

# DEEP LEARNING FOR SPEECH & LANGUAGE

Winter Seminar UPC TelecomBCN, 24 - 31 January 2017

## Instructors



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## Organizers



Image Processing Group  
Signal Theory and Communications Department



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+ info: [TelecomBCN.DeepLearning.Barcelona](https://www.telecombcn.com/deeplearning-barcelona)

[\[course site\]](#)

Day 1 Lecture 4

# Basic Deep Architectures



Xavier Giró-i-Nieto

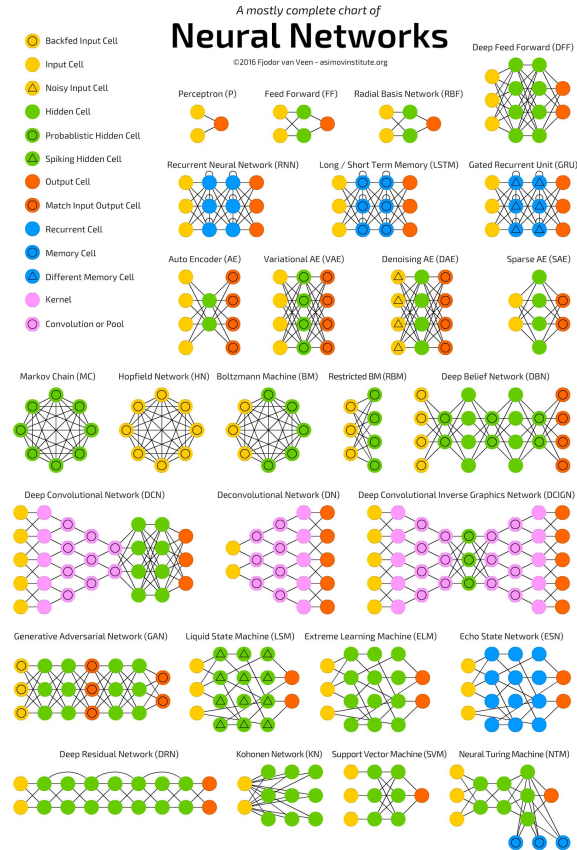


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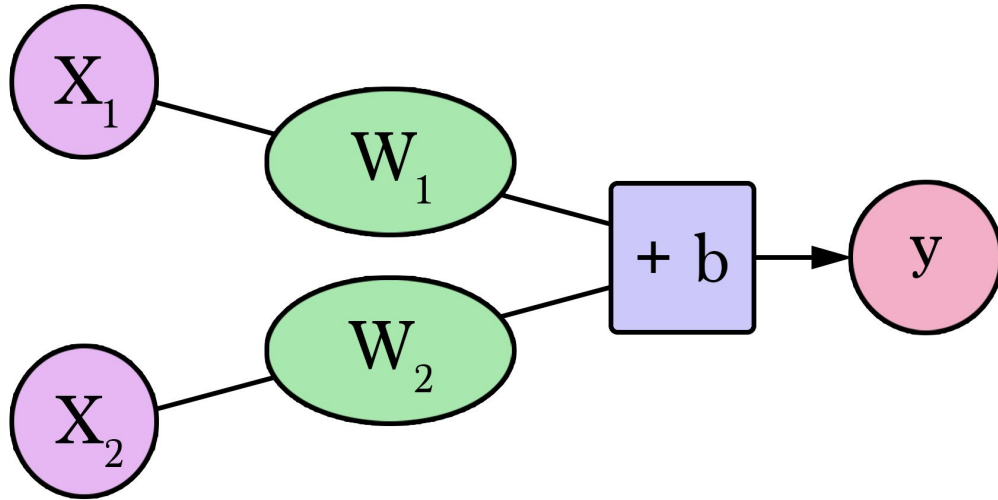
Department of Signal Theory  
and Communications

