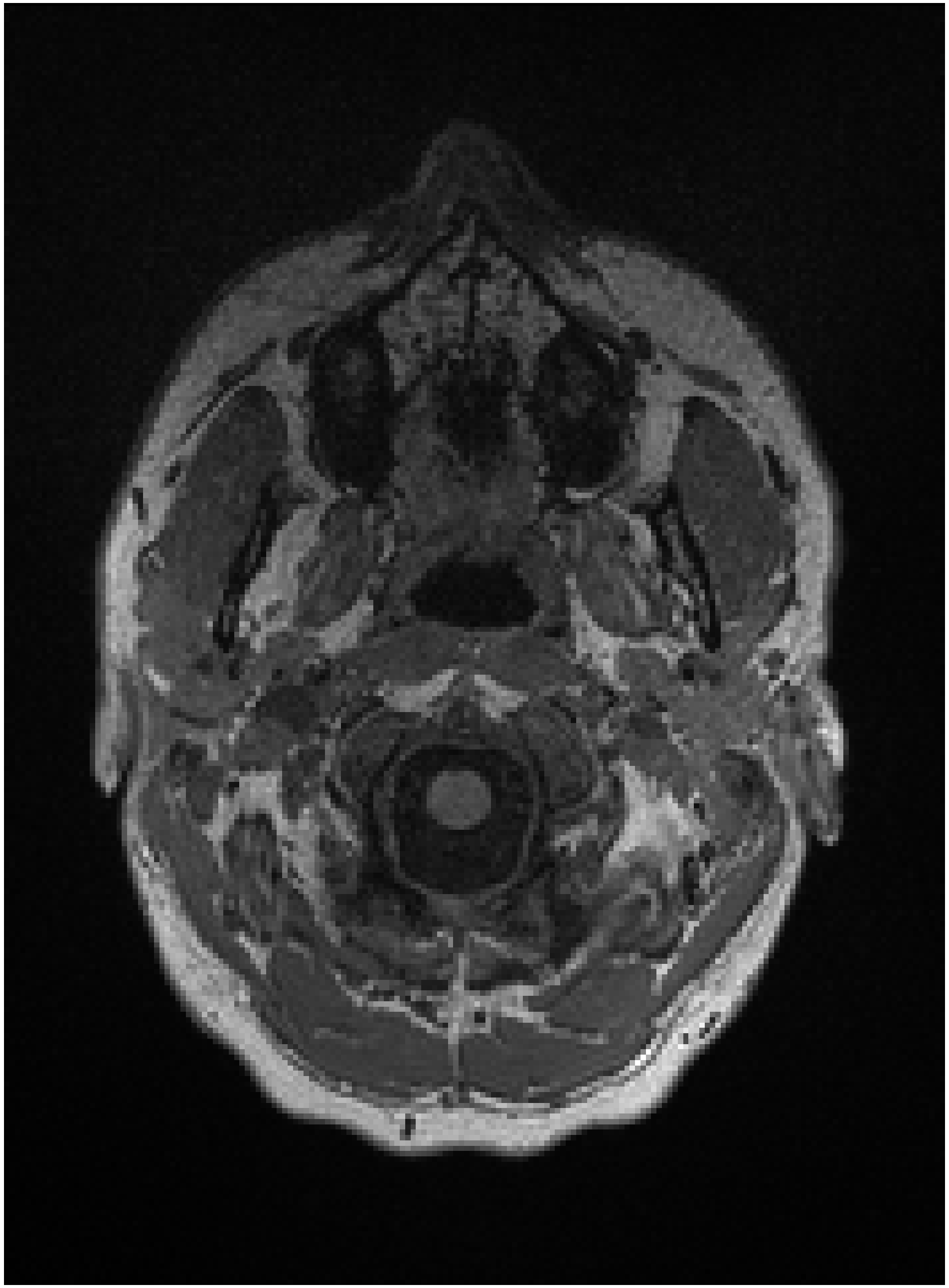
Institut et hôpital neurologiques de Montréal
Montreal Neurological Institute and Hospital

MCIN MCGILL CENTRE for INTEGRATIVE NEUROSCIENCE

CENTRE LUDMER CENTER
NEUROINFORMATIQUE & SANTÉ MENTALE | NEUROINFORMATICS & MENTAL HEALTH

Intro to Deep Learning for NeuroImaging

Andrew Doyle
McGill Centre for Integrative Neuroscience
@crocodoyle



McGill | Centre universitaire de santé McGill | McGill University Health Centre

Outline

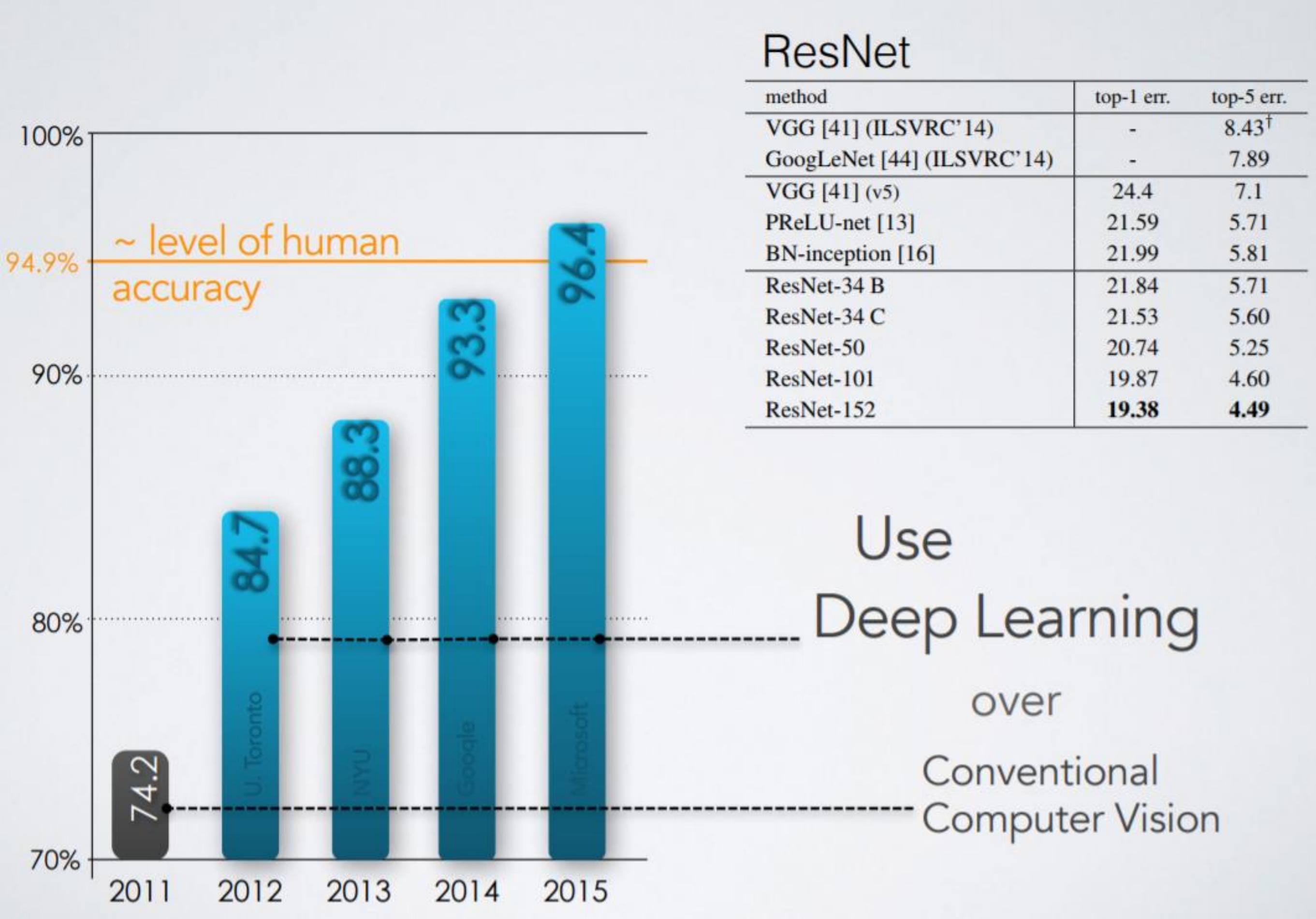
1. GET EXCITED
2. Artificial Neural Networks
3. Backpropagation
4. Convolutional Neural Networ

neuro
Institut et hôpital neurologiques de Montréal
Montreal Neurological Institute and Hospital

McGill

Centre universitaire de santé McGill
McGill University Health Centre

ImageNet-1000 Results

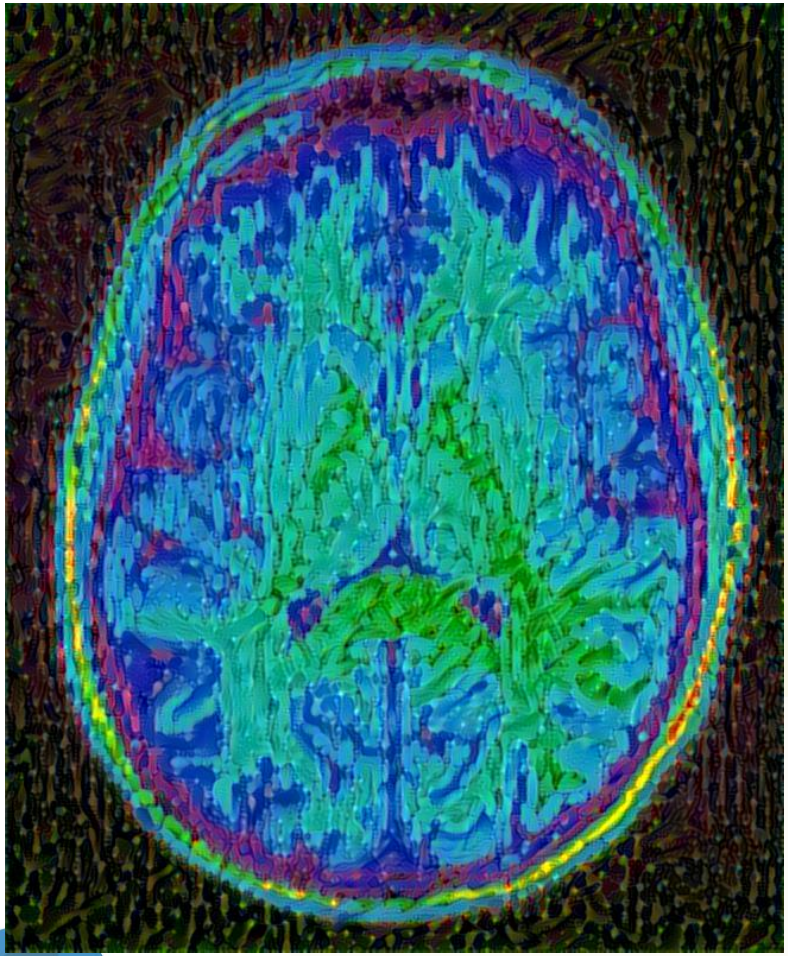


ResNet

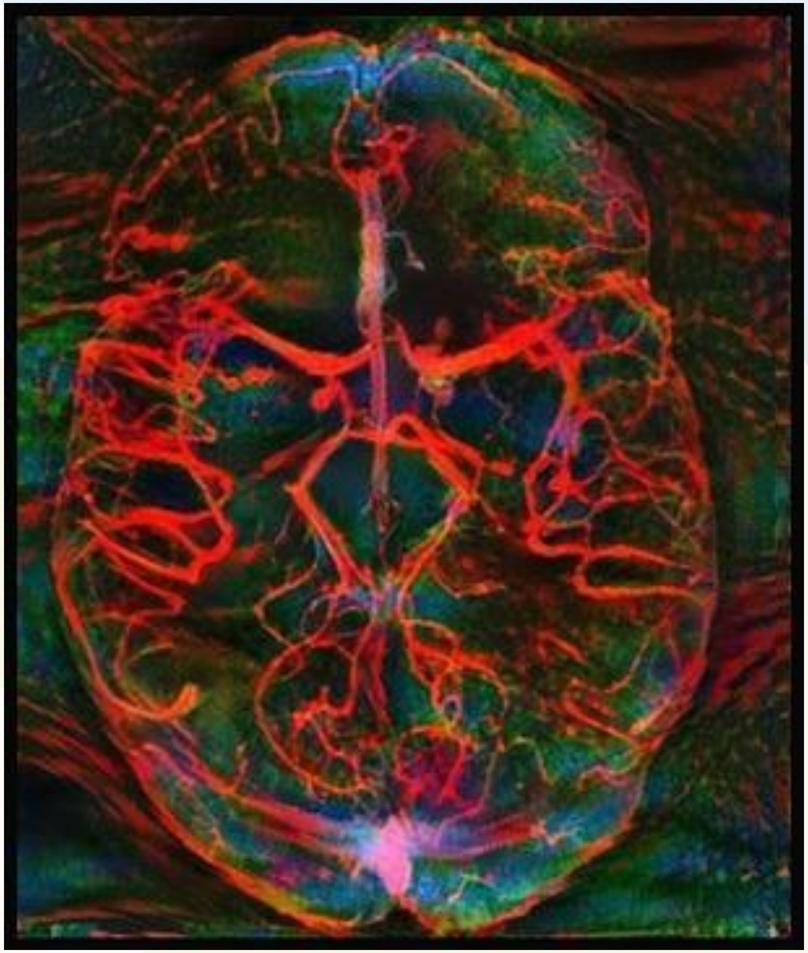
method	top-1 err.	top-5 err.
VGG [41] (ILSVRC'14)	-	8.43†
GoogLeNet [44] (ILSVRC'14)	-	7.89
VGG [41] (v5)	24.4	7.1
PReLU-net [13]	21.59	5.71
BN-inception [16]	21.99	5.81
ResNet-34 B	21.84	5.71
ResNet-34 C	21.53	5.60
ResNet-50	20.74	5.25
ResNet-101	19.87	4.60
ResNet-152	**19.38**	**4.49**

Image courtesy Aaron Courville, 2016

Generative Models



BrainBrush



Deep Blood by Team BloodArt

Gatys, Leon A., Alexander S. Ecker, and Matthias Bethge. "Image style transfer using convolutional neural networks." *Computer Vision and Pattern Recognition (CVPR), 2016 IEEE Conference on*. IEEE, 2016.

