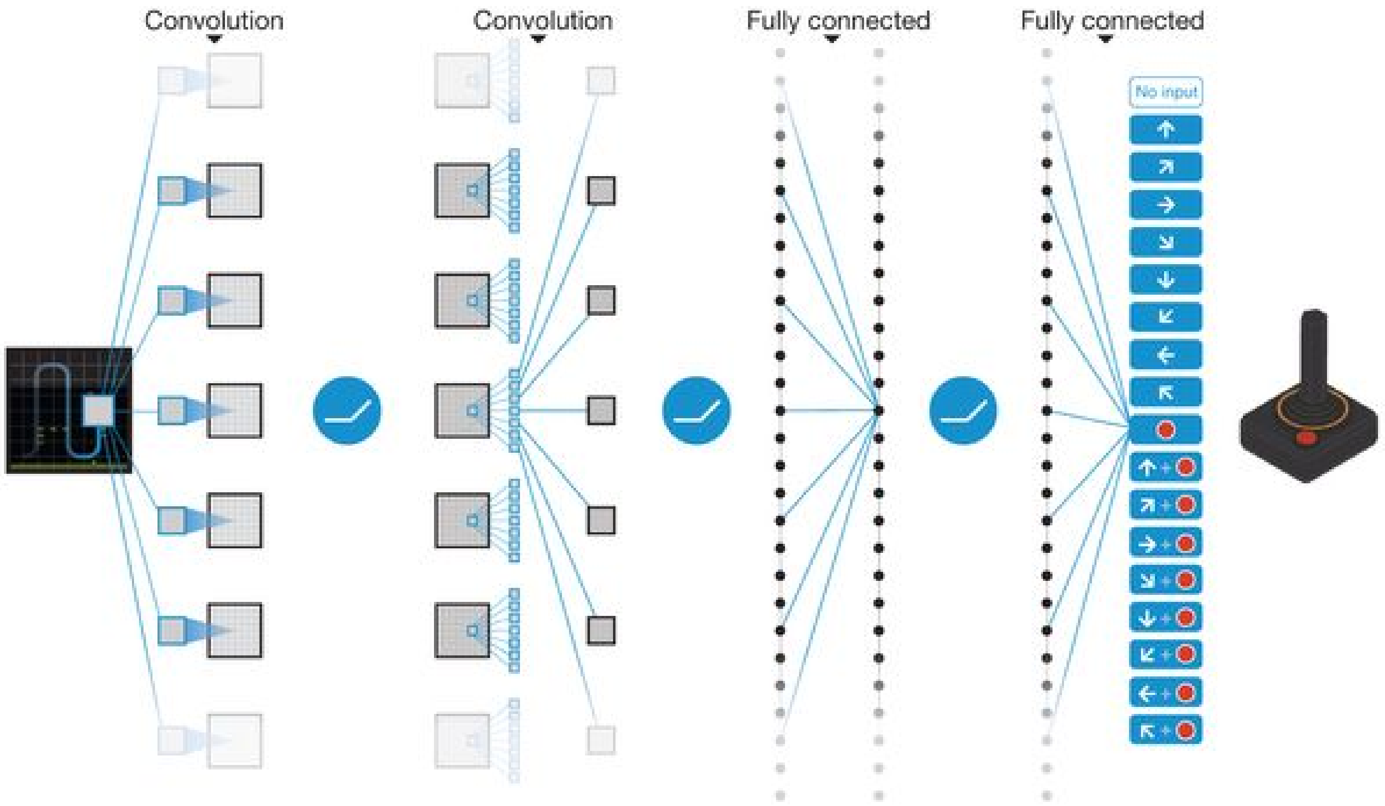


Slide concept: Serena Yeung, "Deep Reinforcement Learning". Stanford University CS231n, 2017.



Schulman, John, Philipp Moritz, Sergey Levine, Michael Jordan, and Pieter Abbeel. "High-dimensional continuous control using generalized advantage estimation." ICLR 2016 [project page]

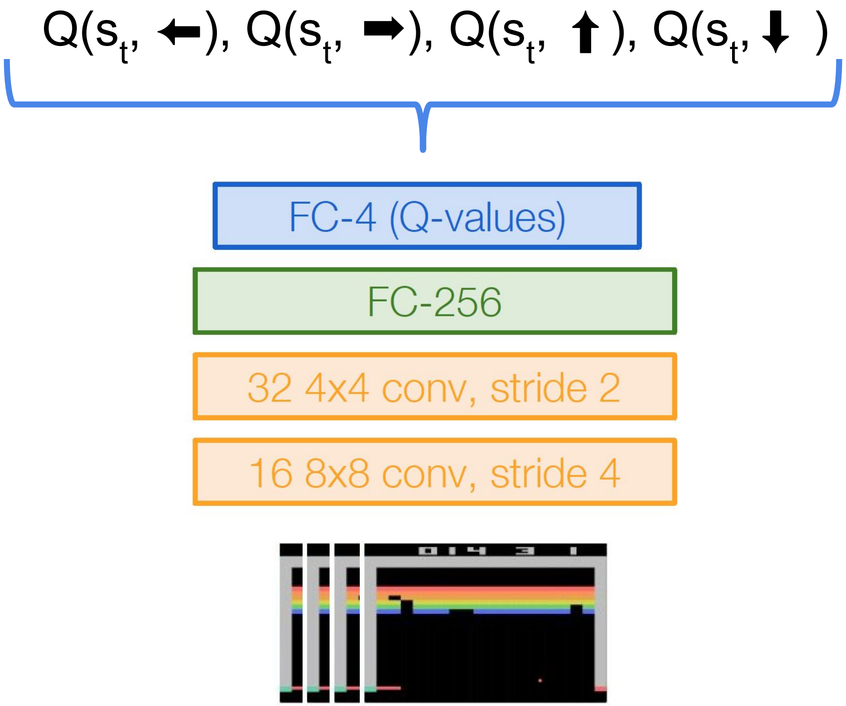
Deep Q-learning: Deep Q-Network DQN



Number of actions between 4-18, depending on the Atari game

Mnih, Volodymyr, Koray Kavukcuoglu, David Silver, Andrei A. Rusu, Joel Veness, Marc G. Bellemare, Alex Graves et al. "Human-level control through deep reinforcement learning." *Nature* 2015.

Deep Q-learning: Deep Q-Network DQN



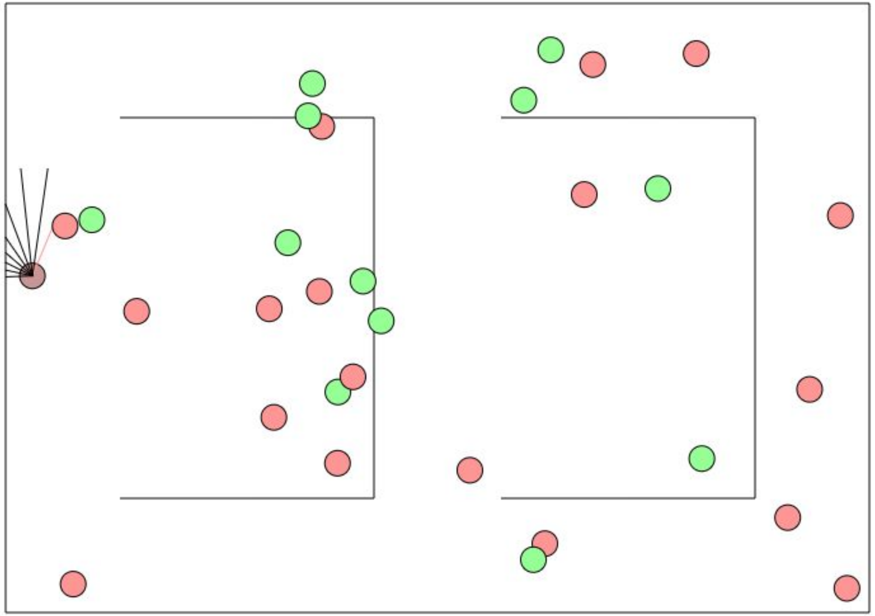
Current state s_t: 84x84x4 stack of last 4 frames
(after RGB->grayscale conversion, downsampling, and cropping)

Slide concept: Serena Yeung, "Deep Reinforcement Learning". Stanford University CS231n, 2017.

Deep Q-learning: Demo

ConvNetJS

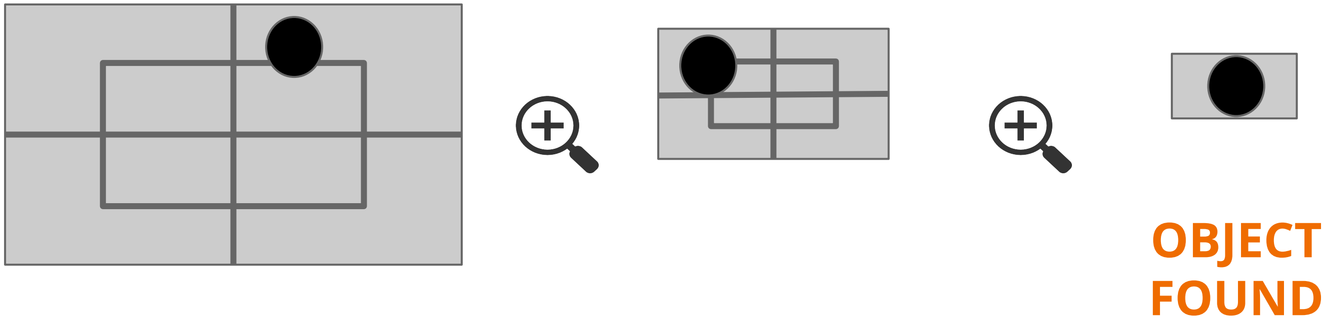
Deep Learning in your browser



Andrej Karpathy, [“ConvNetJS Deep Q Learning Demo”]

Deep Q-learning: DQN: Computer Vision

Method for performing hierarchical object detection in images guided by a **deep reinforcement learning agent**.

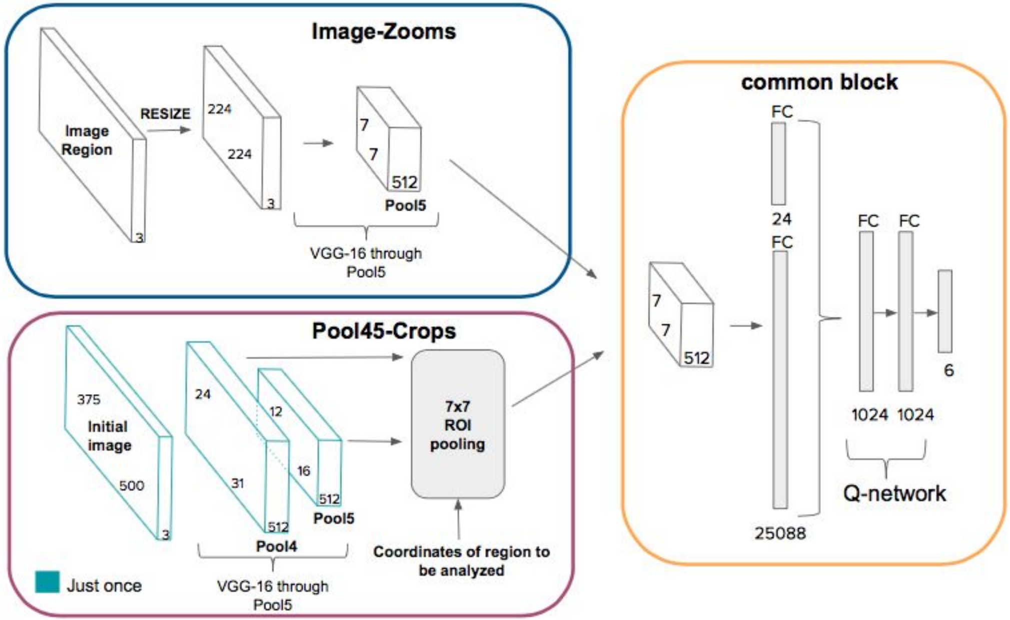


Miriam Bellver, Xavier Giro-i-Nieto, Ferran Marques, and Jordi Torres. "Hierarchical Object Detection with Deep Reinforcement Learning." Deep Reinforcement Learning Workshop NIPS 2016.

Deep Q-learning: DQN: Computer Vision

State: The agent will decide which action to choose based on:

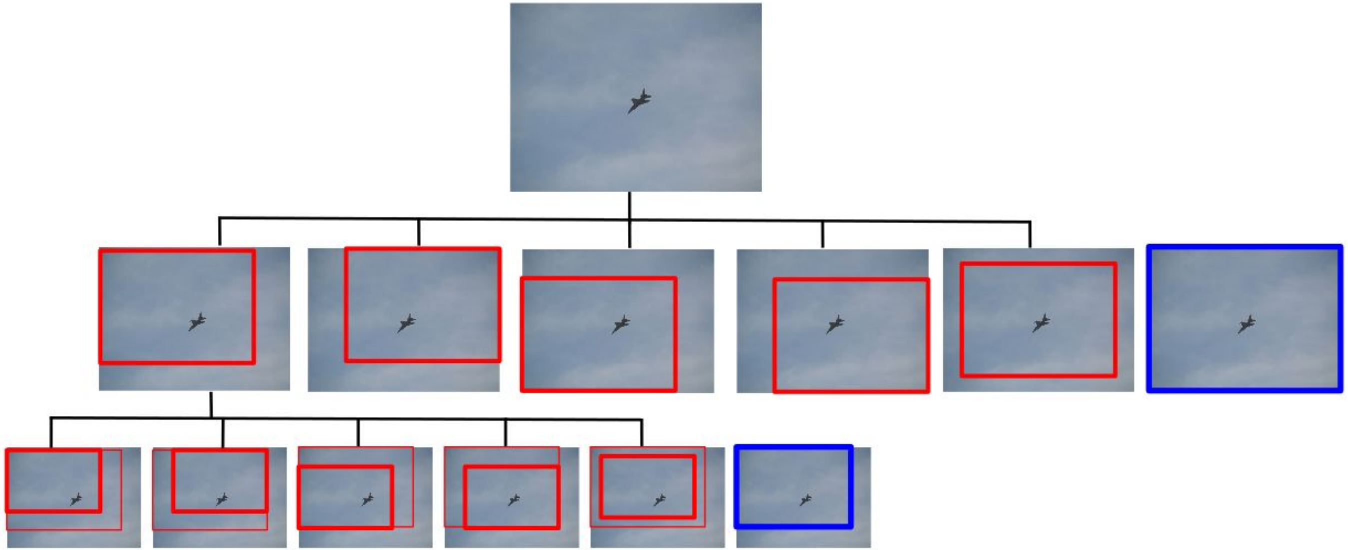
- **visual description** of the current observed region
- **history vector** that maps past actions performed



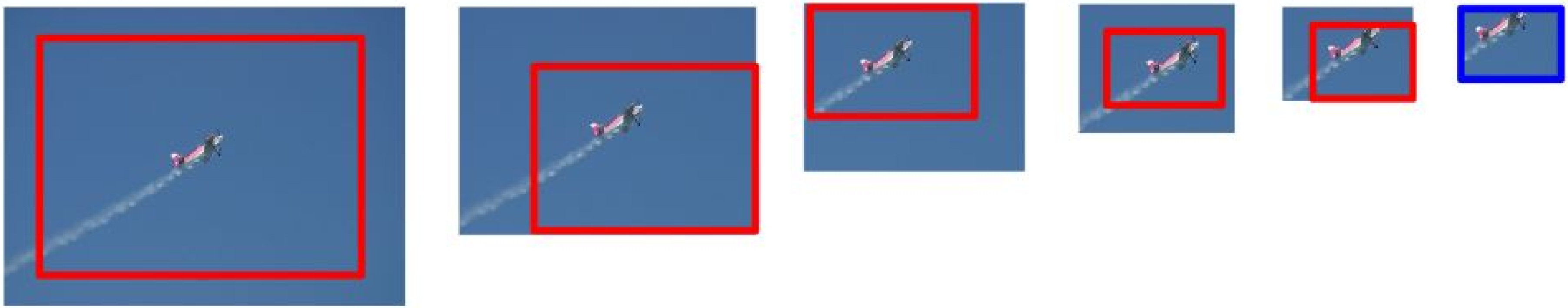
Deep Q-learning: DQN: Computer Vision

Actions: Two kind of actions:

- **movement actions**: to which of the 5 possible regions defined by the hierarchy to move
- **terminal action:** the agent indicates that the object has been found



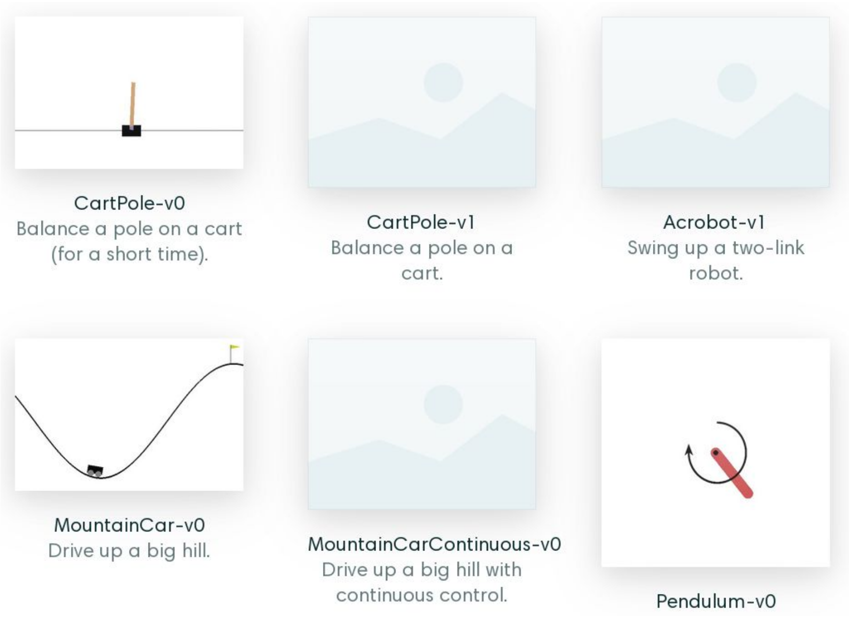
Deep Q-learning: DQN: Computer Vision



Miriam Bellver, Xavier Giro-i-Nieto, Ferran Marques, and Jordi Torres. "Hierarchical Object Detection with Deep Reinforcement Learning." Deep Reinforcement Learning Workshop NIPS 2016.