*Image Processing Group*

# The Full Story

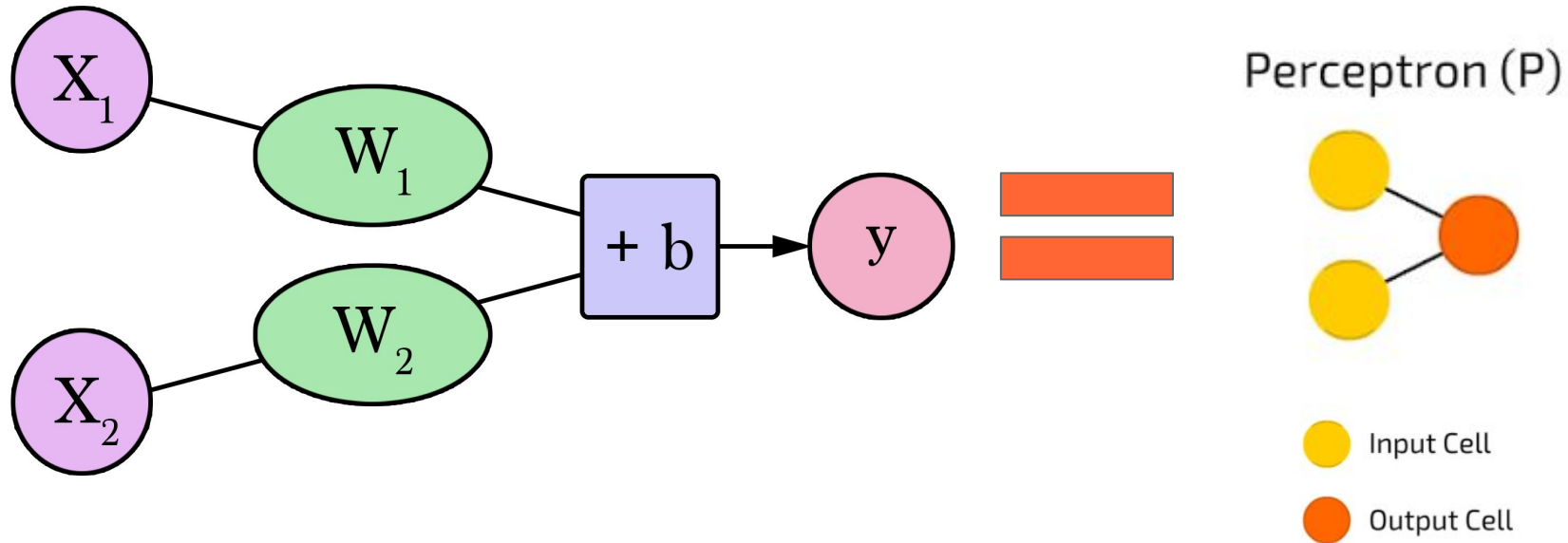


# Previously... A Perceptron



$$y = w_1 x_1 + w_2 x_2 + b$$

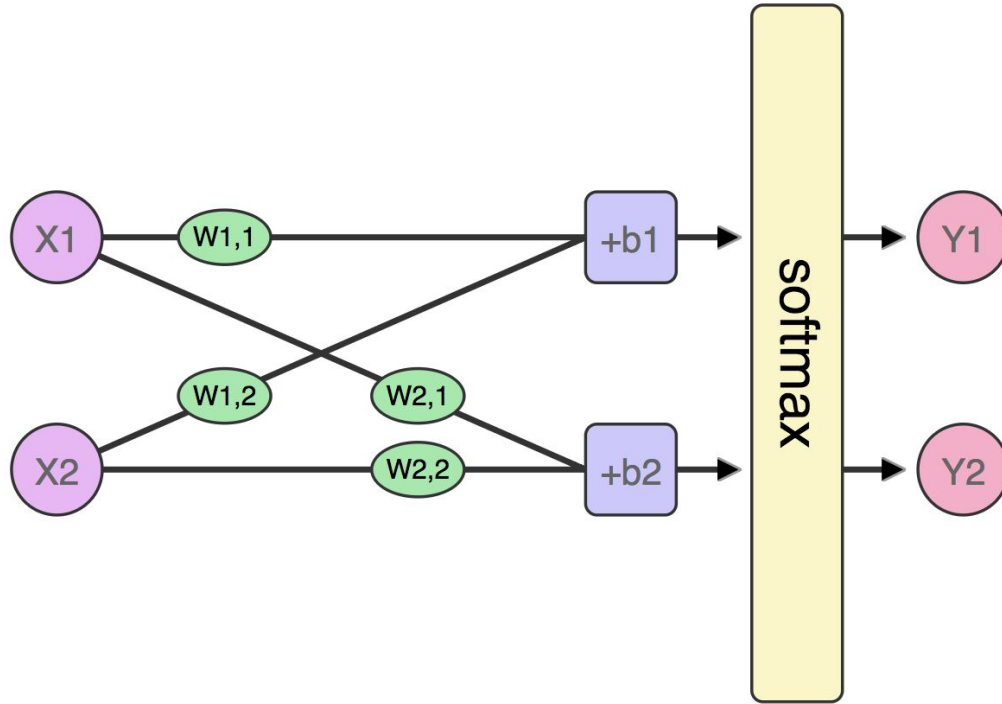
# Previously... A Perceptron



J. Alammar, [“A visual and interactive guide to the Basics of Neural Networks”](#) (2016)

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

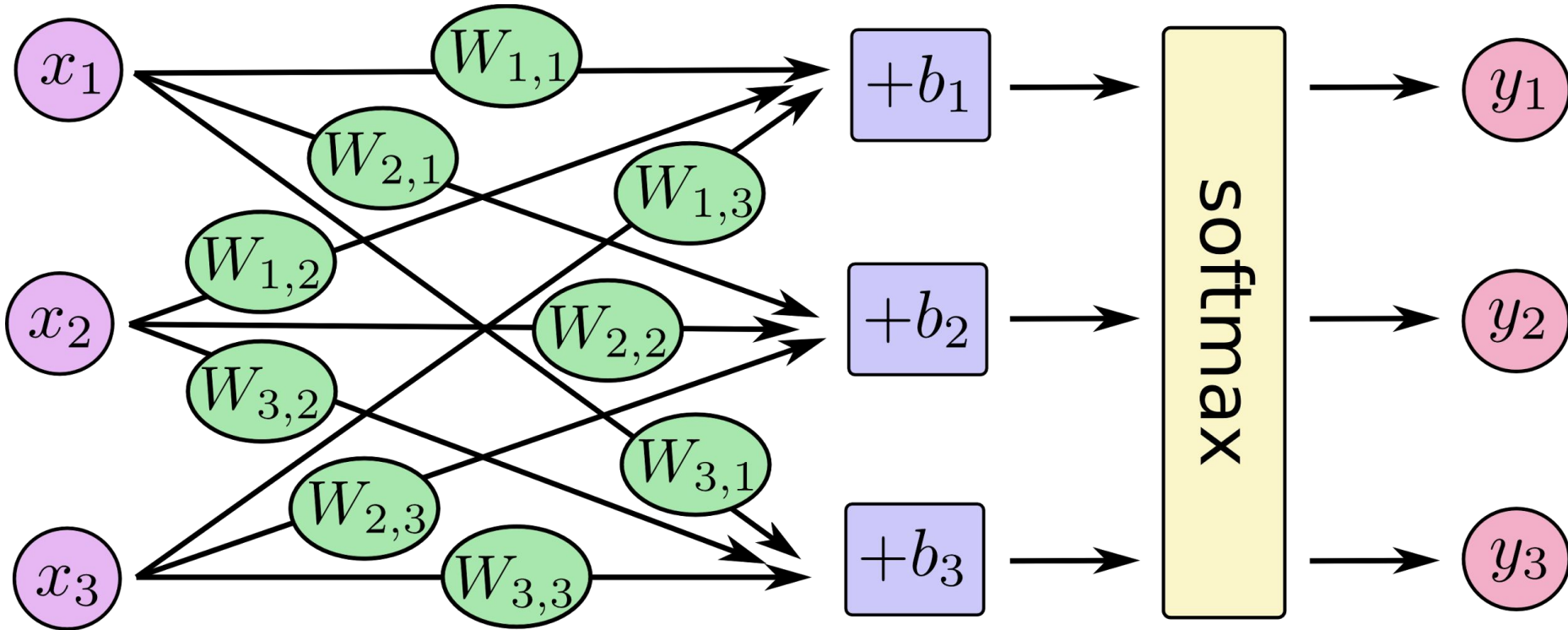
# Two Perceptrons + Softmax classifier



$$\text{evidence}_i = \sum_j W_{i,j} x_j + b_i$$

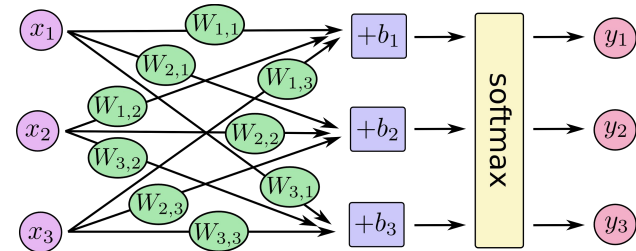
$$\text{softmax}(x)_i = \frac{\exp(x_i)}{\sum_j \exp(x_j)}$$

# Three perceptrons + Softmax classifier



# Three perceptrons + Softmax classifier

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \text{softmax} \begin{bmatrix} W_{1,1}x_1 + W_{1,2}x_2 + W_{1,3}x_3 + b_1 \\ W_{2,1}x_1 + W_{2,2}x_2 + W_{2,3}x_3 + b_2 \\ W_{3,1}x_1 + W_{3,2}x_2 + W_{3,3}x_3 + b_3 \end{bmatrix}$$

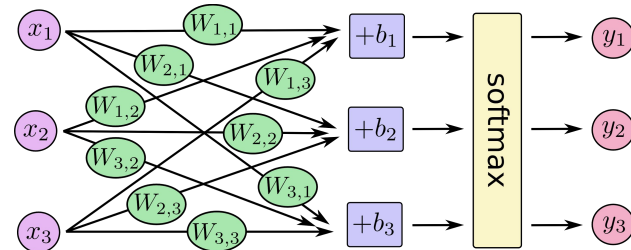


TensorFlow, [“MNIST for ML beginners”](#)

# Three perceptrons + Softmax classifier

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \text{softmax} \left( \begin{bmatrix} W_{1,1} & W_{1,2} & W_{1,3} \\ W_{2,1} & W_{2,2} & W_{2,3} \\ W_{3,1} & W_{3,2} & W_{3,3} \end{bmatrix} \cdot \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} \right)$$

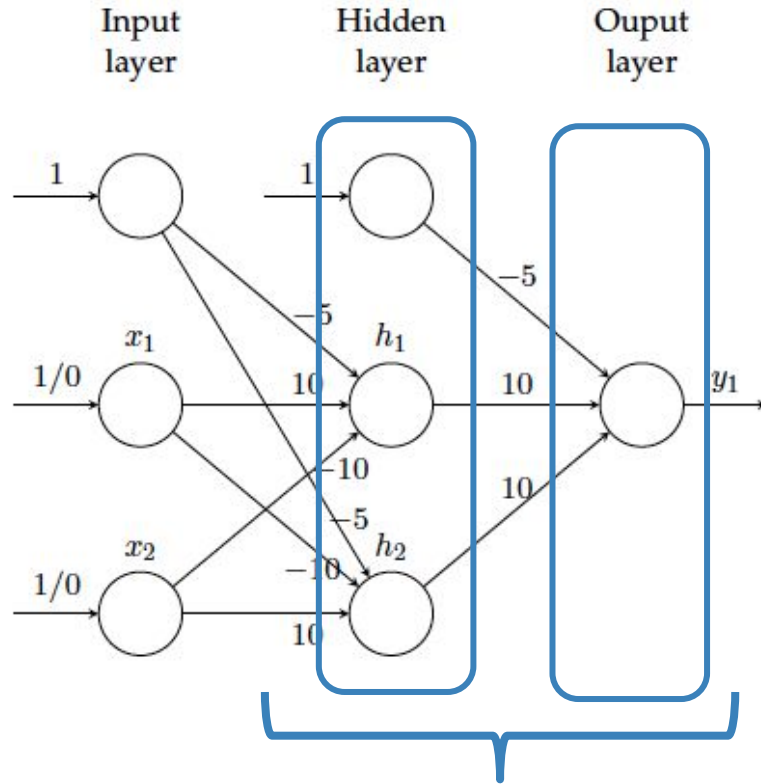
$$y = \text{softmax}(Wx + b)$$



TensorFlow, ["MNIST for ML beginners"](#)



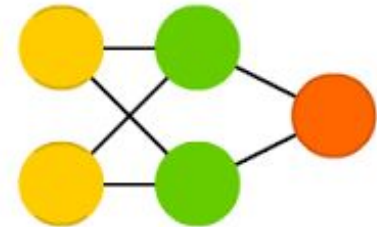
# Neural Network = Multi Layer Perceptron



2 layers of perceptrons

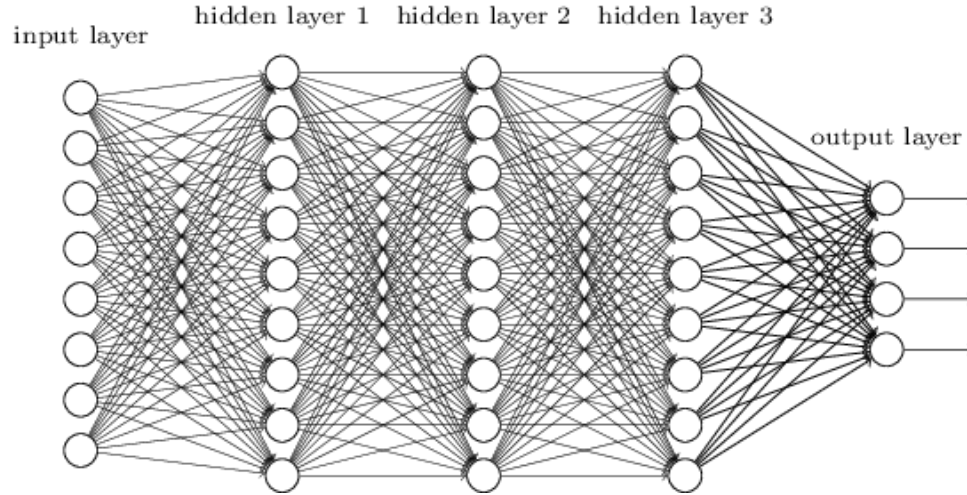


Feed Forward (FF)