Generative Models

StackGAN

Institut et hôpital neurologiques de Montréal
Montreal Neurological Institute and Hospital

Zhang, Han, et al. "StackGAN: Text to photo-realistic image synthesis with stacked generative adversarial networks." *arXiv preprint arXiv:1612.03242* (2016).

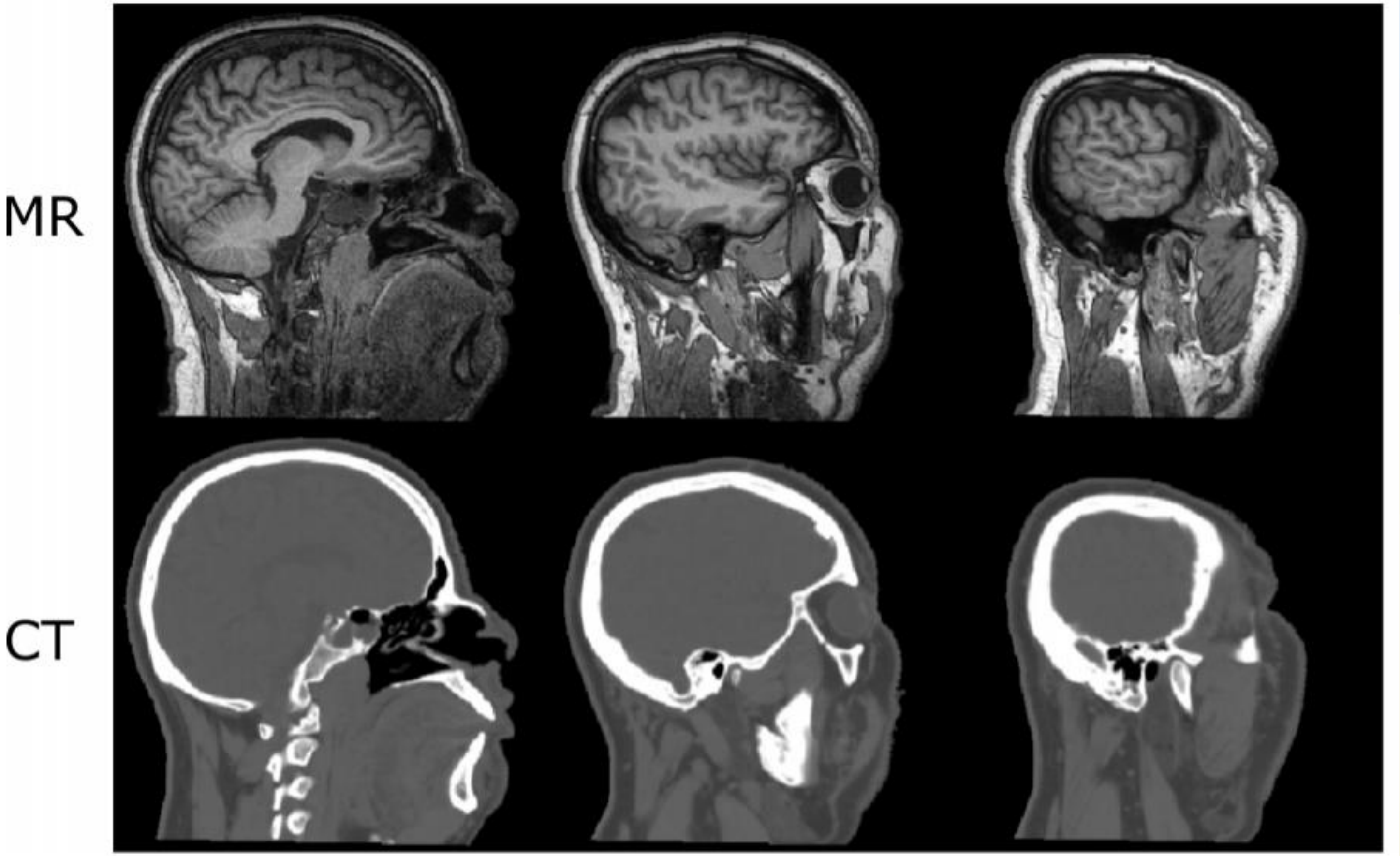
Centre universitaire de santé McGill
McGill University Health Centre

Generative Models

CycleGAN

Zhu, Jun-Yan, et al. "Unpaired image-to-image translation using cycle-consistent adversarial networks." *arXiv preprint arXiv:1703.10593* (2017).

Generative Models



Wolterink, Jelmer M., et al. "Deep MR to CT synthesis using unpaired data." *International Workshop on Simulation and Synthesis in Medical Imaging*. Springer, Cham, 2017.

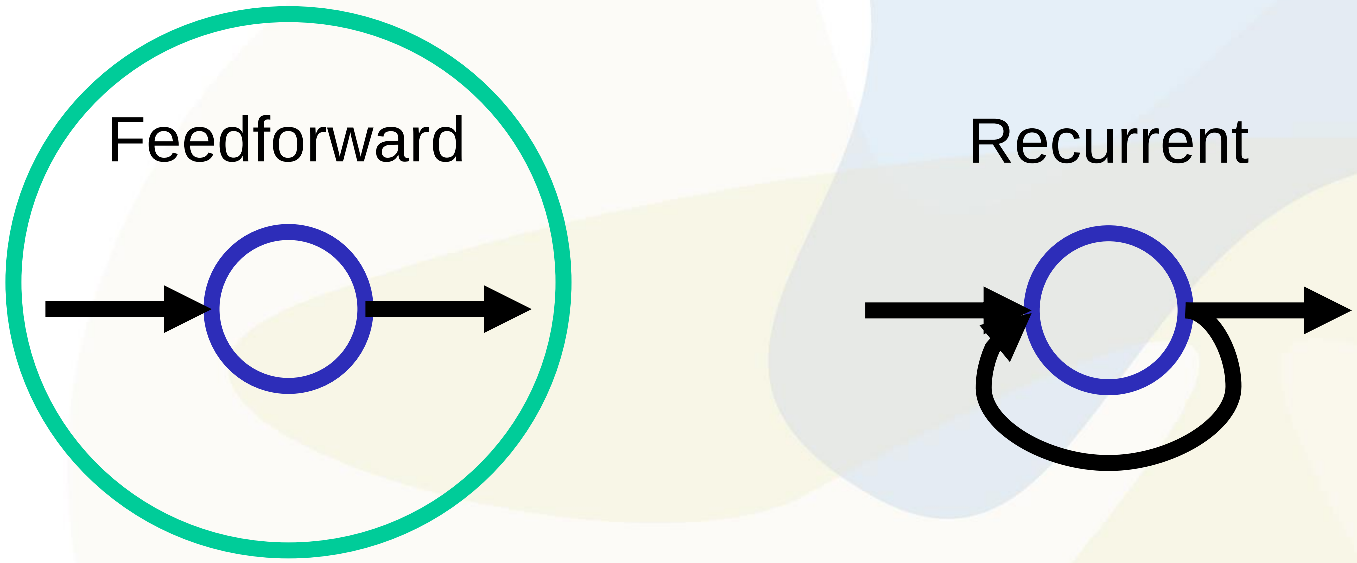
neuro
Institut et hôpital neurologiques de Montréal
Montreal Neurological Institute and Hospital
McGill
Centre universitaire de santé McGill
McGill University Health Centre

Introduction

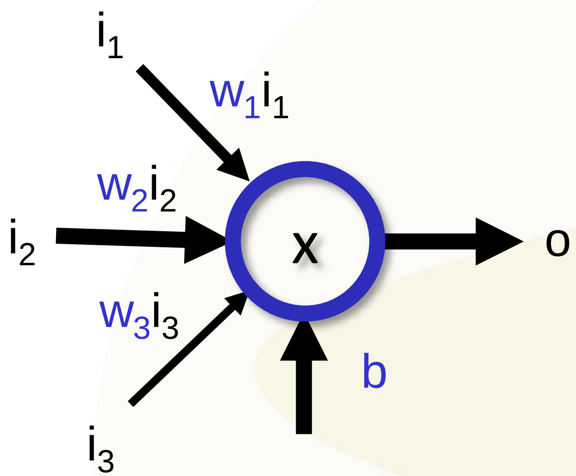
For Deep Learning, you need:

1. Artificial Neural Network
2. Loss
3. Optimizer
4. Data

Artificial Neurons

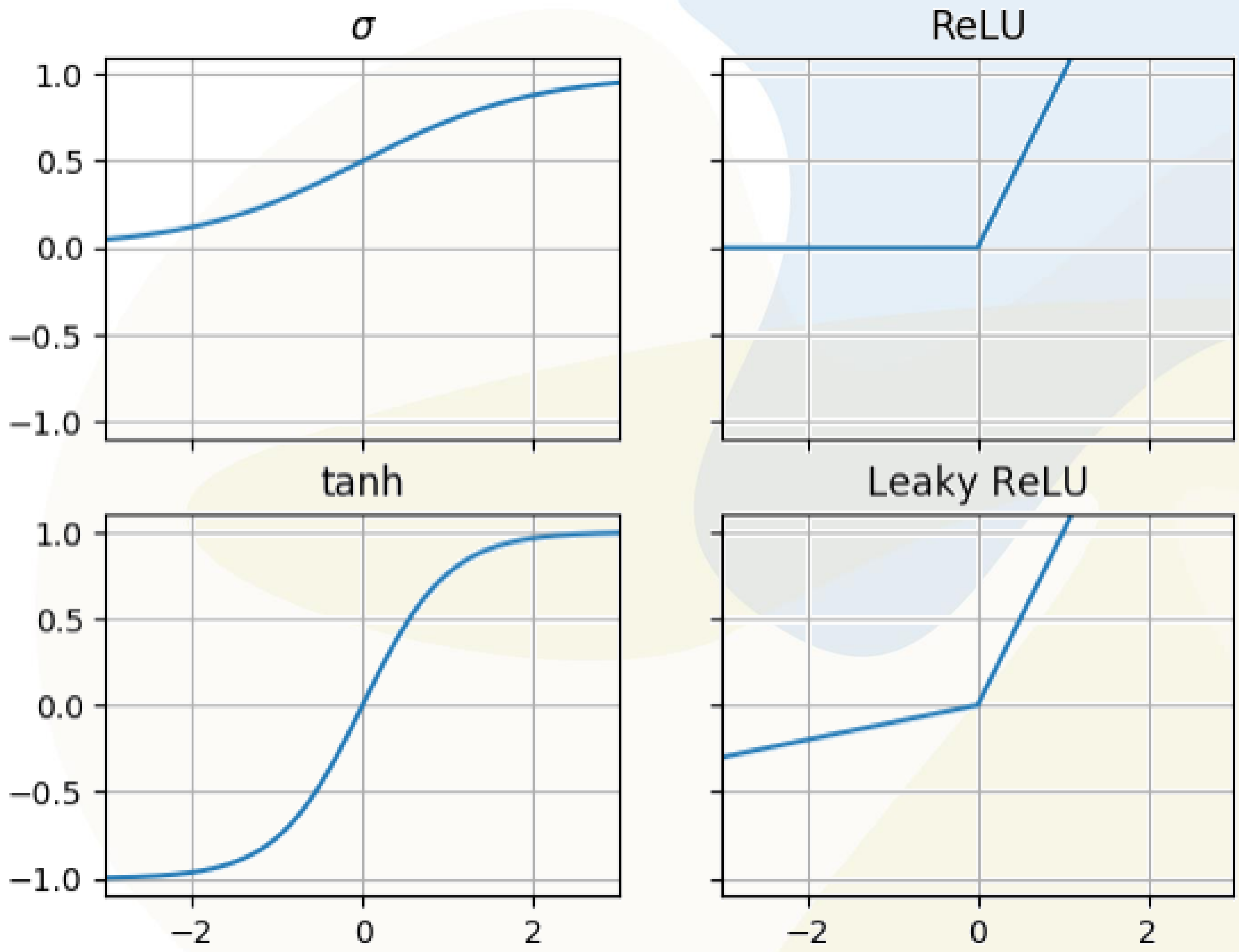


Artificial Neurons



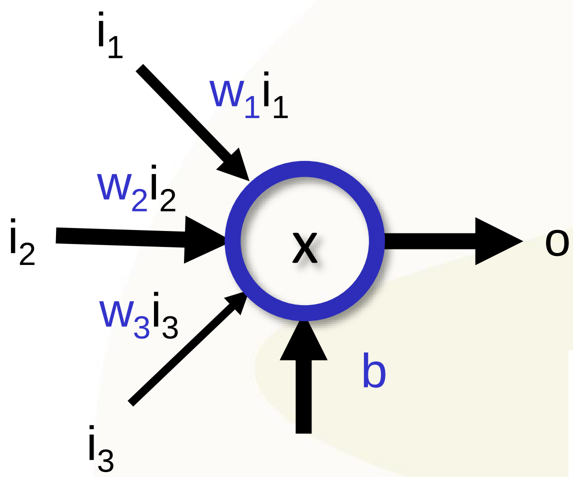
$$o = f(x) = f(\boldsymbol{w}^T\boldsymbol{i} + \boldsymbol{b})$$

Artificial Neurons

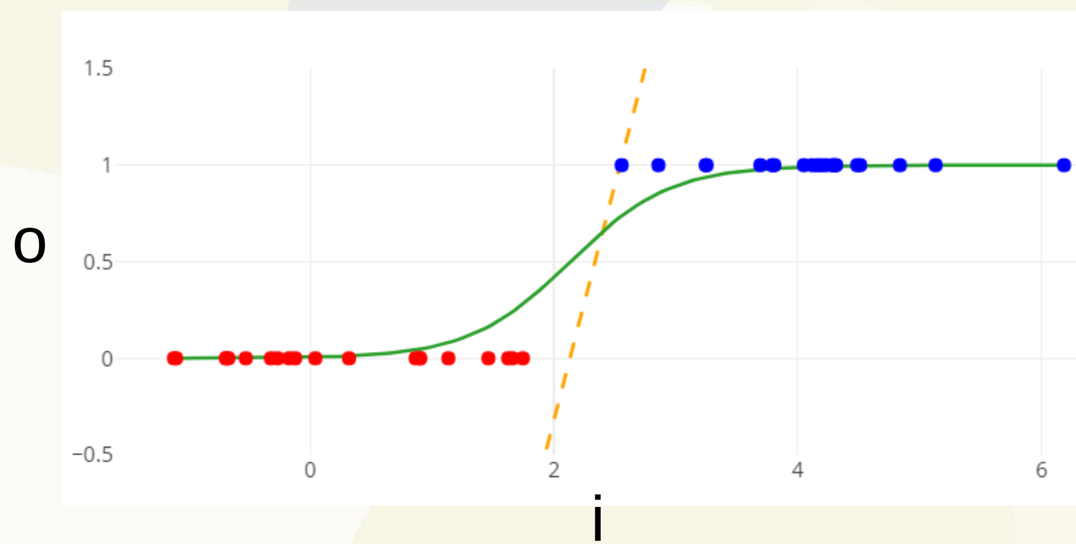


Artificial Neurons

Logistic Regression

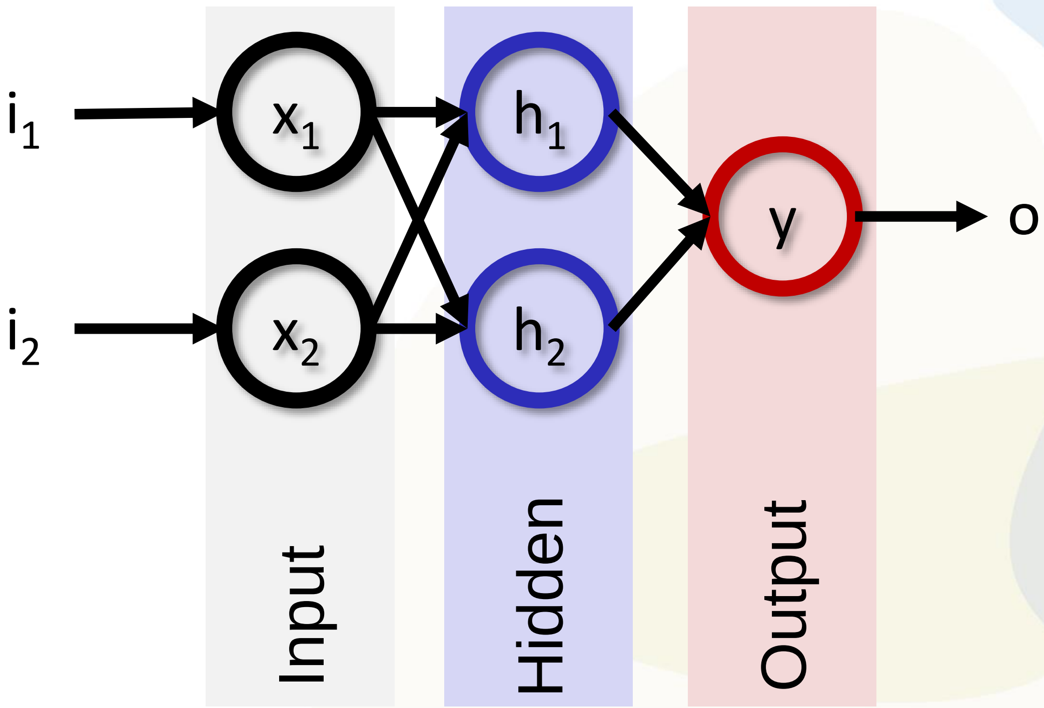


$$o = \sigma(x) = \sigma\left(\boldsymbol{w}^T \boldsymbol{i} + \boldsymbol{b}\right)$$



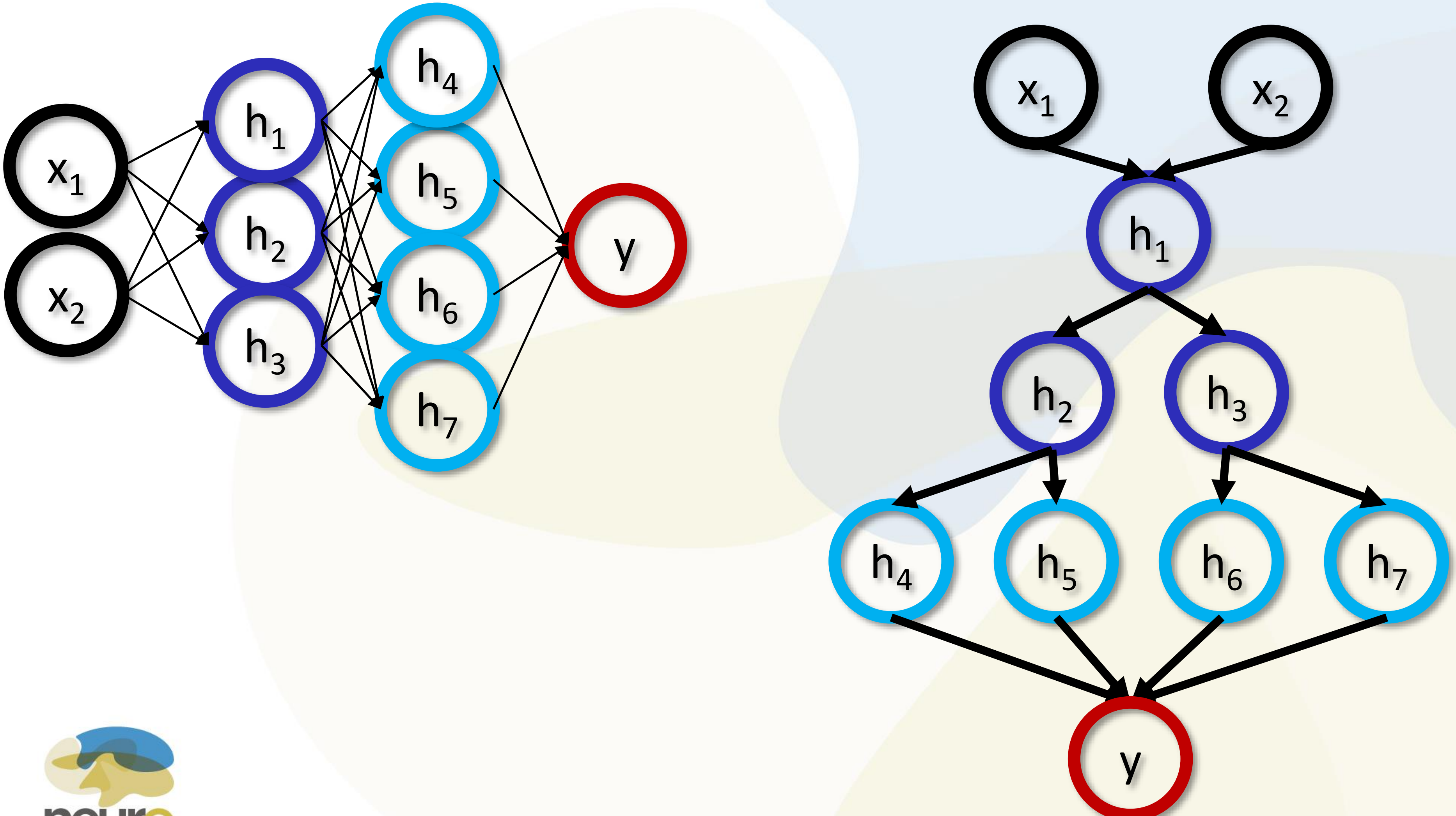
Hartl, Florian. "Logistic Regression – Geometric Intuition"
https://florianhartl.com/logistic-regression-geometric-intuition.html