RL Frameworks

OpenAI Gym + keras-rl



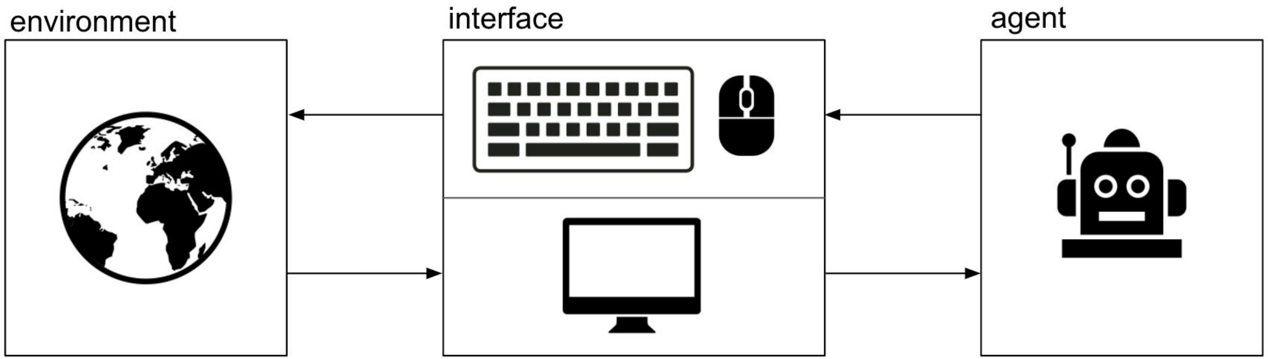
+

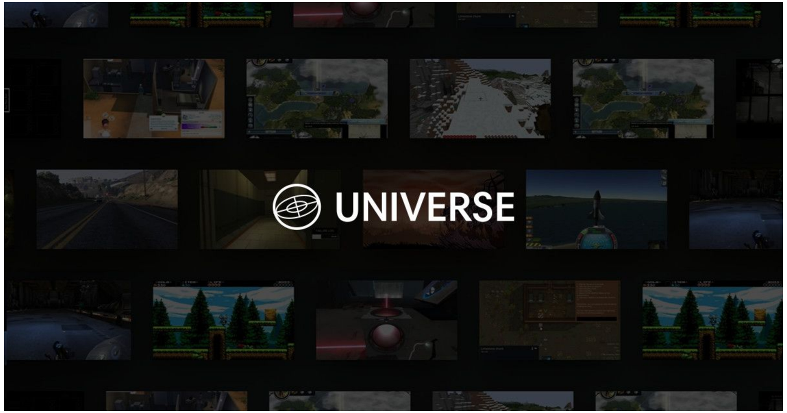
keras-rl

keras-rl implements some state-of-the art deep reinforcement learning algorithms in Python and seamlessly integrates with the deep learning library Keras. Just like Keras, it works with either Theano or TensorFlow, which means that you can train your algorithm efficiently either on CPU or GPU. Furthermore, keras-rl works with OpenAI Gym out of the box.

Slide credit: Míriam Bellver

RL Frameworks



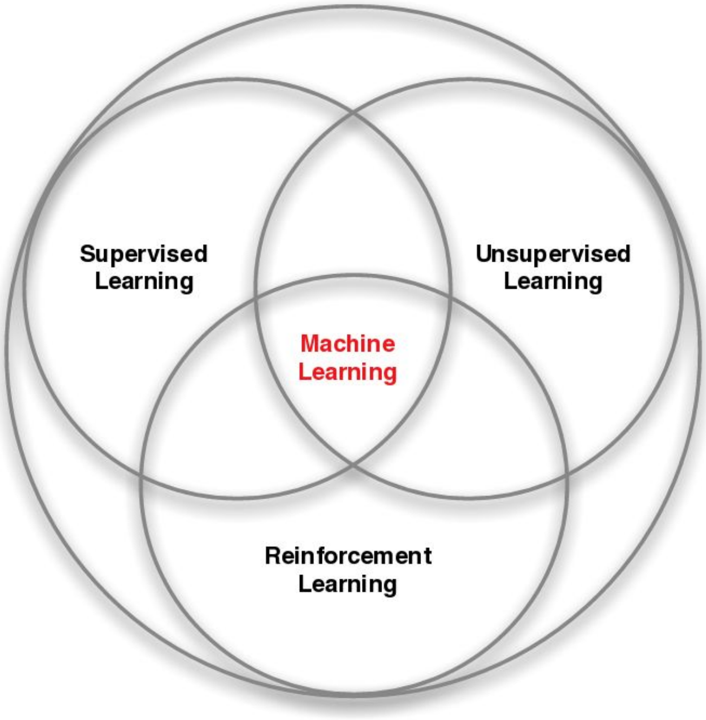


OpenAI Universe
environment

Conclusions

Reinforcement Learning

- There is no supervisor, only reward signal
- Feedback is delayed, not instantaneous
- Time really matters (sequential, non i.i.d data)



Slide credit: [UCL Course on RL by David Silver]

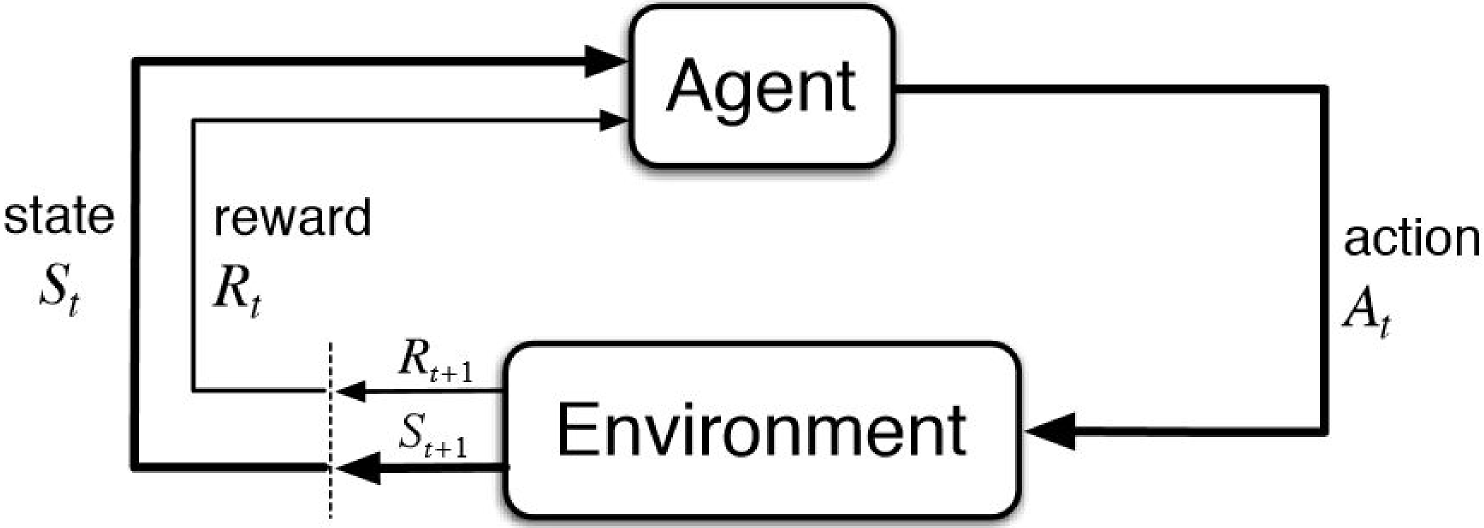
Learn more

Deep Learning TV,
[“Reinforcement learning - Ep. 30”]

Siraj Raval,
Deep Q Learning for Video Games

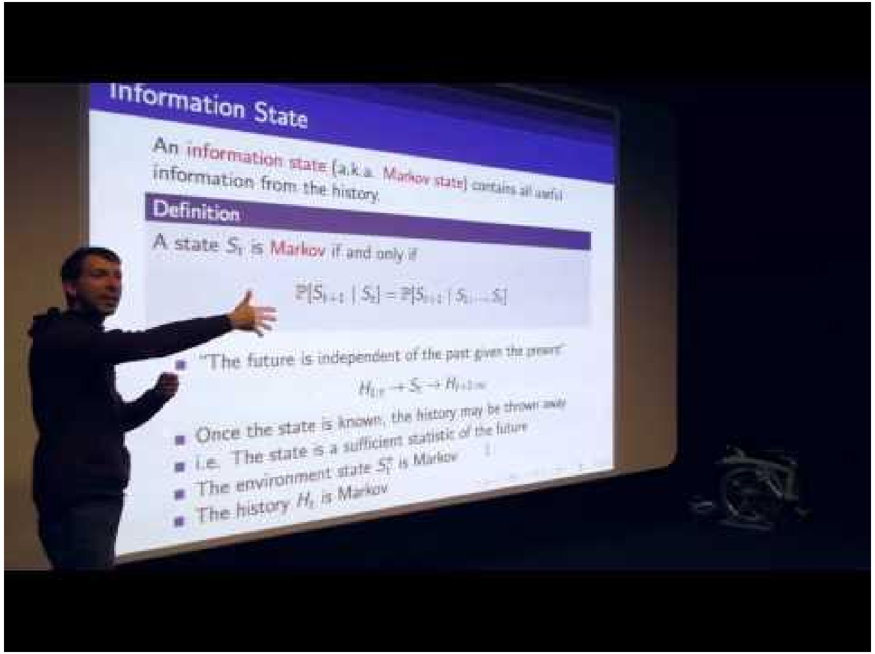
Learn more

Emma Brunskill, [Stanford CS234: Reinforcement Learning]

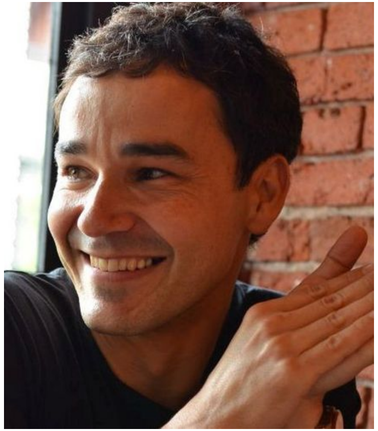


Learn more

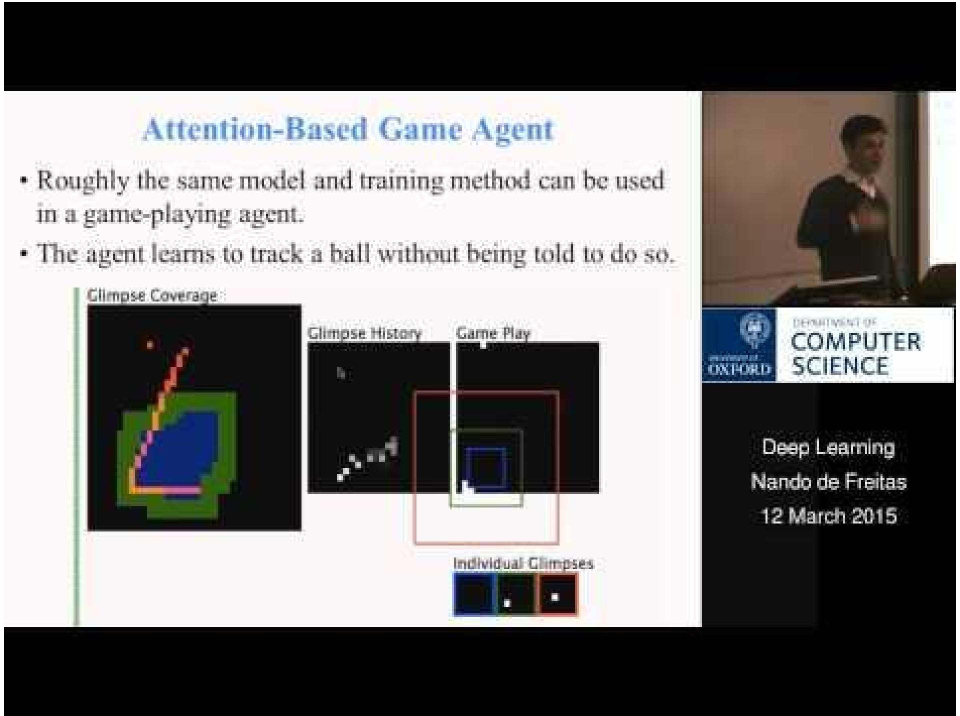
David Silver, UCL COMP050, [Reinforcement Learning]



Learn more



Nando de Freitas, [“Machine Learning”]() (University of Oxford)



Learn more

Pieter Abbeel and John Schulman, [CS 294-112 Deep Reinforcement Learning](), Berkeley.

Slides: [“Reinforcement Learning - Policy Optimization”]() OpenAI / UC Berkeley (2017)

Motivation

We can categorize three types of learning procedures:

1. Supervised Learning:

   $$\mathbf{y} = f(\mathbf{x})$$

2. Unsupervised Learning:

   $$f(\mathbf{x})$$

3. Reinforcement Learning (RL):

   $$\mathbf{y} = f(\mathbf{x})$$

   $$\mathbf{z}$$

Acknowledegments

Kevin McGuinness, “Unsupervised Learning” Deep Learning for Computer Vision.
[Slides 2016] [Slides 2017]

Motivation

Yann LeCun
Monday at 10:15 · Edited ·

Statement from a Slashdot post about the AlphaGo victory: "We know now that we don't need any big new breakthroughs to get to true AI"

That is completely, utterly, ridiculously wrong.

As I've said in previous statements: most of human and animal learning is unsupervised learning. If intelligence was a cake, unsupervised learning would be the cake, supervised learning would be the icing on the cake, and reinforcement learning would be the cherry on the cake. We know how to make the icing and the cherry, but we don't know how to make the cake.

We need to solve the unsupervised learning problem before we can even think of getting to true AI. And that's just an obstacle we know about. What about all the ones we don't know about?

#deeplearning #AI #AlphaGo

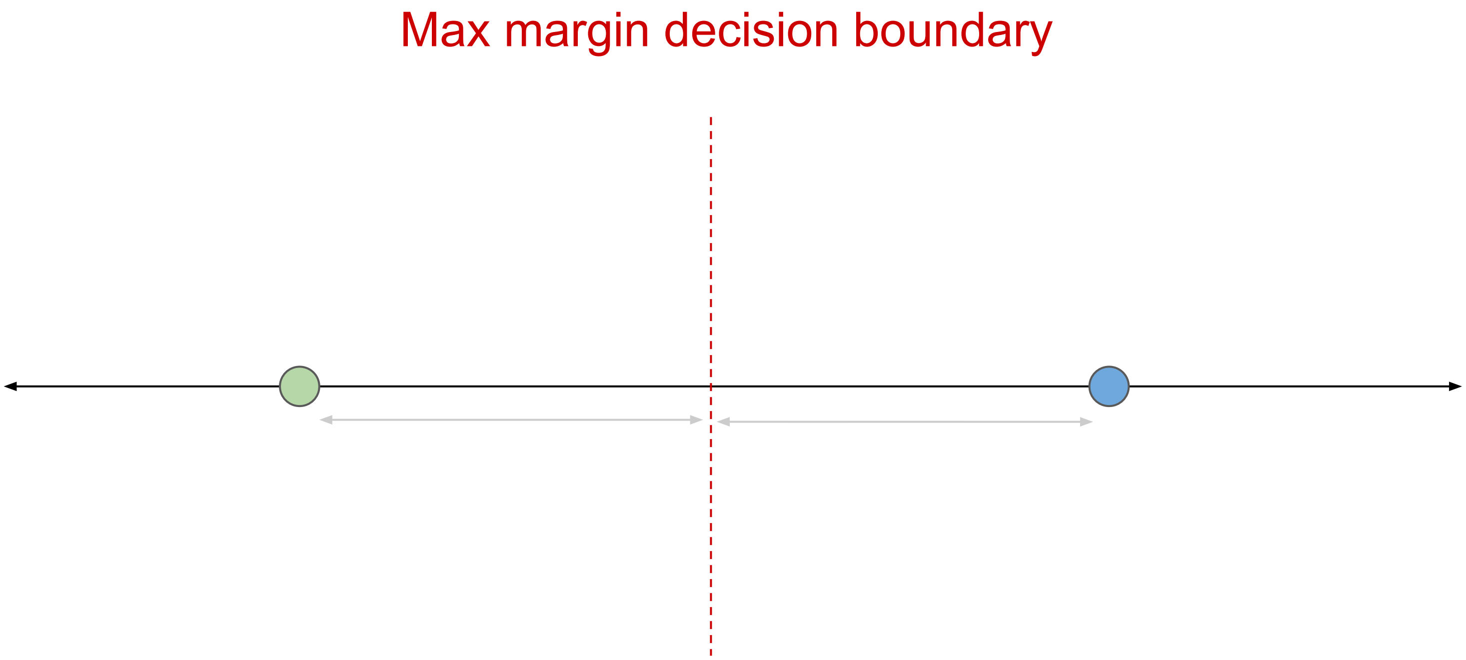
Greff, Klaus, Antti Rasmus, Mathias Berglund, Tele Hao, Harri Valpola, and Juergen Schmidhuber. "Tagger: Deep unsupervised perceptual grouping." NIPS 2016 [video] [code]

Unsupervised Learning

Why Unsupervised Learning?