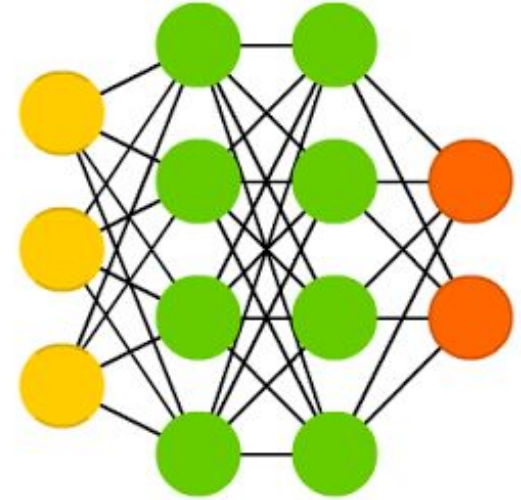
- Input Cell
- Hidden Cell
- Output Cell

# Deep Neural Network (DNN)



=

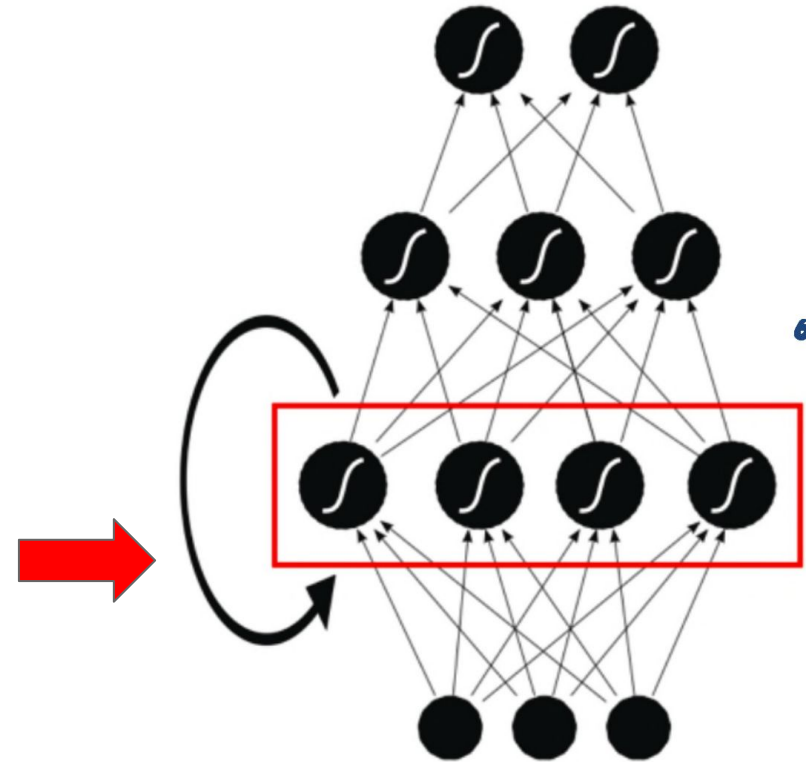
Deep Feed Forward (DFF)



- Input Cell
- Hidden Cell
- Output Cell

# Recurrent Neural Network (RNN)

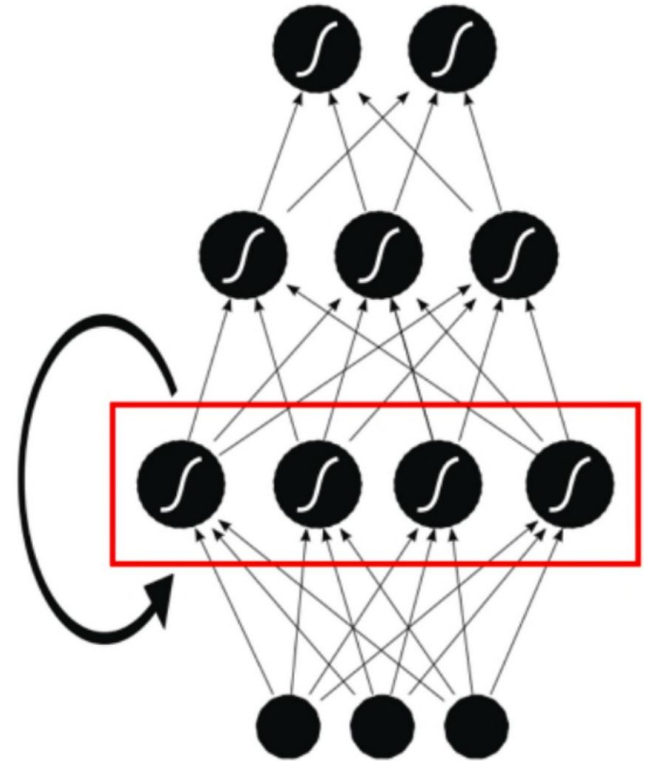
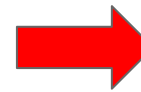
The hidden layers and the output depend from previous states of the hidden layers



# Recurrent Neural Network (RNN)



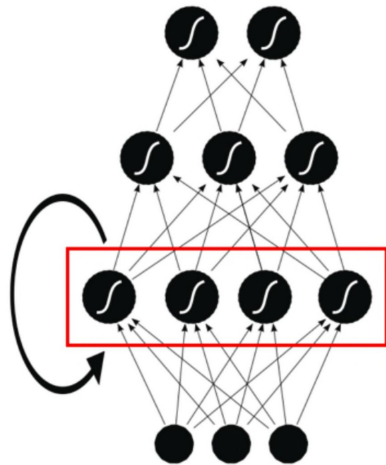
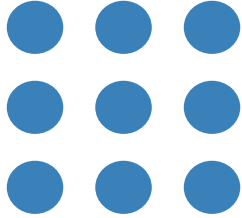
The hidden layers and the output depend from previous states of the hidden layers



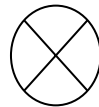
Alex Graves, [“Supervised Sequence Labelling with Recurrent Neural Networks”](#)

# Recurrent Neural Network (RNN)

Front View



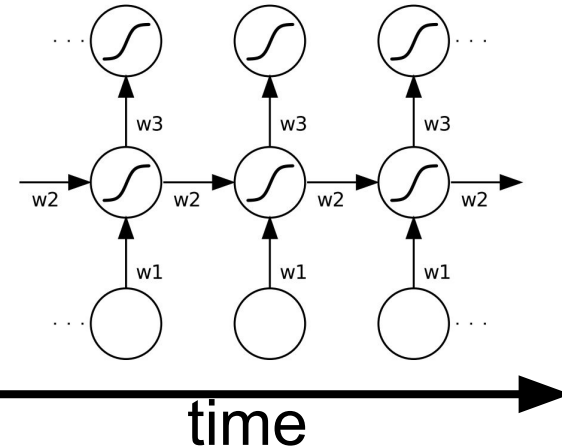
time



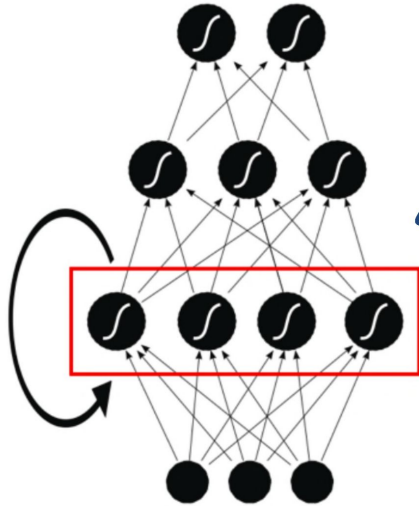
Rotation  
 $90^\circ$

Rotation  
 $90^\circ$

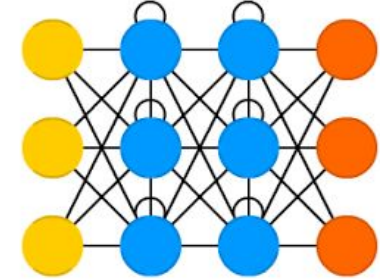
Side View



# Recurrent Neural Network (RNN)



Recurrent Neural Network (RNN)

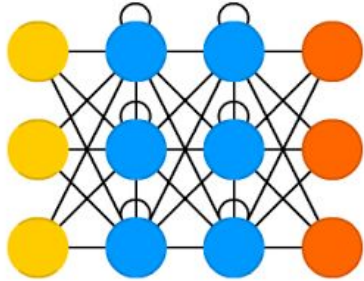


- Input Cell
- Recurrent Cell
- Output Cell

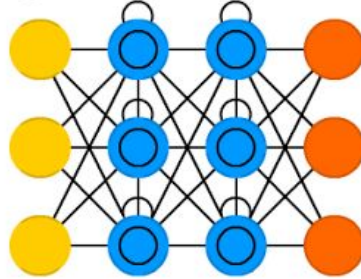
More details:  
D2L2, “Recurrent Neural Networks”