Neural Networks



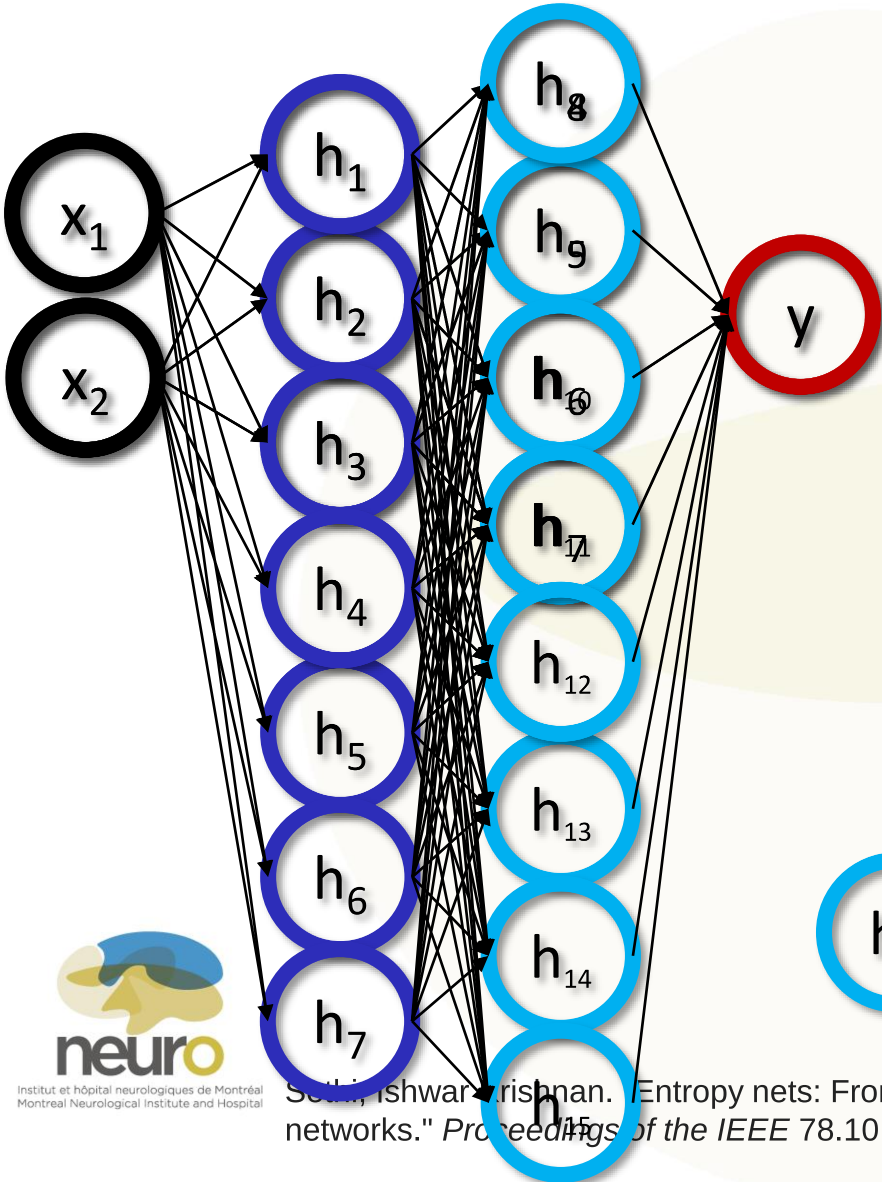
Support
Vector
Machine

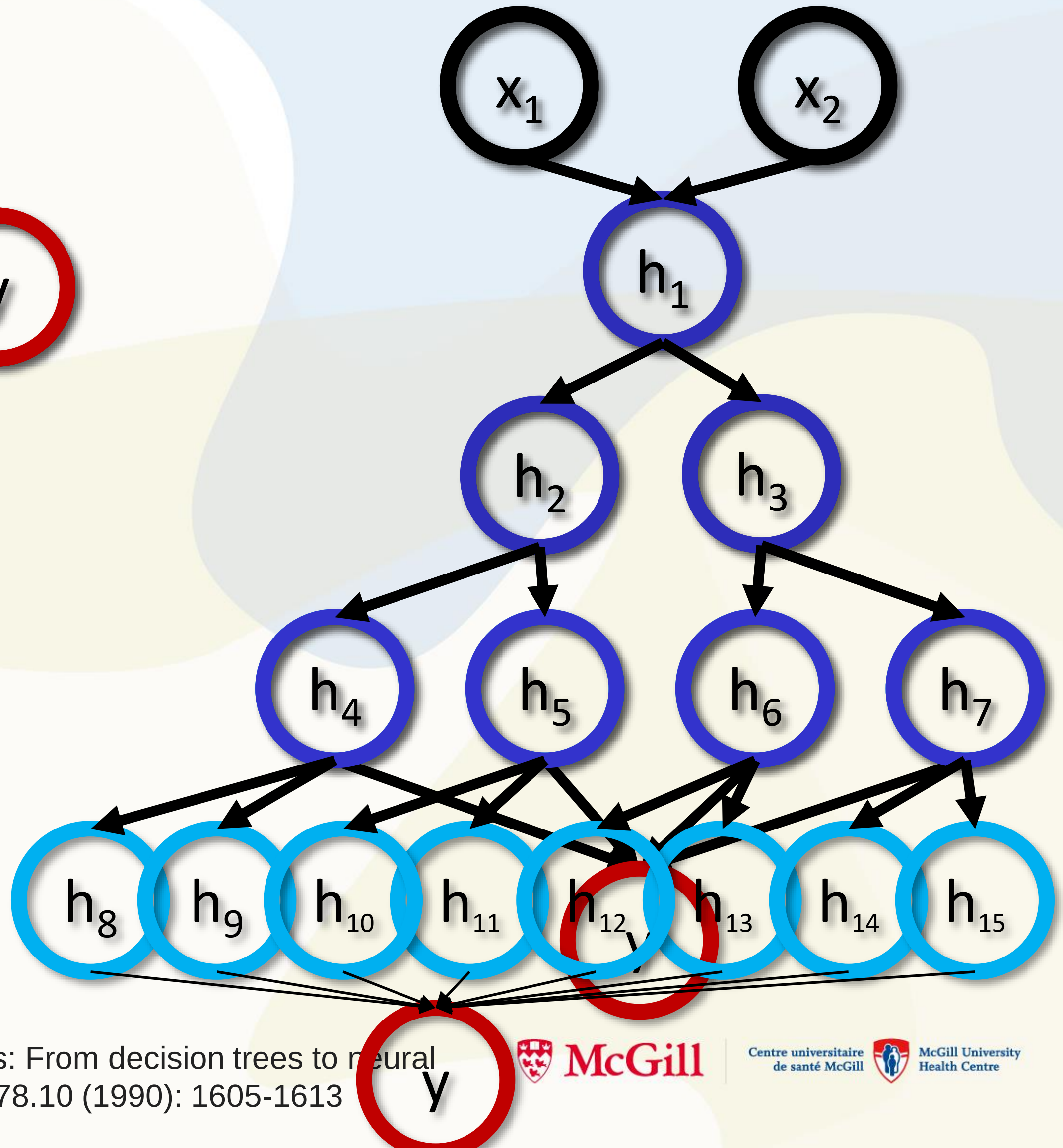
Neural Networks



Sethi, Ishwar Krishnan. "Entropy nets: From decision trees to neural networks." *Proceedings of the IEEE* 78.10 (1990): 1605-1613

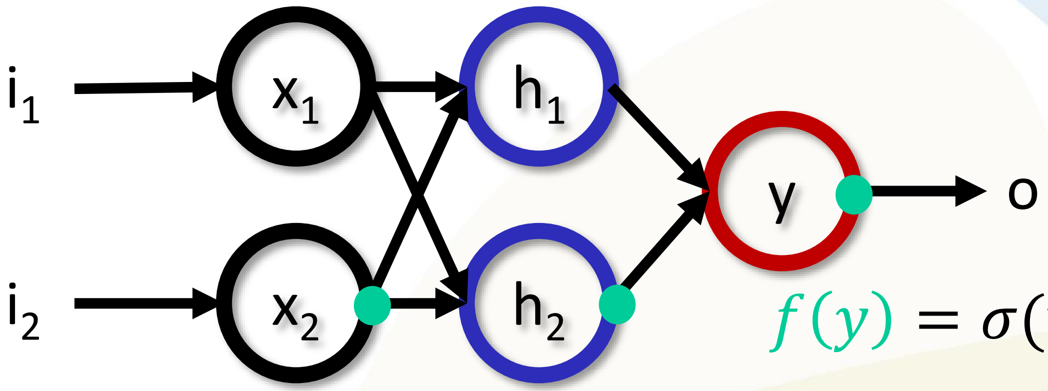
Neural Networks





Sethi, Ishwar Krishnan. "Entropy nets: From decision trees to neural networks." *Proceedings of the IEEE* 78.10 (1990): 1605-1613

Neural Networks



$$f(y) = \sigma(w_{y,h_1} f(h_1) + w_{y,h_2} f(h_2) + b_y)$$

$$= \sigma\big(w_{y,h_1} \sigma\big(w_{h_1,x_1} \sigma(i_1 w_{x_1} + b_{x_1}) + w_{1,x_2} \sigma(i_2 w_{x_2,i_2} + b_{x_2}) + b_{h_1}\big) + w_{y,h_2} \sigma\big(w_{h_2,x_1} \sigma(i_1 w_{x_1,i_1} + b_{x_1}) + w_{h_2,x_2} \sigma(i_2 w_{x_2,i_2} + b_{x_2}) + b_{h_2}\big) + b_y\big)$$

$$f(x_2) = \sigma(i_2 w_{x_2,i_2} + b_{x_2})$$

$$f(h_2) = \sigma(w_{h_2,x_1} f(x_1) + w_{h_2,x_2} f(x_2) + b_{h_2})$$

$$= \sigma(w_{h_2,x_1} \sigma(i_1 w_{x_1,i_1} + b_{x_1}) + w_{h_2,x_2} \sigma(i_2 w_{x_2,i_2} + b_{x_2}) + b_{h_2})$$

17 parameters $\theta = \{\boldsymbol{w}, \boldsymbol{b}\}$

Backpropagation

1. Random θ initialization

Iterate:

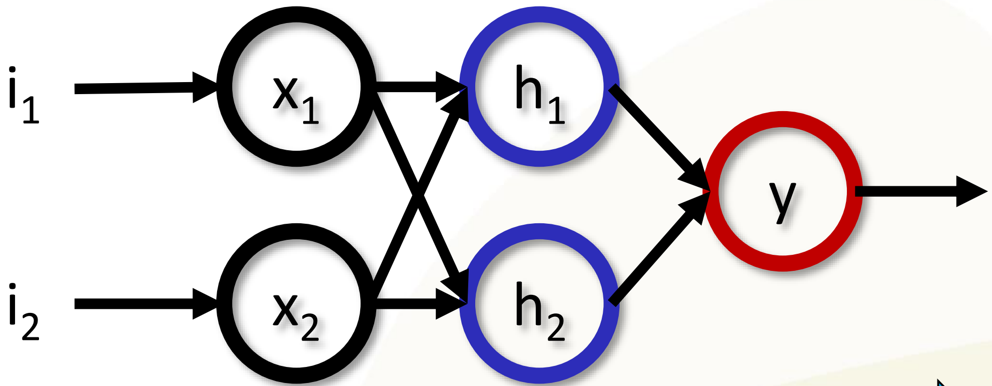
   1. Forward - compute loss

      forward pass

   2. Backward - update parameters

      backward pass

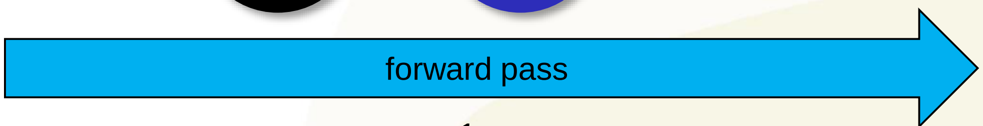
Backpropagation



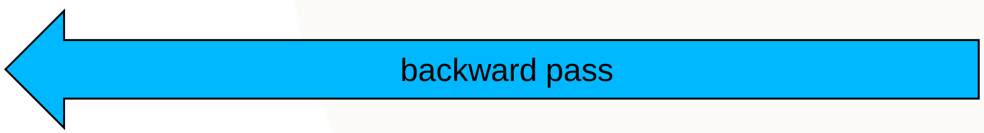
$\hat{y} \approx P(o)$

XOR

i_1	i_2	o
0	0	0
0	1	1
1	0	1
1	1	0

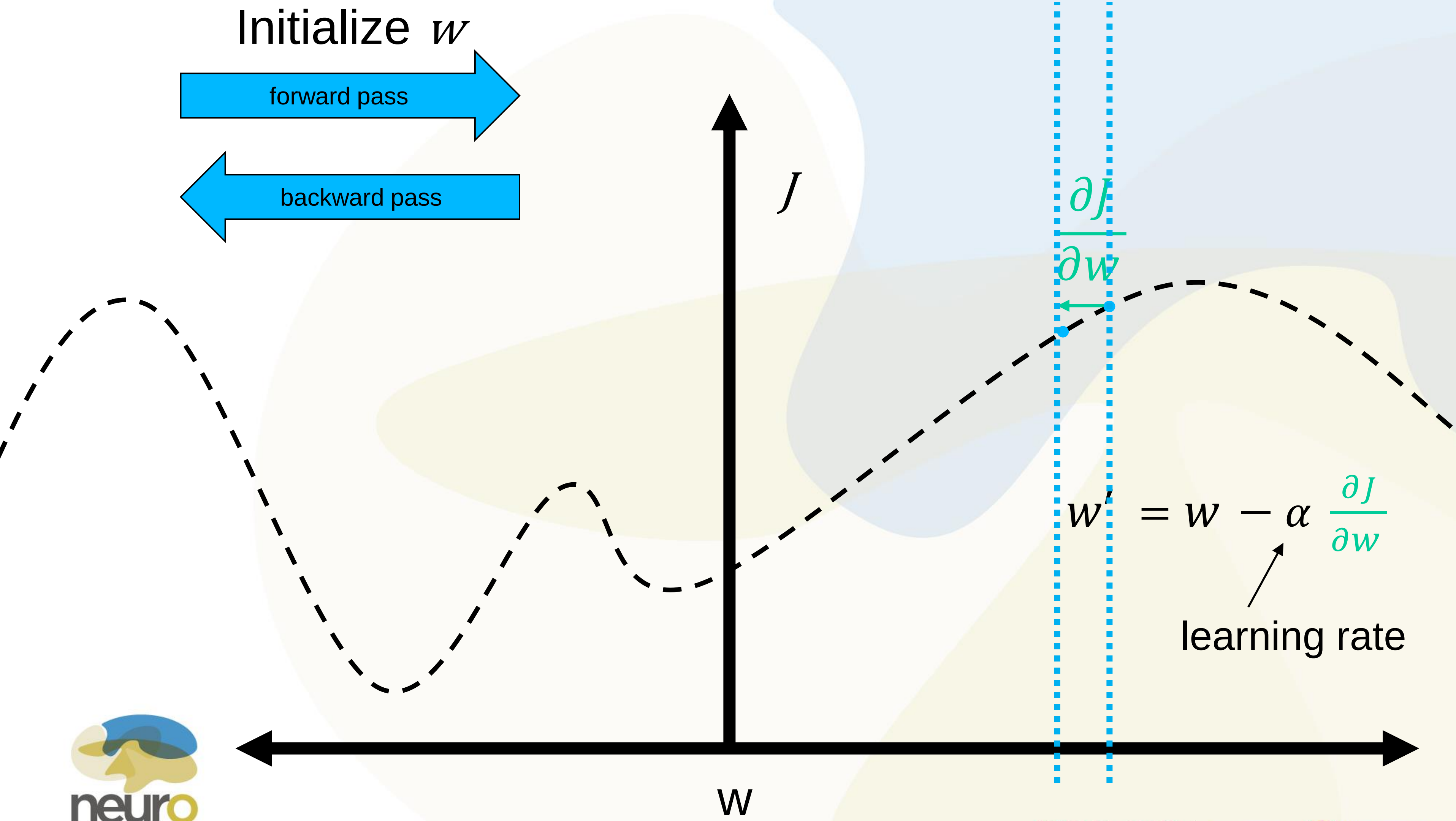


$$J(o, \hat{y}) = \frac{1}{2} \sum (o - \hat{y})^2$$

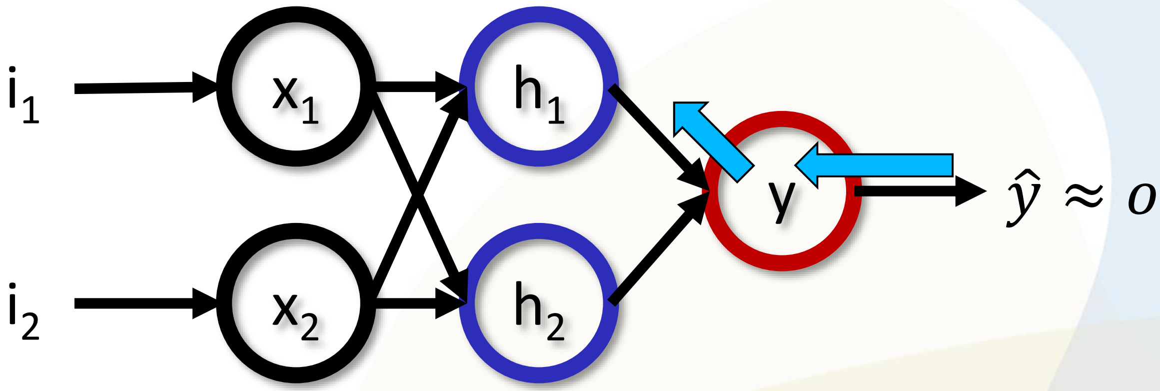


$$\nabla_\theta J(o, \hat{y}) = \left[\frac{\partial J}{\partial w_{x_1, i_1}}, \frac{\partial J}{\partial b_{x_1}}, \frac{\partial J}{\partial w_{x_2, i_2}}, \frac{\partial J}{\partial b_{x_2}}, \ldots, \frac{\partial J}{\partial w_{y, h_2}} \right]^T$$

Backpropagation



Backpropagation

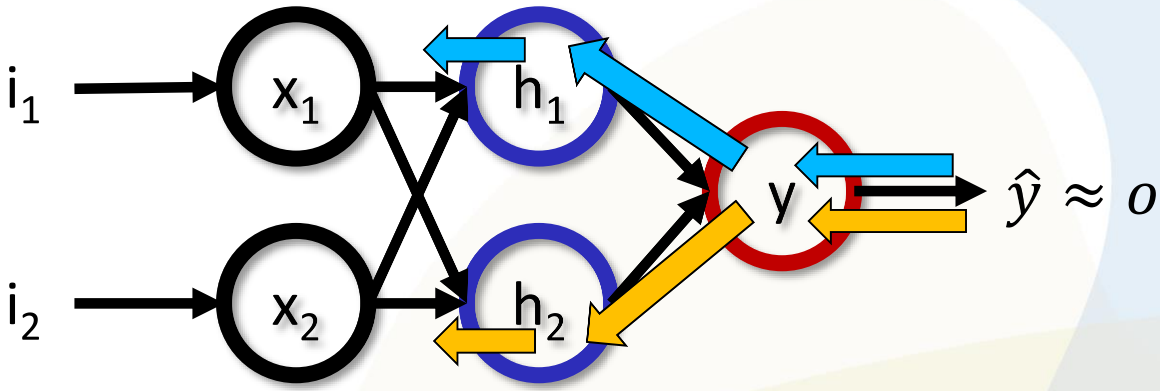


$$\frac{\partial J}{\partial w_{y,h_1}} = \frac{\partial J}{\partial \hat{y}} * \frac{\partial \hat{y}}{\partial w_{y,h_1}}$$

…

$$= \sum -\sigma(\hat{y})\big(1 - \sigma(\hat{y})\big)\, f(h_1)$$

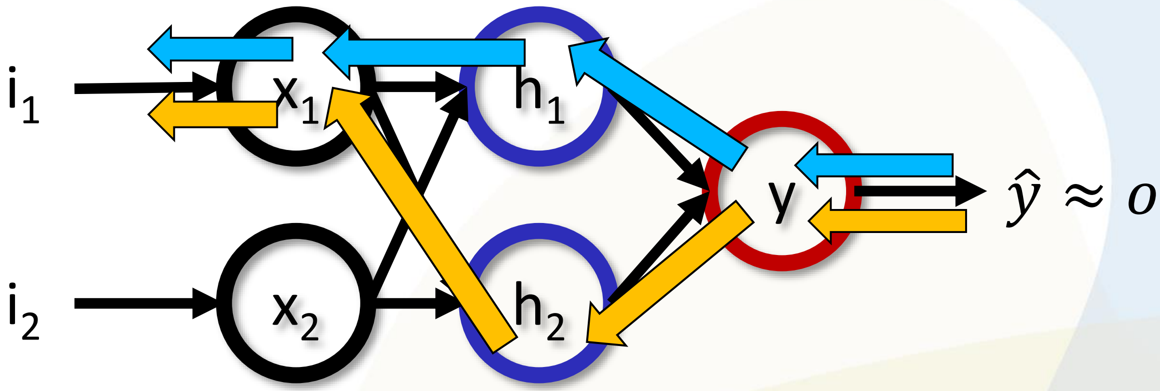
Backpropagation



$$\frac{\partial J}{\partial w_{h_1,x_1}} = \frac{\partial J}{\partial y} * \frac{\partial y}{\partial h_1} * \frac{\partial h_1}{\partial w_{h_1,x_1}}$$

$$\frac{\partial J}{\partial w_{h_2,x_2}} = \frac{\partial J}{\partial y} * \frac{\partial y}{\partial h_2} * \frac{\partial h_2}{\partial w_{h_2,x_2}}$$

Backpropagation



$$\frac{\partial J}{\partial w_{x_1,i_1}} = \frac{\partial J}{\partial y} * \frac{\partial y}{\partial h_1} * \frac{\partial h_1}{\partial x_1} * \frac{\partial x_1}{\partial w_{x_1,i_1}} + \frac{\partial J}{\partial y} * \frac{\partial y}{\partial h_2} * \frac{\partial h_2}{\partial x_1} * \frac{\partial x_1}{\partial w_{x_1,i_1}}$$

Data Manifold

Data distribution:

- Class 1
- Class 2

X-Y grid:

- Param (θ) space

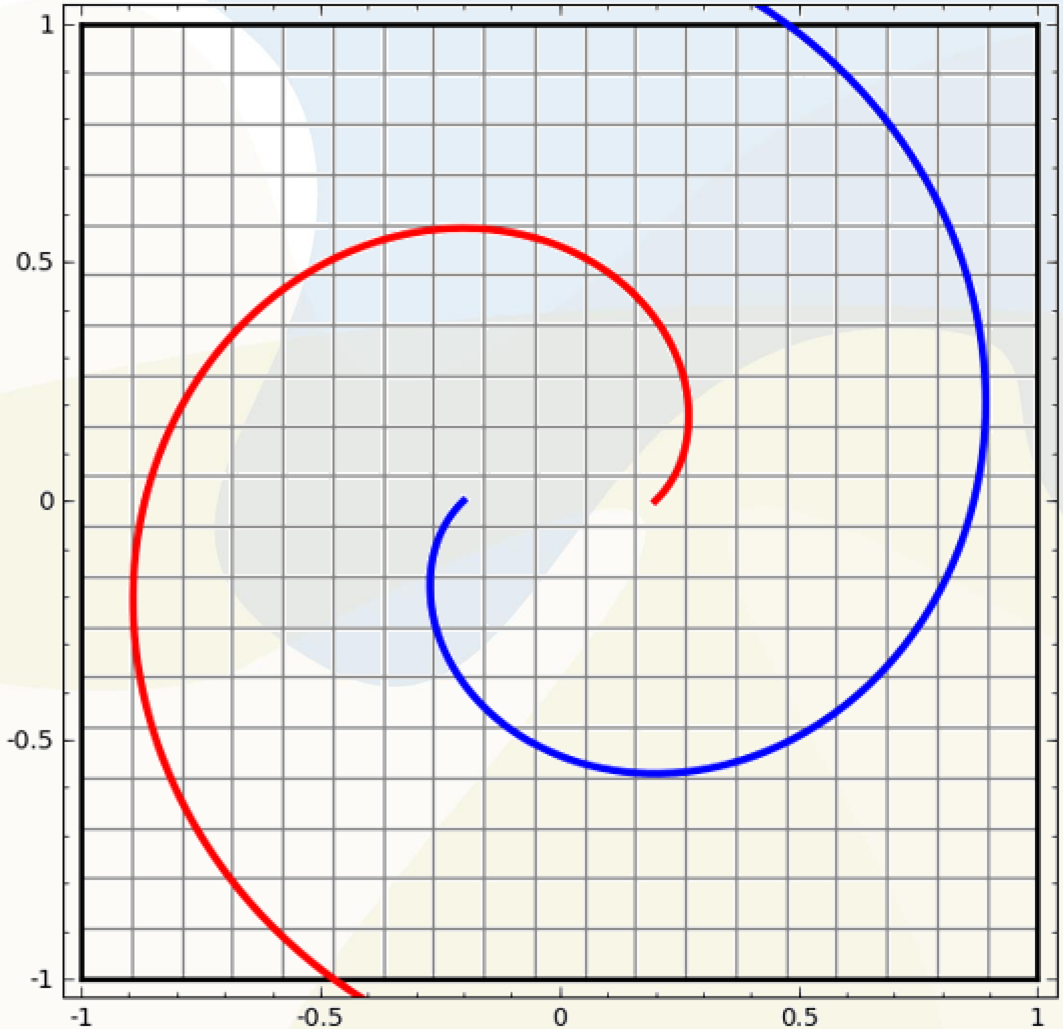


Image courtesy Chris Olah, 2014

Data Manifold

Data distribution:

- Class 1
- Class 2

X-Y grid:

- Param (θ) space

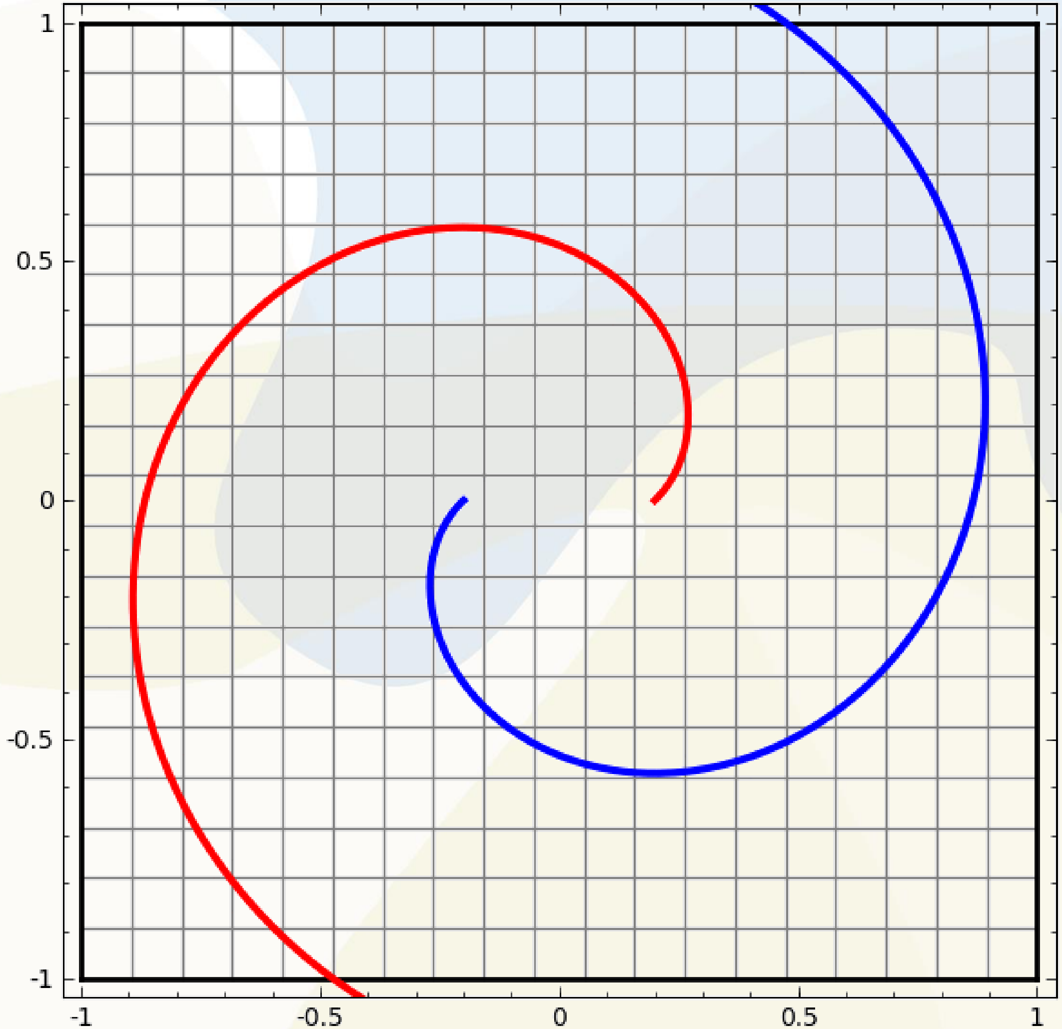


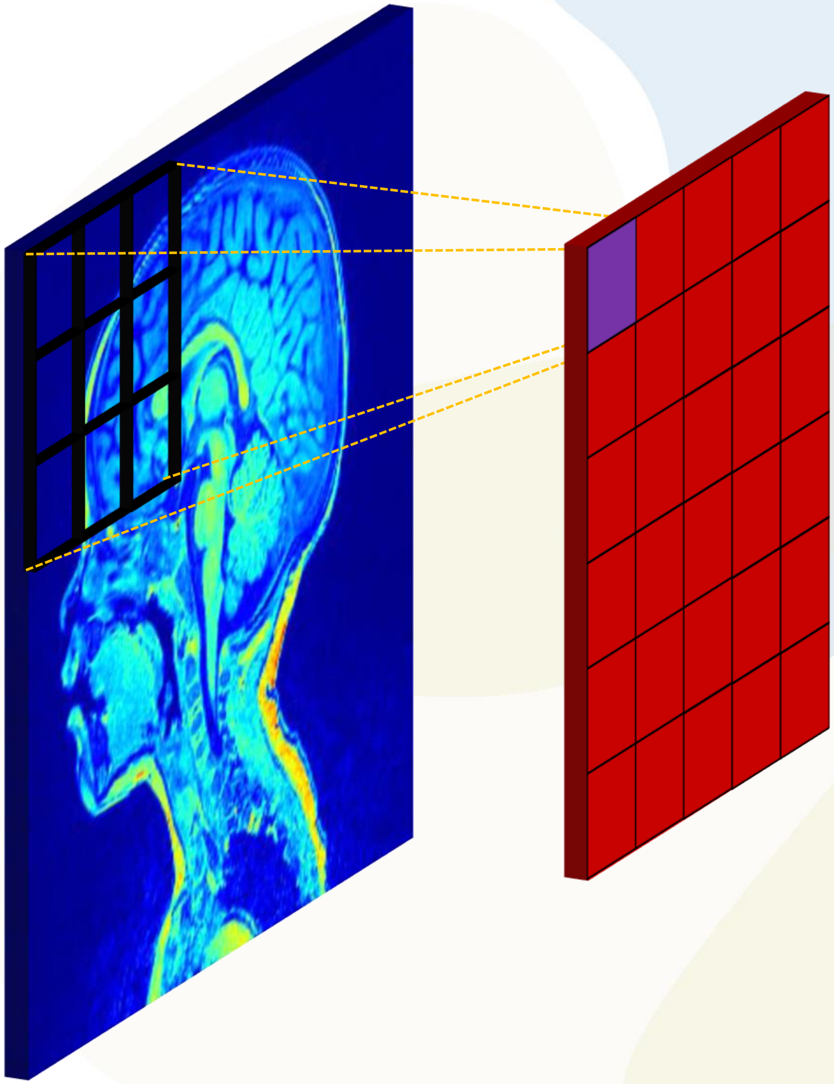
Image courtesy Chris Olah, 2014

Convolutional Neural Networks

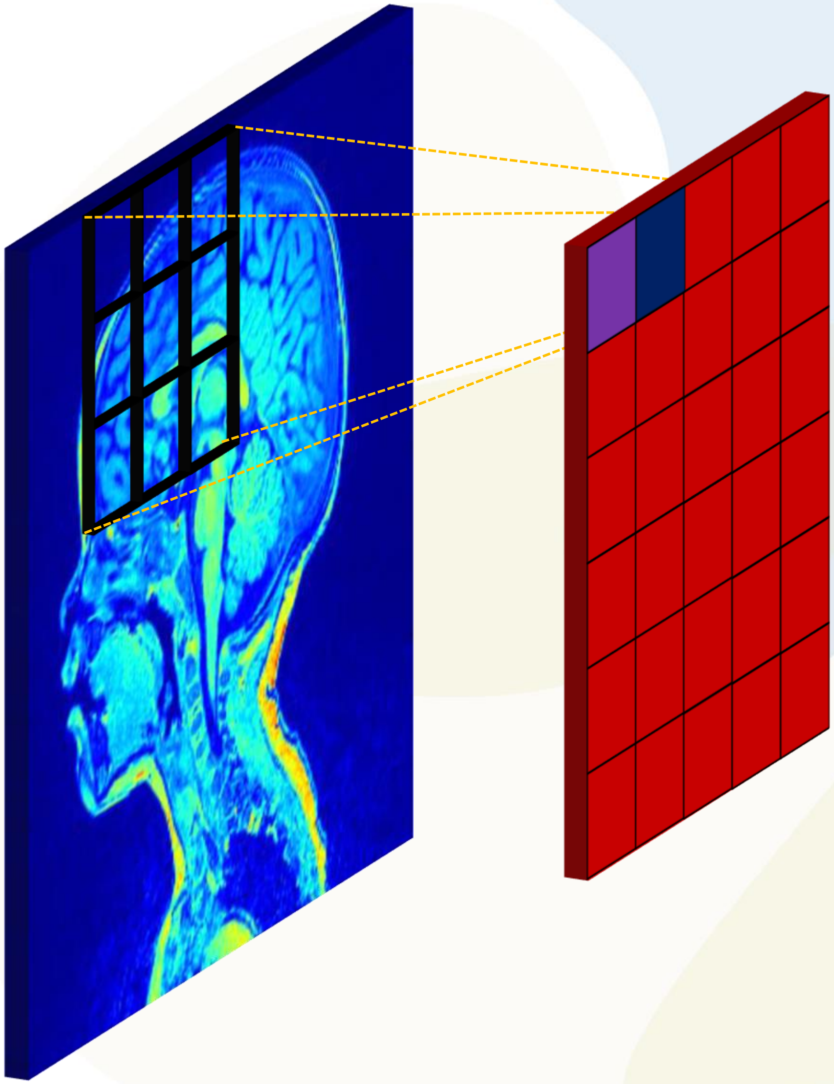
CNN/convnet neurons:

1. Have receptive field
2. Share weights

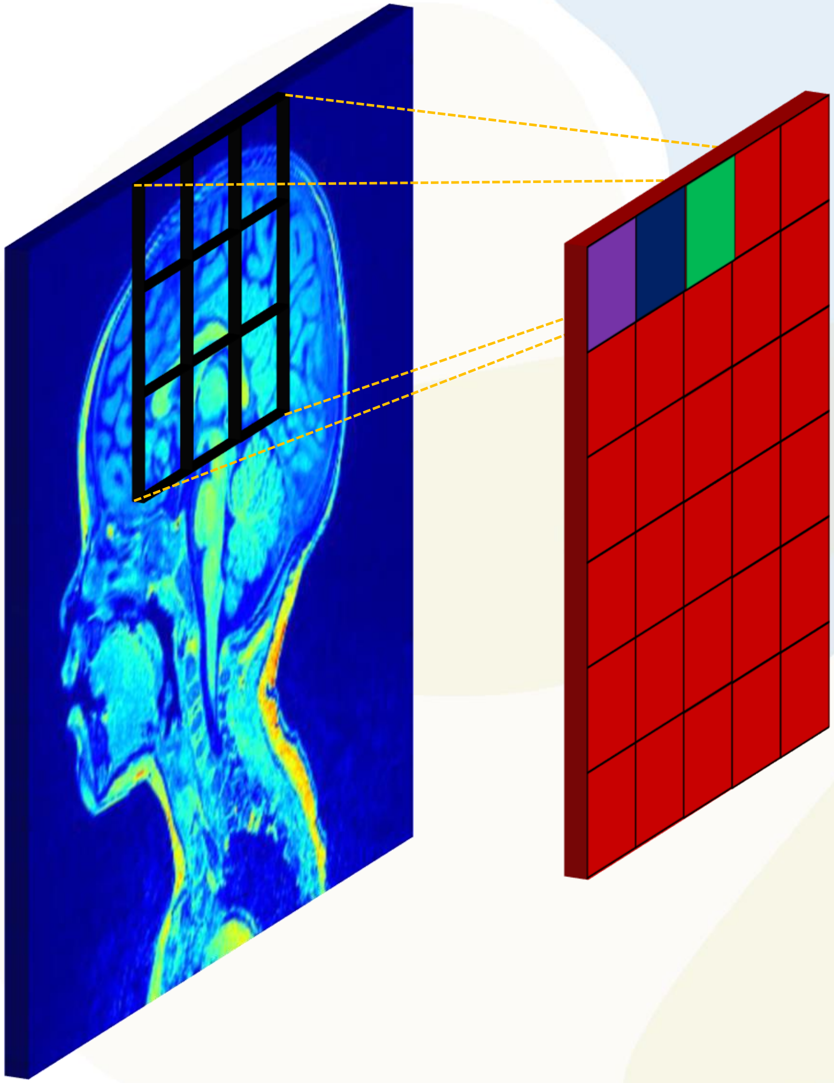
Convolutional Neural Networks



Convolutional Neural Networks



Convolutional Neural Networks

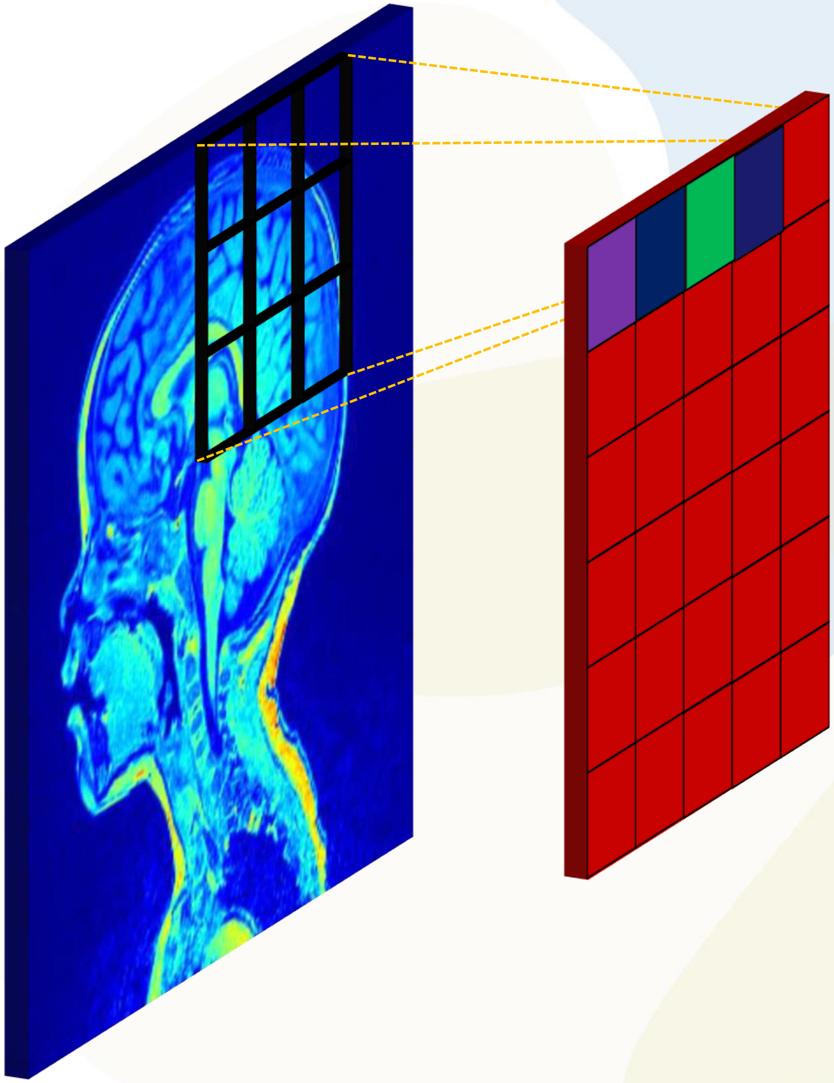


Institut et hôpital neurologiques de Montréal
Montreal Neurological Institute and Hospital