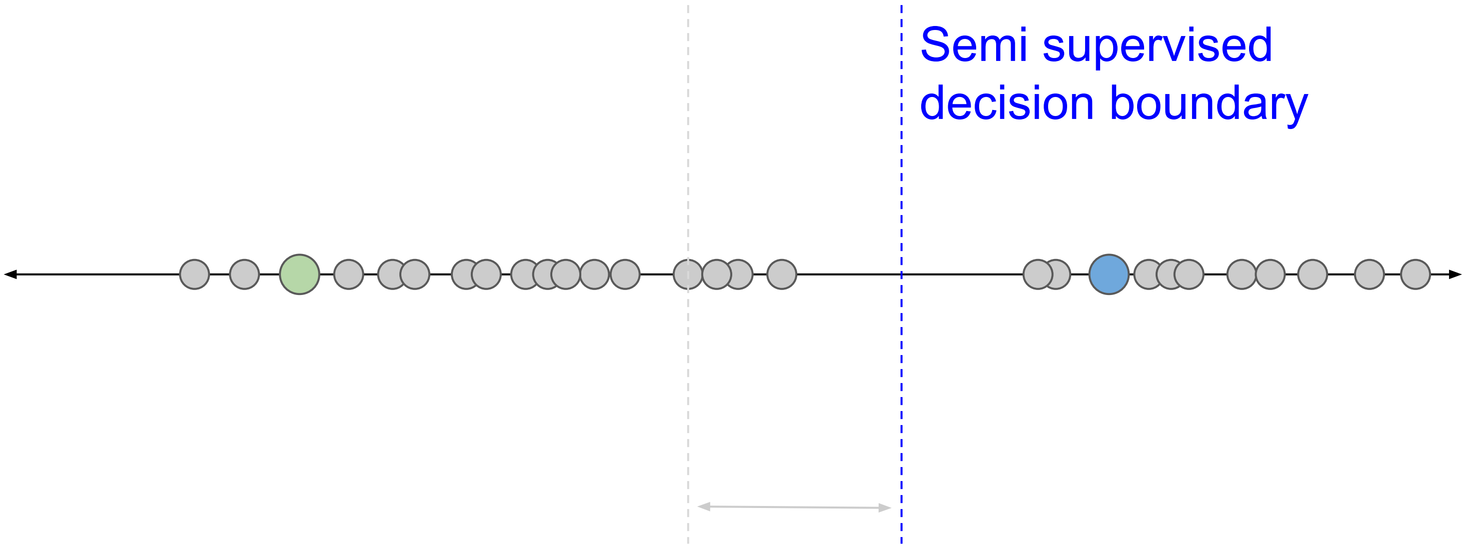
- It is the nature of how intelligent beings percept the world.
- It can save us tons of efforts to build a human-alike intelligent agent compared to a totally supervised fashion.
- Vast amounts of unlabelled data.

How data distribution P(x) influences decisions (1D)



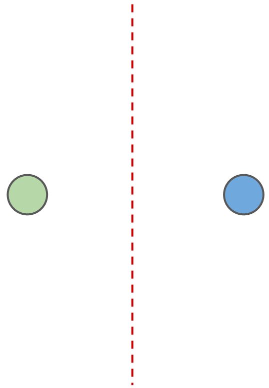
Slide credit: Kevin McGuinness (DLCV UPC 2017)

How data distribution P(x) influences decisions (1D)



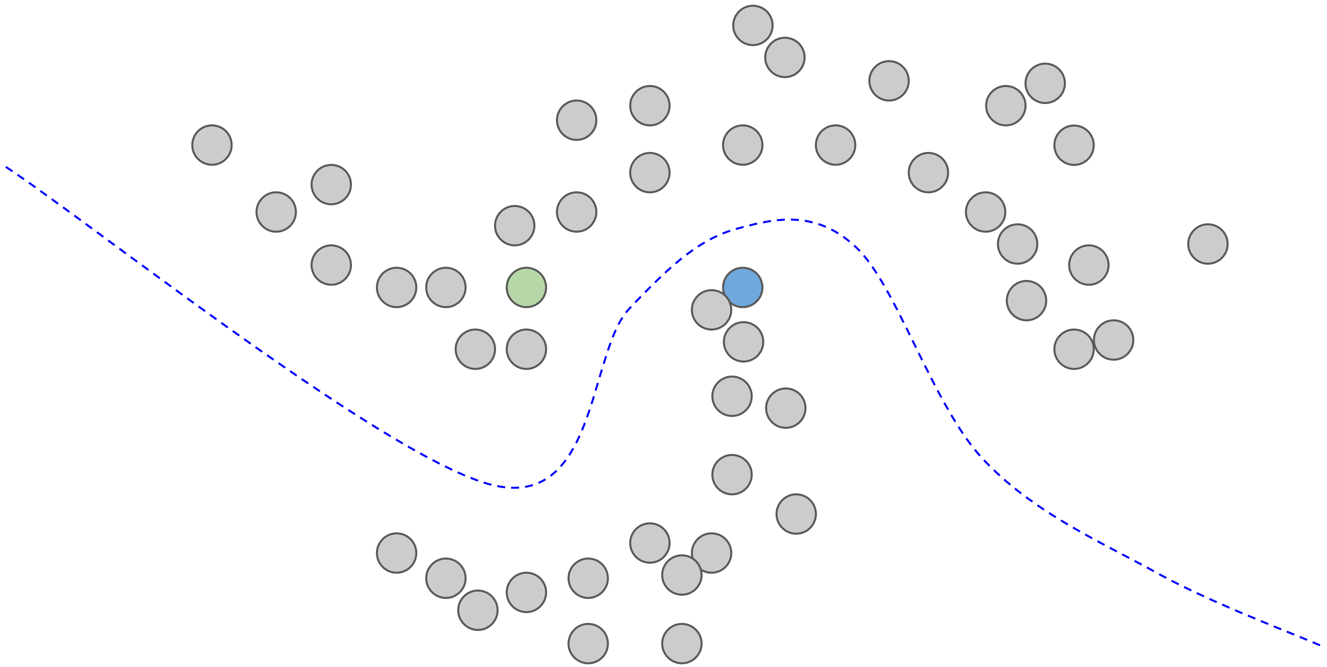
Slide credit: Kevin McGuinness (DLCV UPC 2017)

How data distribution P(x) influences decisions (2D)



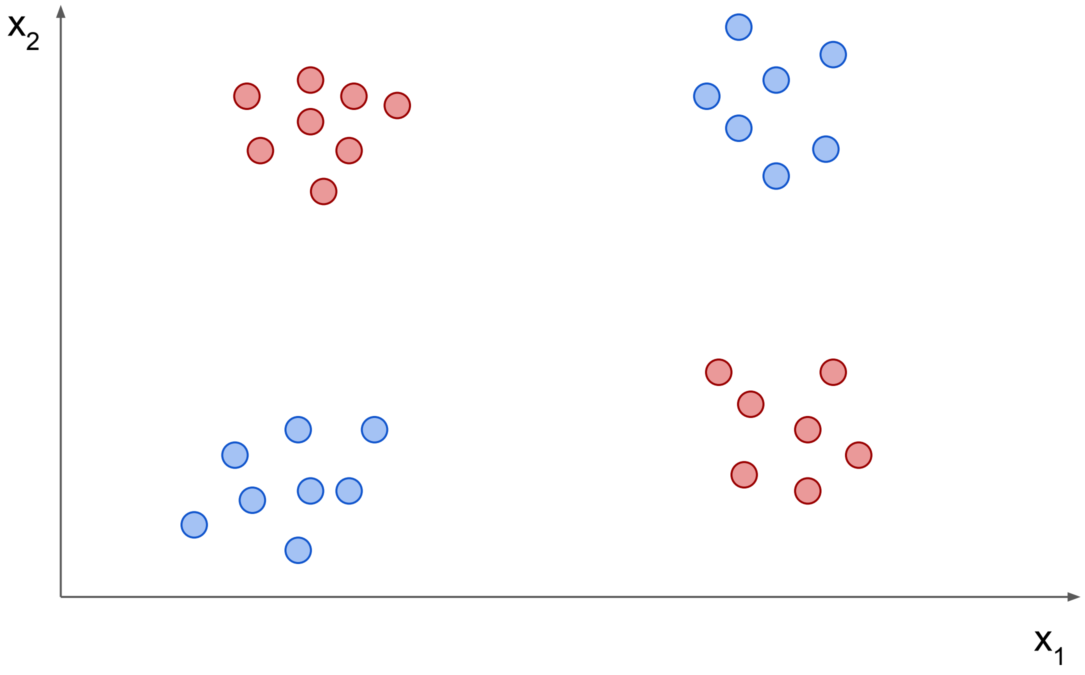
Slide credit: Kevin McGuinness (DLCV UPC 2017)

How data distribution P(x) influences decisions (2D)



Slide credit: Kevin McGuinness (DLCV UPC 2017)

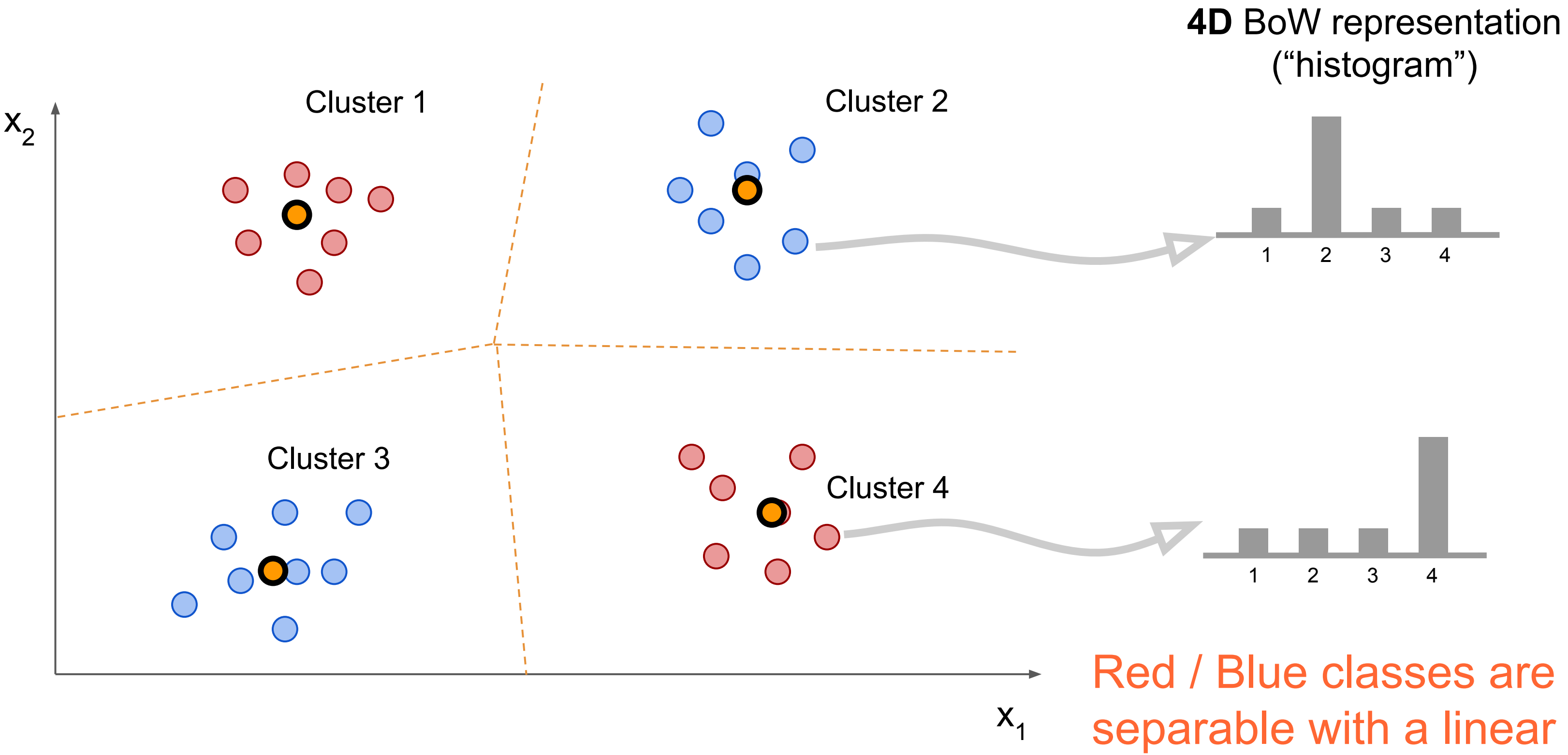
How clustering is valuable for linear classifiers



Red / Blue classes are nt linearly separable in this 2D space :(

Slide credit: Kevin McGuinness (DLCV UPC 2017)

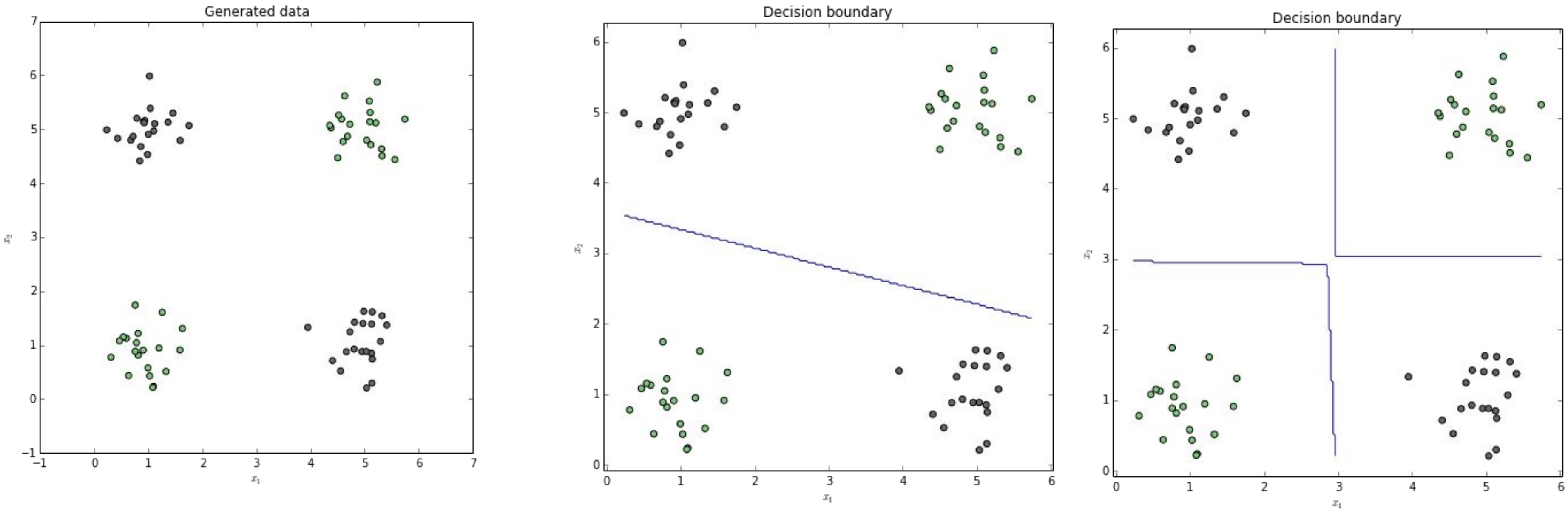
How clustering is valuable for linear classifiers



Red / Blue classes are now separable with a linear classifiers in a 4D space :)

Slide credit: Kevin McGuinness (DLCV UPC 2017)

How clustering is valueble for linear classifiers



Example from Kevin McGuinness Juyter notebook.

Assumptions for unsupervised learning

To model P(X) given data, it is necessary to make some assumptions

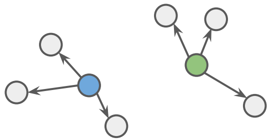
"You can't do inference without making assumptions"
-- David MacKay, Information Theory, Inference, and Learning Algorithms

Typical assumptions:

- Smoothness assumption
  - Points which are close to each other are more likely to share a label.
- Cluster assumption
  - The data form discrete clusters; points in the same cluster are likely to share a label
- **Manifold assumption**
  - The data lie approximately on a manifold of much lower dimension than the input space.

Slide credit: Kevin McGuinness (DLCV UPC 2017)

Assumptions for unsupervised learning



Smoothness assumption

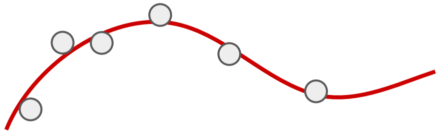
- Label propagation
  - Recursively propagate labels to nearby points
  - Problem: in high-D, your nearest neighbour may be very far away!

