AI & CV

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Today's goal

- Dataset:
  - Caltech101
  - http://www.vision.caltech.edu/Image_Datasets/Caltech101/
  - 101 categories.
  - About 40 to 800 images per category.
  - The size of image: about 300 x 200 pixels.
  - Collected in September 2003 by Fei-Fei Li, Marco Andreetto, and Marc 'Aurelio Ranzato.



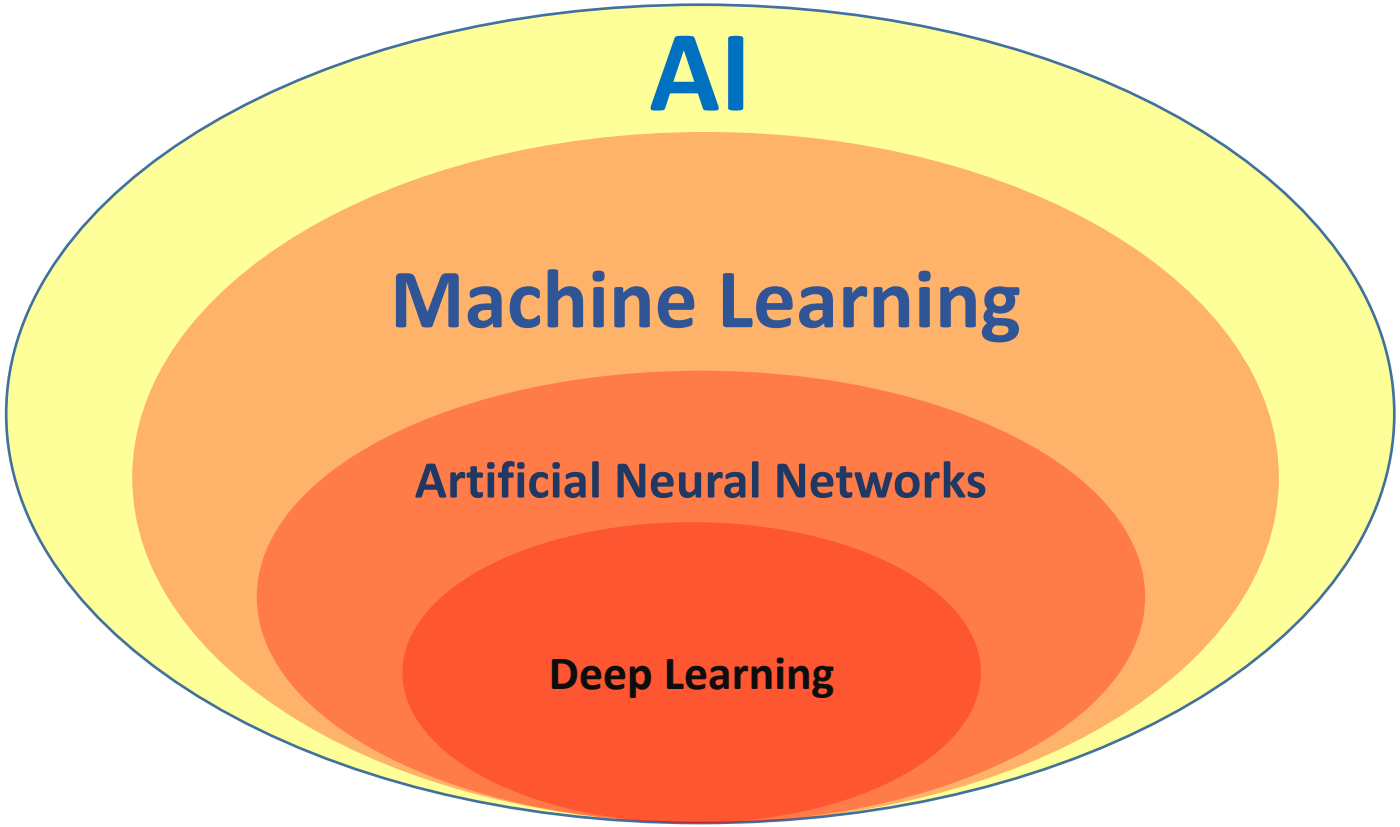

- Using Caltech256 to train your CNN
- Then, using the trained CNN to recognize any picture.

Programs

- Download the program templates from my GitHub:
- https://github.com/jameschengcs/dl

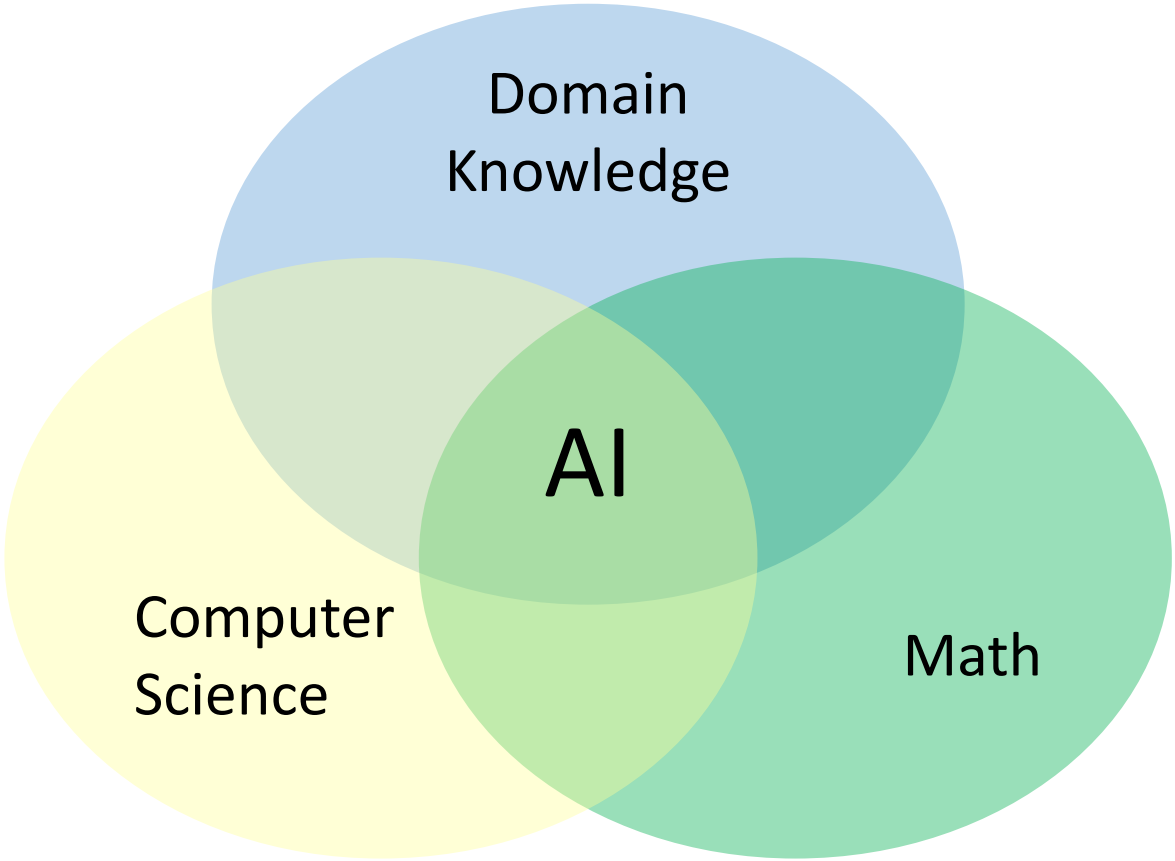
What is AI?

- **AI, artificial intelligence**, is an area of computer science that emphasizes the creation of intelligent machines that work and react like humans.

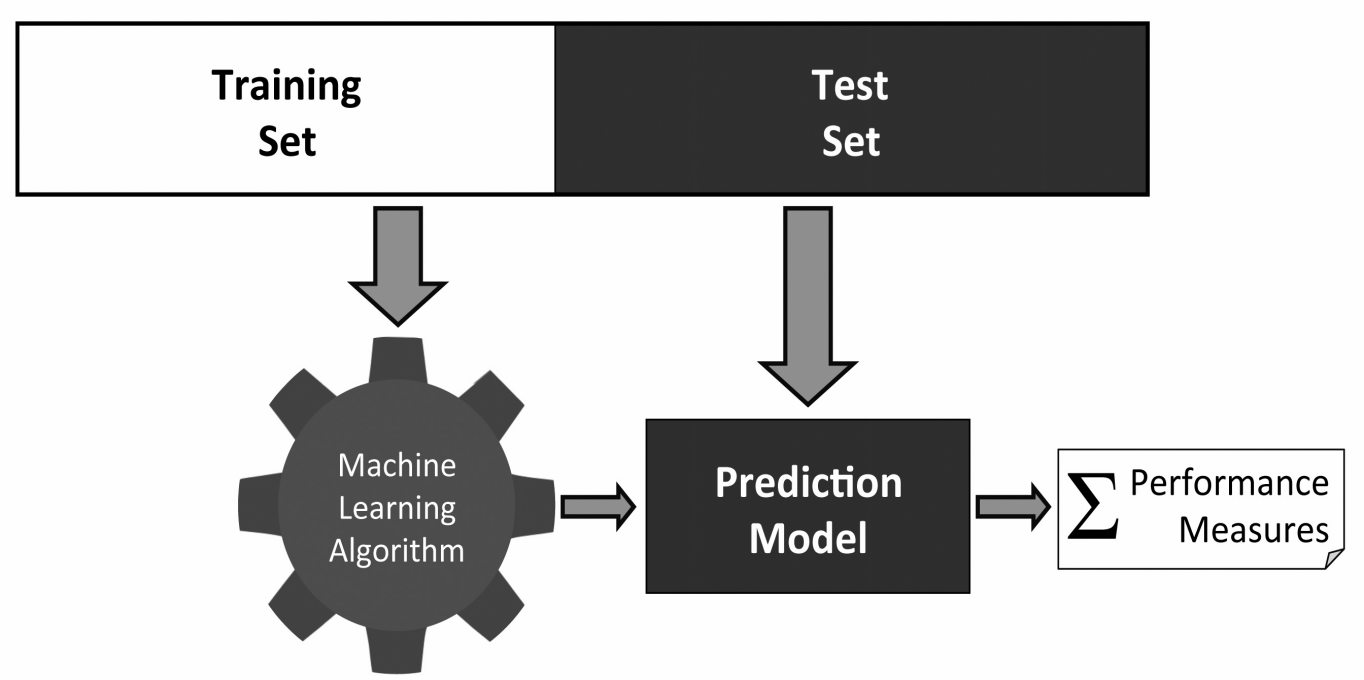


Artificial Intelligence Fundamentals

- Three primary fundamentals:



A Simple Machine Learning Model



Machine Learning with Python

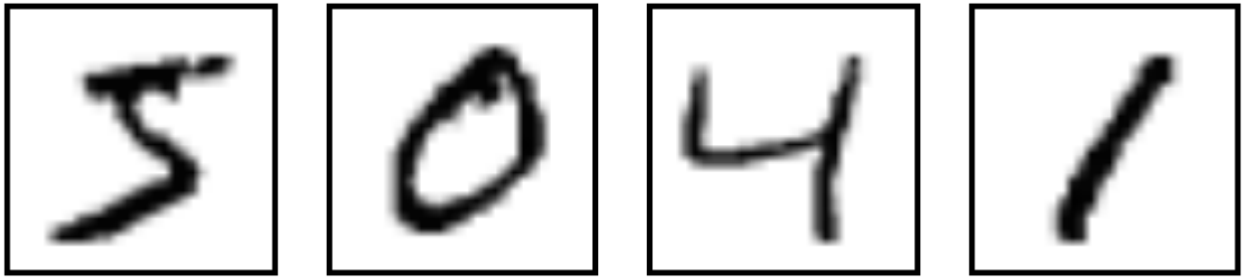
- TensorFlow
  - An open-source library for artificial intelligence applications including mathematics, machine learning, and artificial neural network.
  - Developed by Google Brain Team
  - API: Python (the most complete and the easiest to use), C++, JAVA, and Go.
  - It supports GPU (CUDA)

Online Resource

- Kaggle
  - https://www.kaggle.com/
  - An open platform for machine learning
  - Open datasets
  - Open software and source code
  - Google Cloud team

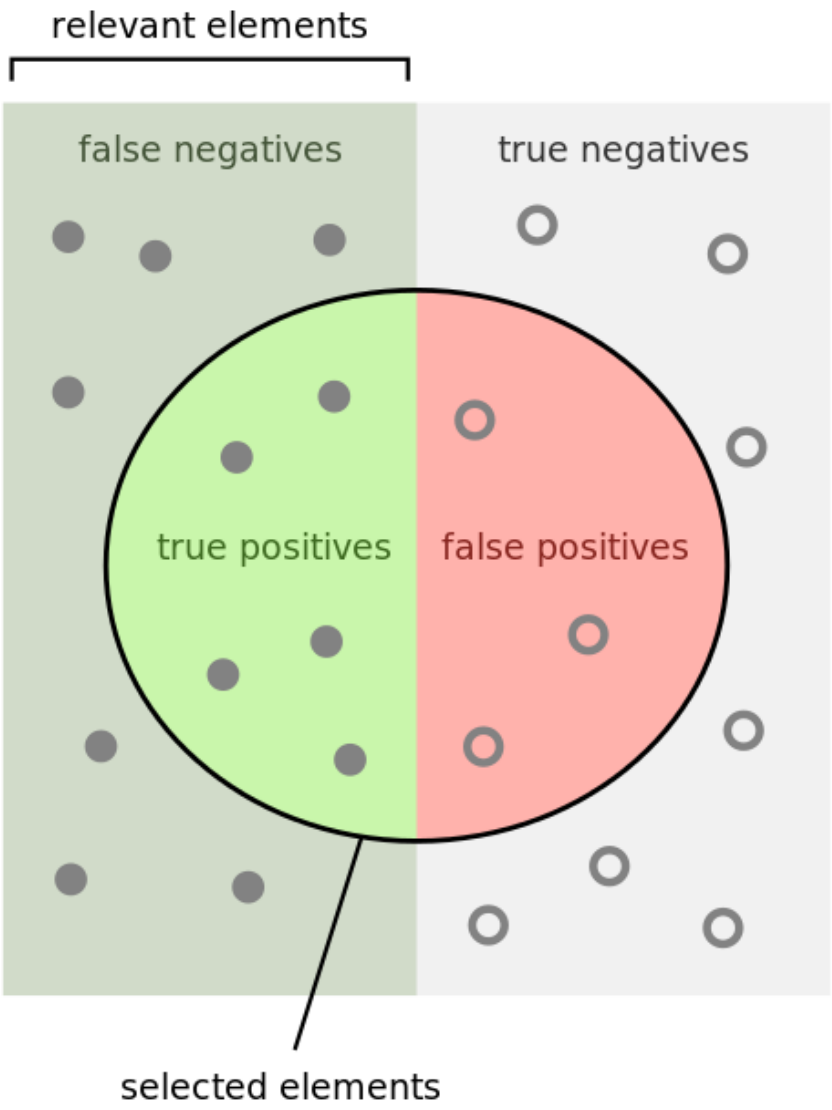
Popular Datasets for Research

- MNIST
  - A simple computer vision dataset.
  - It consists of images of handwritten digits
  - Each image has 28 x 28 = 784 pixels
  - Each pixel has a single value in [0, 1]
  - Each image has a labels. For example, the labels for the above images are 5, 0, 4, and 1.