# Recurrent Neural Network (RNN)

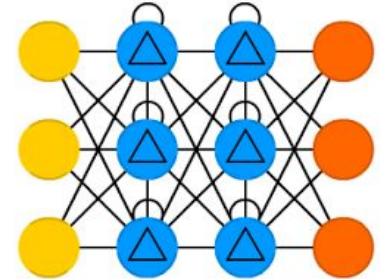
Recurrent Neural Network (RNN)








Long / Short Term Memory (LSTM)



Gated Recurrent Unit (GRU)



-  Input Cell
-  Recurrent Cell
-  Memory Cell
-  Different Memory Cell
-  Output Cell

More details:  
D2L2, “Recurrent Neural Networks”



# Recurrent Neural Network (RNN)

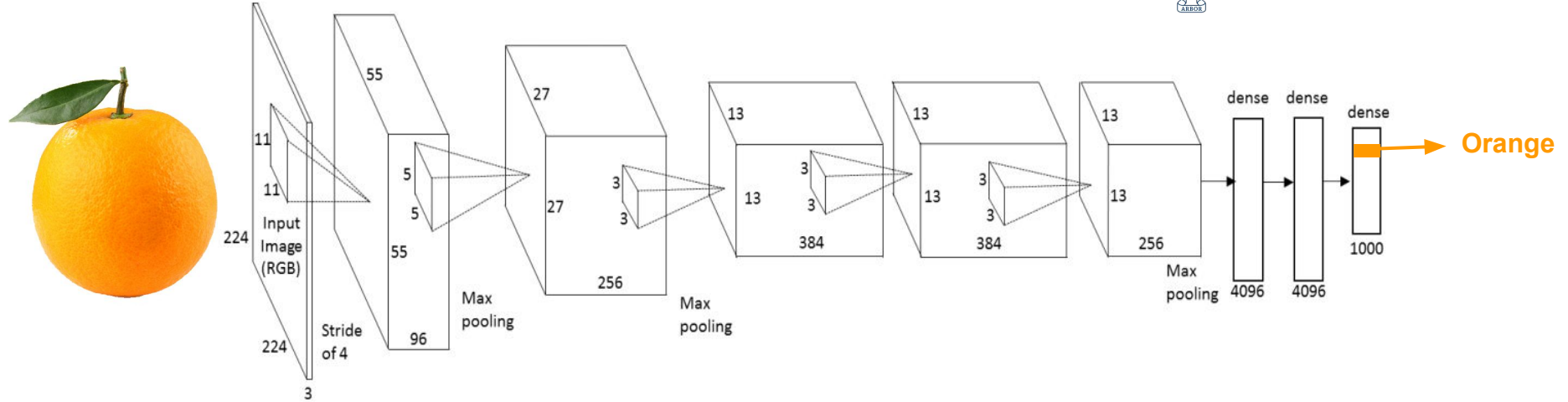




# Convolutional Neural Network (CNN)

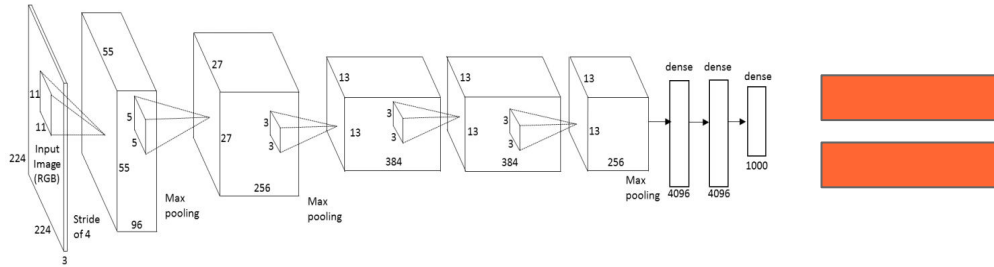


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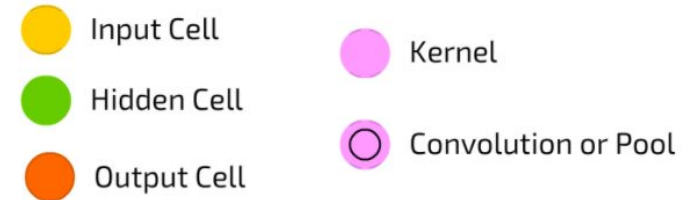
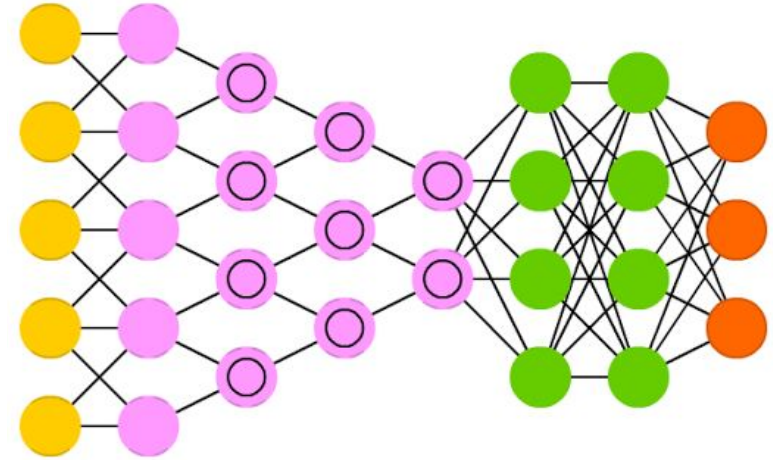
A Krizhevsky, I Sutskever, GE Hinton “[Imagenet classification with deep convolutional neural networks](#)” Part of: [Advances in Neural Information Processing Systems 25 \(NIPS 2012\)](#)

# Convolutional Neural Network (CNN)

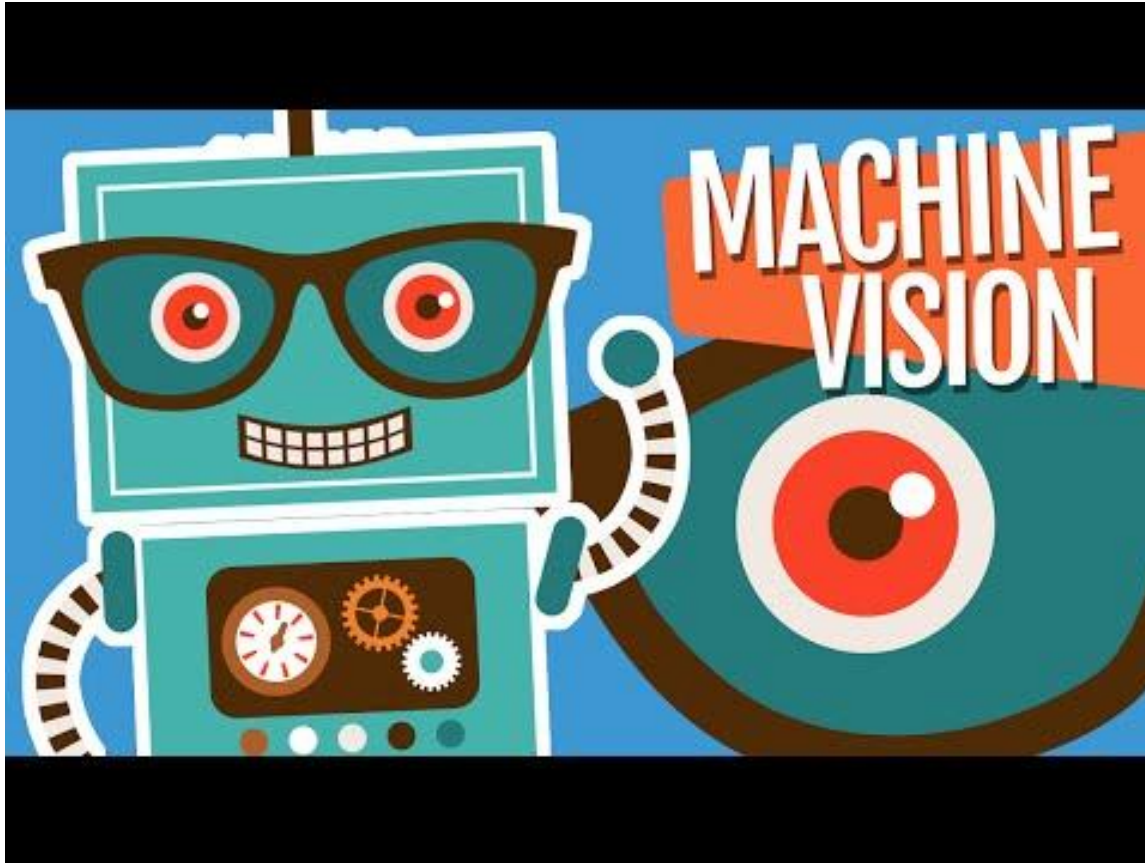


More details:  
D1L3, [“Convolutional Neural Networks”](#)