Cluster assumption

- Bag of words models
  - K-means, etc.
  - Represent points by cluster centers
  - Soft assignment
  - VLAD
- Gaussian mixture models
  - Fisher vectors

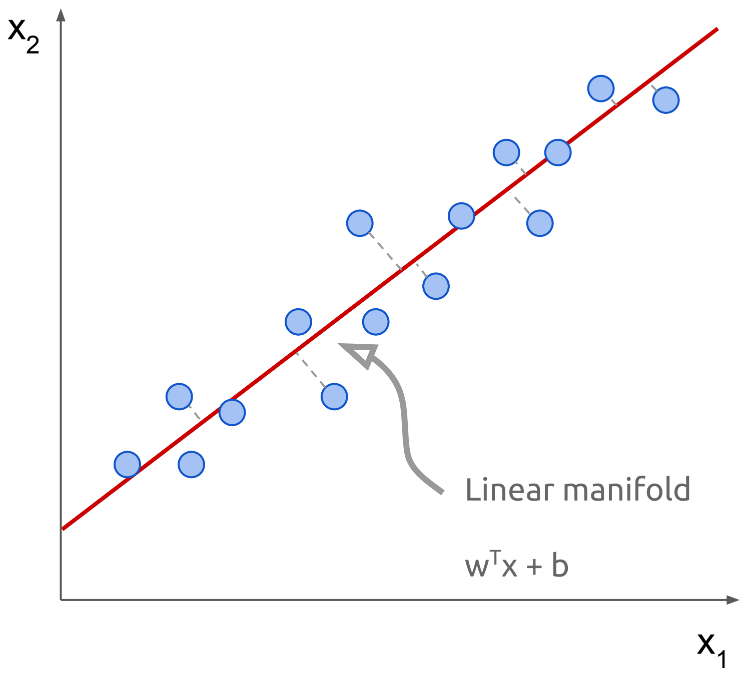
Manifold assumption

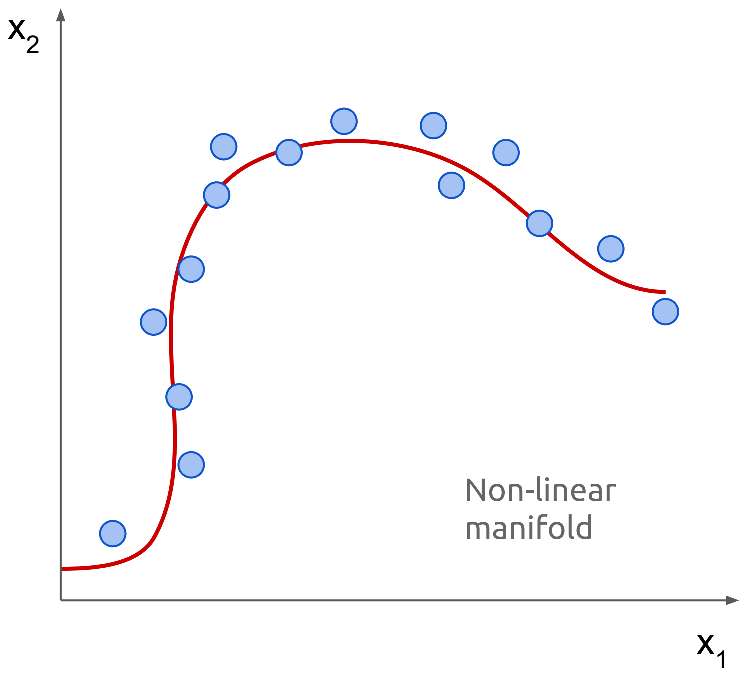
- Linear manifolds
  - PCA
  - Linear autoencoders
  - Random projections
  - ICA
- Non-linear manifolds:
  - Non-linear autoencoders
  - Deep autoencoders
  - Restricted Boltzmann machines
  - Deep belief nets



Slide credit: Kevin McGuinness (DLCV UPC 2017)

The manifold hypothesis





Slide credit: Kevin McGuinness (DLCV UPC 2017)

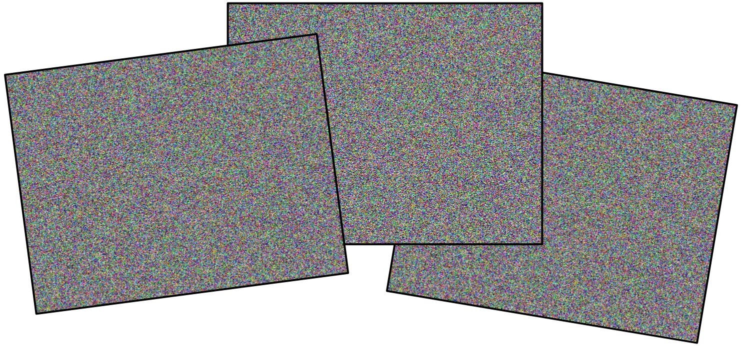
The manifold hypothesis

The data distribution lies close to a low-dimensional manifold

Example: **consider image data**

- Very high dimensional (1,000,000D)
- A randomly generated image will almost certainly not look like any real world scene
  - The space of images that occur in nature is almost completely empty
- Hypothesis: real world images lie on a smooth, low-dimensional manifold
  - Manifold distance is a good measure of similarity

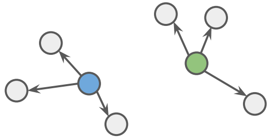
Similar for audio and text



Slide credit: Kevin McGuinness (DLCV UPC 2017)

Assumptions for unsupervised learning

Smoothness assumption



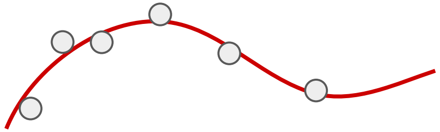
- Label propagation
  - Recursively propagate labels to nearby points
  - Problem: in high-D, your nearest neighbour may be very far away!

Cluster assumption

- Bag of words models
  - K-means, etc.
  - Represent points by cluster centers
  - Soft assignment
  - VLAD
- Gaussian mixture models
  - Fisher vectors

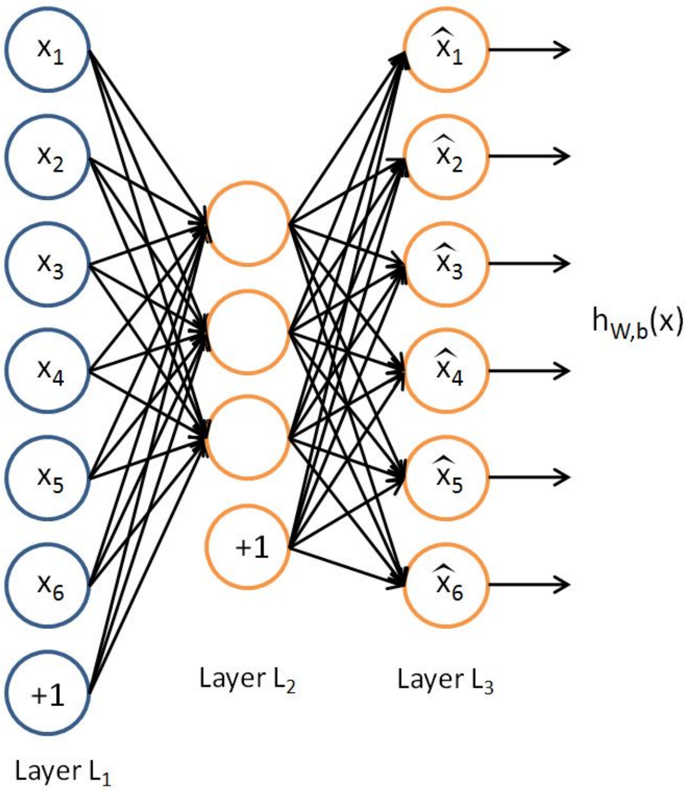
Manifold assumption

- Linear manifolds
  - PCA
  - Linear autoencoders
  - Random projections
  - ICA
- Non-linear manifolds:
  - Non-linear autoencoders
  - Deep autoencoders
  - Restricted Boltzmann machines
  - Deep belief nets



Slide credit: Kevin McGuinness (DLCV UPC 2017)

Autoencoder (AE)



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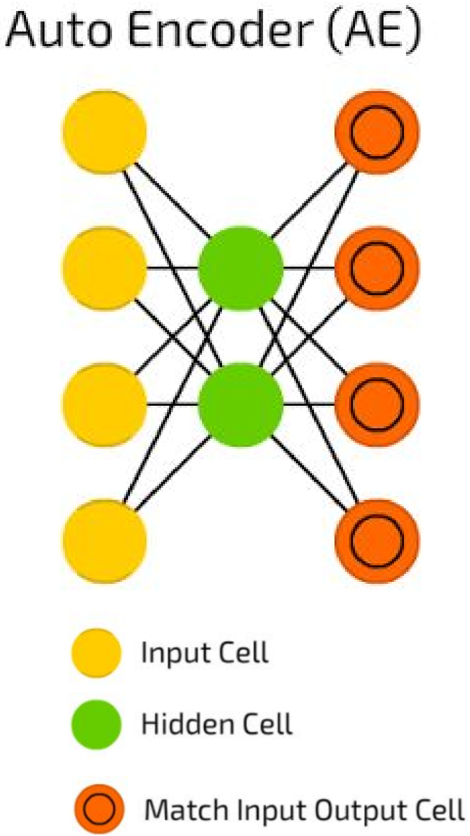
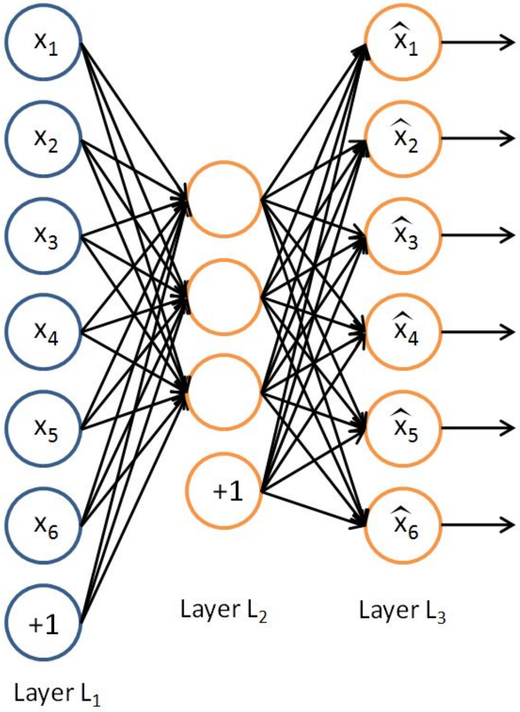


F. Van Veen, [“The Neural Network Zoo”] (2016)

Autoencoder (AE)

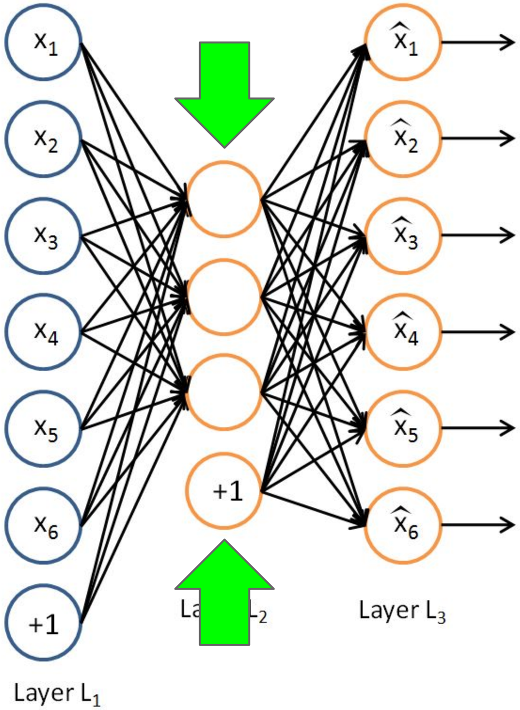


Autoencoders:

- Predict at the output the same input data.
- Do not need labels:

"Deep Learning Tutorial", Dept. Computer Science, Stanford

Autoencoder (AE)



Application #1

Dimensionality reduction:

- Use hidden layer as a feature extractor of any desired size.

[“Deep Learning Tutorial”](), Dept. Computer Science, Stanford

Autoencoder (AE)

Application #2

Pretraining:

1. Initialize a NN solving an autoencoding problem.

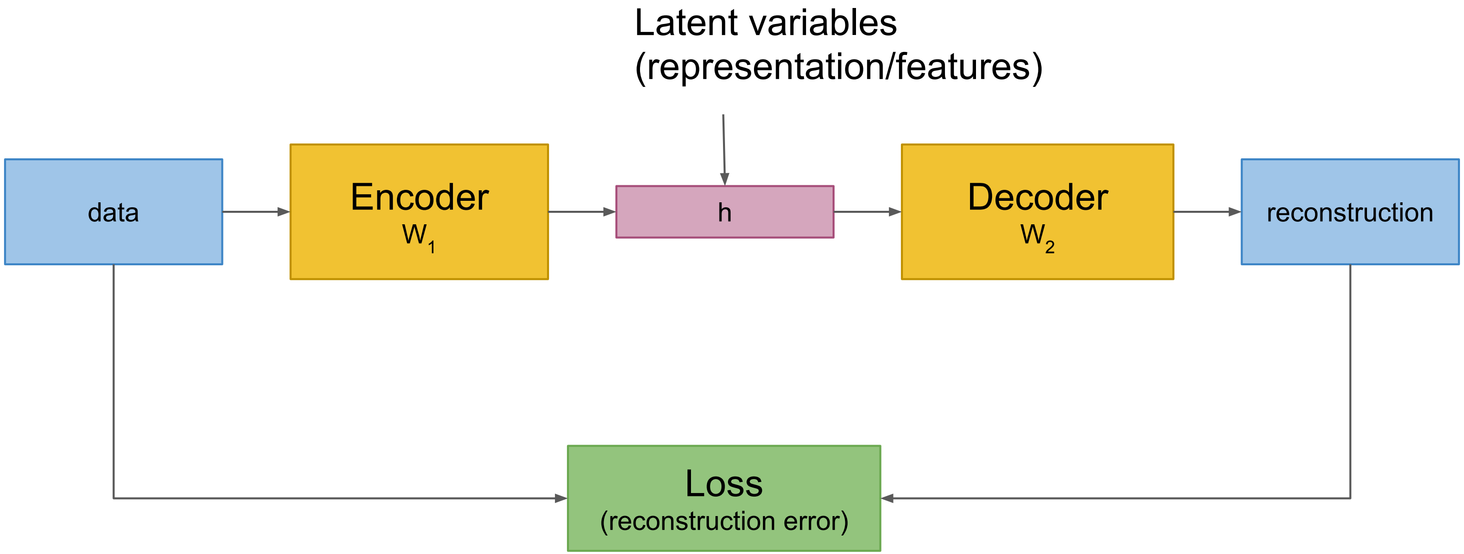


Figure: Kevin McGuinness (DLCV UPC 2017)

Autoencoder (AE)

Application #2

Pretraining:

1. Initialize a NN solving an autoencoding problem.
2. Train for final task with “few” labels.

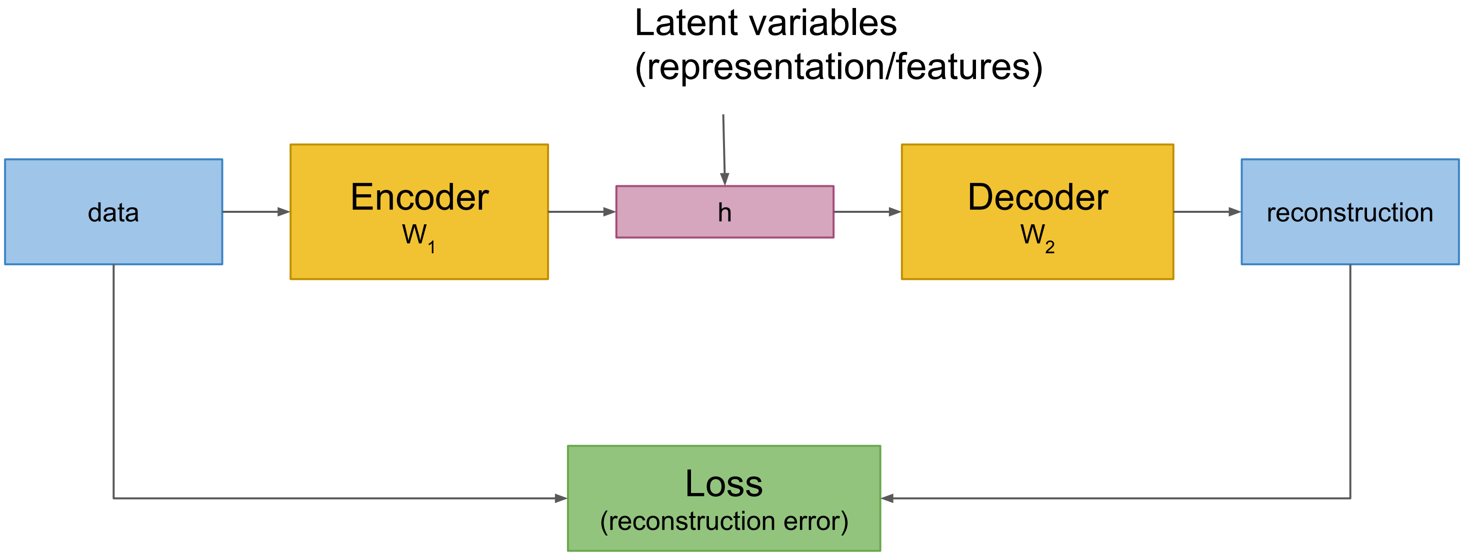
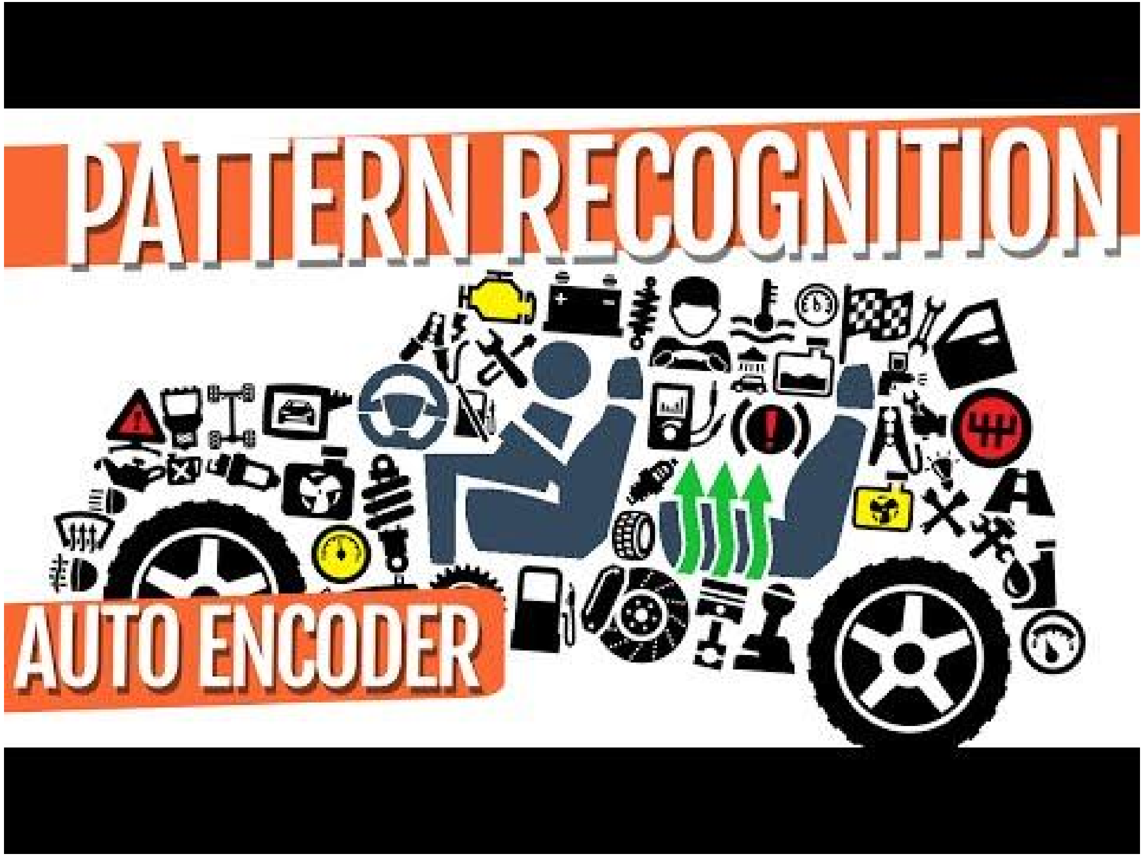