Evaluation

- Four possible outcomes
  - True Positive (TP)
  - True Negative (TN)
  - False Positive (FP)
  - False Negative(FN)



Figuring by: Wikipedia, https://en.wikipedia.org/wiki/Sensitivity_and_specificity

Evaluation

- Confusion matrix

		Prediction	
		positive	negative
Target	positive	*TP*	*FN*
	negative	*FP*	*TN*

Evaluation

- Misclassification accuracy

$$\frac{(FP + FN)}{(TP + TN + FP + FN)}$$

$$\frac{(2+3)}{(6+9+2+3)} = 0.25$$

- Classification accuracy

$$\frac{(TP + TN)}{(TP + TN + FP + FN)}$$

$$\frac{(6+9)}{(6+9+2+3)} = 0.75$$

Evaluation

- TP rate (TPR) $\frac{TP}{(TP + FN)}$
- TN rate (TNR) $\frac{TN}{(TN + FP)}$
- FP rate (FPR) $\frac{FP}{(TN + FP)}$
- FN rate (FNR) $\frac{FN}{(TP + FN)}$

Evaluation

- Precision

$$\frac{TP}{(TP + FP)}$$

- Recall

$$\frac{TP}{(TP + FN)}$$

Evaluation

- Multinomial targets

$$precision(l) = \frac{TP(l)}{TP(l) + FP(l)}$$

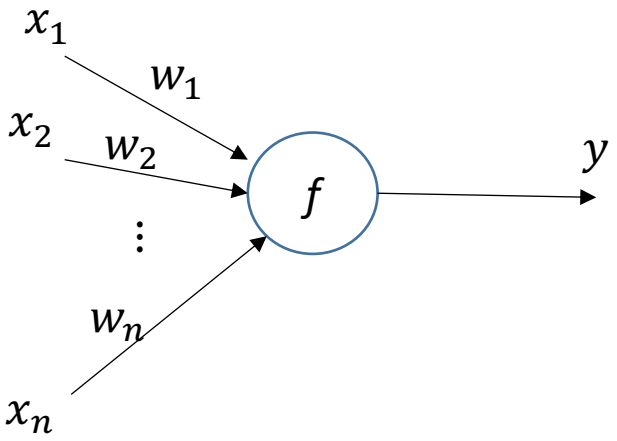
$$recall(l) = \frac{TP(l)}{TP(l) + FN(l)}$$

  - where l is a target level

Artificial Neural Network

- Artificial neuron
  - Also called "Perceptron"
  - A set of inputs $\mathbf{x} = [x_1 \quad x_2 \quad \cdots \quad x_n]$ and weights $\mathbf{w} = [w_1 \quad w_2 \quad \cdots \quad w_n]$
  - output $y = f(\mathbf{x}, \mathbf{w})$
  - For example:
    -

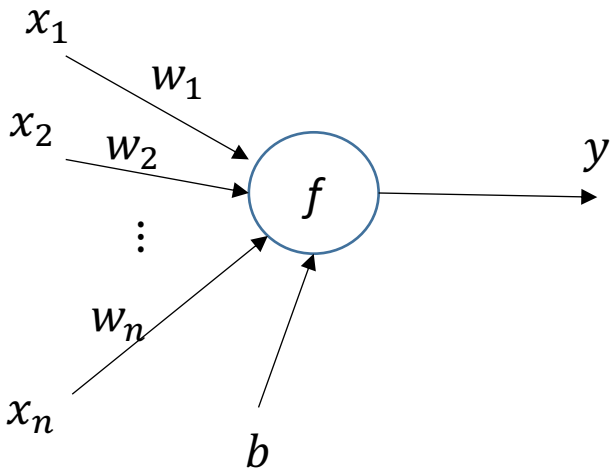
$$f(\mathbf{x}, \mathbf{w}) = \sum_{i=1}^{n} x_i w_i$$



Artificial Neural Network

- Artificial neuron
  - Biased perceptron

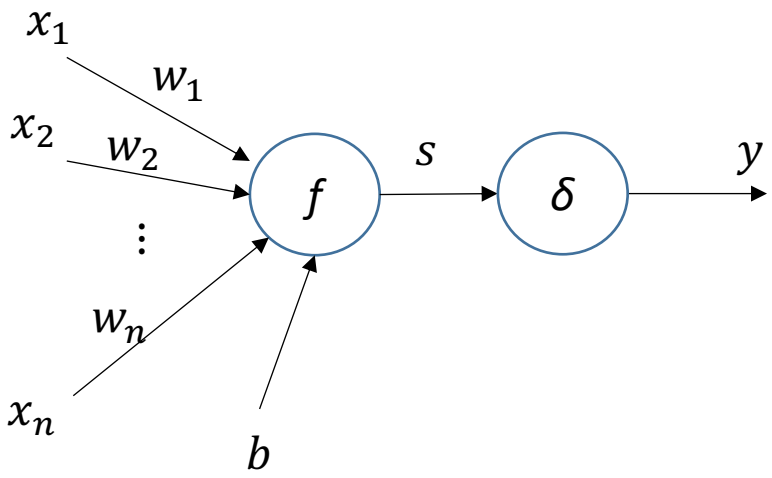
$$f(\mathbf{x}, \mathbf{w}, b) = \sum_{i=1}^{n} x_i w_i + b$$

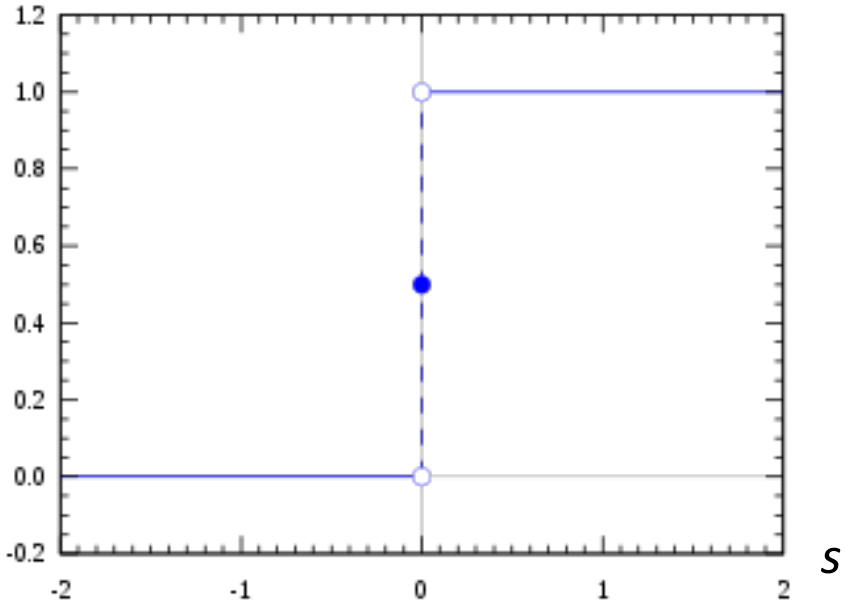


Artificial Neural Network

- Activation functions
  - Step activation

$$y = \delta(s) = \begin{cases} 0 & \text{if } s \leq 0 \\ 1 & \text{if } s > 0 \end{cases}$$



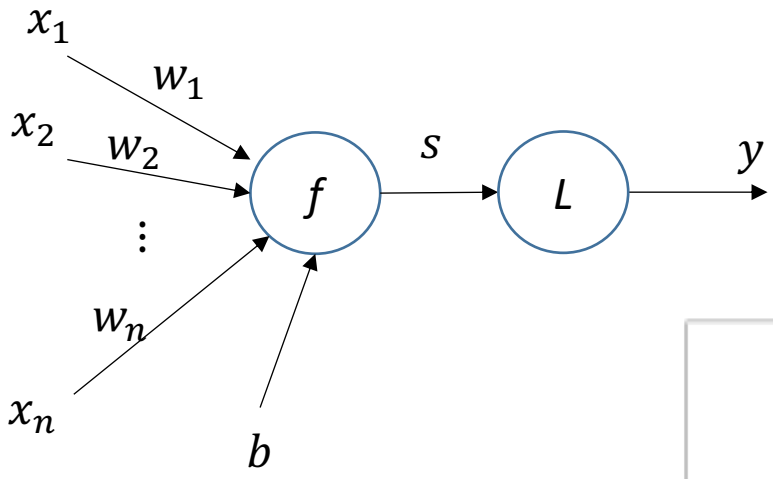


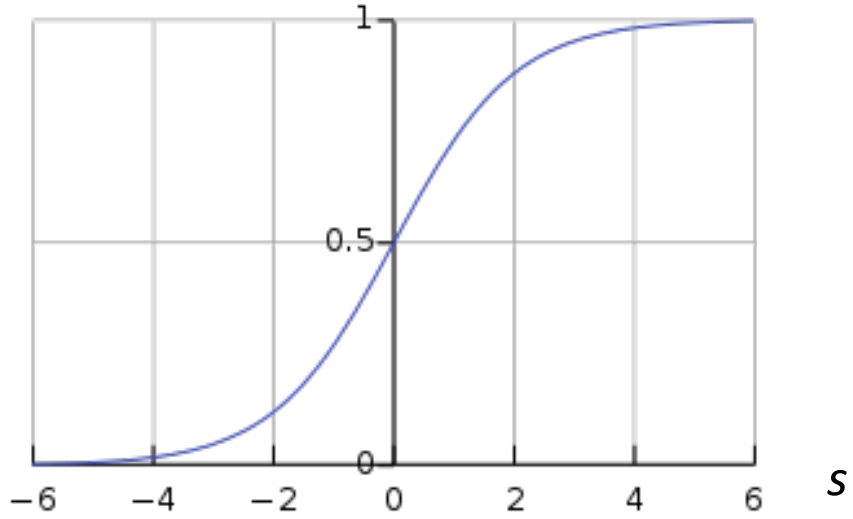
  - where $\delta(y)$ is the step function

Artificial Neural Network

- Activation functions
  - Sigmoid activation

$$y = L(s) = \frac{1}{1 + e^{-s}}$$





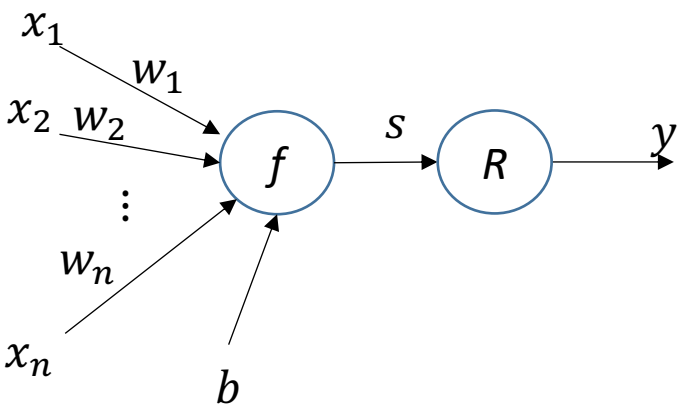
Artificial Neural Network

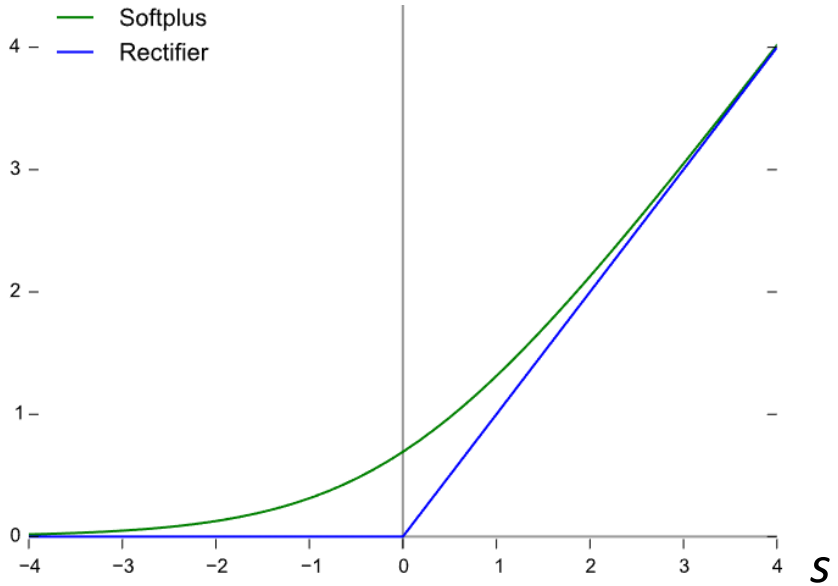
- Activation functions
  - Rectified linear unit, ReLU (or rectifier):

$$y = R(s) = \max(0, s)$$

  - Softplus, a smooth approximation to the ReLU

$$y = SR(s) = \ln(1 + e^s)$$



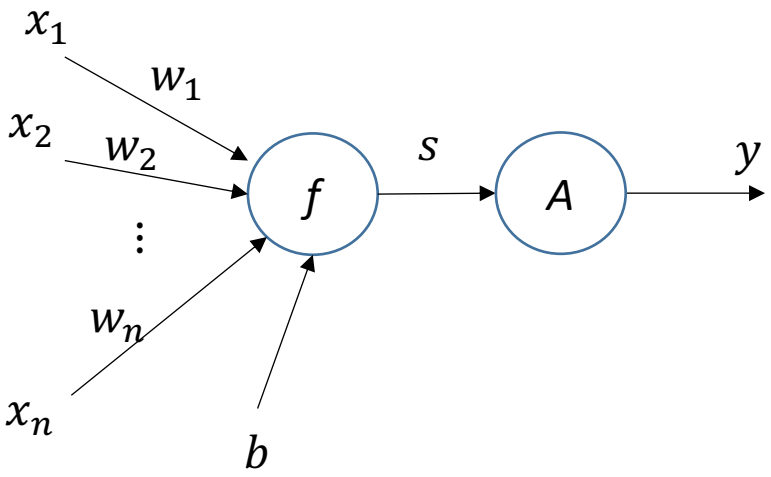


Artificial Neural Network

- Finding the best weights and bias so that the error of output is minimum.
- Error-based machine learning model (logistic model or SVM)
- $X = \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_m\}$, each $\mathbf{x} = \{x_1, x_2, \dots, x_n\}$ has a target result t
- $\mathbf{w} = \{w_1, w_2, \dots, w_n\}$

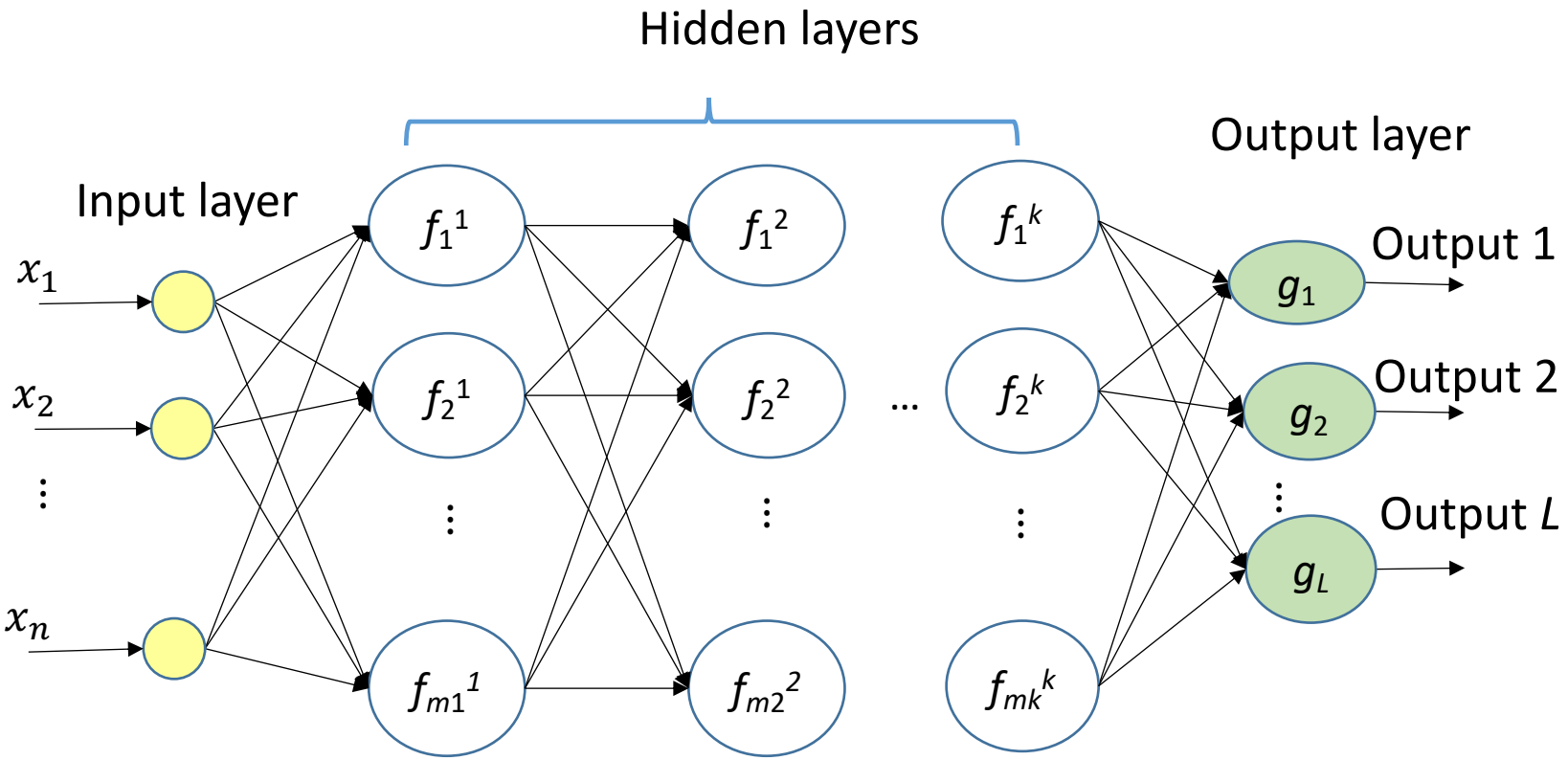
$$\mathbf{w} = \arg\min_{\mathbf{w}'} \sum_{i=1}^{m} E(t_i, y_i)$$

where $E(t, y)$ is the error of t with y.



Artificial Neural Network

- Artificial Neural network, ANN
  - Each circle in the hidden layers and output layer is a neuron
  - Each edge that goes to a neuron represents an input with a weight
  - W. McCulloch and P. Walter, "**A Logical Calculus of Ideas Immanent in Nervous Activity**". *Bulletin of Mathematical Biophysics*. 5 (4): 115–133, 1943.