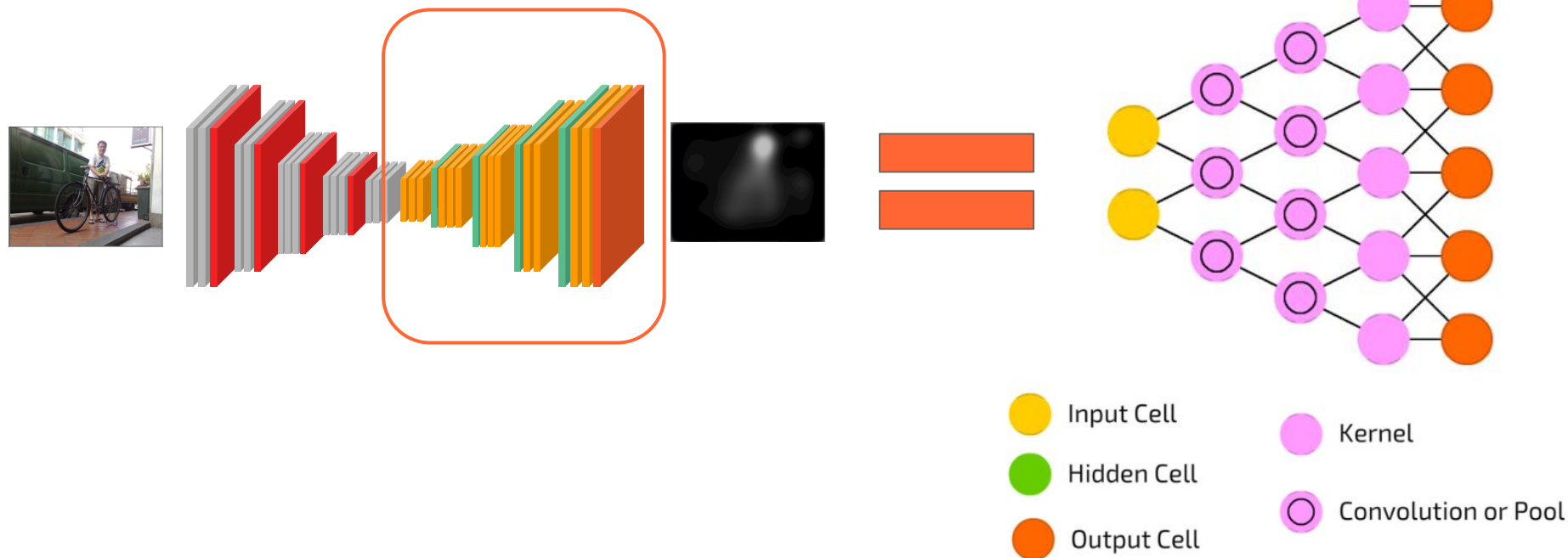
Deep Convolutional Network (DCN)



# Convolutional Neural Network (CNN)



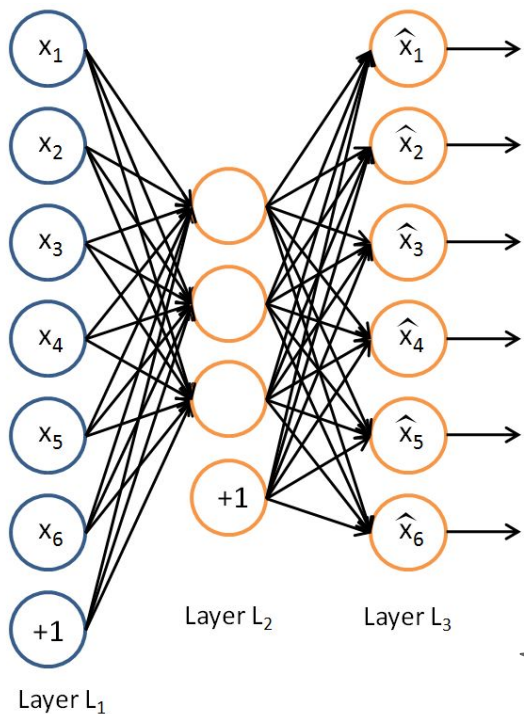
# Deconvolutional Neural Network (Deconv)



Junting Pan, [SalGAN](#) (2017)

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

# Autoencoder (AE)



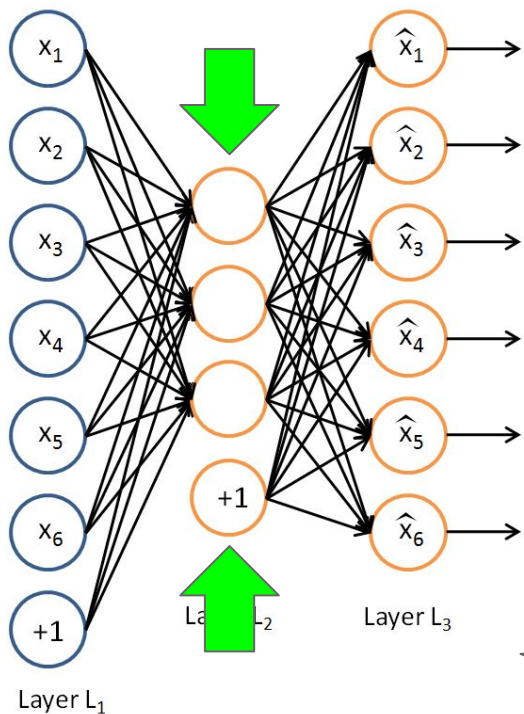
Autoencoders:

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

Unsupervised  
learning

# Autoencoder (AE)

## WHY?



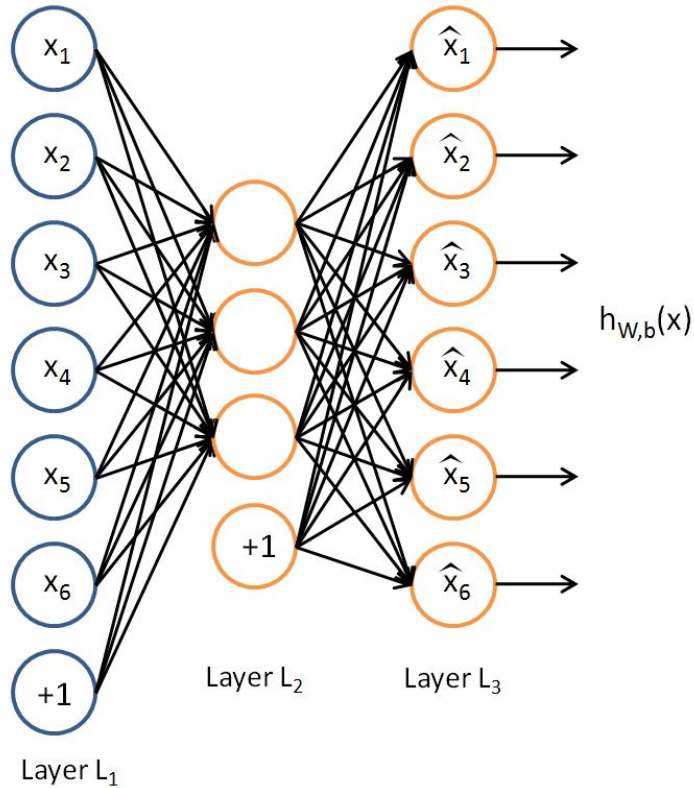
Dimensionality reduction:

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

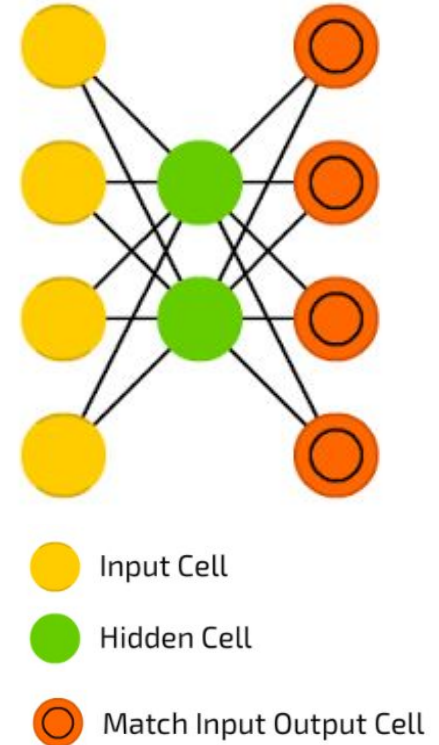
Unsupervised  
learning



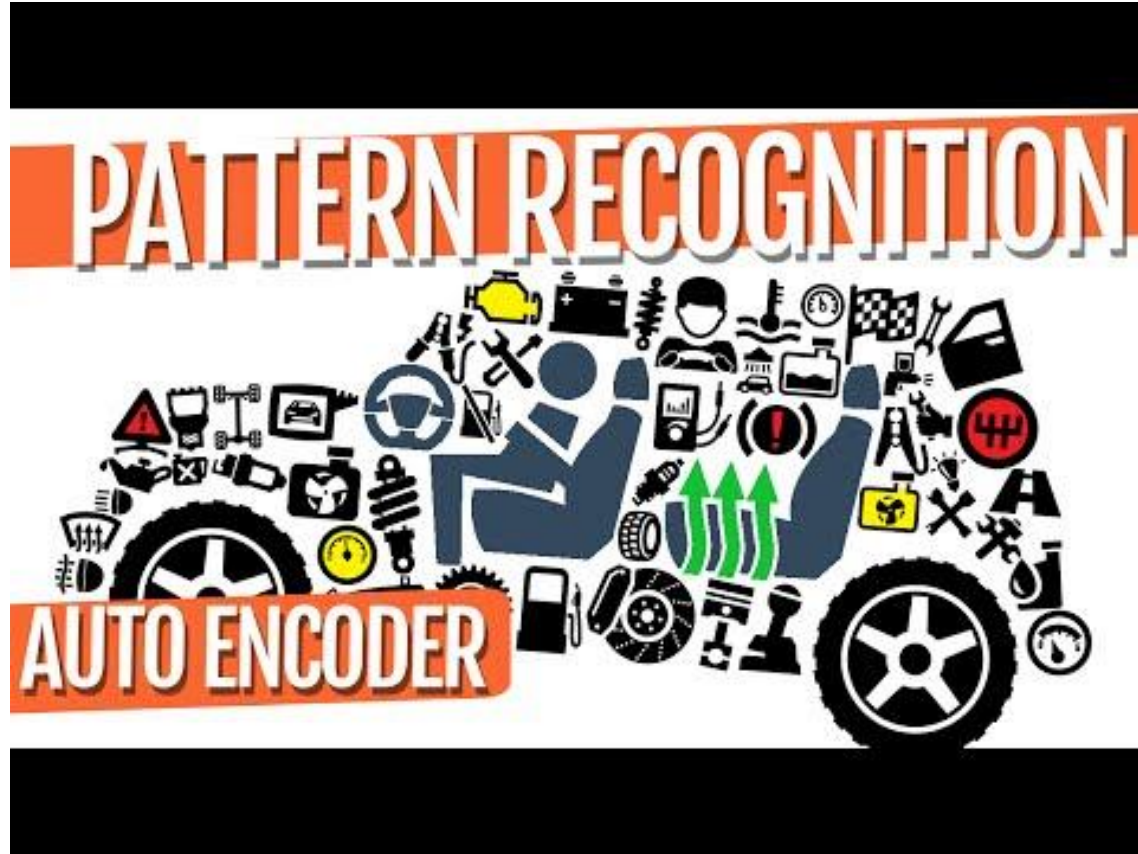
# Autoencoder (AE)



## Auto Encoder (AE)



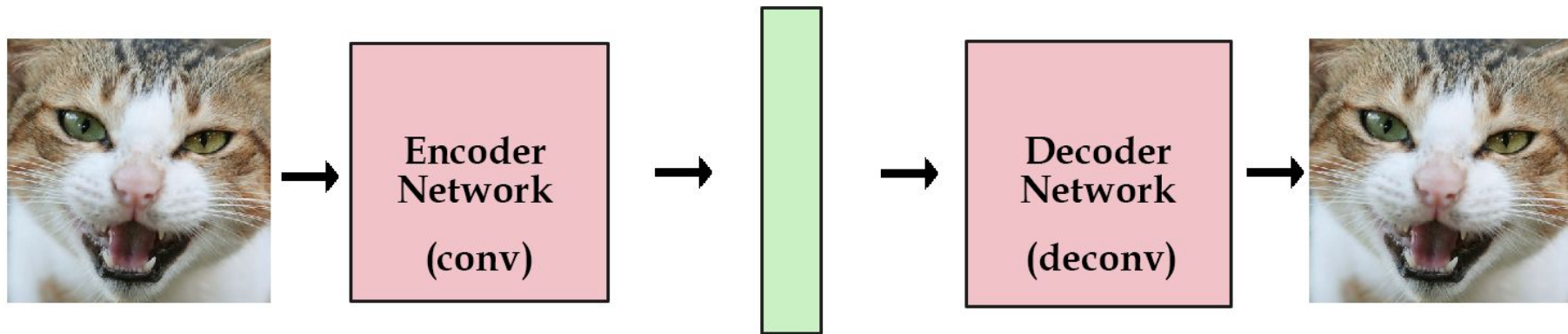
# Autoencoder (AE)





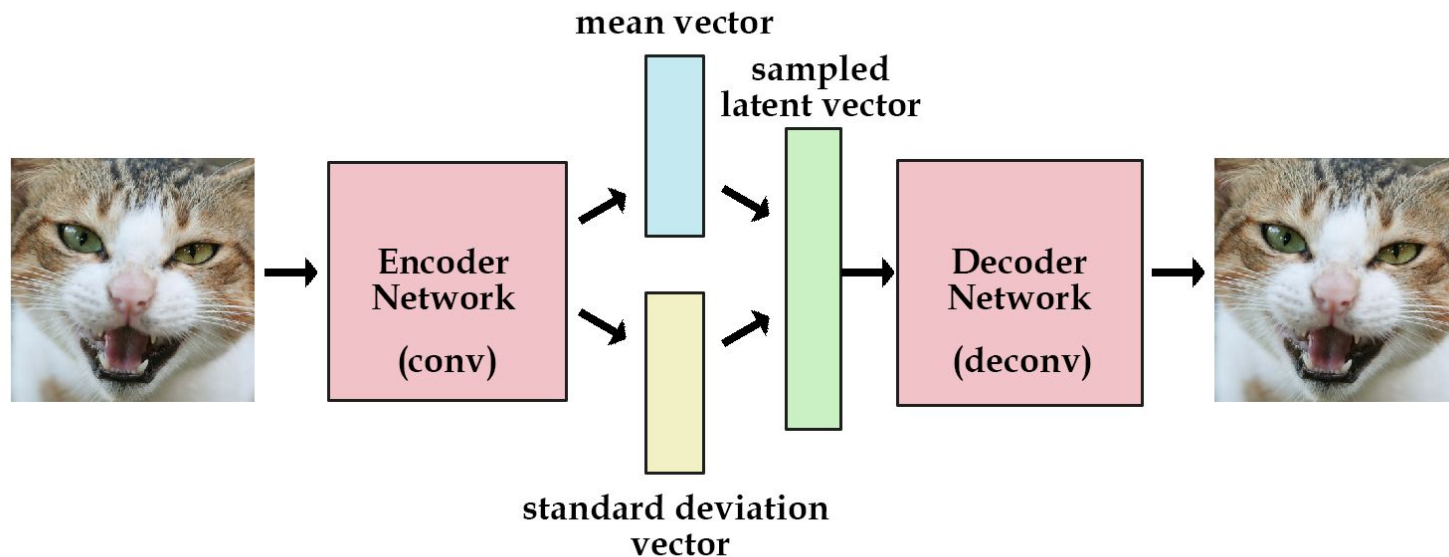
# Variational Autoencoder (VAE)

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



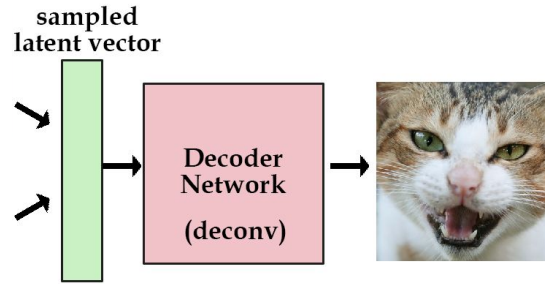
# Variational Autoencoder (VAE)

...is forced to follow a unit Gaussian distribution in VAEs.



# Variational Autoencoder (VAE)

## WHY?



Generative model:

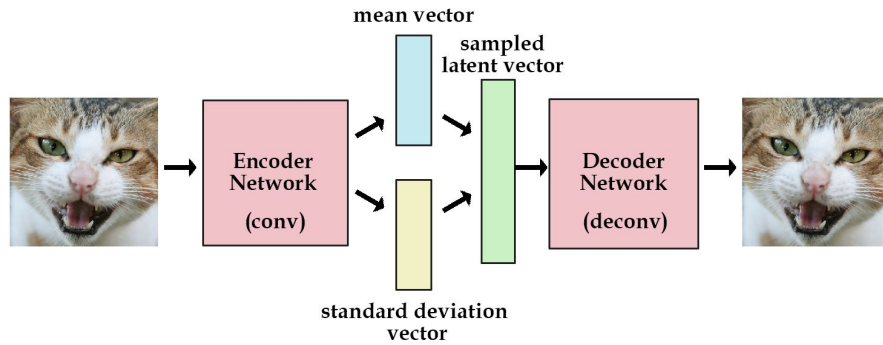
- Create new samples by drawing from a Gaussian distribution.