Figure: Kevin McGuinness (DLCV UPC 2017)

Autoencoder (AE)

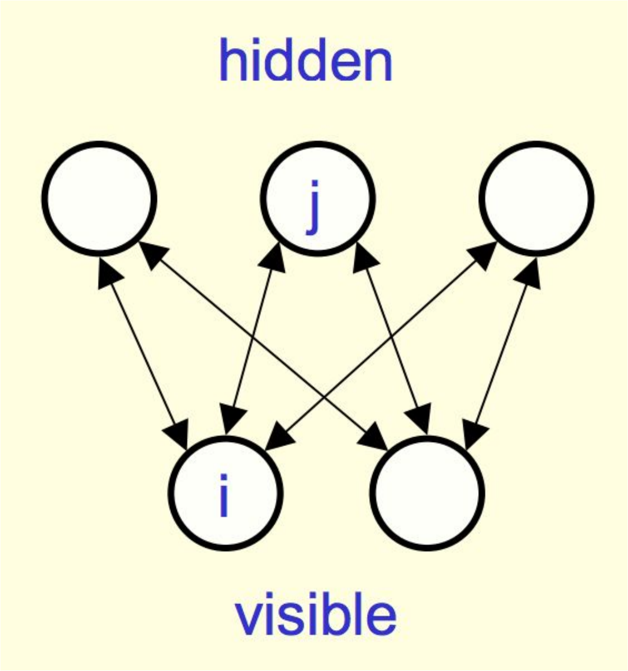


Deep Learning TV, [“Autoencoders - Ep. 10”]

Restricted Boltzmann Machine (RBM)

F. Van Veen, [“The Neural Network Zoo”](#) (2016)

Restricted Boltzmann Machine (RBM)

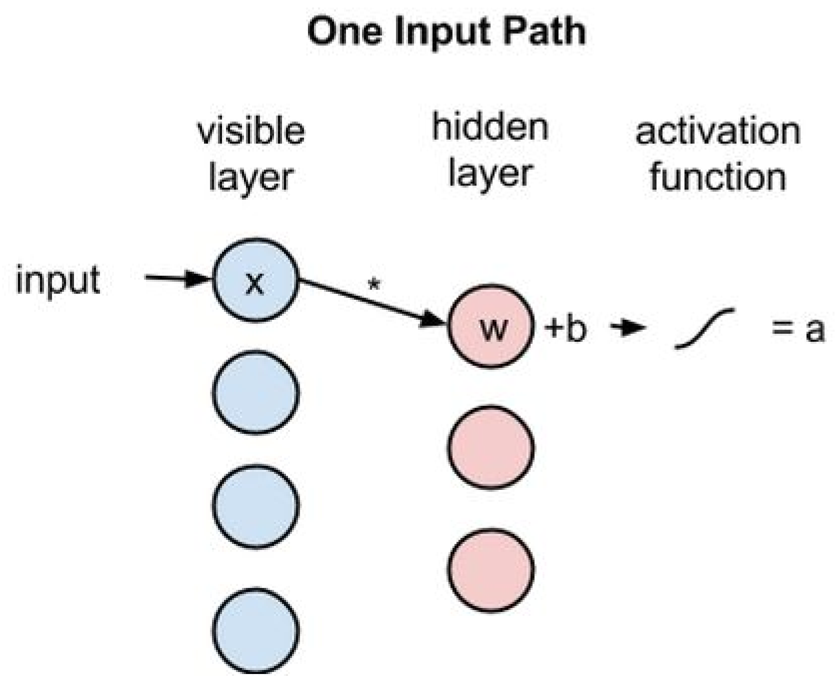


- Shallow two-layer net.
- Restricted = No two nodes in a layer share a connection
-
- Bipartite graph.
- Bidirectional graph
  - Shared weights.
  - Different biases.

Figure: Geoffrey Hinton (2013)

Salakhutdinov, Ruslan, Andriy Mnih, and Geoffrey Hinton. "Restricted Boltzmann machines for collaborative filtering." Proceedings of the 24th international conference on Machine learning. ACM, 2007.

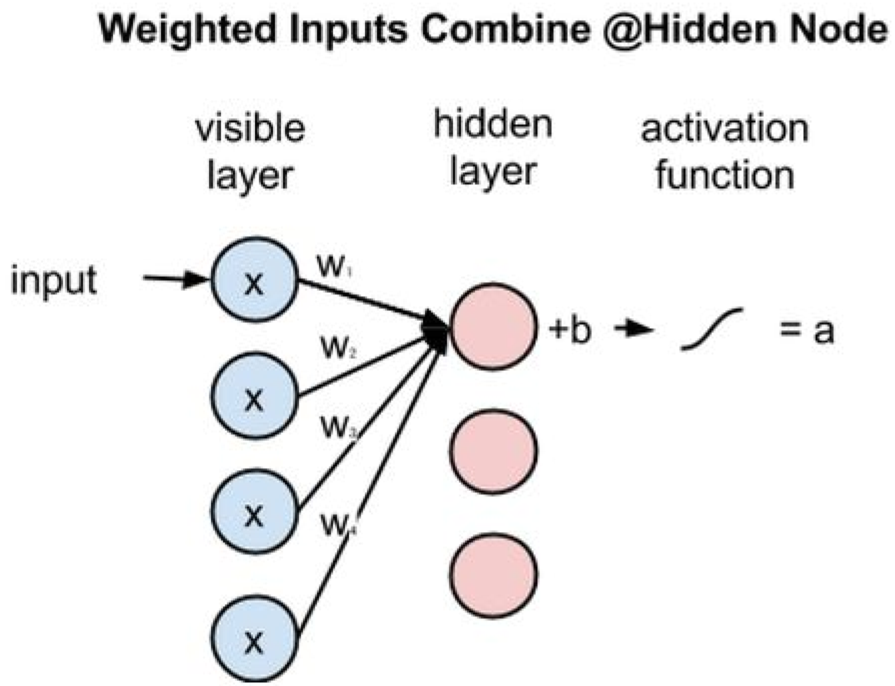
Restricted Boltzmann Machine (RBM)

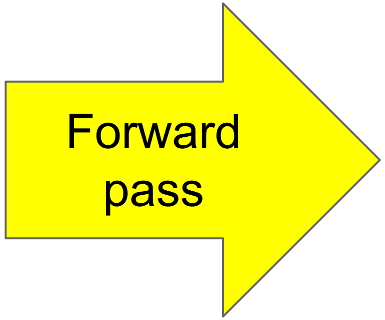


Forward pass

DeepLearning4j, [“A Beginner’s Tutorial for Restricted Boltzmann Machines”.]()

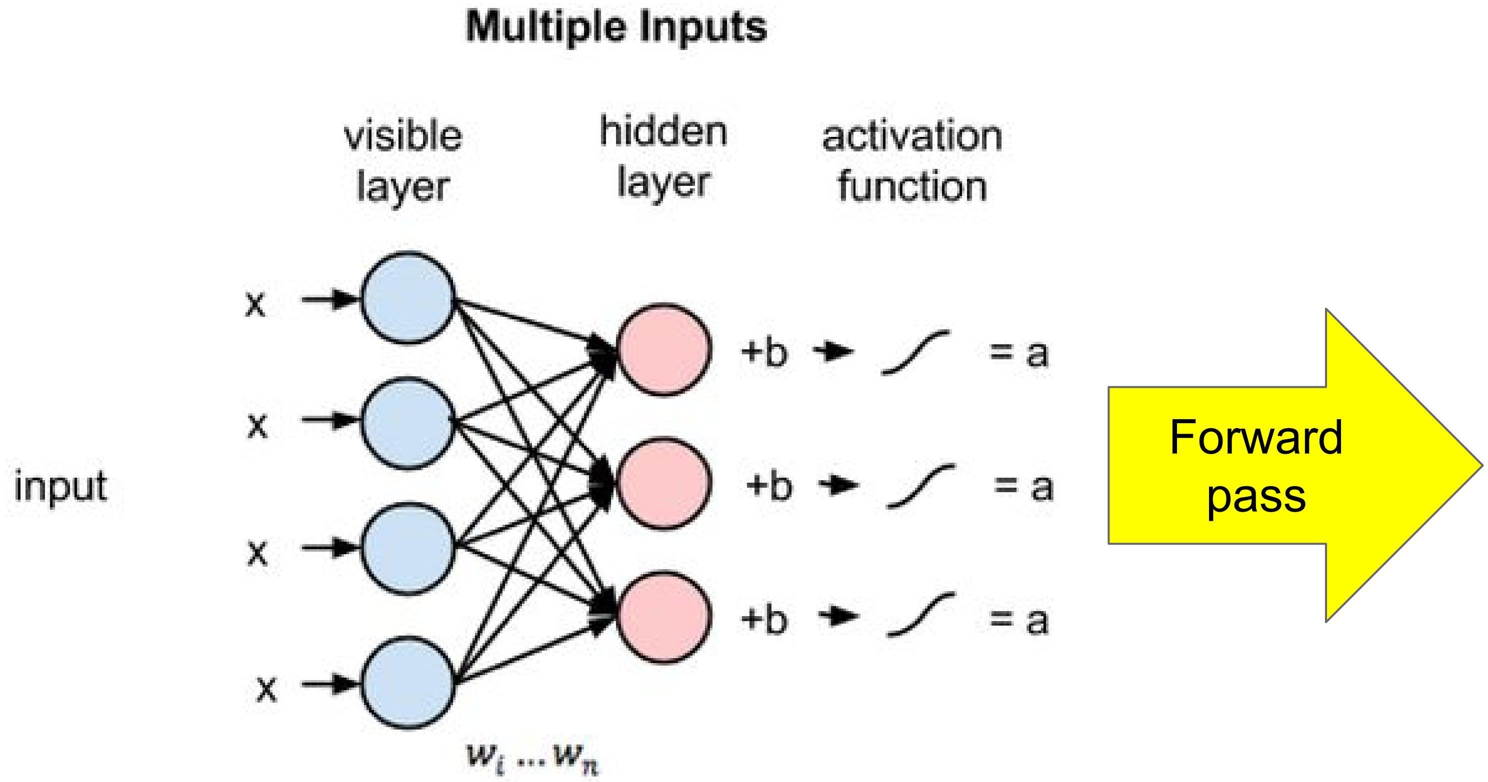
Restricted Boltzmann Machine (RBM)





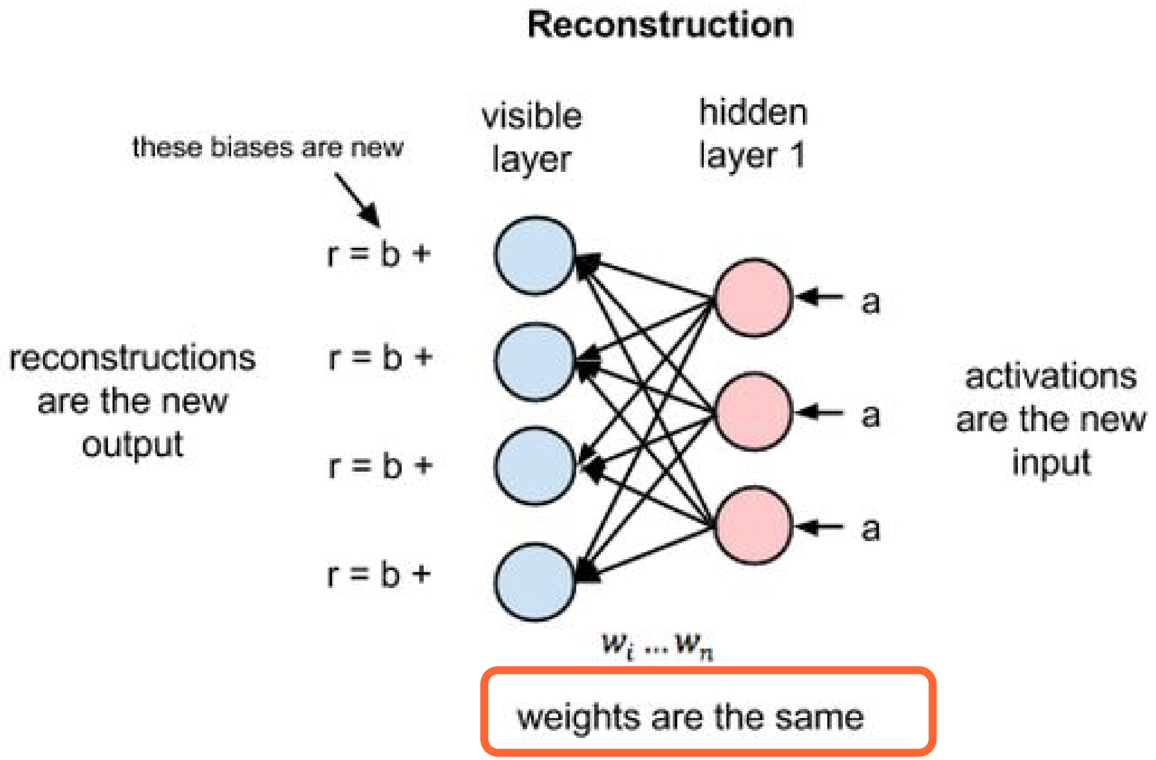
DeepLearning4j, “A Beginner’s Tutorial for Restricted Boltzmann Machines”.

Restricted Boltzmann Machine (RBM)



DeepLearning4j, [“A Beginner’s Tutorial for Restricted Boltzmann Machines”.]

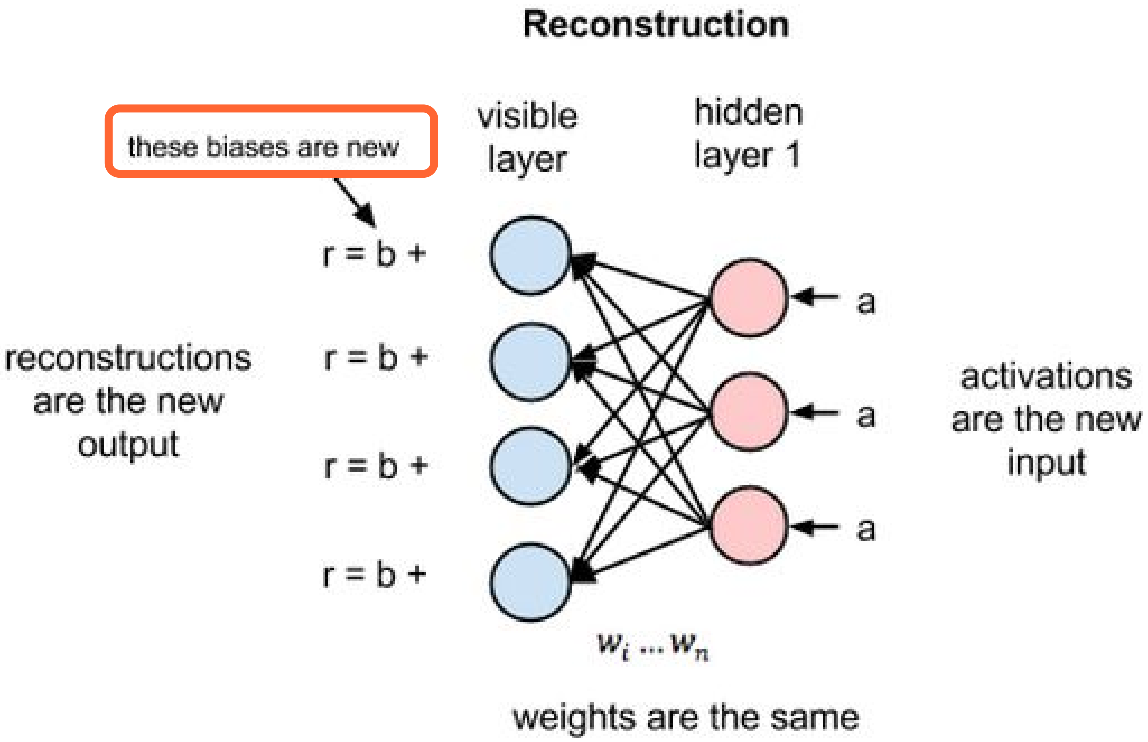
Restricted Boltzmann Machine (RBM)



Backward pass

DeepLearning4j, [“A Beginner’s Tutorial for Restricted Boltzmann Machines”.]()

Restricted Boltzmann Machine (RBM)



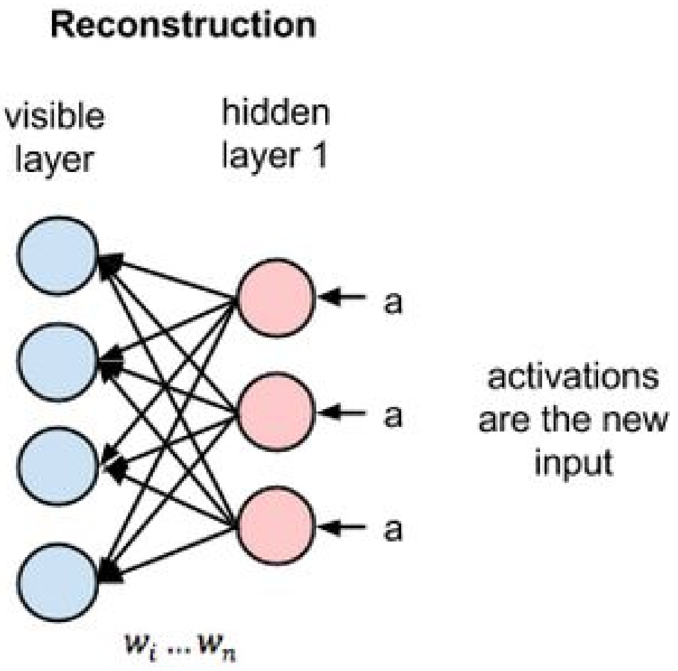
Backward pass

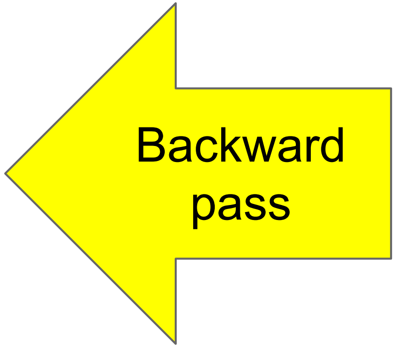
DeepLearning4j, [“A Beginner’s Tutorial for Restricted Boltzmann Machines”.]