Artificial Neural Network

- Softmax function
  - To deal with the classification of multicategory

$$P(y_i|\mathbf{x}) = \frac{e^{\mathbf{x}^{\mathrm{T}}\mathbf{w}}}{\sum_{l=1}^{L} e^{\mathbf{x}^{\mathrm{T}}\mathbf{w}_l}}$$

$$y = \arg\max_{y_i} P(y_i|\mathbf{x})$$

Artificial Neural Network

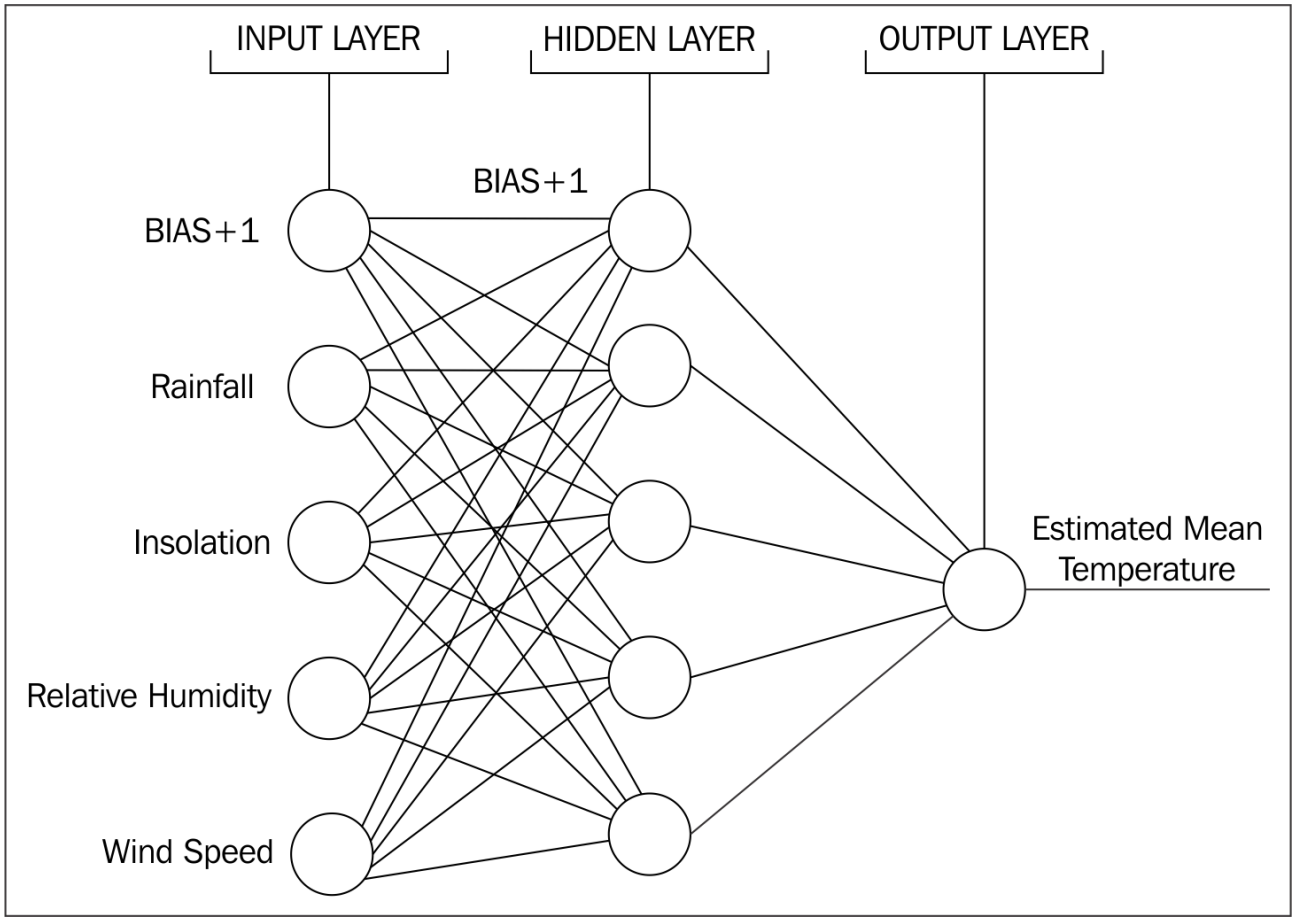
- Deep neural network, DNN
  - Multiple hidden layers
  - The number of hidden layers ≥ 1
  - Also called deep learning neural network
  - Some problem must be solved by DNN, for example XOR problem
    - Marvin Lee Minsky, Seymour Papert, "**Perceptrons: An Introduction to Computational Geometry,**" Mit Press, 1972.

input1	input2	output
1	1	0
1	0	1
0	1	1
0	0	0

Marvin Lee Minsky
1927-2016,
1969 Turing Award winner

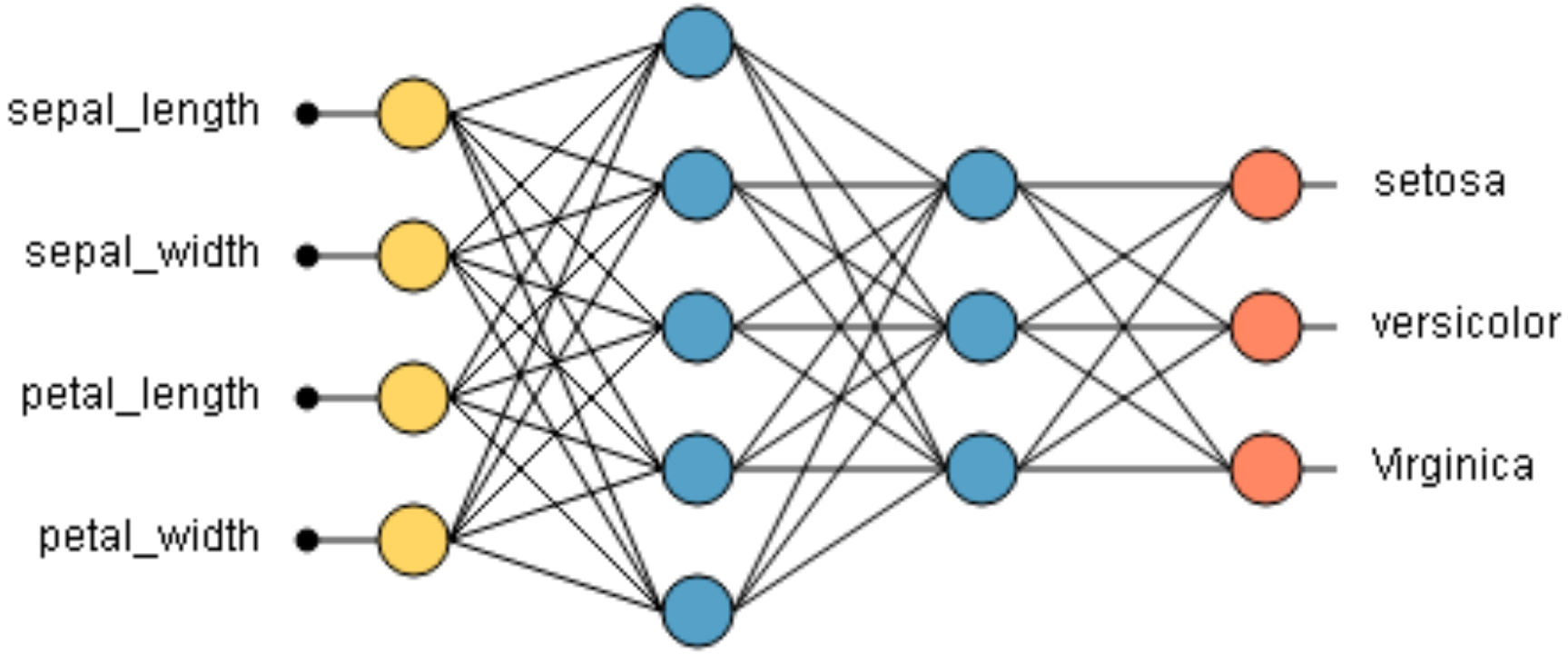
Artificial Neural Network

- Example: Forecasting weather via neural network
  - Fabio Soares and Alan Souza, "Neural Network Programming with Java", Packt, 2016.



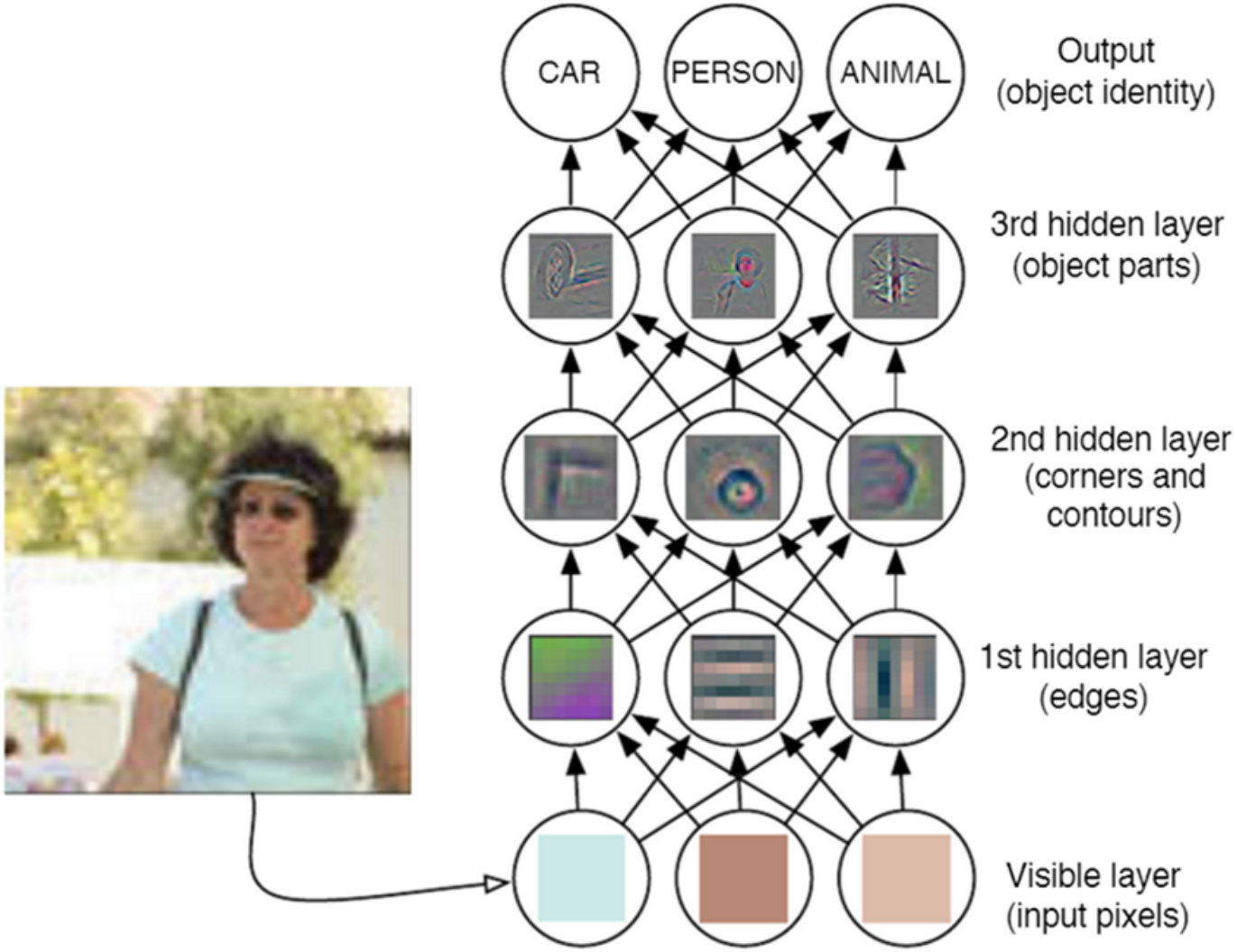
Artificial Neural Network

- Example: Iris flowers
  - Roberto Lopez, "Introduction to neural networks, " Neural Designer.



Artificial Neural Network

- Example: Object recognizing from images
  - I. Goodfellow, Y. Bengio, and A. Courville, "**Deep Learning**," *MIT Press*, 2016.

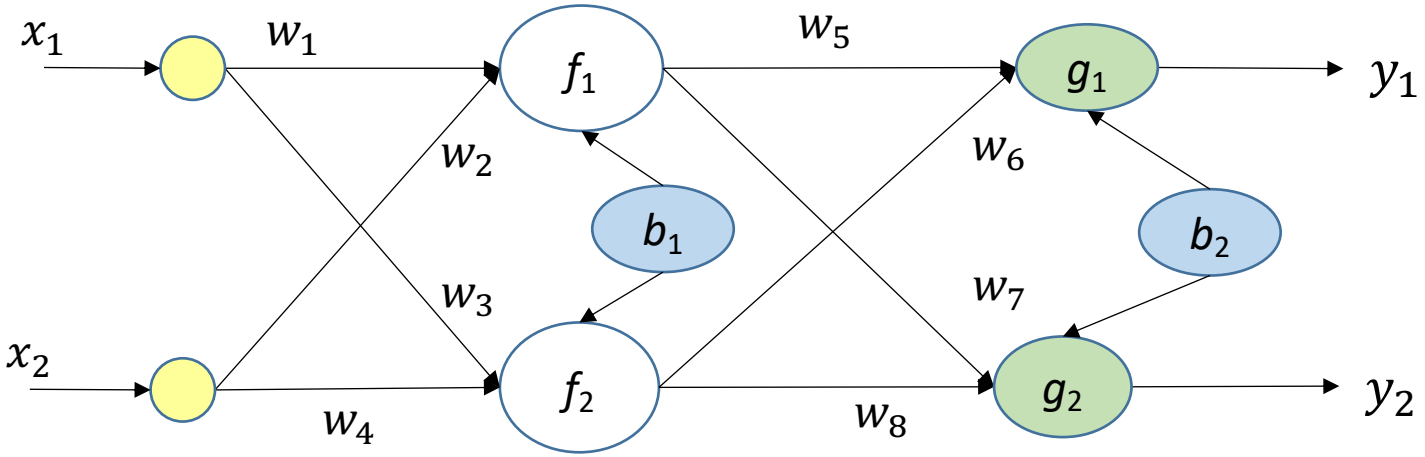


Backpropagation

- How to decide all weights in a neural network?
- We have a training dataset and each training instance has a target result.
- According the errors of the target results with the outputs of neural network to adjust the weights from the last layer to the first layer.

Backpropagation

- Error calculation



$$y_1 = g_1(f_1 w_5 + f_2 w_6 + b_2)$$

$$= g_1(\,(x_1 w_1 + x_2 w_2 + b_1) w_5 + (x_1 w_3 + x_2 w_4 + b_1) w_6 + b_2)$$

$$E = \frac{1}{2}\sum_{i=1}^{2}(t_i - y_i)^2 = \sum_{i=1}^{2} E(t_i, y_i)$$

Backpropagation

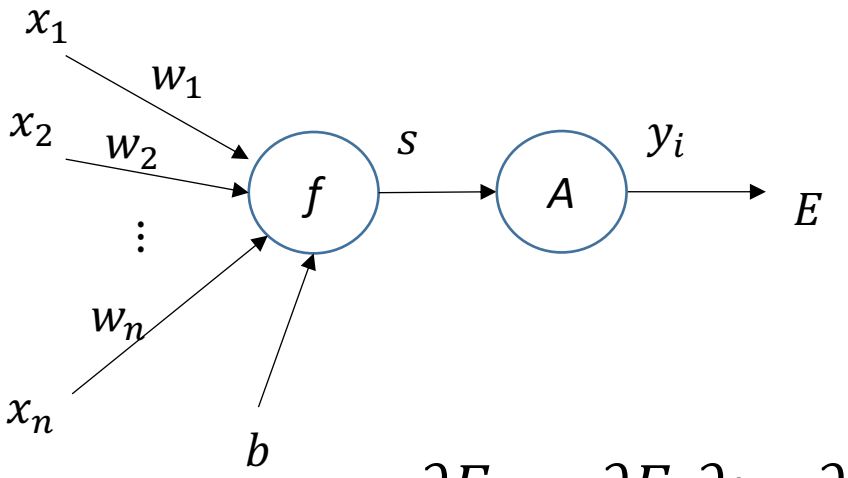
- From the last layer to the first layer

1. Estimate the partial derivative of E with respect to w_i.
2. Then apply gradient descent to update the weight w_i
3. Repeat step 1.

$$\frac{\partial E}{\partial w_5} \Rightarrow \text{update } w_5 \Rightarrow \frac{\partial E}{\partial w_6} \Rightarrow \text{update } w_6 \Rightarrow$$
$$\frac{\partial E}{\partial w_7} \Rightarrow \text{update } w_7 \Rightarrow \frac{\partial E}{\partial w_8} \Rightarrow \text{update } w_8 \Rightarrow$$
$$\frac{\partial E}{\partial w_1} \Rightarrow \text{update } w_1 \Rightarrow \frac{\partial E}{\partial w_2} \Rightarrow \text{update } w_2 \Rightarrow$$
$$\frac{\partial E}{\partial w_3} \Rightarrow \text{update } w_3 \Rightarrow \frac{\partial E}{\partial w_4} \Rightarrow \text{update } w_4$$

Backpropagation

- For the output layer



$$\frac{\partial E}{\partial w_j} = \frac{\partial E}{\partial y_i}\frac{\partial y_i}{\partial s}\frac{\partial s}{\partial w_j}$$