Unsupervised  
learning

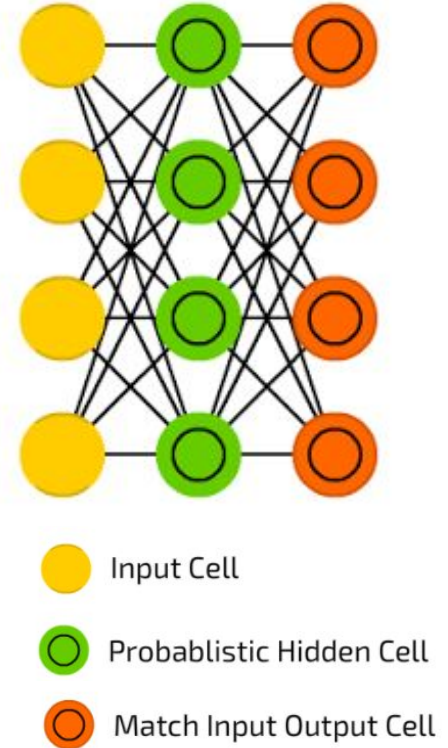
# Variational Autoencoder (VAE)



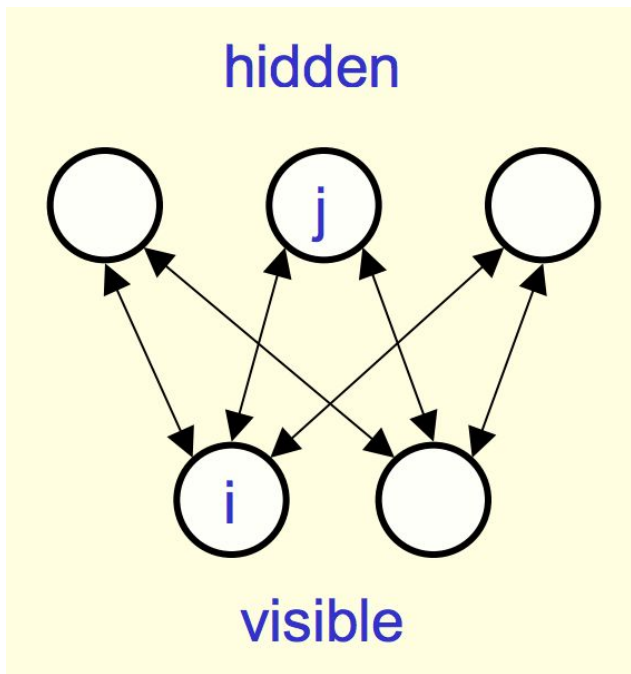
# Variational Autoencoder (VAE)



## Variational AE (VAE)



# 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)

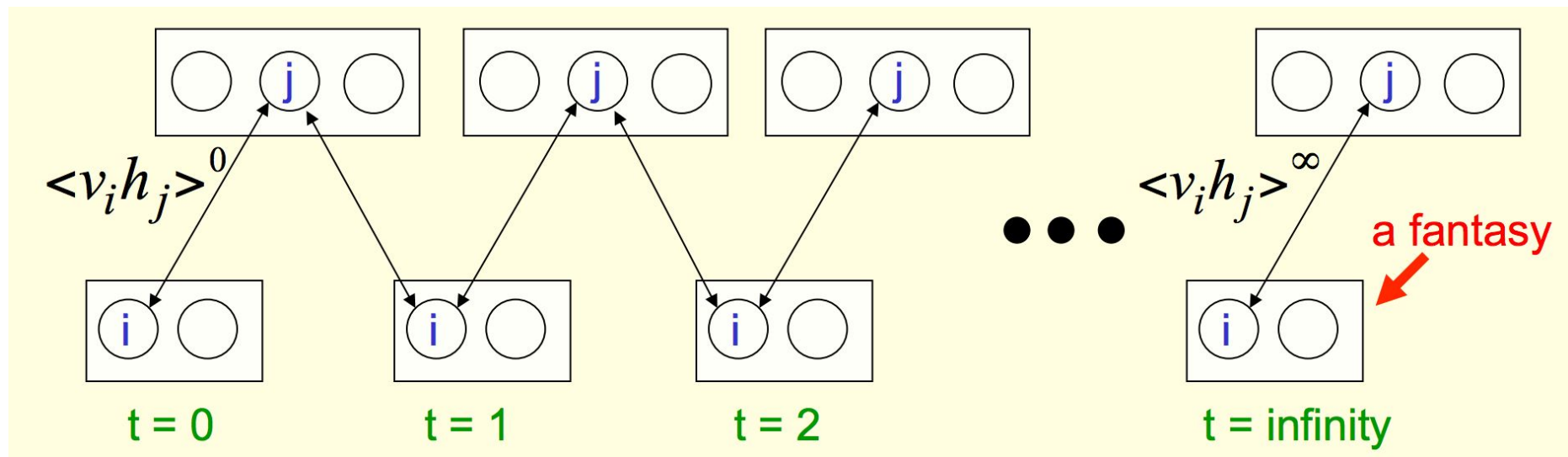
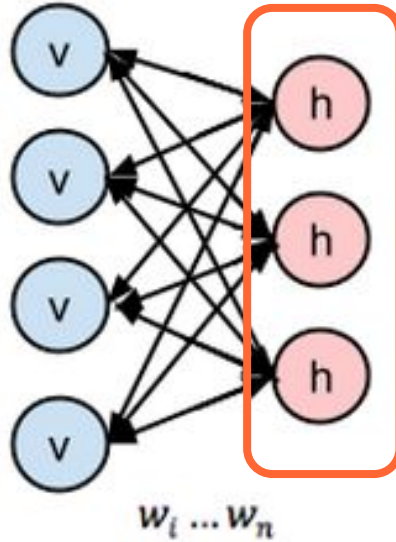


Figure: Geoffrey Hinton (2013)

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)

## WHY?

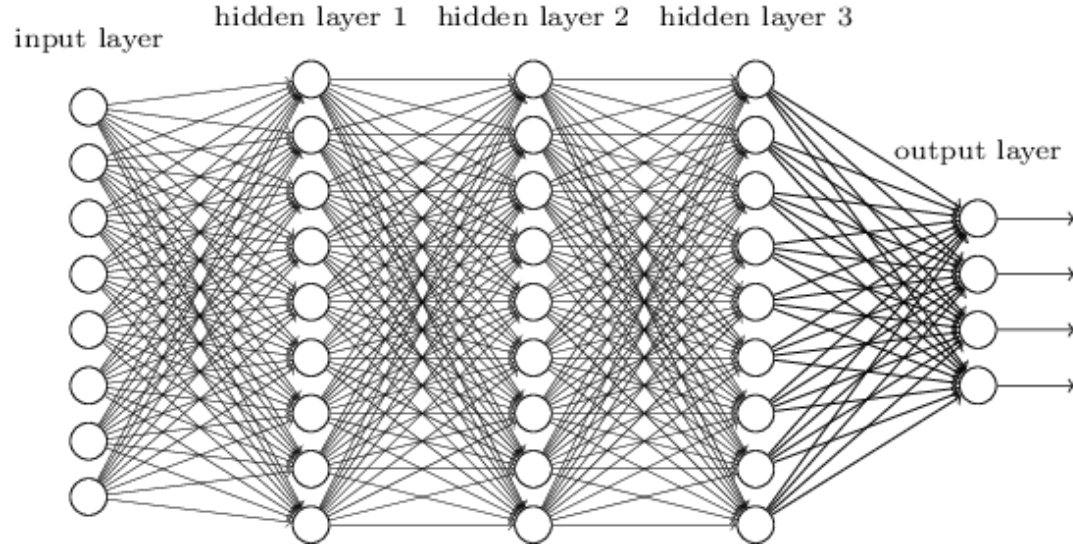


RBM is a specific type of autoencoder.

Unsupervised  
learning



# Deep Belief Networks (DBN)

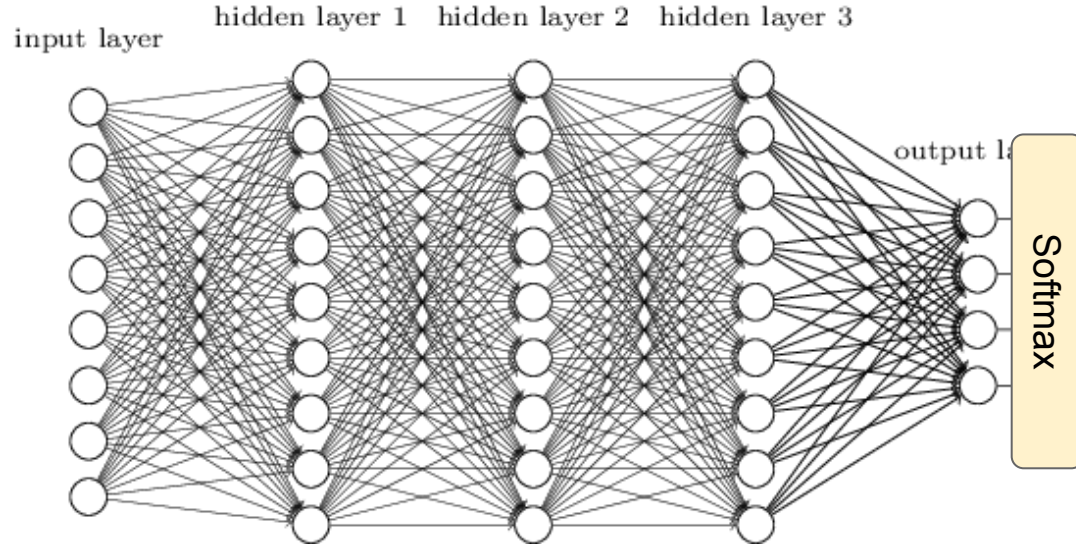


- Architecture like an MLP.
- Training as a stack of RBMs...
- ...so they do not need labels:

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)



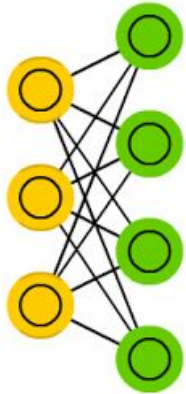
After the DBN is trained, it can be fine-tuned with a **reduced amount of labels** to solve a supervised task with superior performance.