McGill

Centre universitaire de santé McGill
McGill University Health Centre

Convolutional Neural Networks

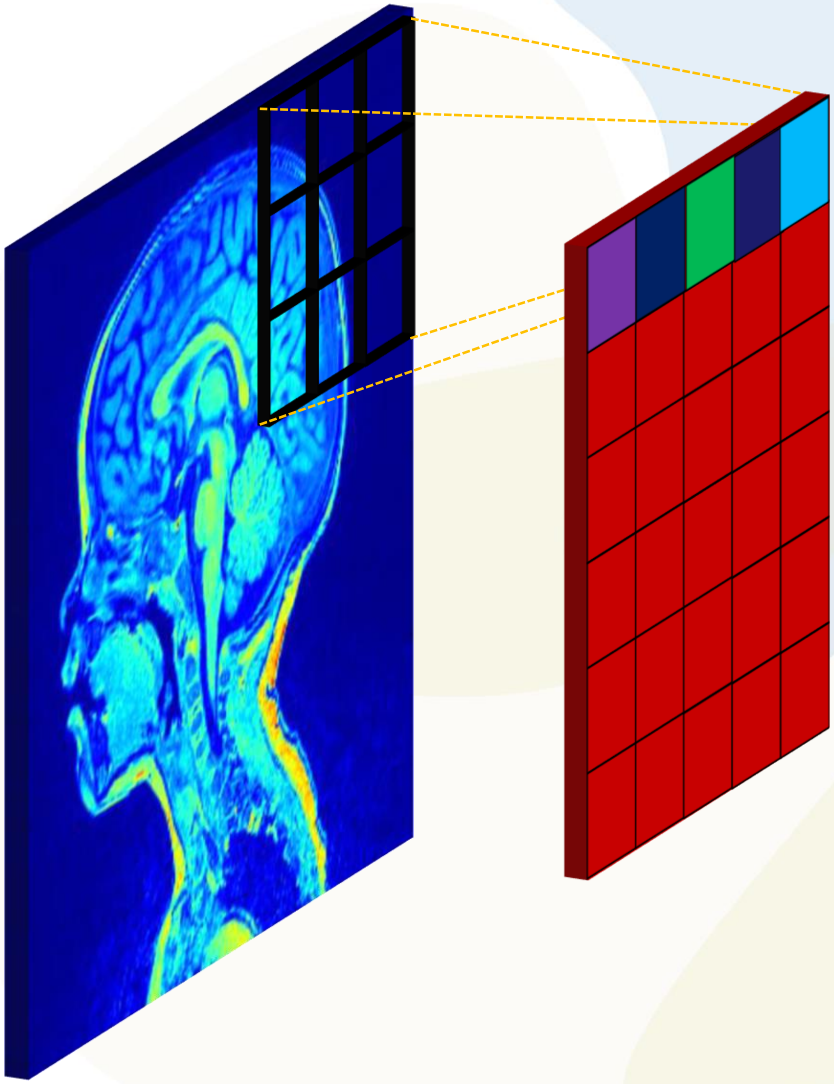


Institut et hôpital neurologiques de Montréal
Montreal Neurological Institute and Hospital

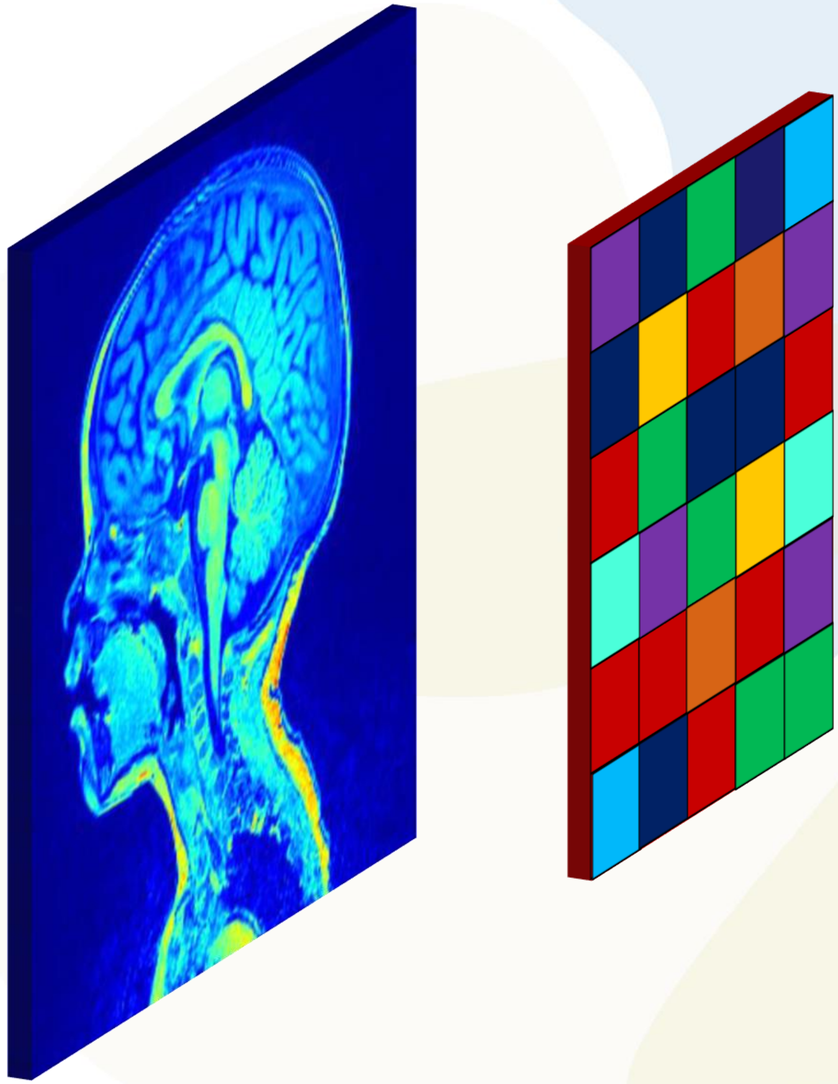
McGill

Centre universitaire de santé McGill
McGill University Health Centre

Convolutional Neural Networks



Convolutional Neural Networks

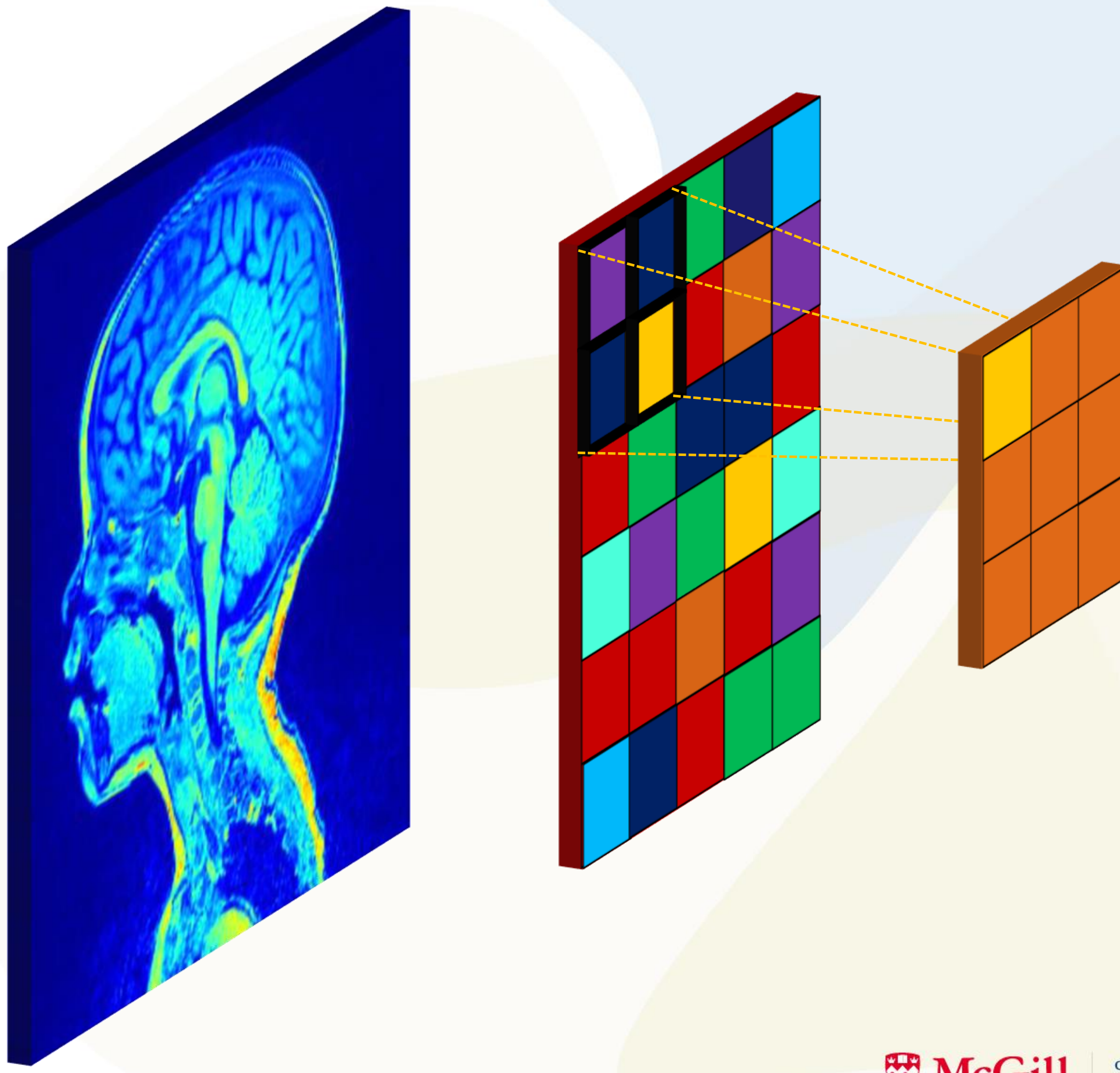


neuro
Institut et hôpital neurologiques de Montréal
Montreal Neurological Institute and Hospital