- Applying the gradient descent

$$\Delta w_j = -\frac{\partial E}{\partial w_j}$$

Backpropagation

- Since

$$\frac{\partial E}{\partial y_i} = \frac{\partial(\frac{1}{2}\sum_{i=1}^{h}(t_i - y_i)^2)}{\partial y_i} = \frac{\partial E(t_i, y_i)}{\partial y_i} = -(t_i - y_i) = y_i - t_i$$

- Assuming that *A* is a logistic function = *L*(s)

$$\frac{\partial y_i}{\partial s} = \frac{\partial L(s)}{\partial s} = L(s)(1 - L(s))$$

- And

$$\frac{\partial s}{\partial w_j} = \frac{\partial(\sum_{i=1}^{n} x_i w_i + b)}{\partial w_j} = x_j$$

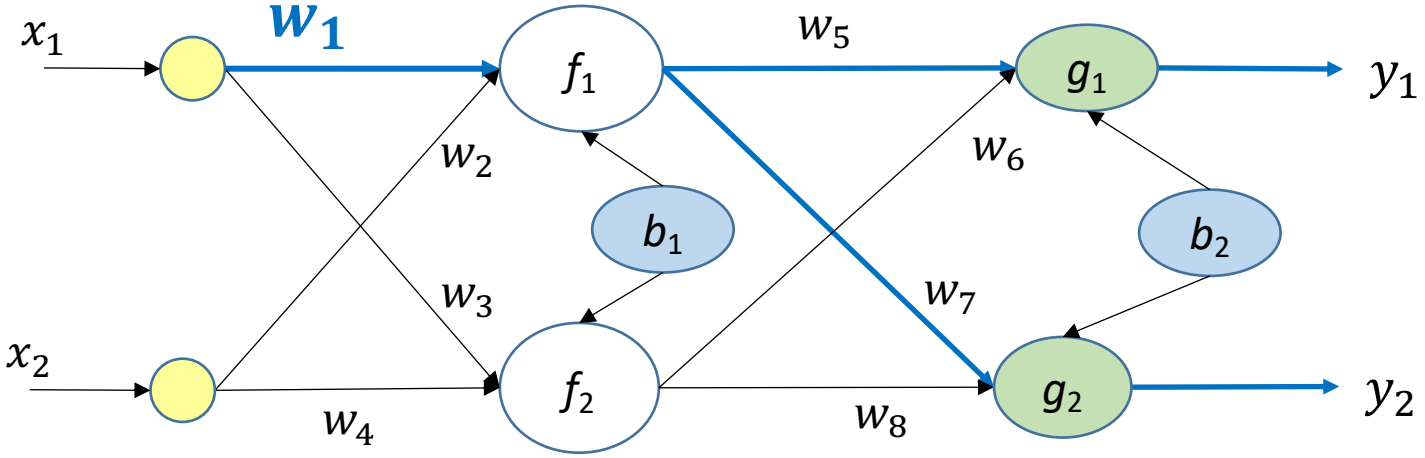
Backpropagation

- Therefore,

$$\Delta w_j = -\frac{\partial E}{\partial w_j} = -(y_i - t_i)L(s)(1 - L(s))x_j$$

Backpropagation

- For hidden layers



$$\frac{\partial E}{\partial w_1} = \frac{\partial E}{\partial f_1}\frac{\partial f_1}{\partial w_1}$$

Chain rule

$$= \left(\frac{\partial E(t_1, y_1)}{\partial f_1} + \frac{\partial E(t_2, y_2)}{\partial f_1}\right)\frac{\partial f_1}{\partial w_1}$$

Backpropagation

- For hidden layers

$$\frac{\partial E(t_1, y_1)}{\partial f_1} = \frac{\partial s_1}{\partial f_1} \frac{\partial E(t_1, y_1)}{\partial s_1}$$

$$= \frac{\partial (f_1 w_5 + f_2 w_6 + b_2)}{\partial f_1} \frac{\partial E(t_1, y_1)}{\partial s_1}$$

$$= w_5 \frac{\partial E(t_1, y_1)}{\partial y_1} \frac{\partial y_1}{\partial s_1}$$

These are calculated before

Backpropagation

- A neuron in hidden layer may has the logistic activation

$$\frac{\partial f_1}{\partial w_1} = \frac{\partial f_1}{\partial r_1}\frac{\partial r_1}{\partial w_1} = L(r_1)(1 - L(r_1))x_1$$

- Therefore,

$$\Delta w_1 = -\frac{\partial E}{\partial w_1} = \frac{\partial E}{\partial f_1}\frac{\partial f_1}{\partial w_1}$$

$$= \left(\frac{\partial E(t_1, y_1)}{\partial f_1} + \frac{\partial E(t_2, y_2)}{\partial f_1}\right)L(r_1)(1 - L(r_1))x_1$$

  - where

$$\frac{\partial E(t_1, y_1)}{\partial f_1} = w_5 \frac{\partial E(t_1, y_1)}{\partial y_1}\frac{\partial y_1}{\partial s_1}$$

$$\frac{\partial E(t_2, y_2)}{\partial f_1} = w_7 \frac{\partial E(t_2, y_2)}{\partial y_2}\frac{\partial y_2}{\partial s_1}$$

Backpropagation

- Vanishing gradient problem
  - In the final layer *k*, $\frac{\partial E}{\partial w_j^k}$ is large ➔ OK!
  - In (*k* – 1)th layer, $\frac{\partial E}{\partial w_j^{k-1}}$ is smaller than $\frac{\partial E}{\partial w_j^k}$ ➔ Still OK!
  - …
  - In the first layer, $\frac{\partial E}{\partial w_j^1}$ is closed to zero ➔ Not OK!
  - The sigmoid activation may cause this problem

$$0 \leq \frac{\partial L(s)}{\partial s} = L(s)\big(1 - L(s)\big) \leq 0.25$$

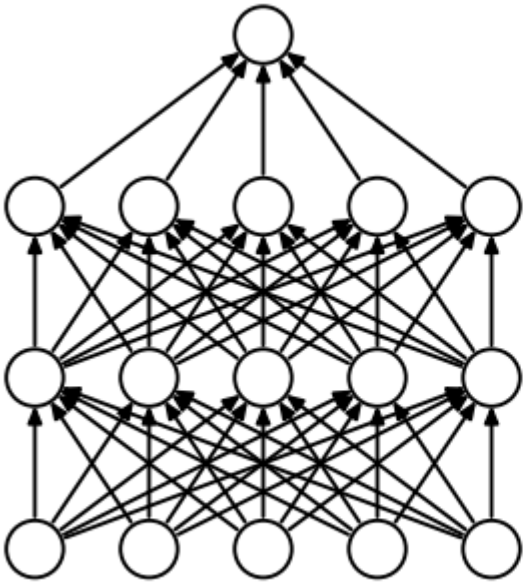
  - Using ReLU can solve this problem

$$\frac{\partial R(s)}{\partial s} = \begin{cases} 1 & s \geq 0 \\ 0 & s < 0 \end{cases}$$

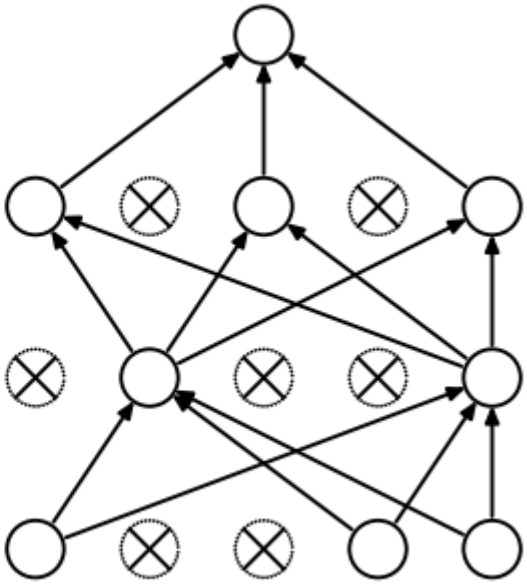
Dropout

- N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, "Dropout: A Simple Way to Prevent Neural Networks from Overfitting," JMLR, vol. 15, pp. 1929-1958, 2014.
- Some problems of a neural network
  - High computational cost
  - Overfitting
- At each round of training
  - Each unit is retained with a probability p.
  - Typically, p is 0.5
- At test time
  - The network is used as a whole.
  - The weights are multiplied by a factor of p.

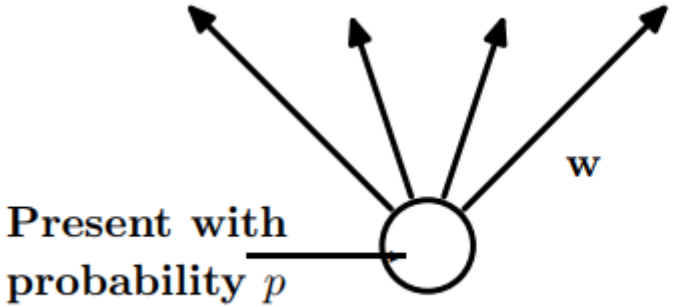
Dropout



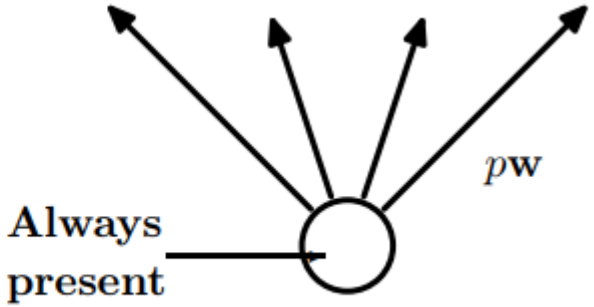
(a) Standard Neural Net



(b) After applying dropout.



(a) At training time



(b) At test time

N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, "Dropout: A Simple Way to Prevent Neural Networks from Overfitting," JMLR, vol. 15, pp. 1929-1958, 2014

Early Stopping

- When training a learner with a iterative method
  - Too few epochs ➔ underfitting
  - Too many epochs ➔ overfitting
- Stop the learner from overfitting
- Validation-based early stopping
  1. Split the training data into a training set and a validation set, e.g. in a 2-to-1 proportion.
  2. Train only on the training set and evaluate the per-example error on the validation set once in a while, e.g. after every fifth epoch.
  3. Stop training as soon as the error on the validation set is higher than it was the last time it was checked.
  4. Use the weights the network had in that previous step as the result of the training run.

DNN in TensorFlow

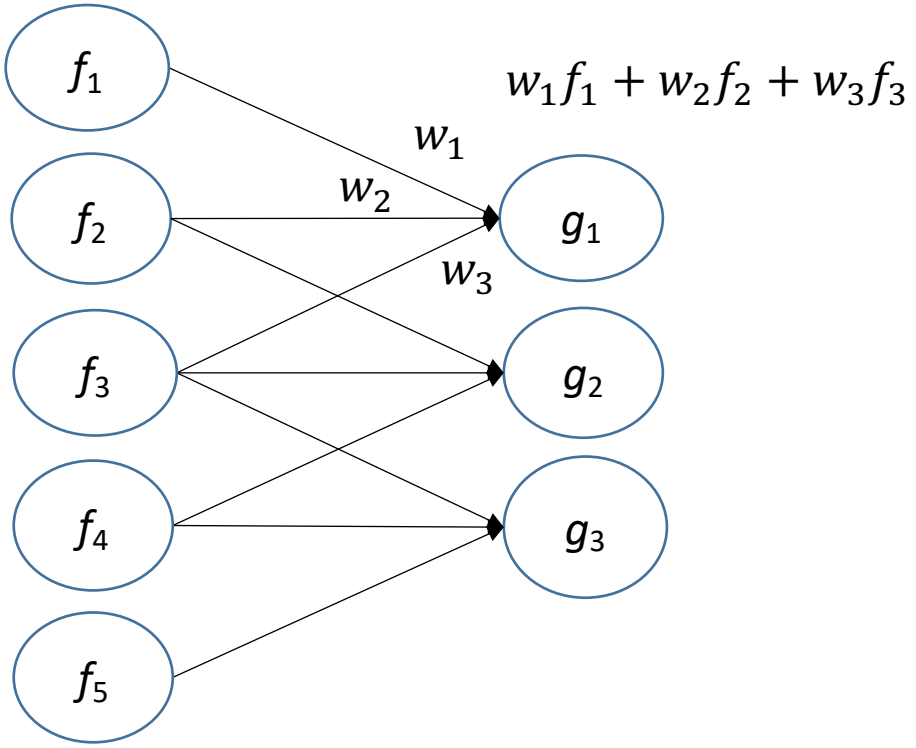
- An example of MNIST:
  - https://github.com/jameschengcs/ml/blob/master/dnn_mnist.py

Convolutional Neural Network, CNN

- Fully-connected neural network
  - In a fully connected layer, each neuron is connected to every neuron in the previous layer, and each connection has it's own weight.
  - General purpose connection pattern
  - No assumptions about the features
  - High consumption of memory (weights) and computation (connections).

Convolutional Neural Network, CNN

- In a convolutional layer
  - Each neuron only connected form a set of related neurons in the previous layer
  - Locality relation
  - Shared weights
    - Each neuron using the same weights for the input

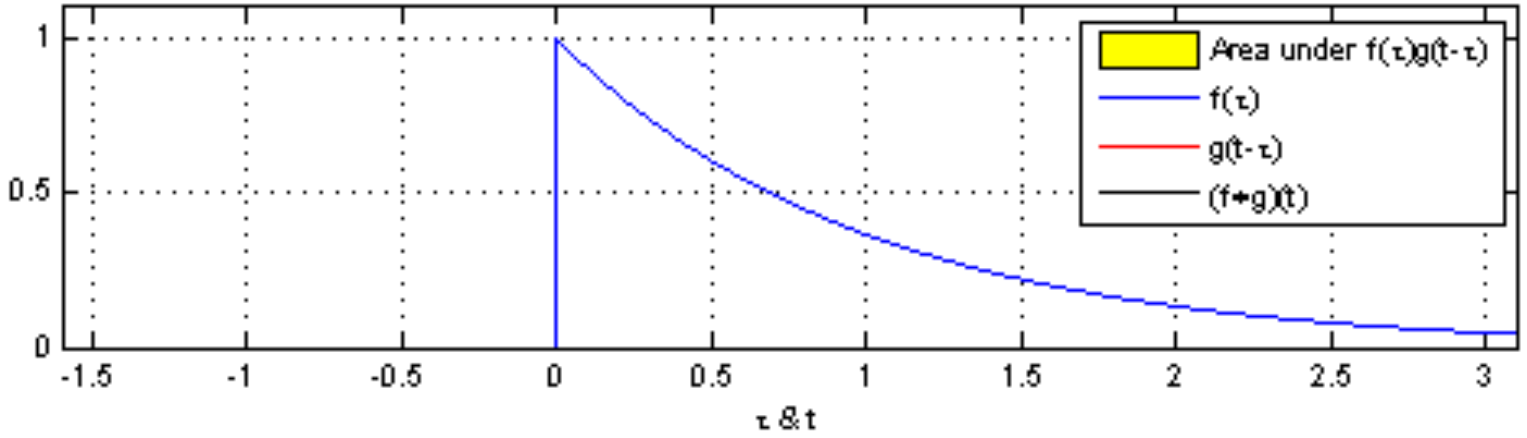


Convolutional Neural Network, CNN

- Convolution

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau) g(t - t) d\tau$$

  - *g* is called **convolution kernel, operator, or mask.**



Convolutional Neural Network, CNN

- Discrete convolution

$$(f * g)[n] = \sum_{m=-M}^{M} f[n-m]g[m]$$

  - where *M* is the index range of *g*
  - example:
    - f [-3: 3] = {1, 9, 0, 5, 2, 4, 3}
    - g [-1: 1] = {-2, 0, 2}
    - $(f * g)[2] = f[2 - (-1)]g[-1] + f[2 - 0]g[0] + f[2 - 1]g[1]$

$$= f[3]g[-1] + f[2]g[0] + f[1]g[1]$$

$$= 3(-2) + 4(0) + 2(2)$$

$$= -2$$

Convolutional Neural Network, CNN

- 2D discrete convolution

$$(f * g)[m][n] = \sum_{y=-H}^{H} \sum_{x=-W}^{W} f[m-y][n-x]g[y][x]$$

f[-3:2][-3:2]

1	4	5	8	2	1
0	3	1	5	7	2
1	2	1	4	7	1
2	2	0	3	6	2
0	1	7	3	5	3
1	3	4	1	2	4

f[-3][-3]

g[-1:1][-1:1]

-1	0	1
-2	0	2
-3	0	3

$(f * g)[0][0] = -45$

1(3)	5(0)	7(-3)
1(2)	4(0)	7(-2)
0(1)	3(0)	6(-1)

Convolutional Neural Network, CNN

- Zero padding

f[-3:2][-3:2] ➔ f[-4:3][-4:3]

0	0	0	0	0	0	0	0
0	1	4	5	8	2	1	0
0	0	3	1	5	7	2	0
0	1	2	1	4	7	1	0
0	2	2	0	3	6	2	0
0	0	1	7	3	5	3	0
0	1	3	4	1	2	4	0
0	0	0	0	0	0	0	0

g[-1:1][-1:1]

-1	0	1
-2	0	2
-3	0	3

$(f * g)[2][2] = 11$

0(3)	0(0)	0(-3)
2(2)	1(0)	0(-2)
7(1)	2(0)	0(-1)