Restricted Boltzmann Machine (RBM)

The reconstructed values at the visible layer are compared with the actual ones with the [KL Divergence](#).

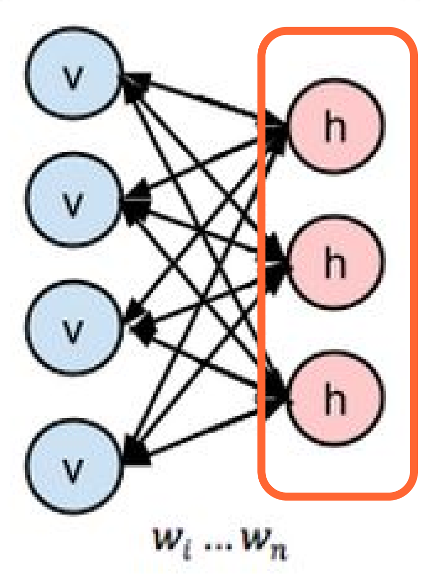
$$D_{\mathrm{KL}}(P\|Q) = -\sum_i P(i)\,\log\frac{Q(i)}{P(i)},$$





DeepLearning4j, “A Beginner’s Tutorial for Restricted Boltzmann Machines”.

Restricted Boltzmann Machine (RBM)



RBMs are a specific type of **autoencoder**.

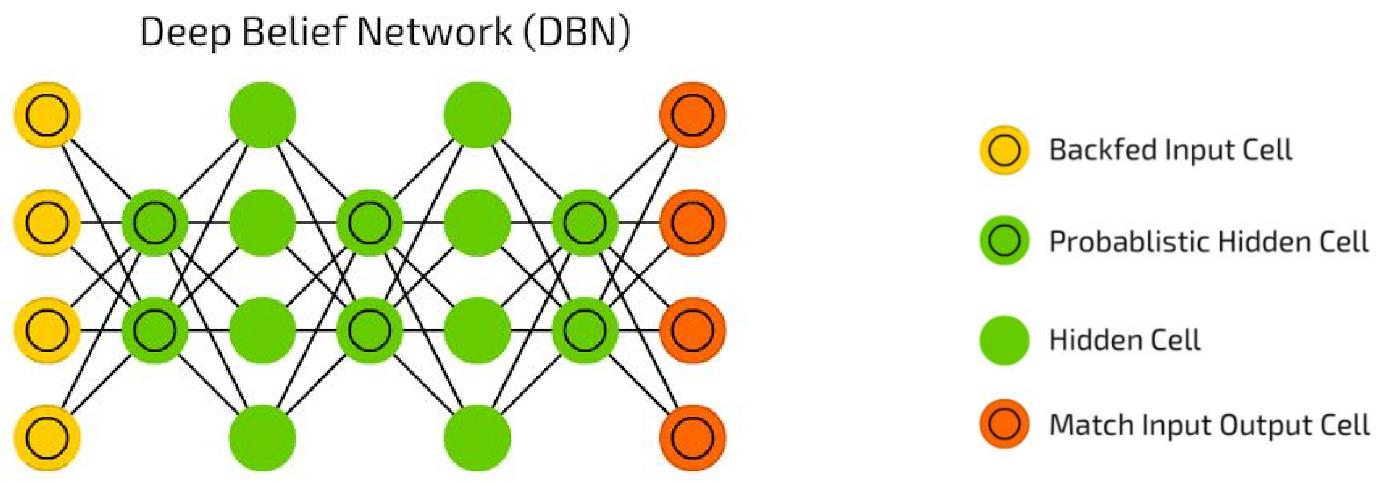
Unsupervised learning

DeepLearning4j, "A Beginner's Tutorial for Restricted Boltzmann Machines".

Restricted Boltzmann Machine (RBM)

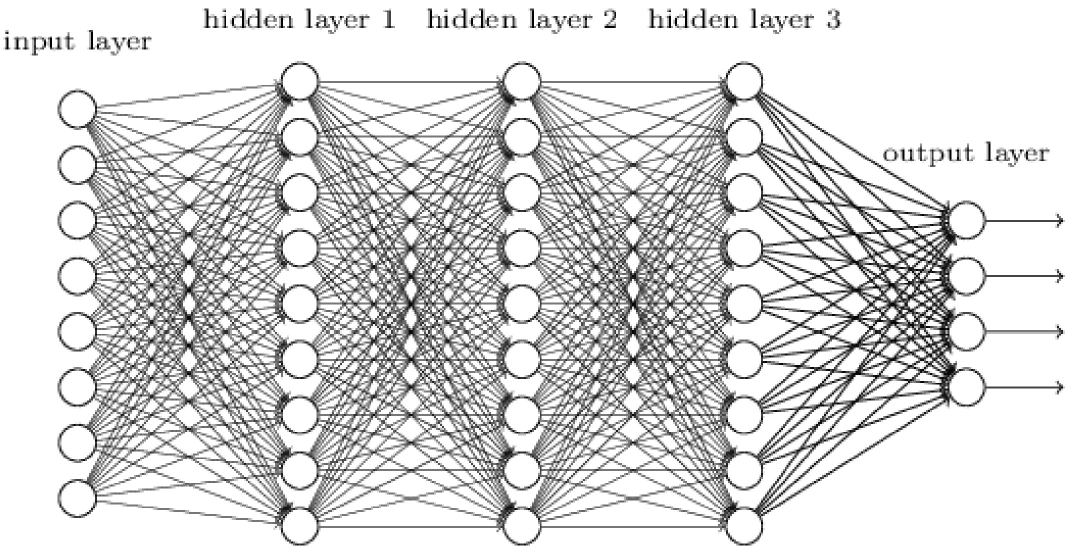
Deep Learning TV, “Restricted Boltzmann Machines”.

Deep Belief Networks (DBN)



F. Van Veen, [“The Neural Network Zoo”]() (2016)

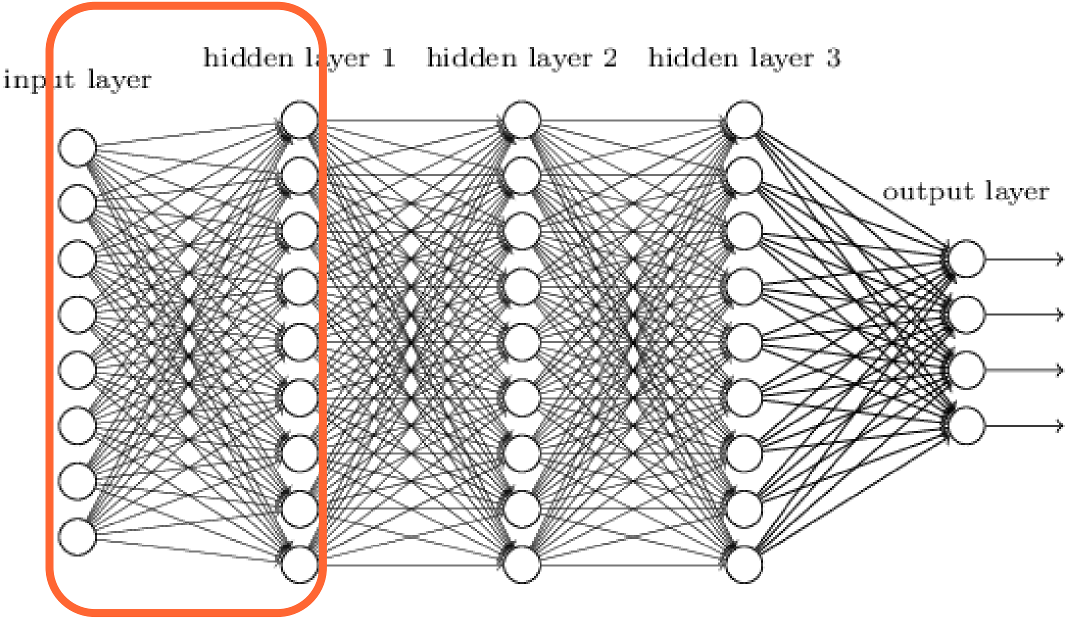
Deep Belief Networks (DBN)



- Architecture like an MLP.
- Training as a stack of RBMs.

Hinton, Geoffrey E., Simon Osindero, and Yee-Whye Teh. "A fast learning algorithm for deep belief nets." Neural computation 18, no. 7 (2006): 1527-1554.

Deep Belief Networks (DBN)



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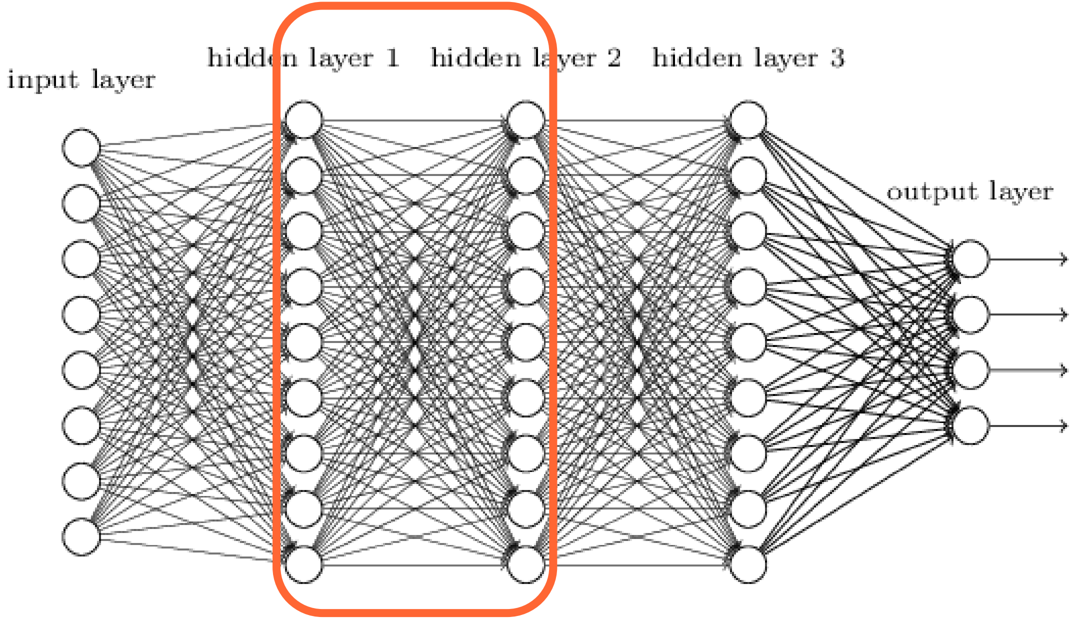

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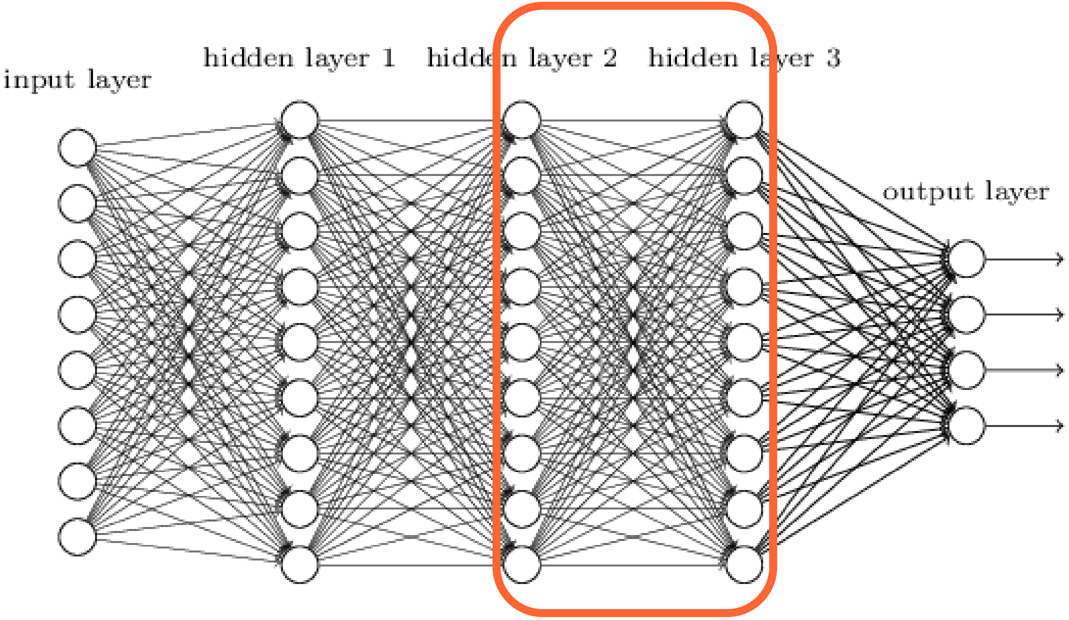
Deep Belief Networks (DBN)



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Hinton, Geoffrey E., Simon Osindero, and Yee-Whye Teh. "A fast learning algorithm for deep belief nets." Neural computation 18, no. 7 (2006): 1527-1554.