Supervised  
learning

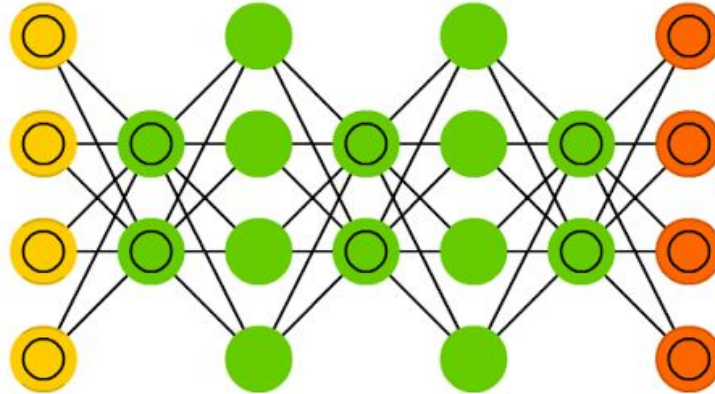
Hinton, Geoffrey E., Simon Osindero, and Yee-Whye Teh. ["A fast learning algorithm for deep belief nets."](#) Neural computation 18, no. 7 (2006): 1527-1554.





# Deep Belief Networks (DBN)

Restricted BM (RBM)



Deep Belief Network (DBN)



-  Backfed Input Cell
-  Probablistic Hidden Cell
-  Hidden Cell
-  Match Input Output Cell

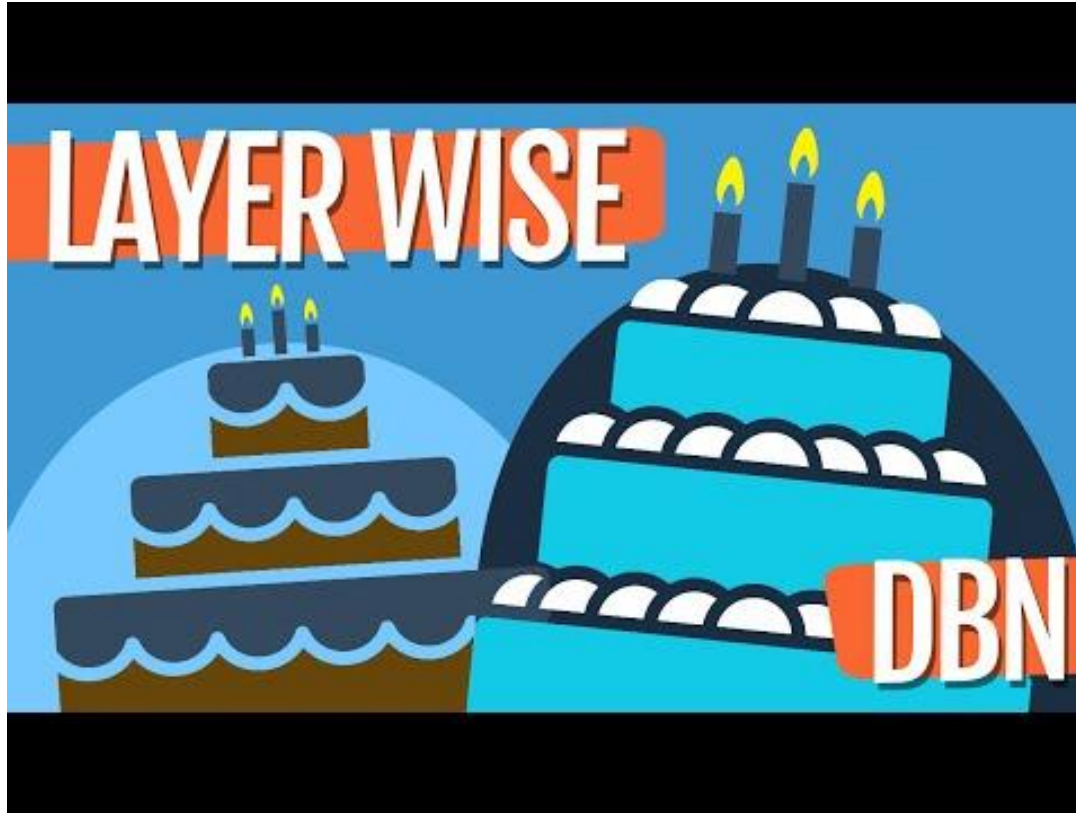


More details:  
D2L1, ["Deep Belief Networks"](#)

# Restricted Boltzmann Machine (RBM)



# Deep Belief Networks (DBN)



# Deep Belief Networks (DBN)

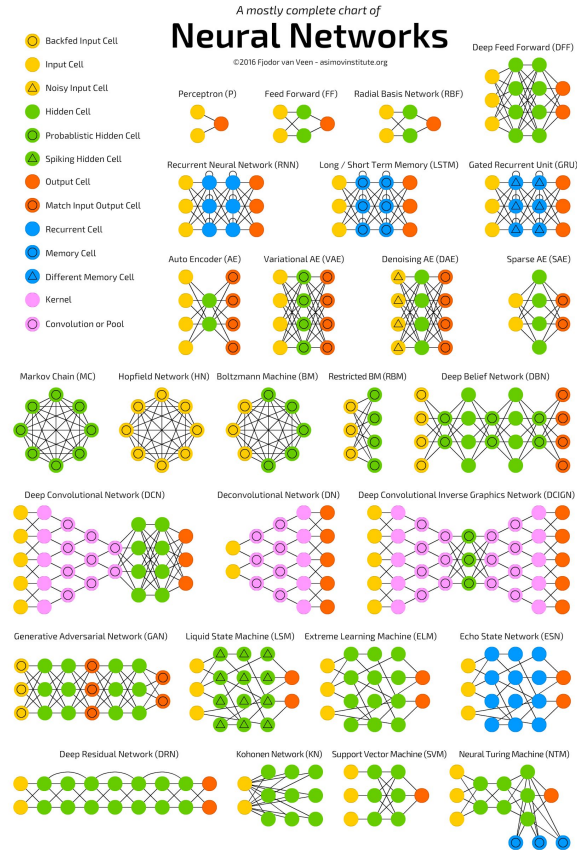


Geoffrey Hinton, ["Introduction to Deep Learning & Deep Belief Nets"](#) (2012)

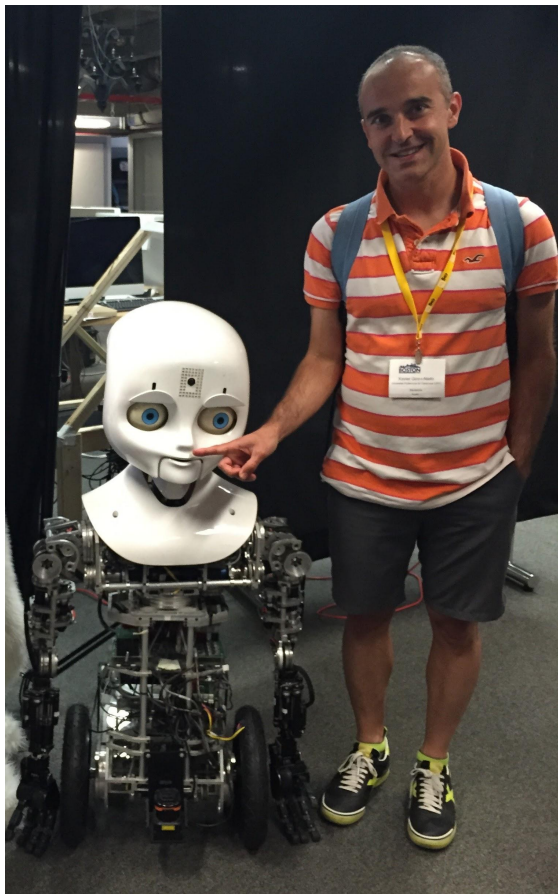
Geoffrey Hinton, ["Tutorial on Deep Belief Networks"](#). NIPS 2007.



# The Full Story



# Thanks ! Q&A ?



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<https://imatge.upc.edu/web/people/xavier-giro>