Convolutional Neural Network, CNN

- Commonly-used 2D kernels
  - Mean $g(x,y) = \frac{1}{(2H+1)\times(2W+1)}$

1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9

  - Gaussian $g(x,y,\sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$

$\frac{1}{273}$

1	4	7	4	1
4	16	26	16	4
7	26	41	26	7
4	16	26	16	4
1	4	7	4	1

Convolutional Neural Network, CNN

- Commonly-used 2D kernels
  - X derivative, $g_x =$

a	0	-a
b	0	-b
a	0	-a

a = b = 1

1	0	-1
1	0	-1
1	0	-1

  - Y derivative , $g_y =$

-a	-b	-a
0	0	0
a	b	a

a = 2, b = 5

-2	-5	-2
0	0	0
2	5	2

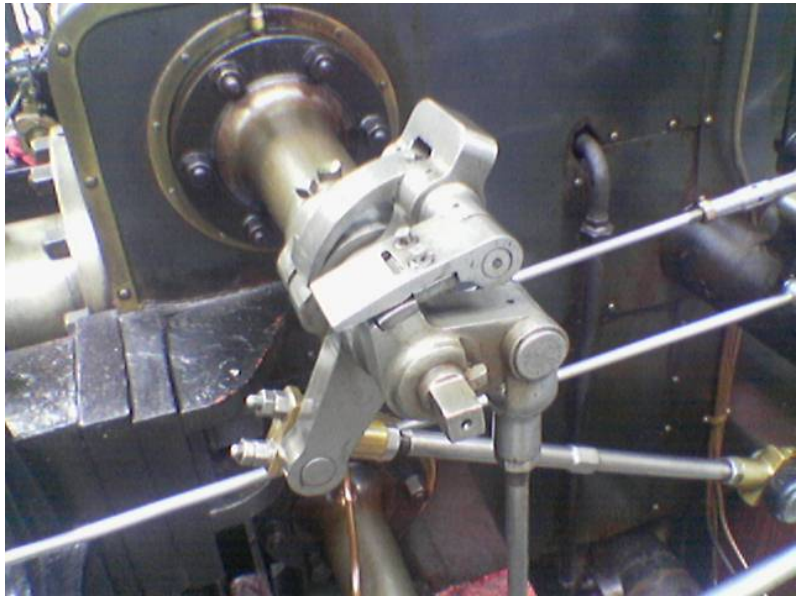
  - Edge detection: $|(f * g_x), (f * g_y)|$
    - Sobel operator

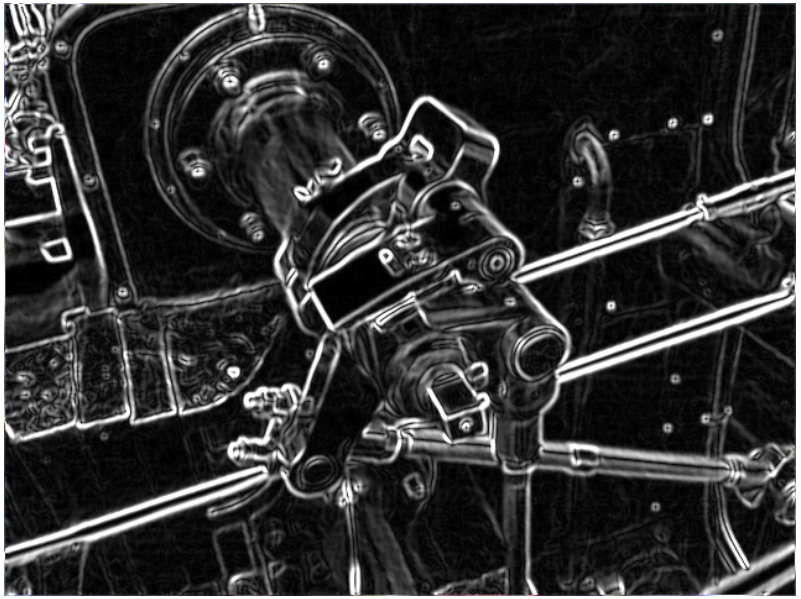
Convolutional Neural Network, CNN

- Convolution in image processing
  - Filtering
  - Gaussian filtering

Convolutional Neural Network, CNN

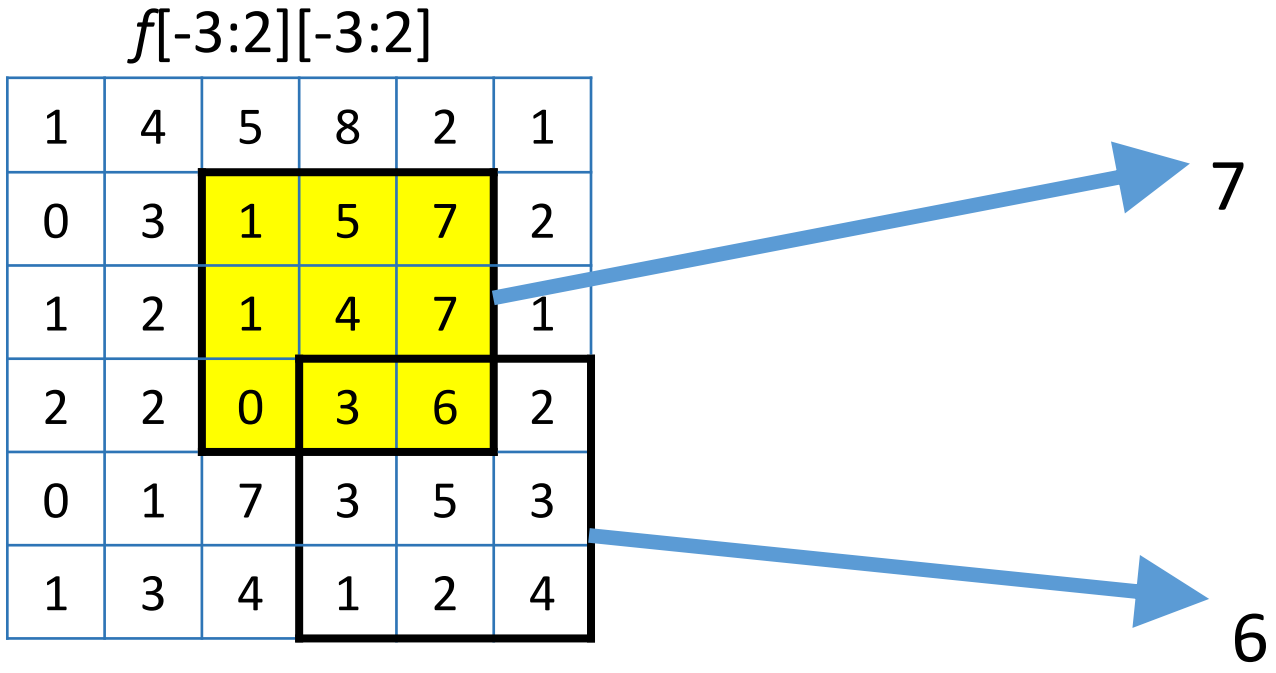
- Convolution in image processing
  - Edge detection (Sobel operator)





Convolutional Neural Network, CNN

- Max pooling
  - Finding the maximum from a masked area



Convolutional Neural Network, CNN

- Stride
  - The step of the convolution operation
  - It affects the output size

Input size: 6 x 6

Kernel size: 3 x 3 (max pooling)

Stride: 1

1	4	5	8	2	1
0	3	1	5	7	2
1	2	1	4	7	1
2	2	0	3	6	2
0	1	7	3	5	3
1	3	4	1	2	4

Output size: 4 x 4

5	8	8	8
3	5	7	7
7	7	7	7
7	7	7	6

Convolutional Neural Network, CNN

- Stride

Input size: 6 x 6

Kernel size: 3 x 3 (max pooling)

Stride: 3

1	4	5	8	2	1
0	3	1	5	7	2
1	2	1	4	7	1
2	2	0	3	6	2
0	1	7	3	5	3
1	3	4	1	2	4

Output size: 2 x 2

5	8
7	6

Open Dataset for AI

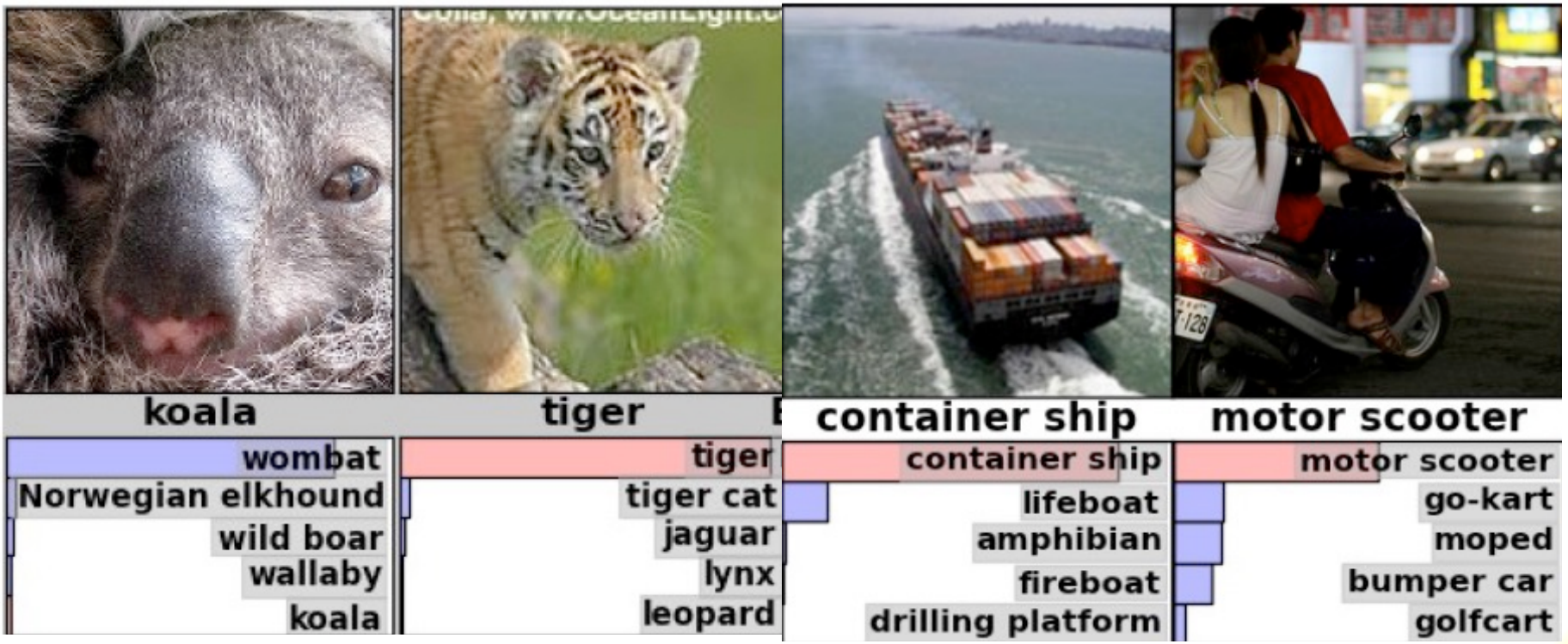
- Images
  - Imagenet
    - http://image-net.org/index
  - COCO
    - http://cocodataset.org/#home
  - Caltech101
    - http://www.vision.caltech.edu/Image_Datasets/Caltech101/
- Others:
  - http://deeplearning.net/datasets/

CNN in Tensorflow

- An example of MNIST
  - https://github.com/jameschengcs/ml/blob/master/cnn_mnist.py

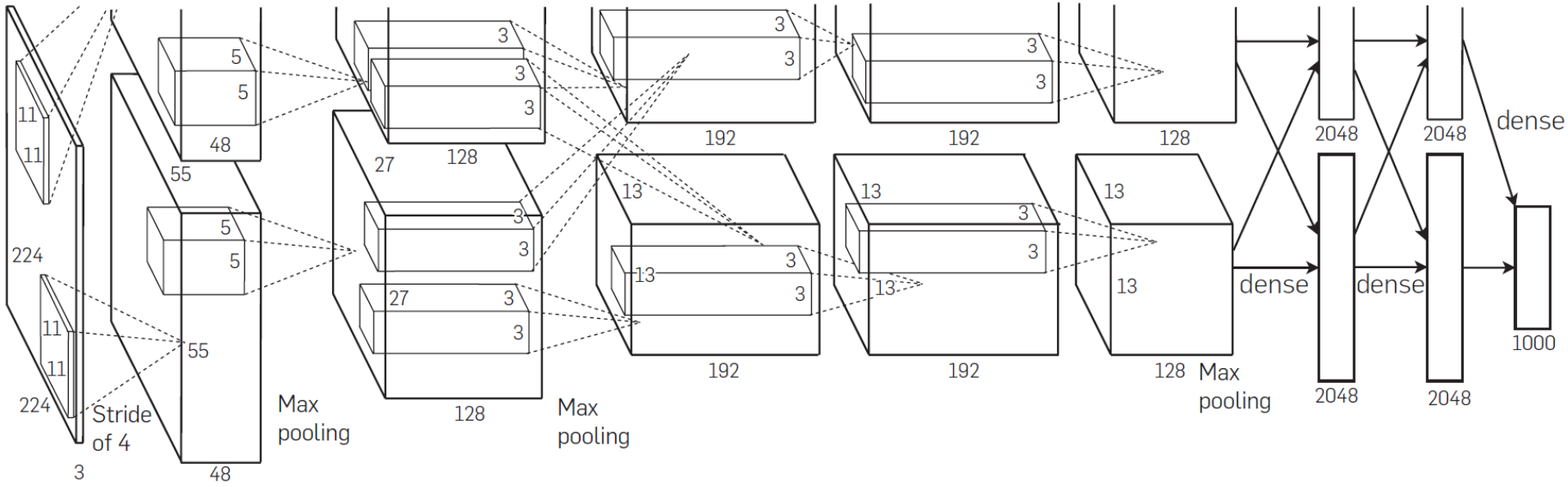
Convolutional Neural Network, CNN

- Example 1: Image classification
  - Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton. 2017. **ImageNet classification with deep convolutional neural networks**. *Commun. ACM* 60, 6 (May 2017), 84-90.
  - Using CNN to classify the 1.2 million high-resolution images



Convolutional Neural Network, CNN

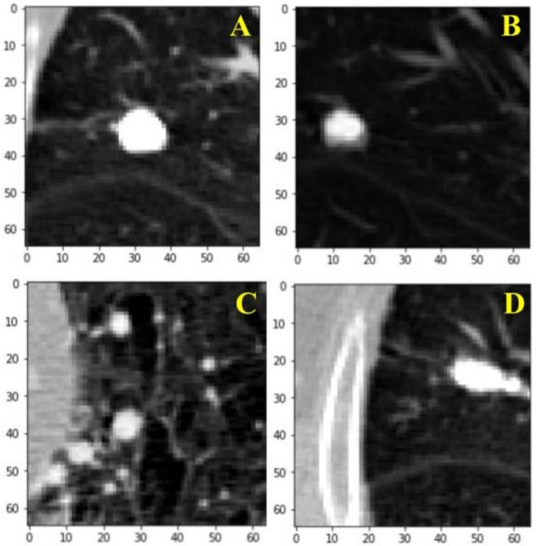
- Example 1: Image classification

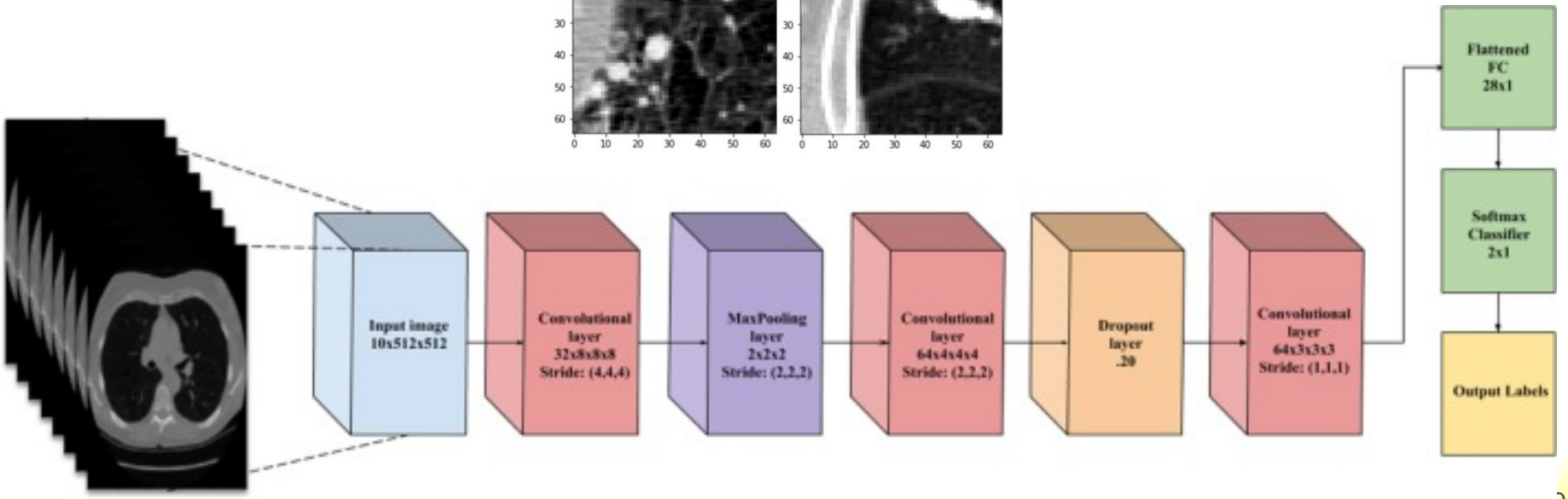


- In the first convolution layer
  - Number of kernels: 96
  - Kernel size: 11 x 11
  - Stride: 4 ➔(0, 4, 8, …, 220)
  - Zero padding
  - ➔ output size: 55 x 55 x 96