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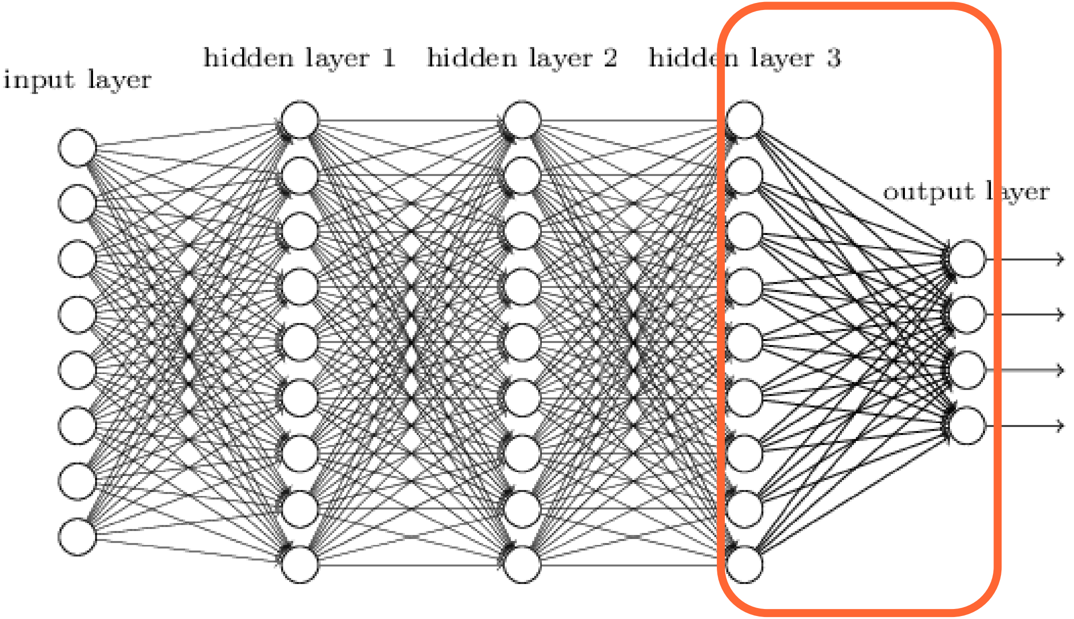
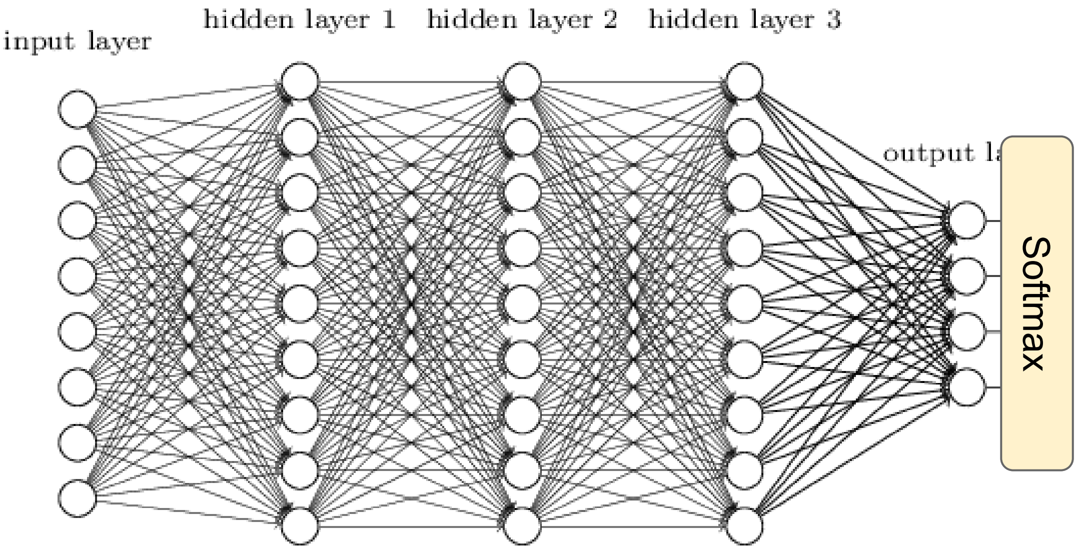


- Architecture like an MLP.
- Training as a stack of RBMs…
- ...so they do not need labels:

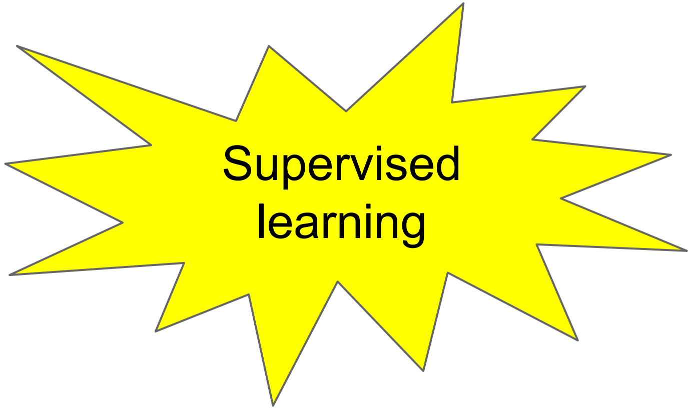
Unsupervised learning

Hinton, Geoffrey E., Simon Osindero, and Yee-Whye Teh. ["A fast learning algorithm for deep belief nets."](#) Neural computation 18, no. 7 (2006): 1527-1554.

Deep Belief Networks (DBN)

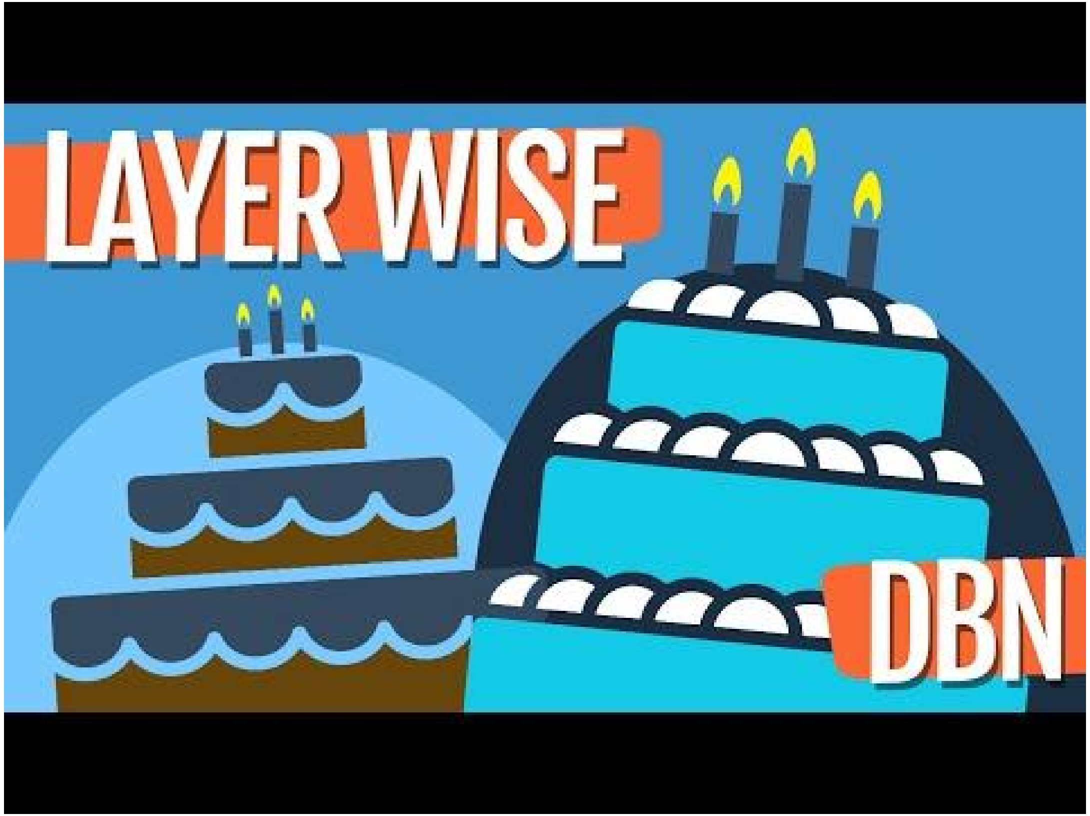


After the DBN is trained, it can be fine-tuned with a <u>**reduced amount of labels**</u> to solve a supervised task with superior performance.



Hinton, Geoffrey E., Simon Osindero, and Yee-Whye Teh. ["A fast learning algorithm for deep belief nets."]() Neural computation 18, no. 7 (2006): 1527-1554.

Deep Belief Networks (DBN)



Deep Learning TV, “Deep Belief Nets”

Deep Belief Networks (DBN)

Geoffrey Hinton, ["Introduction to Deep Learning & Deep Belief Nets”]() (2012)
Geoorey Hinton, [“Tutorial on Deep Belief Networks”](). NIPS 2007.

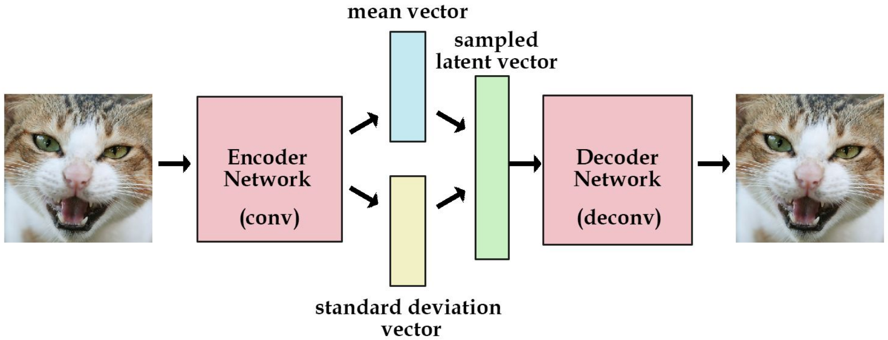
Deep Belief Networks (DBN)

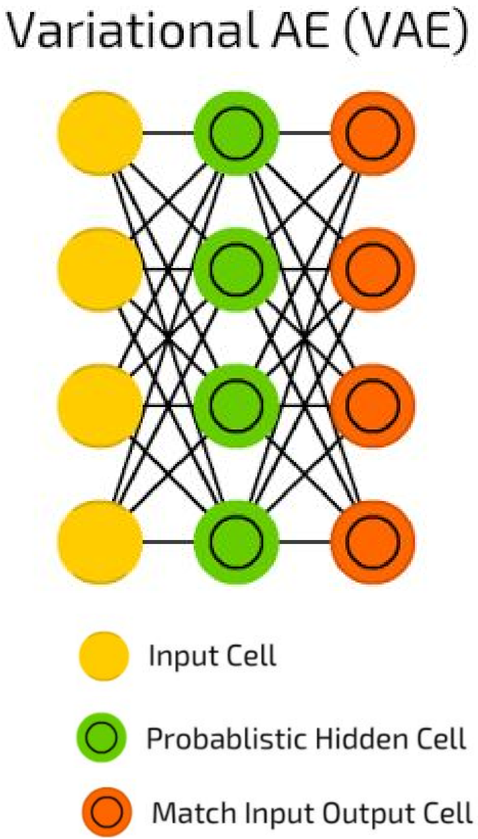
Geoffrey Hinton

UNIVERSITY OF TORONTO

Research at Google

Variational Autoencoder (VAE)

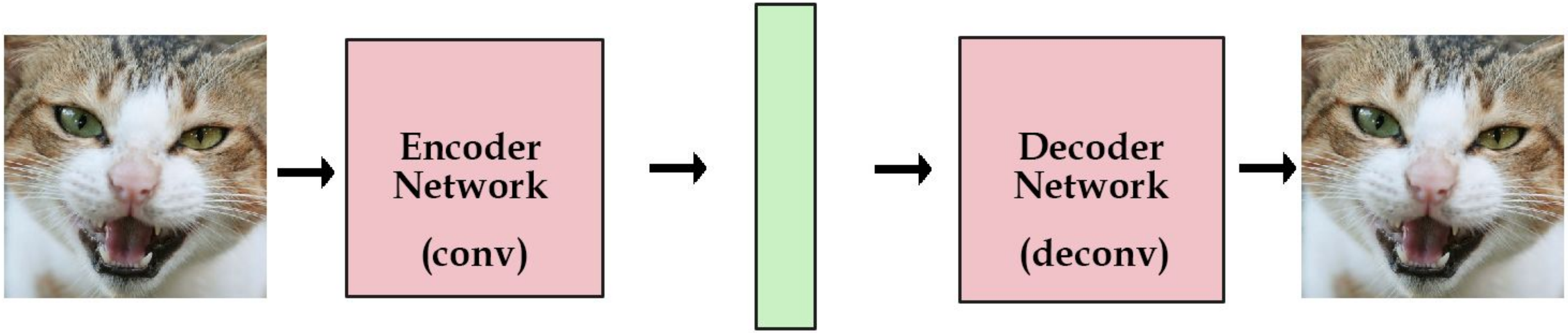




F. Van Veen, [“The Neural Network Zoo”]() (2016)

Variational Autoencoder (VAE)

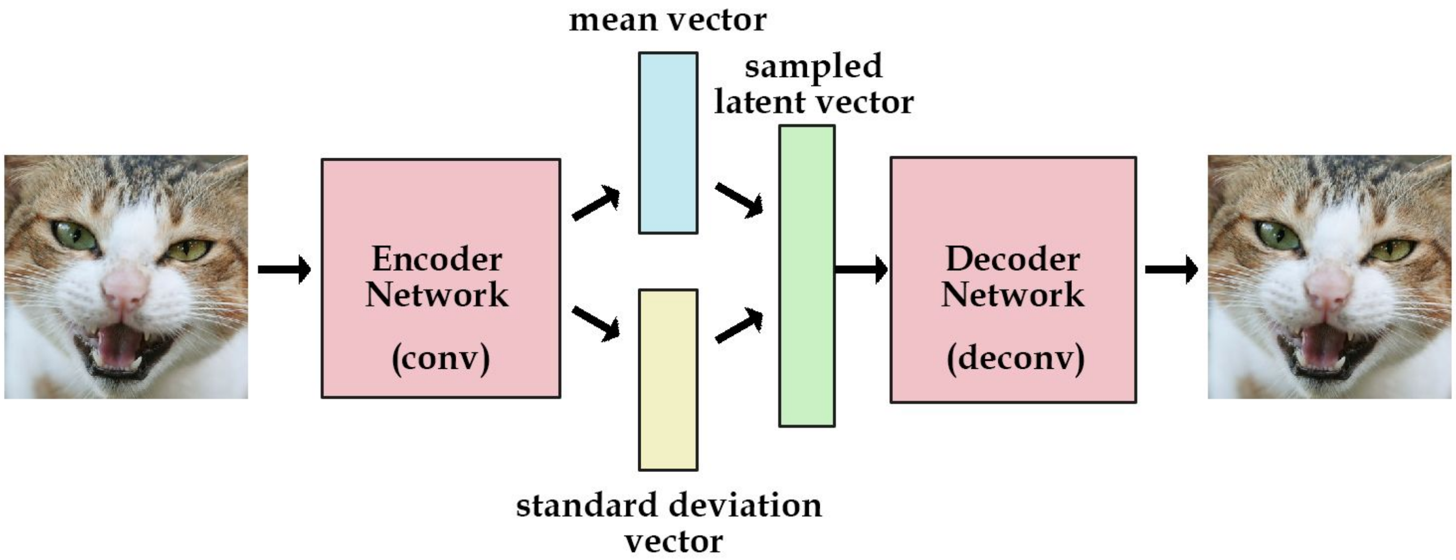
The latent vector learned in the hidden layer of the basic autoencoder (in green)...



Kevin Frans, [“Variational Autoencoders explained”]() (2016)

Variational Autoencoder (VAE)

The latent vector learned in the hidden layer of the basic autoencoder (in green)...
...is forced to follow a unit Gaussian distribution in VAEs.



Kevin Frans, [“Variational Autoencoders explained”]() (2016)

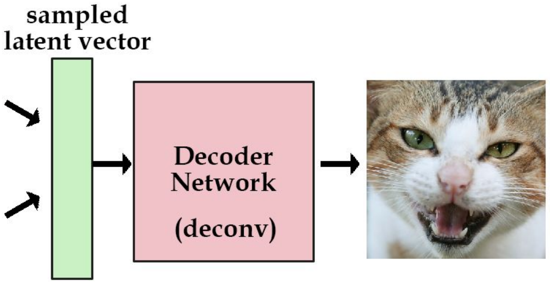
Variantional Autoencoder (VAE)

Application #3

Generative model:

- Create new samples by drawing from a Gaussian distribution.

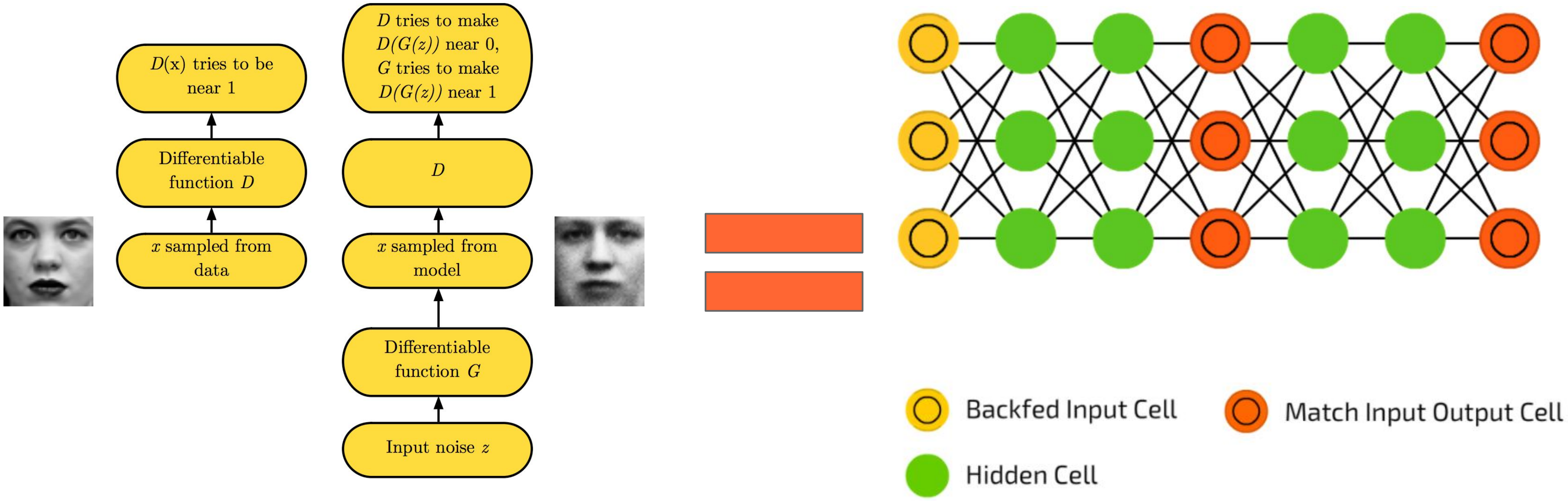
WHY?