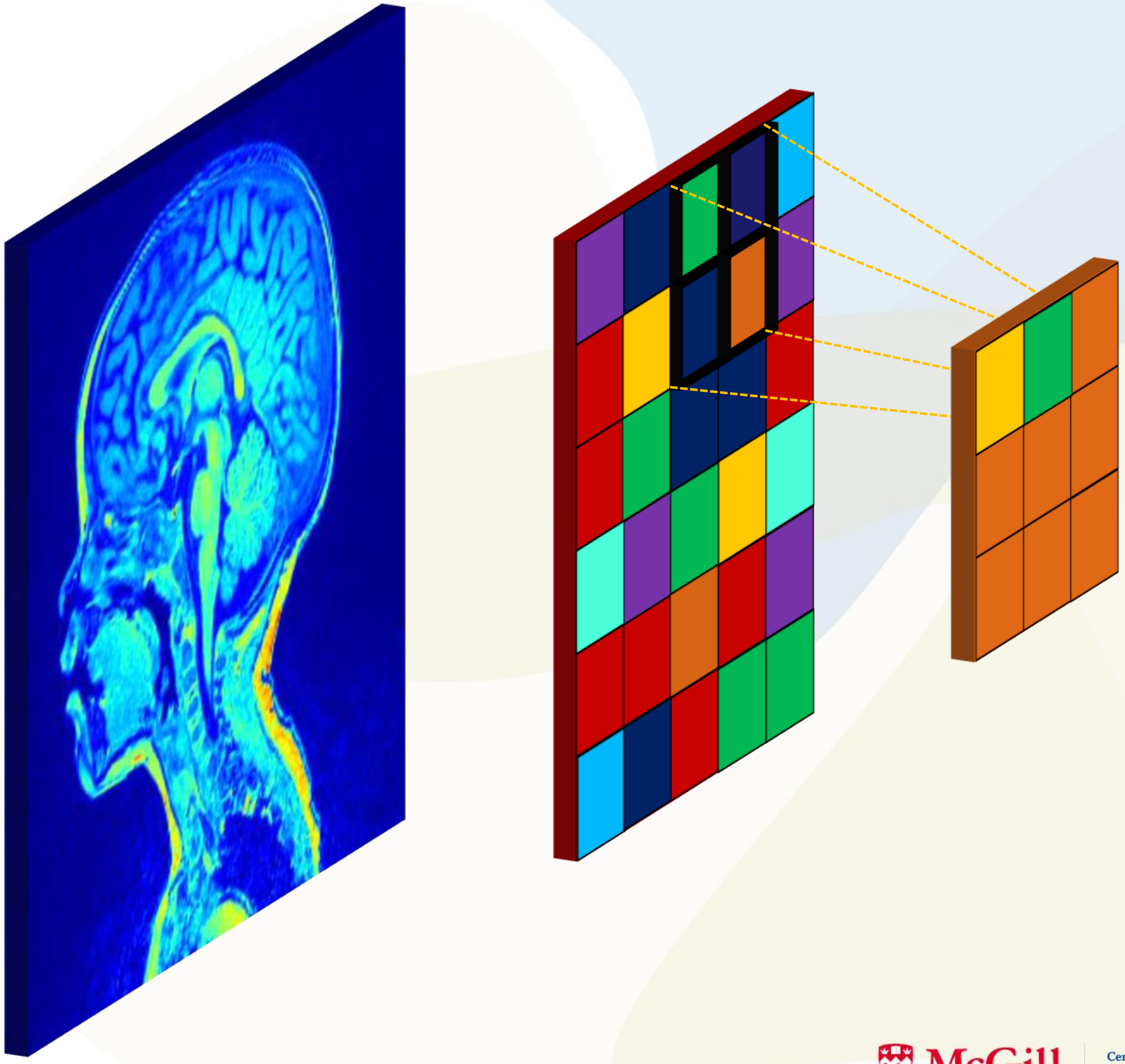
McGill

Centre universitaire de santé McGill
McGill University Health Centre

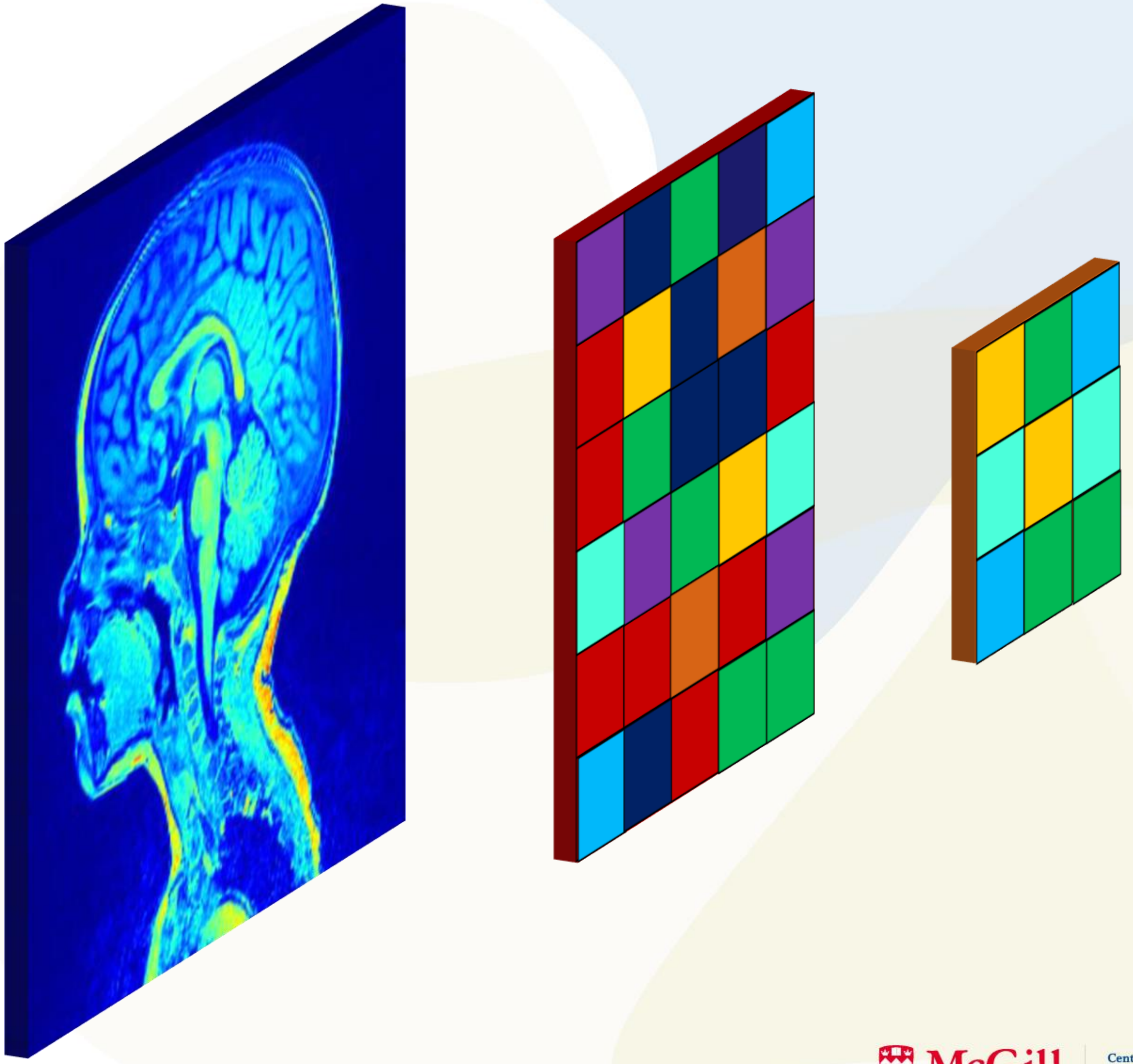
Convolutional Neural Networks



Convolutional Neural Networks



Convolutional Neural Networks

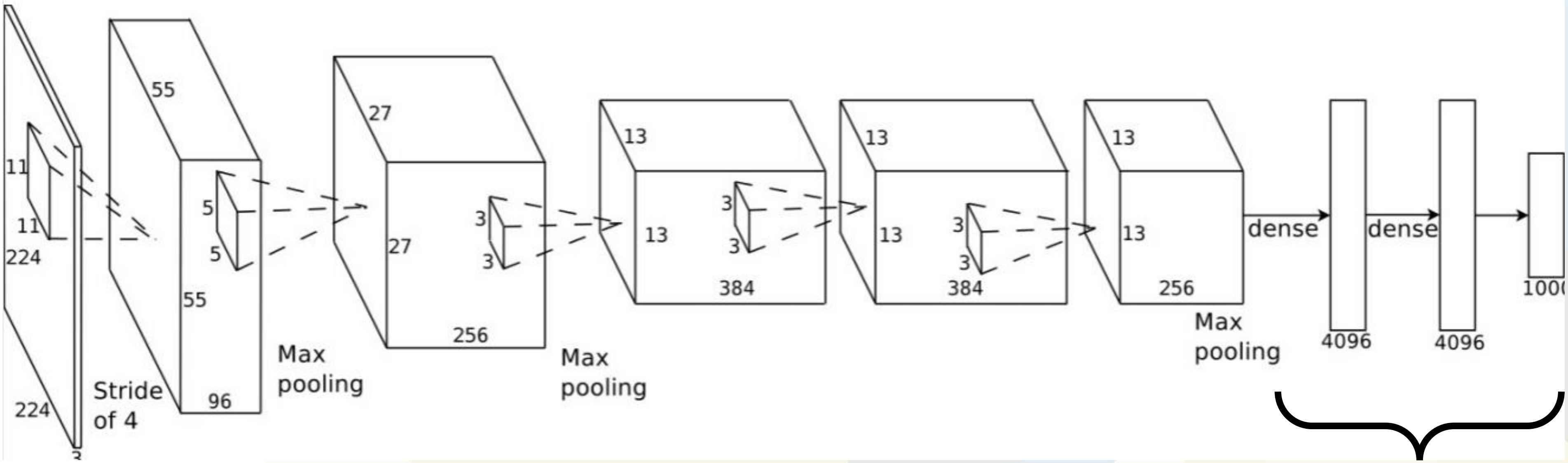


neuro
Institut et hôpital neurologiques de Montréal
Montreal Neurological Institute and Hospital

McGill

Centre universitaire de santé McGill
McGill University Health Centre

Convolutional Neural Networks



AlexNet trained using:

1. Dropout
2. Batch Normalization

90% parameters

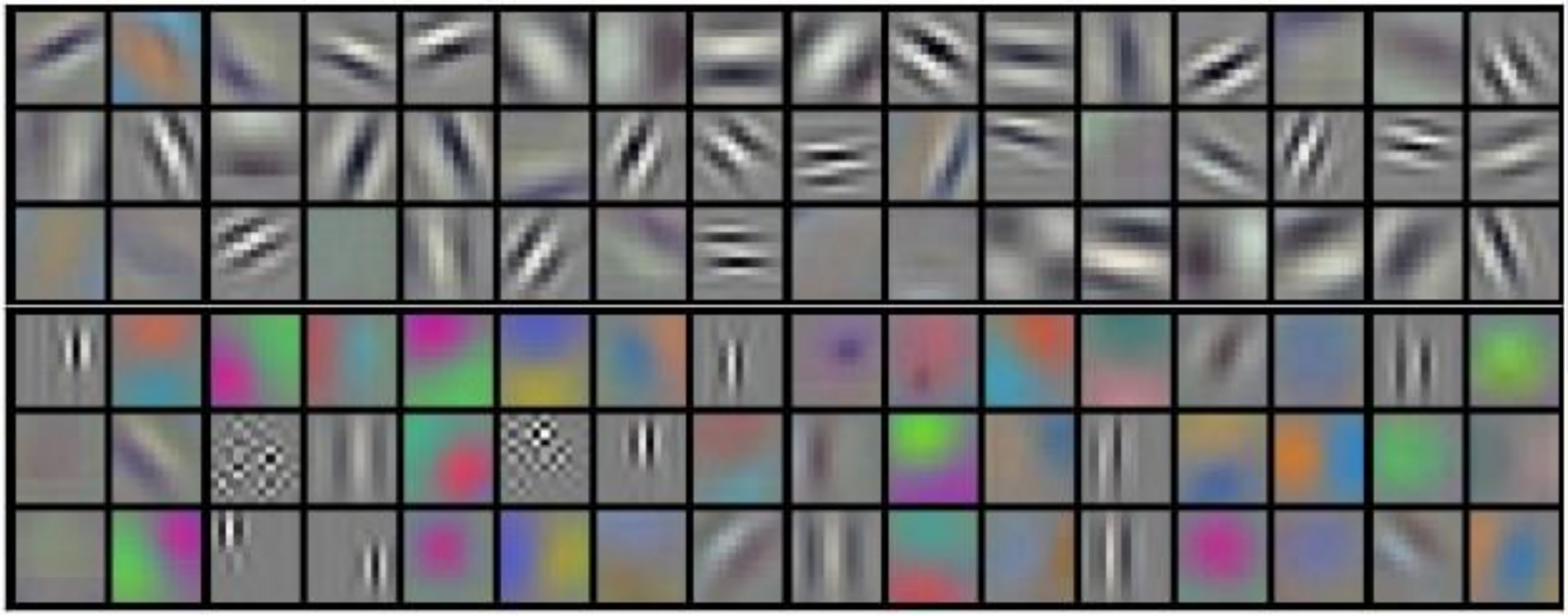
Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "ImageNet classification with deep convolutional neural networks." *Advances in neural information processing systems*. 2012.

neuro
Institut et hôpital neurologiques de Montréal
Montreal Neurological Institute and Hospital

McGill

Centre universitaire de santé McGill
McGill University Health Centre

Convolutional Neural Networks



Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "ImageNet classification with deep convolutional neural networks." *Advances in neural information processing systems*. 2012.

Challenges

1. Data quantity
2. Data size
3. Data quality
4. Data variability
5. Unexpected pathology