Convolutional Neural Network, CNN

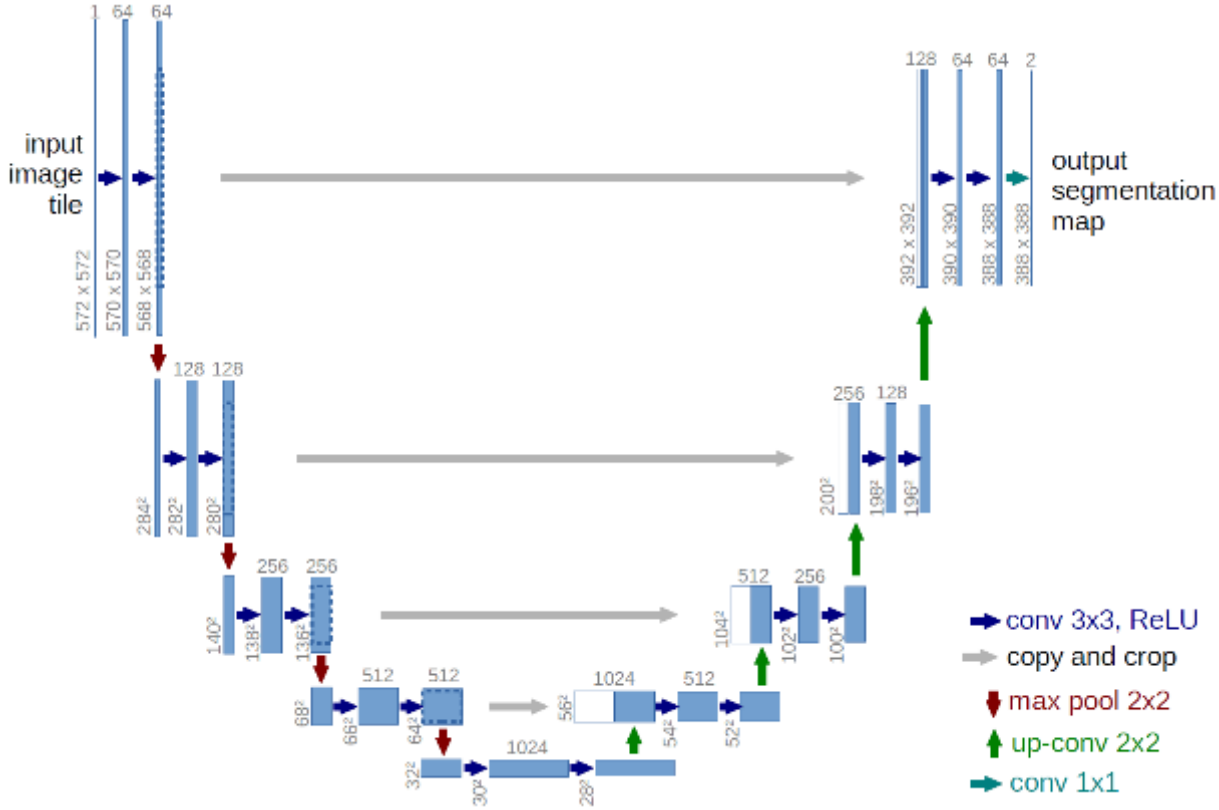
- Lung nodule detection from low-dose CT
  - Ali, Issa et al. “Lung Nodule Detection via Deep Reinforcement Learning.” *Frontiers in Oncology* 8 (2018): 108. PMC. Web. 23 Aug. 2018.





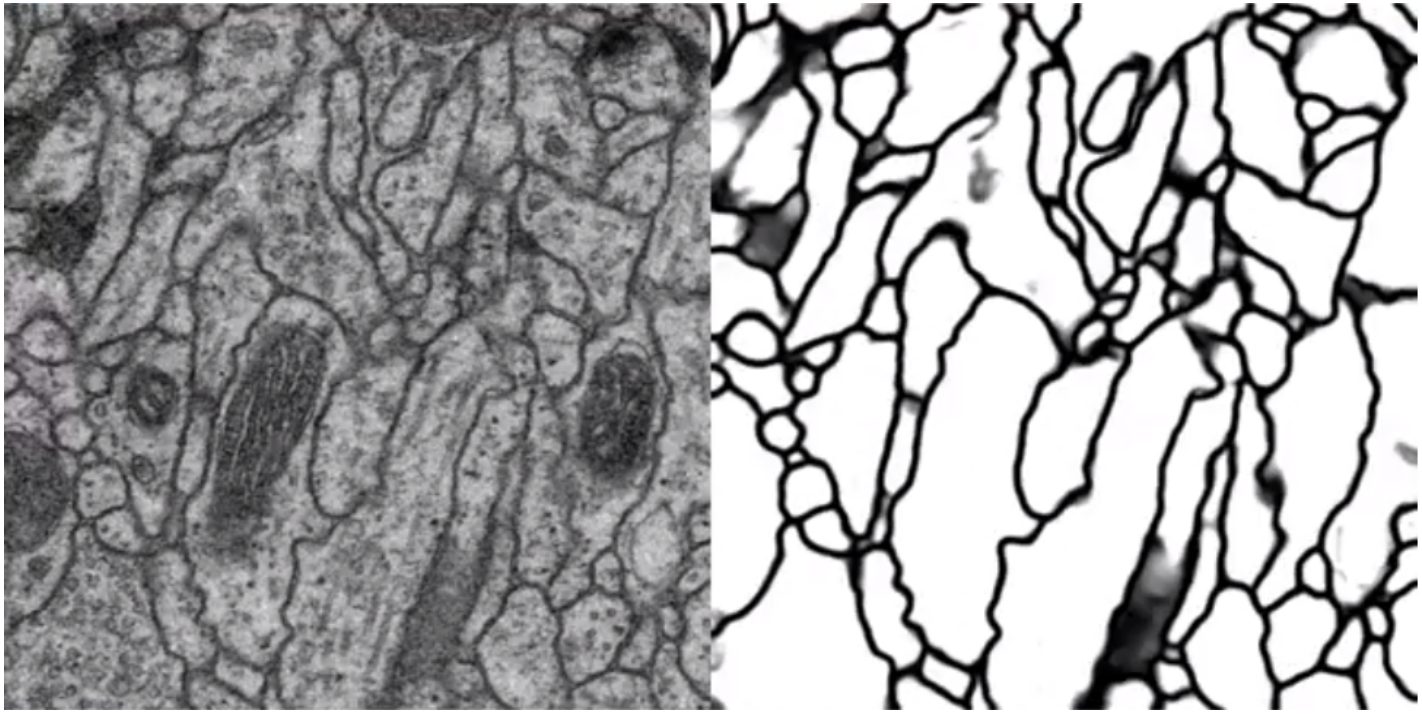
U-Net

- The u-net is a CNN for fast and precise segmentation of images.
  - O. Ronneberger, et al., "**U-Net: Convolutional Networks for Biomedical Image Segmentation**, " *Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, Springer, LNCS, Vol.9351: pp. 234-241, 2015.



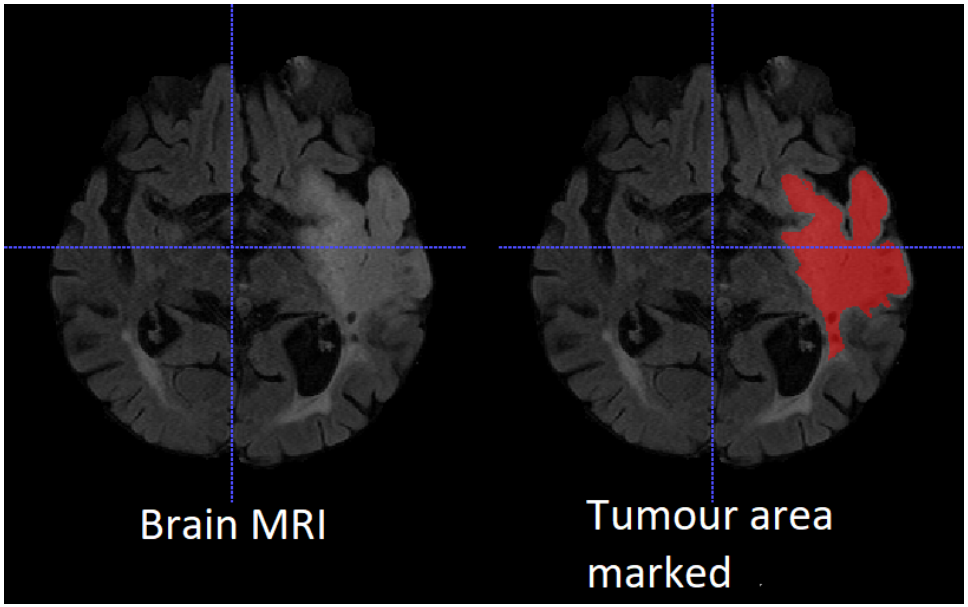
U-Net

- Segmentation of neuronal structure in EM



U-Net

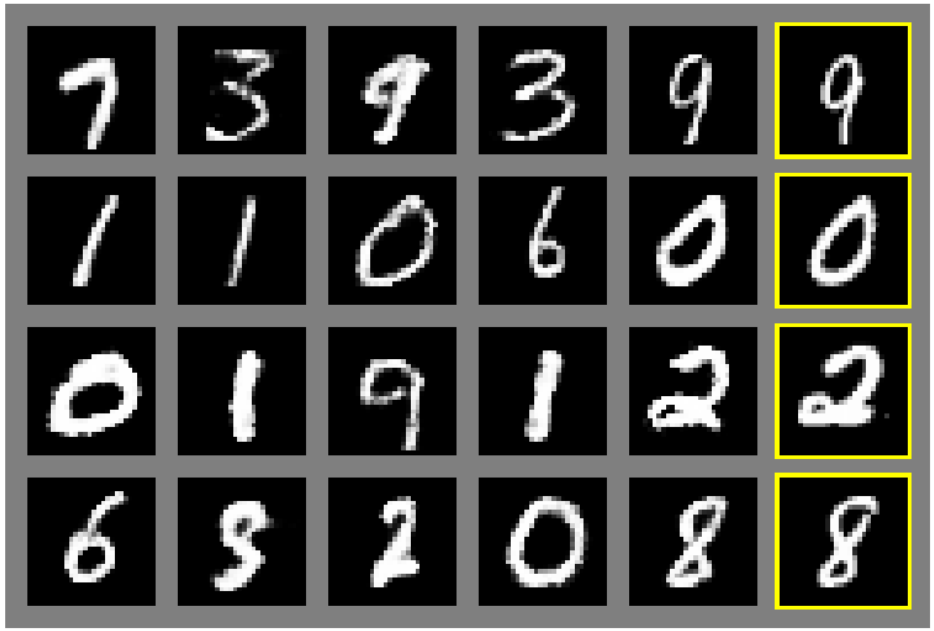
- Philipp Schnell, "Automated Brain Tumour Segmentation based on MR Images using U-Net and its application for Mutation Status Prediction"



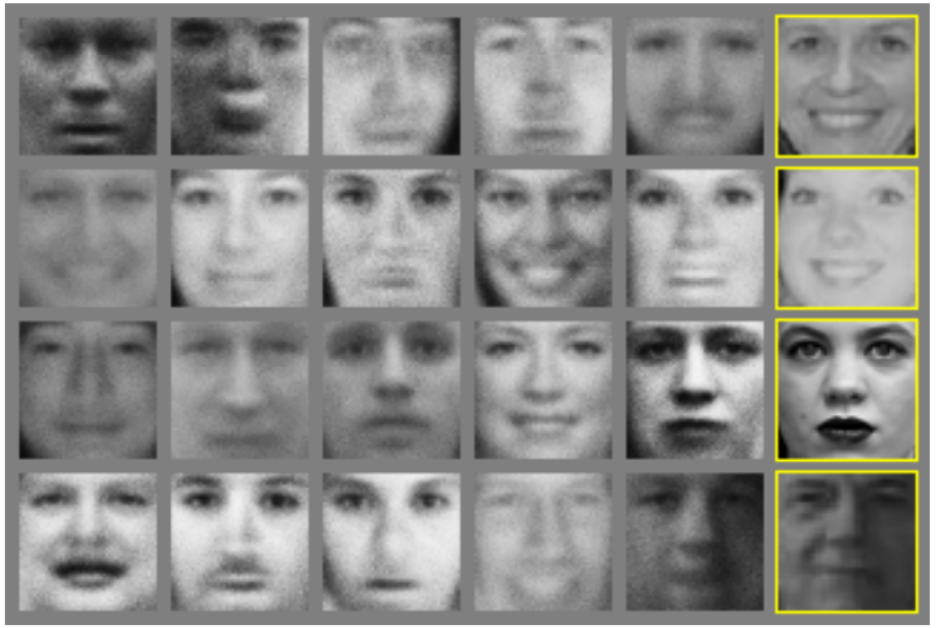
GAN

- GAN, Generative Adversarial Network
  - Ian J. Goodfellow et. al, "Generative Adversarial Networks," arXiv, Jun. 2014.