Unsupervised learning

Alec Radford, “Face manifold from conv/deconv variational autoencoder” (2015)

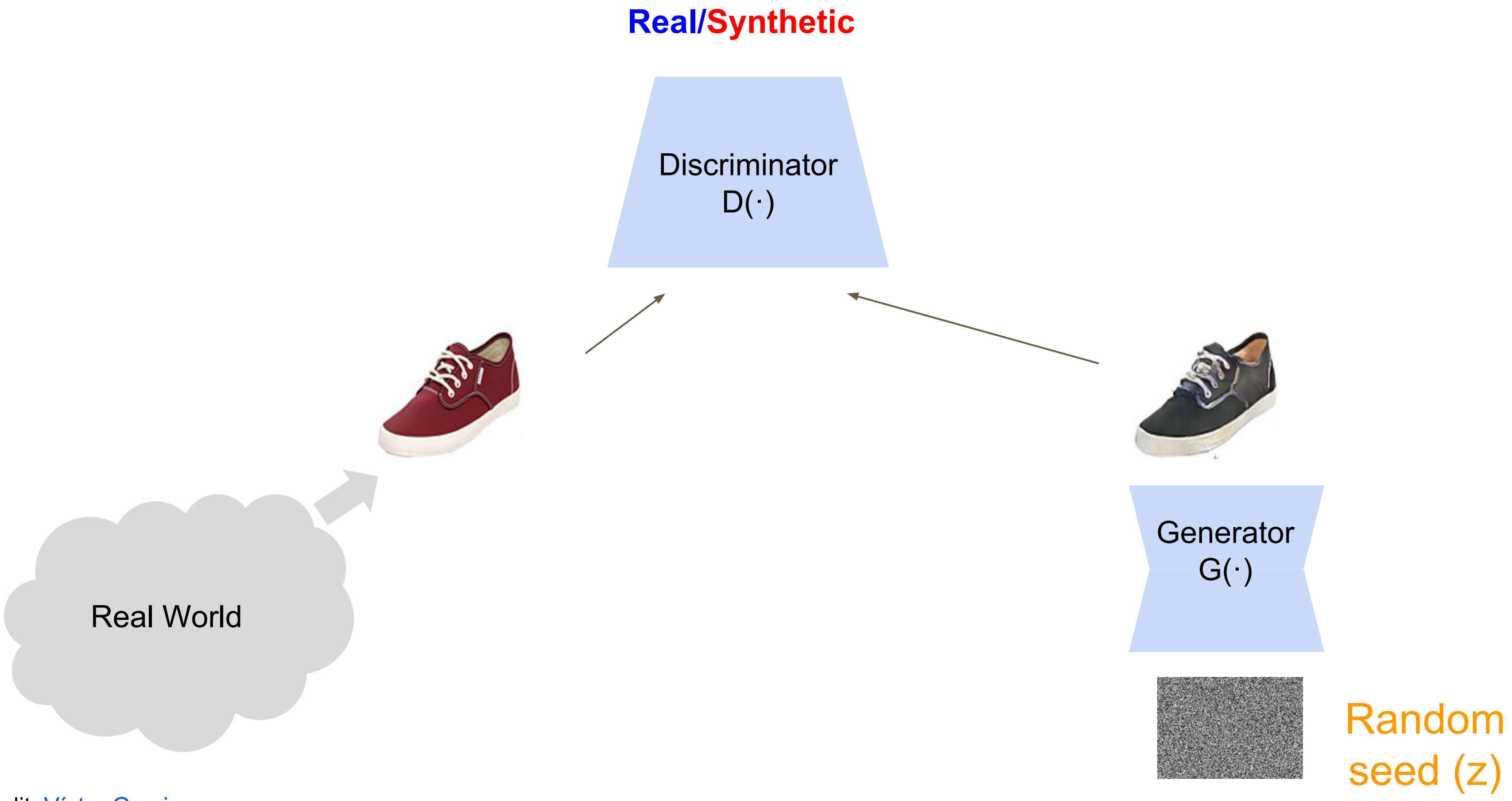
Adversarial Networks



Goodfellow, Ian, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. ["Generative adversarial nets."]() NIPS 2014
Goodfellow, Ian. ["NIPS 2016 Tutorial: Generative Adversarial Networks."]() *arXiv preprint arXiv:1701.00160* (2016).

F. Van Veen, [“The Neural Network Zoo”]() (2016)

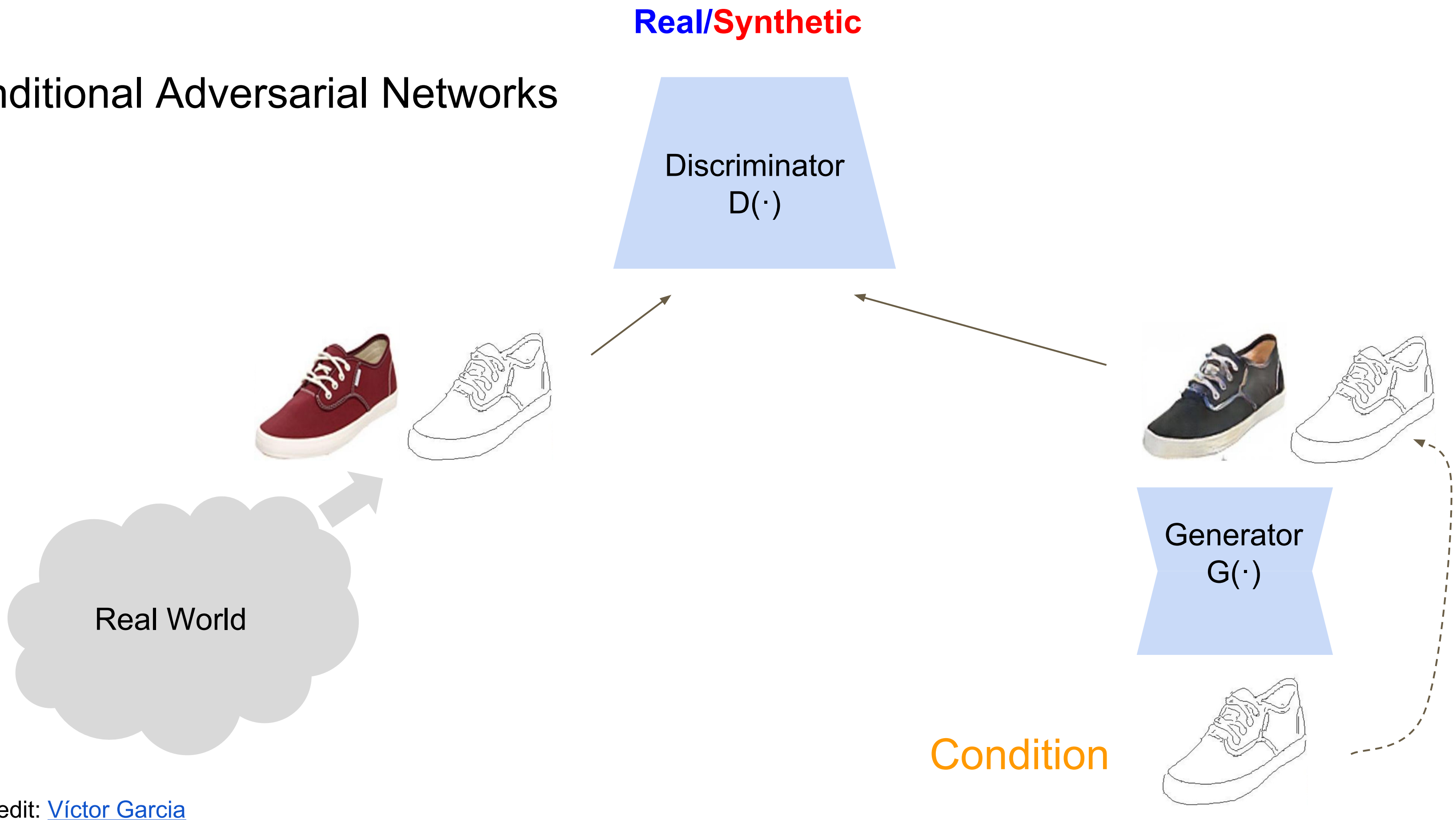
Adversarial Networks



Slide credit: [Víctor Garcia]

Adversarial Networks

Conditional Adversarial Networks



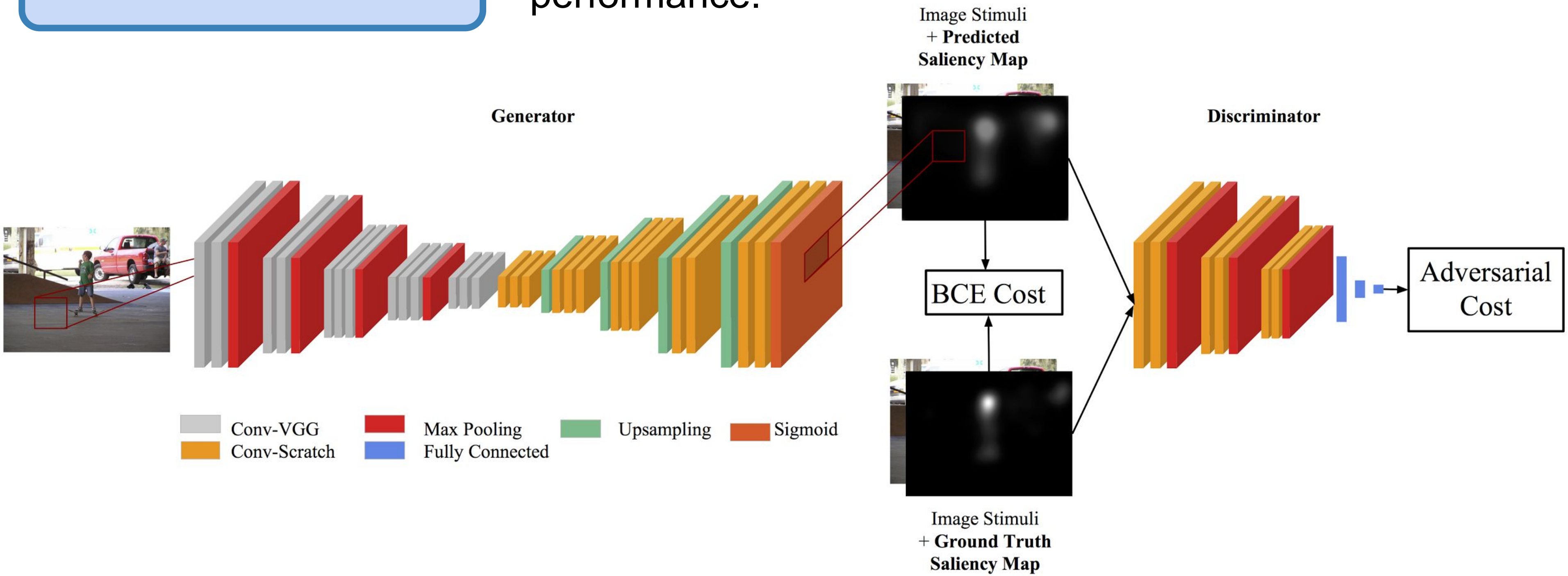
Slide credit: [Víctor Garcia]

Tero Karras, Timo Aila, Samuli Laine, Jaakko Lehtinen, "Progressive Growing of GANs for Improved Quality, Stability, and Variation" (submitted to ICLR 2018)

Adversarial Networks

Application #4

Introduce an additional term to the less to improve performance.

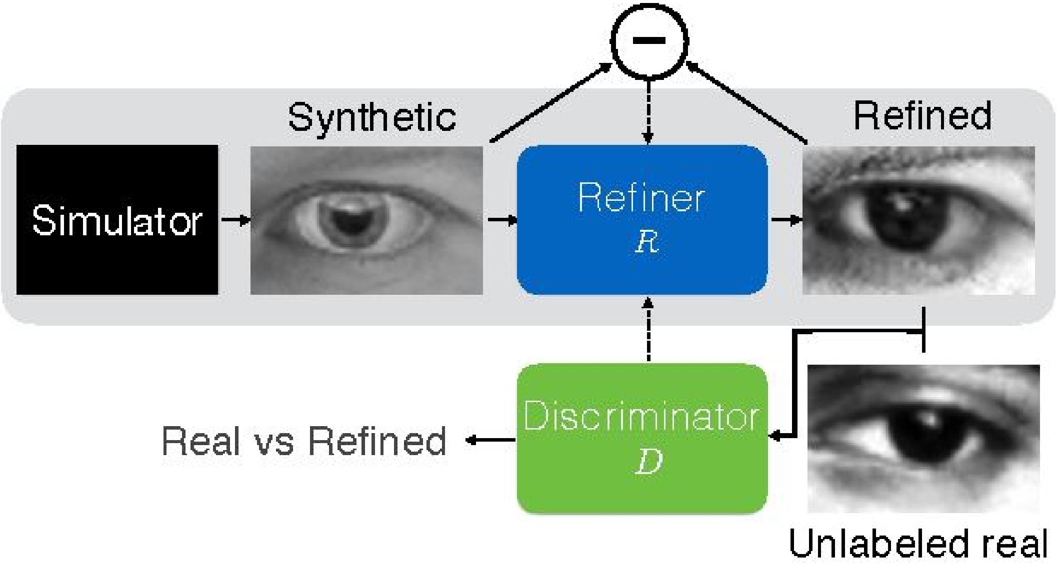


Junting Pan, Cristian Canton, Kevin McGuinness, Noel E. O'Connor, Jordi Torres, Elisa Sayrol and Xavier Giro-i-Nieto. "SalGAN: Visual Saliency Prediction with Generative Adversarial Networks." CVPRW 2017.

Adversarial Networks

Application #5

Generate realistic data for training.



Shrivastava, Ashish, Tomas Pfister, Oncel Tuzel, Josh Susskind, Wenda Wang, and Russ Webb. "Learning from simulated and unsupervised images through adversarial training." CVPR 2017 (best paper) [video]

Adversarial Networks

Victòria Miró / Oriol Esteve, [“La meitat de les notícies que consumirem el 2022 seran falses”](). TN Vespre, TV3 (26 de Novembre, 2017)

Conclusions

We can categorize three types of learning procedures:

1. Supervised Learning:

$$\mathbf{y} = f(\mathbf{x})$$

Predict label y corresponding to observation x

2. Unsupervised Learning:

$$f(\mathbf{x})$$

Estimate the distribution of observation x

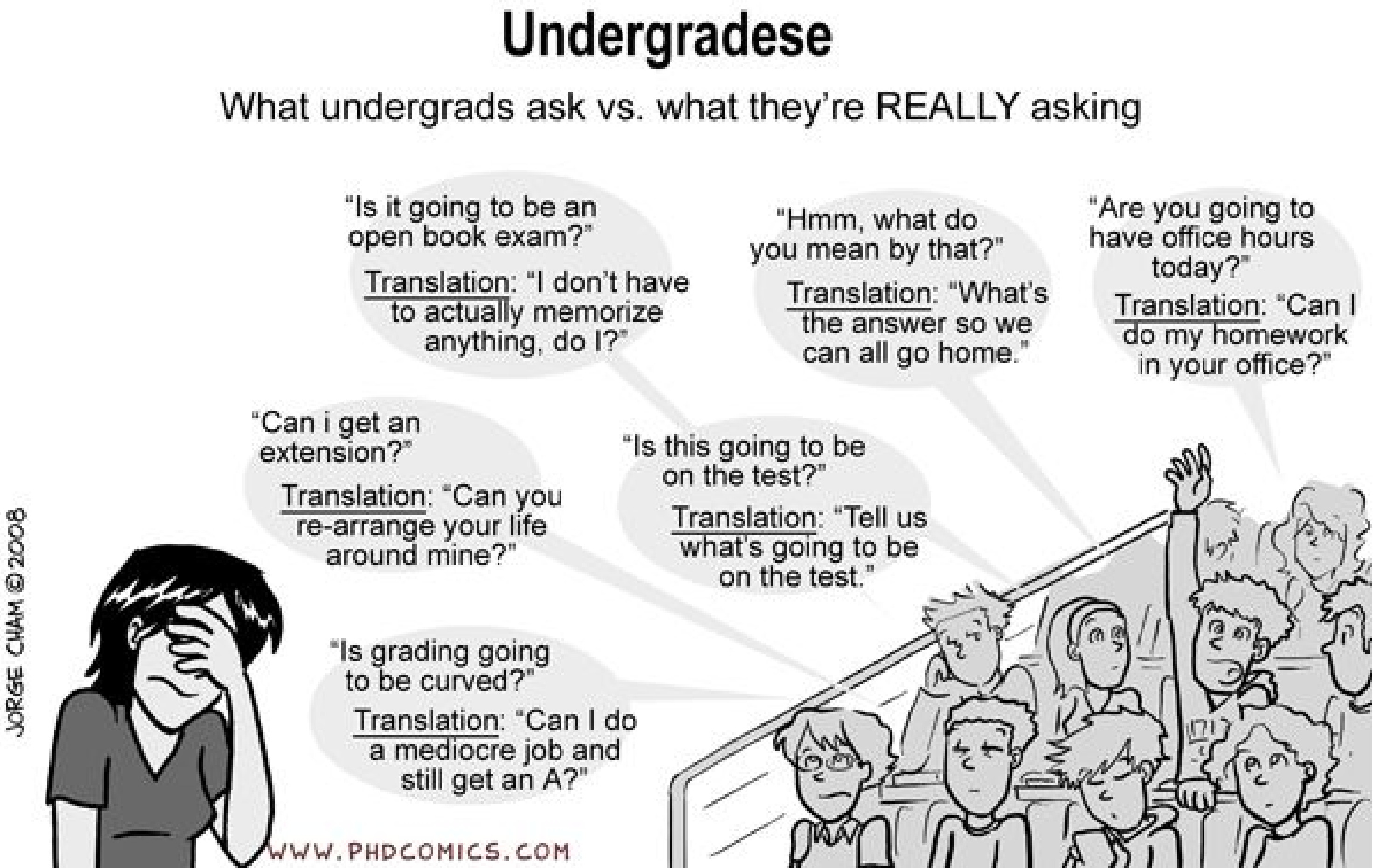
3. Reinforcement Learning (RL):

$$\mathbf{y} = f(\mathbf{x})$$

$$\mathbf{z}$$

Predict action y based on observation x, to maximize a future reward z

Questions ?


Undergradese
What undergrads ask vs. what they're REALLY asking
"Is it going to be an open book exam?" Translation: "I don't have to actually memorize anything, do I?"
"Hmm, what do you mean by that?" Translation: "What's the answer so we can all go home."
"Are you going to have office hours today?" Translation: "Can I do my homework in your office?"
"Can i get an extension?" Translation: "Can you re-arrange your life around mine?"
"Is this going to be on the test?" Translation: "Tell us what's going to be on the test."
"Is grading going to be curved?" Translation: "Can I do a mediocre job and still get an A?"
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