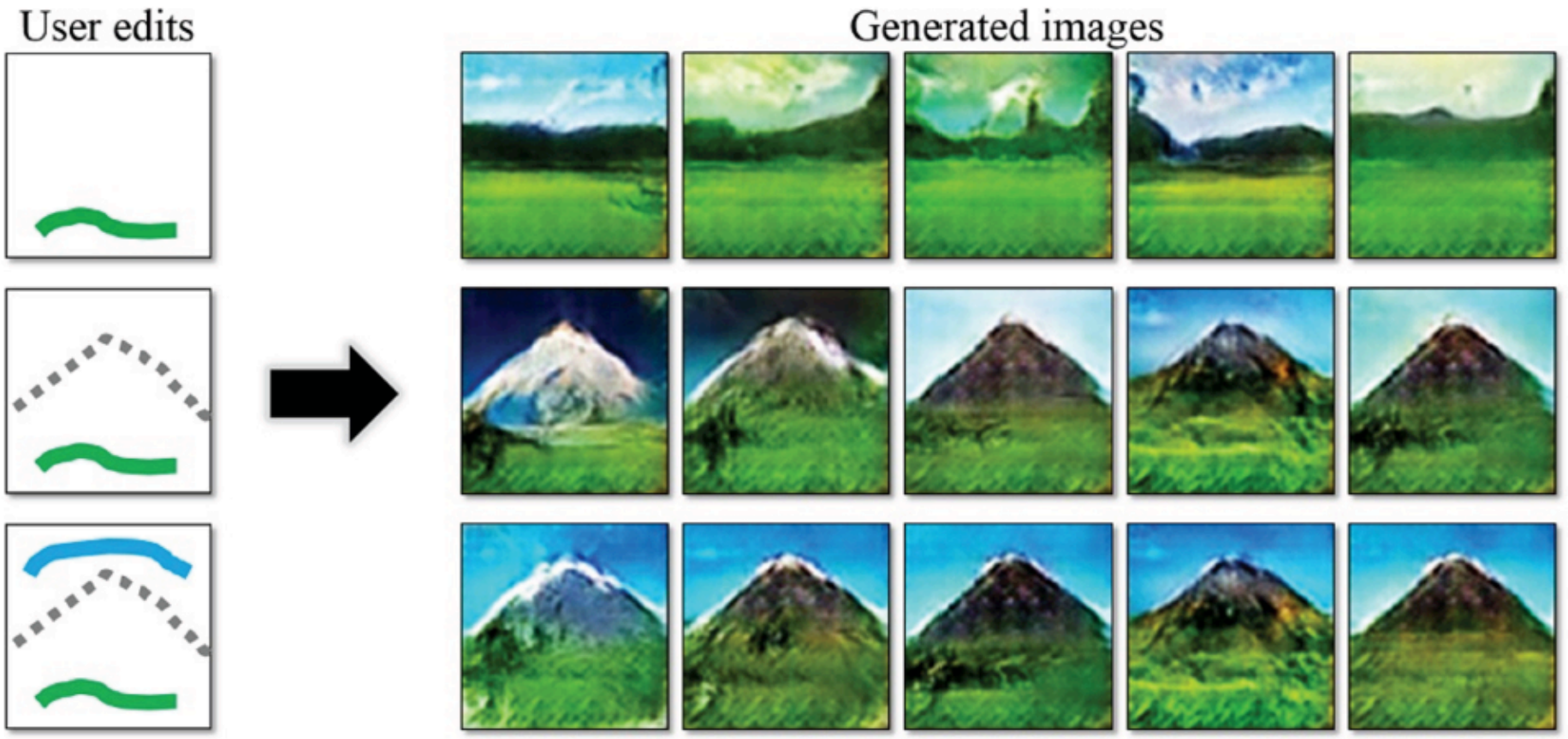
Real data ↓



Real data ↓



GAN



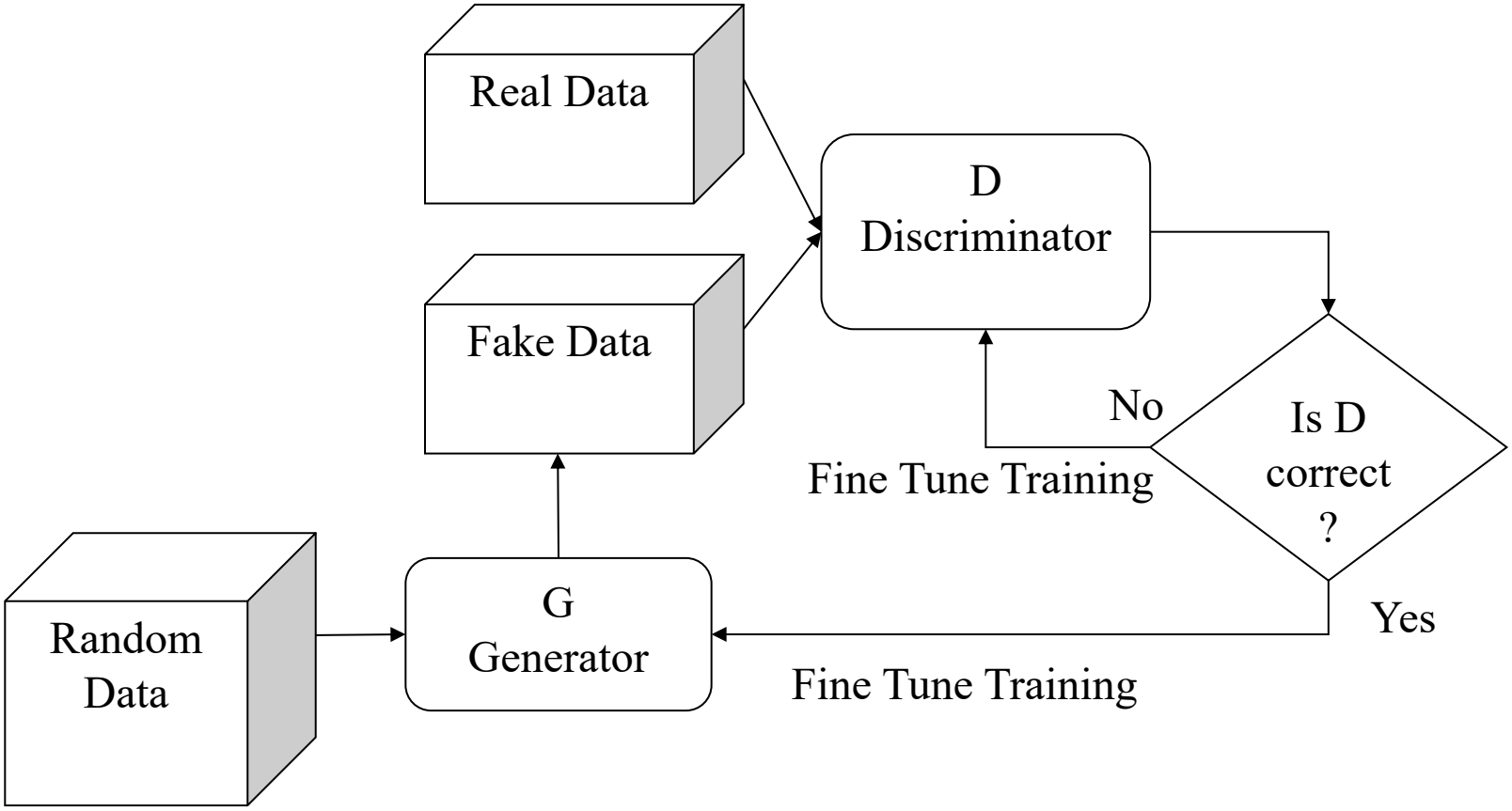
http://people.eecs.berkeley.edu/~junyanz/projects/gvm/

GAN

- Generative
  - Learn a generative model
- Adversarial
  - Trained in an adversarial setting

GAN

- Architecture



GAN

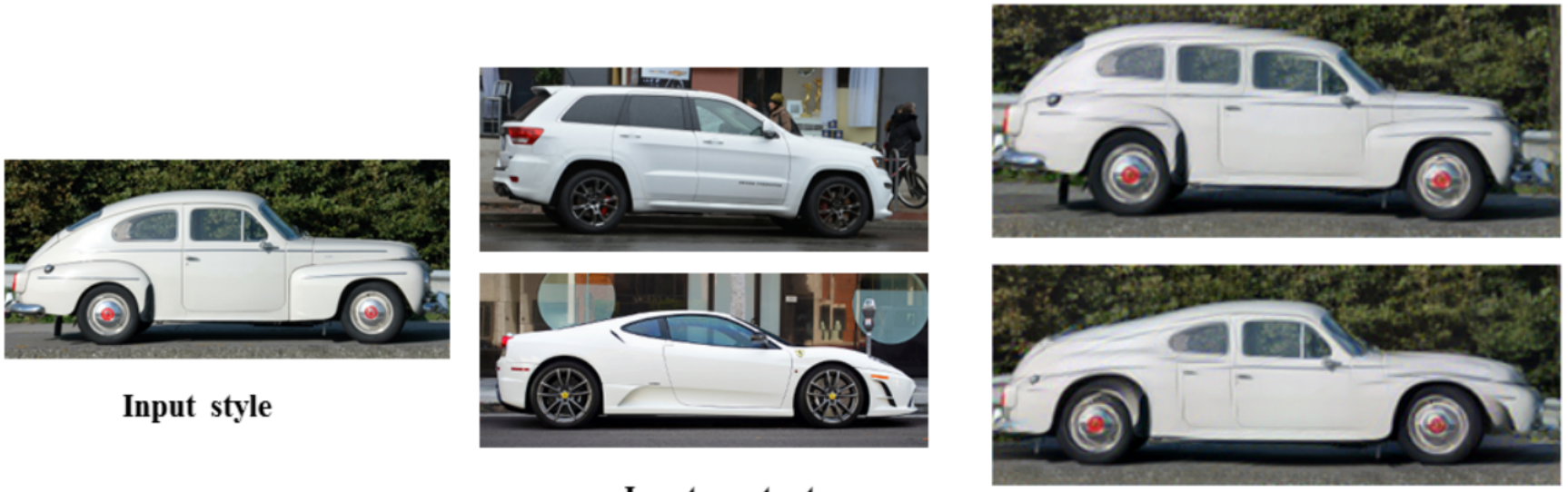
- Model

$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))]$$

Image Synthesis by AI

- C. Li and M. Wand, "Combining Markov Random Fields and Convolutional Neural Networks for Image Synthesis," *arXiv*, 2016.

Input A | Input B | Content A + Style B | Content B + Style A



Input style

Input content

Image Synthesis by AI

- A. Brock, J. Donahue, and K. Simonyan, "Large Scale GAN Training for High Fidelity Natural Image Synthesis," *ICLR 2019*.

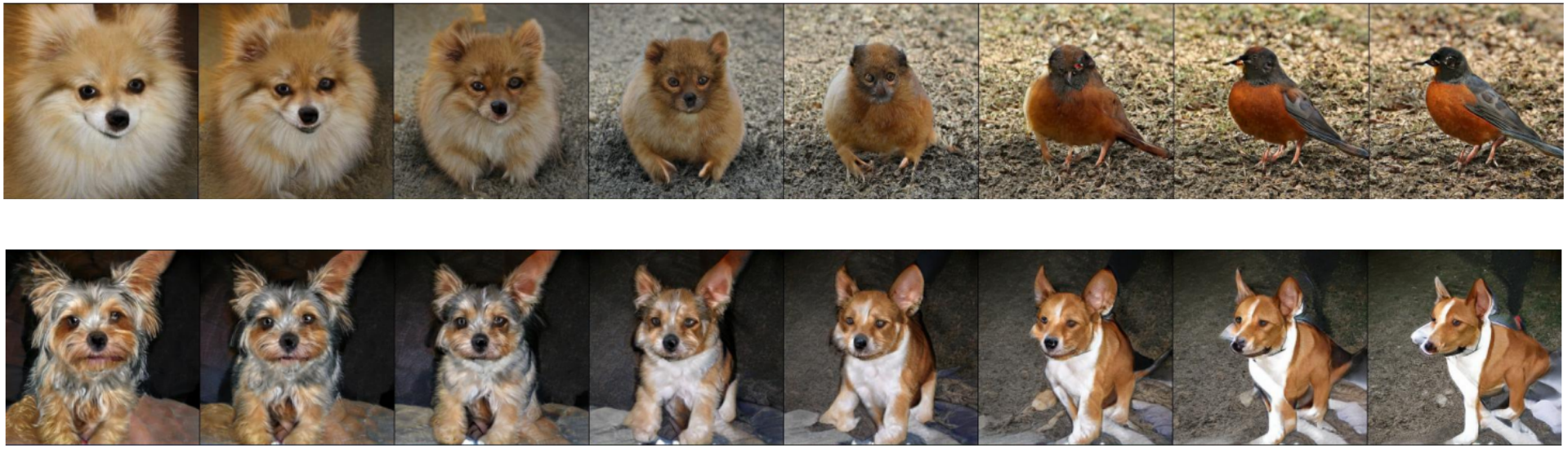


Image Synthesis by AI

- J.Y. Z, T. Park, P. Isola, and A. A. Efros, "Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks," ICCV 2017.

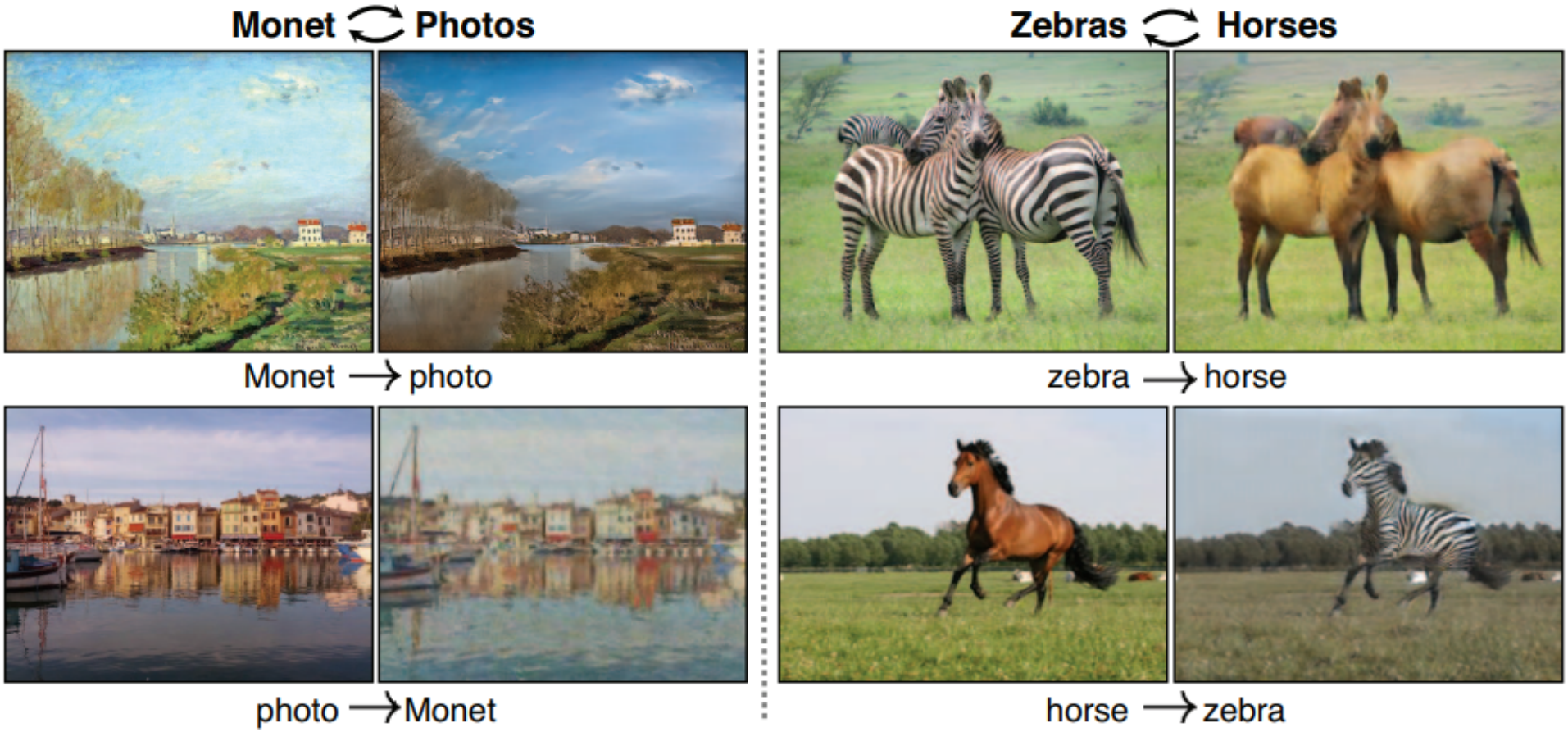
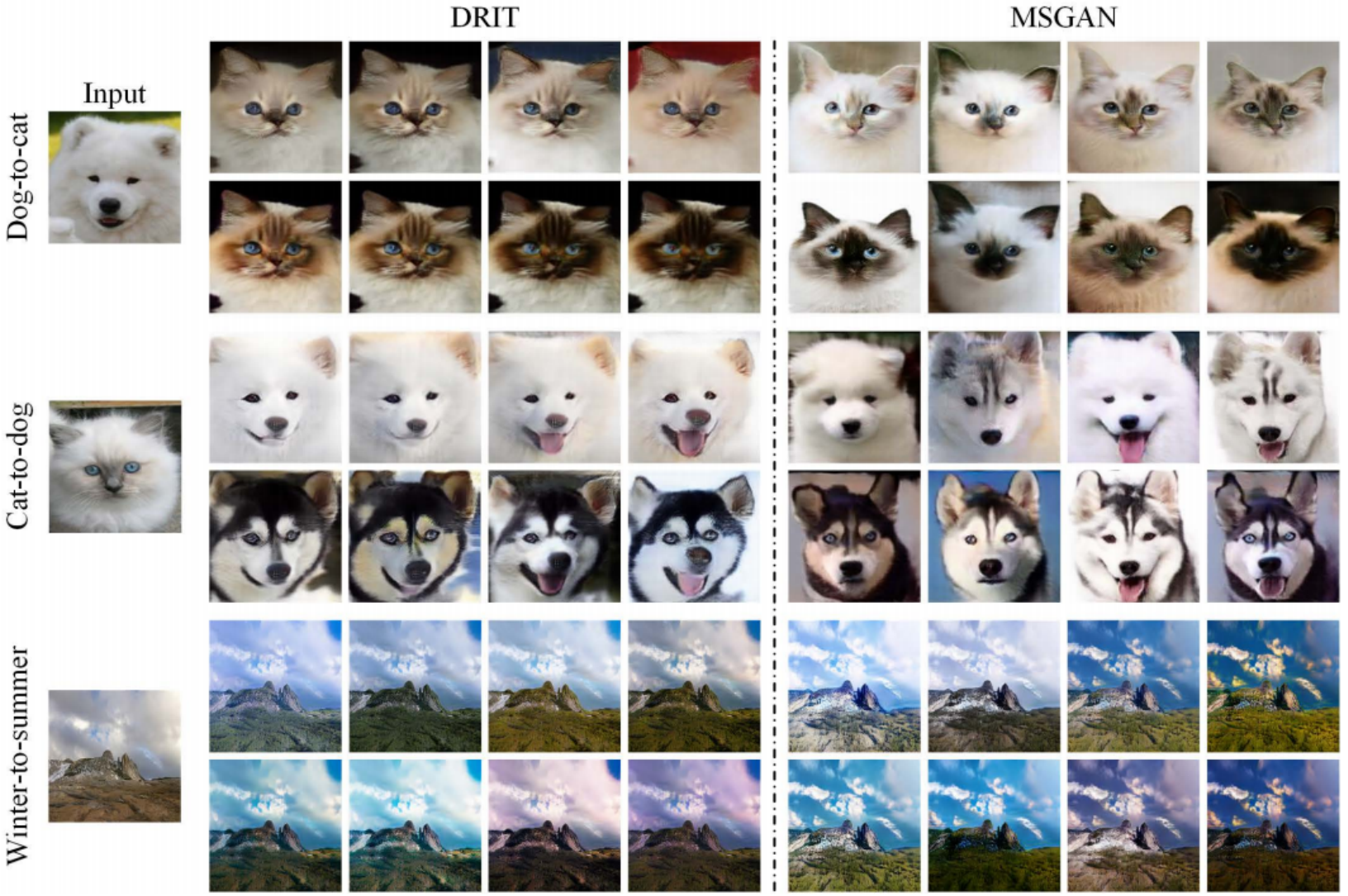


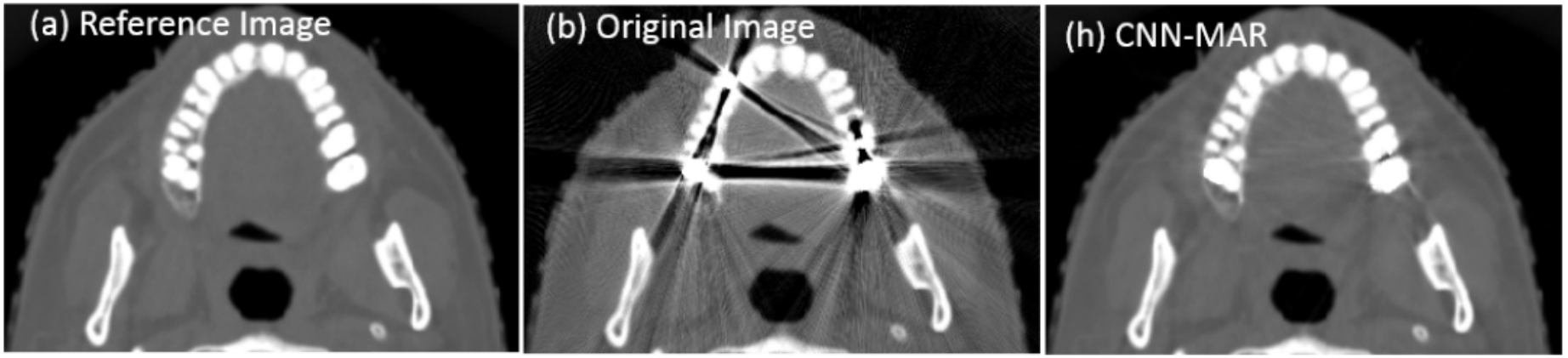
Image Synthesis by AI

- Q. Miao et al, "Mode Seeking Generative Adversarial Networks for Diverse Image Synthesis, " CVPR 2019



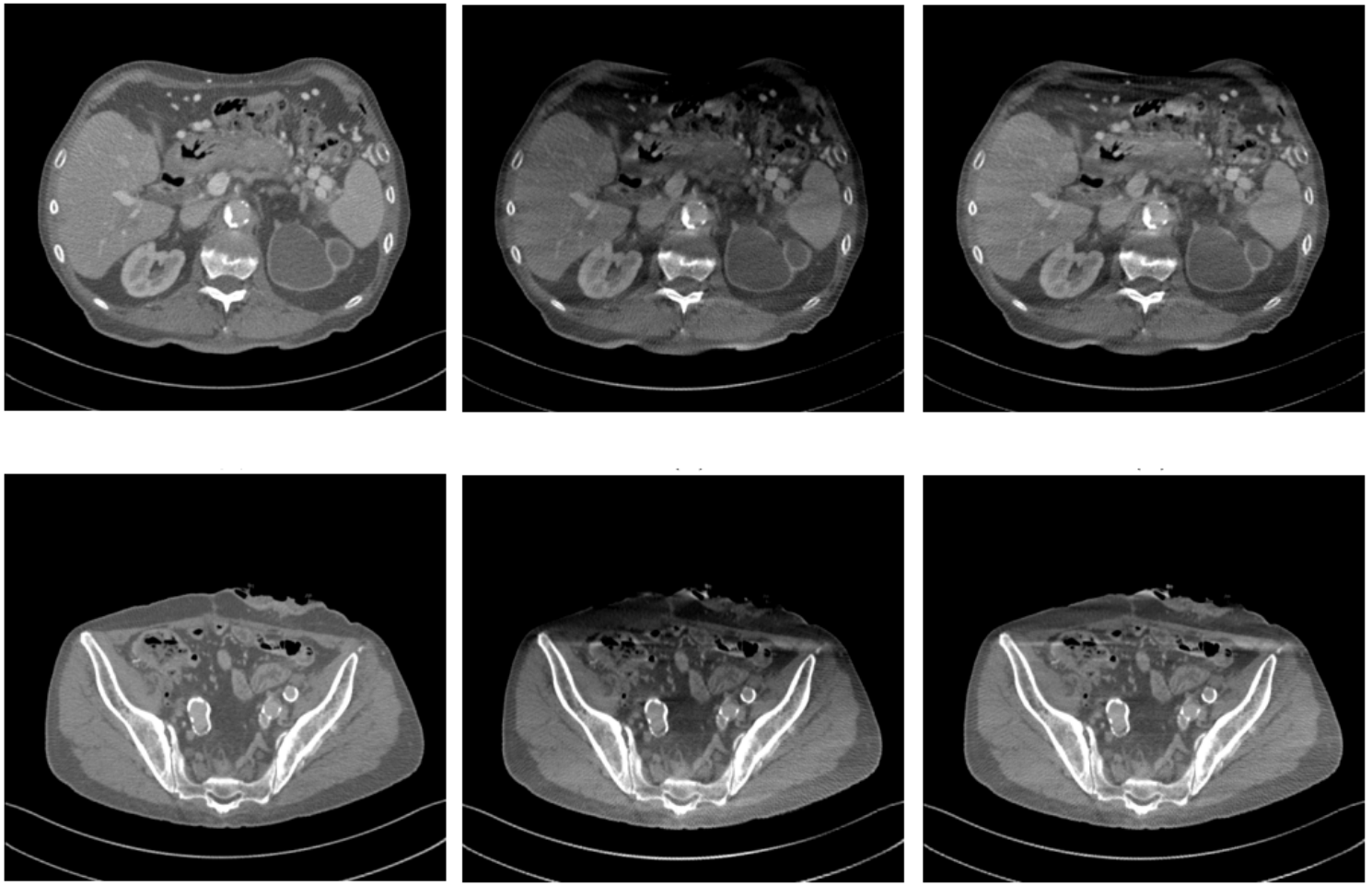
CT and AI

- Y. Zhang and H. Yu, "Convolutional Neural Network Based Metal Artifact Reduction in X-Ray Computed Tomography," *IEEE Transactions on Medical Imaging*, vol. 37, no. 6, pp. 1370-1381, Jun. 2018.



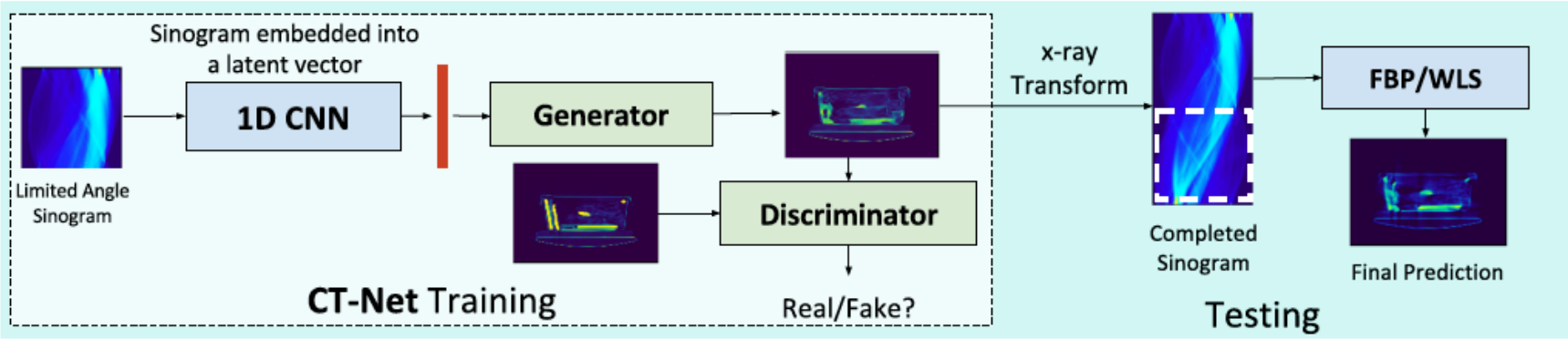
CT and AI

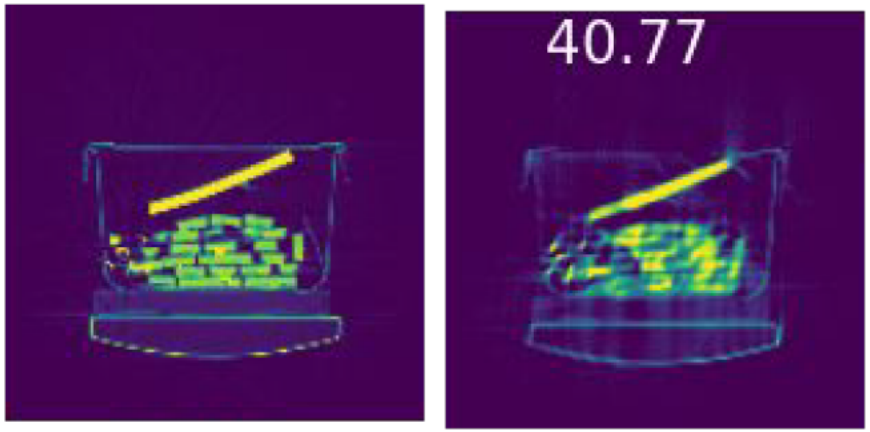
- T. Würfl et al., "Deep Learning Computed Tomography: Learning Projection-Domain Weights From Image Domain in Limited Angle Problems," *IEEE Transactions on Medical Imaging*, vol. 37, no. 6, pp. 1454-1463, Jun. 2018.



CT and AI

- R. Anirudh, et al., "**Lose The Views: Limited Angle CT Reconstruction via Implicit Sinogram Completion**, " *arXiv*, Jul. 2018.





Ground truth
128*128

CT-Net Result
sonogram: 0°-90°

3D Modeling and AI

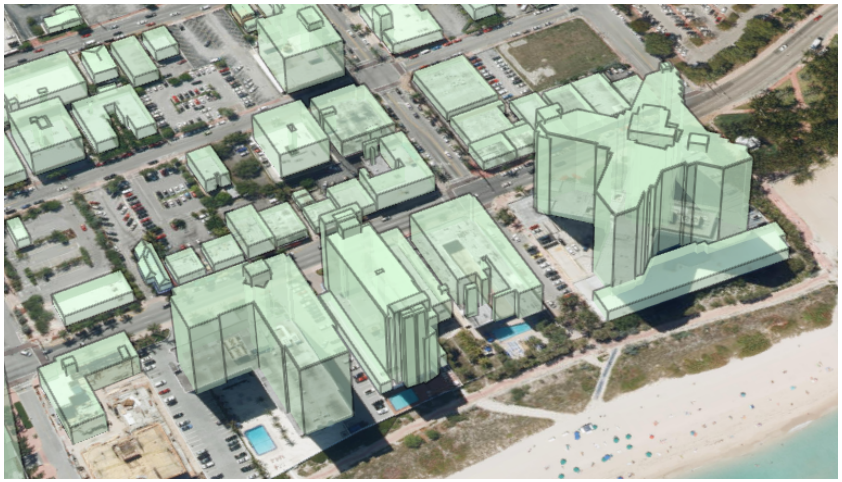
- D. Kudinov and D. Hedges, "Reconstructing 3D buildings from aerial LiDAR with AI"

RGB channels

Rasterized Aerial LiDAR

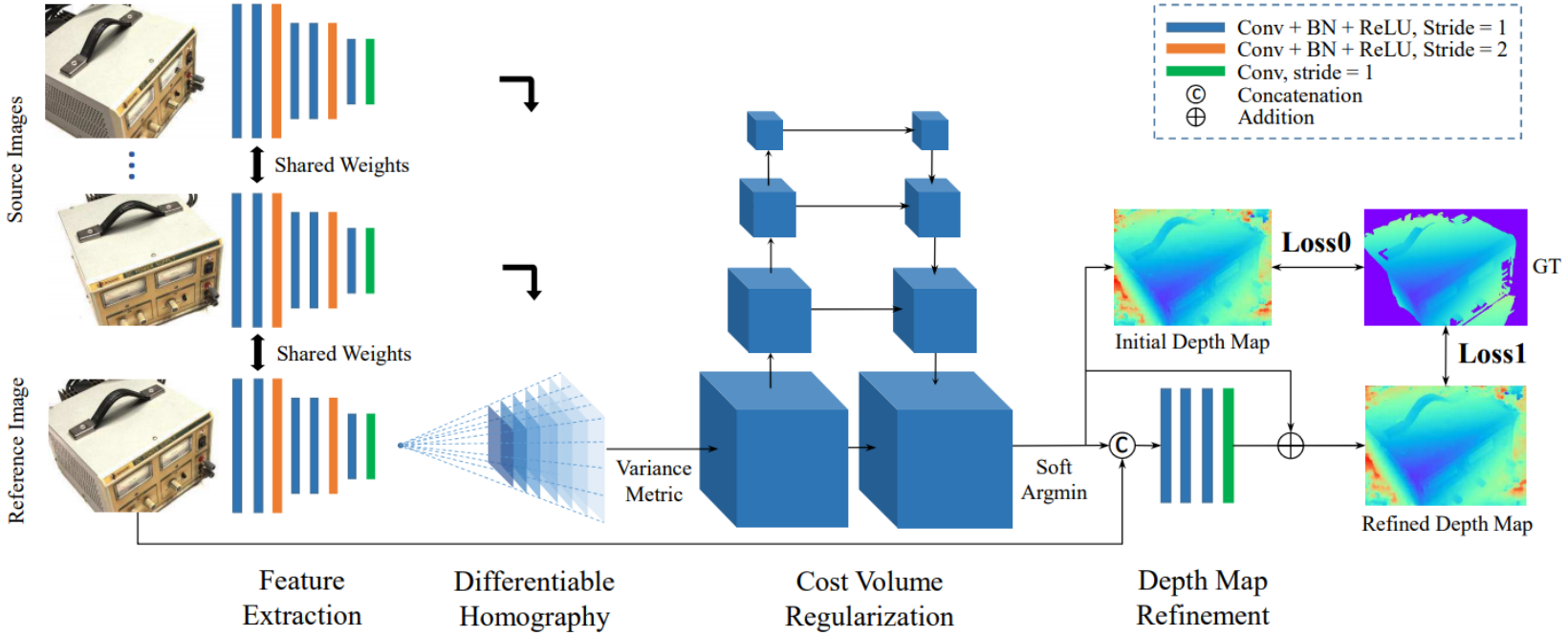
Manually digitized Hip (purple) and Gable (orange) segments

3D reconstruction of building using manually digitized segments



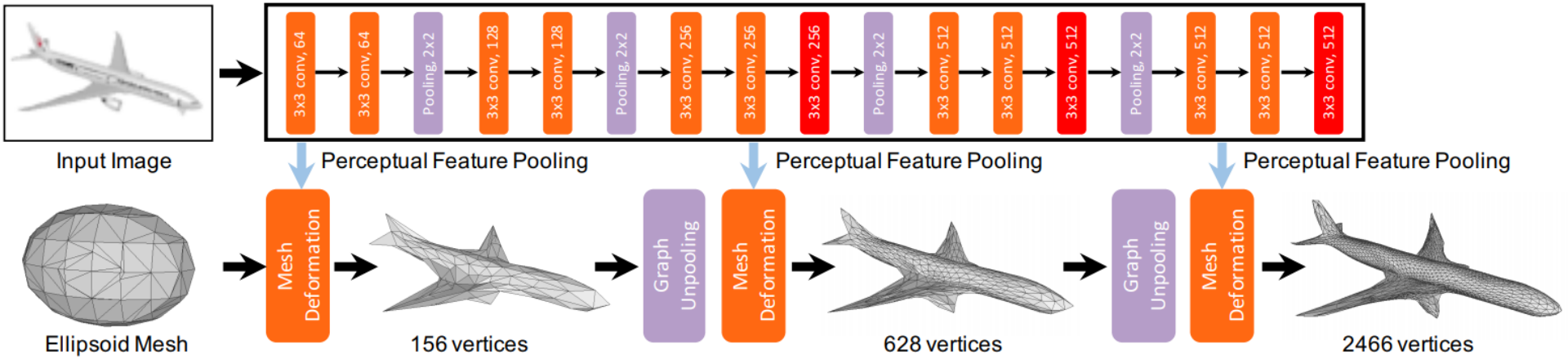
3D Modeling and AI

- Y. Yao, Z. Luo, S. Li, T. Fang, and L. Quan, "MVSNet: Depth Inference for Unstructured Multi-view Stereo," ECCV 2018.



3D Modeling and AI

- N. Wang, et al, "Pixel2Mesh: Generating 3D Mesh Models from Single RGB Images," ECCV 2018.



Poincaré Conjecture

- In 1904, a French mathematician, **Jules Henri Poincaré** (1854 – 1912), conjectured a theorem.

Every simply connected, closed 3-manifold is homeomorphic to the 3-sphere.

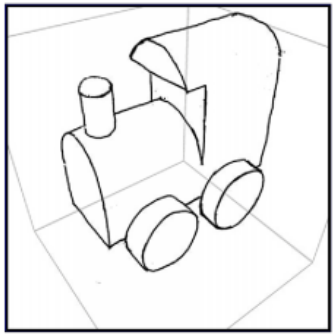
Henri Poincaré

Grigori Perelman

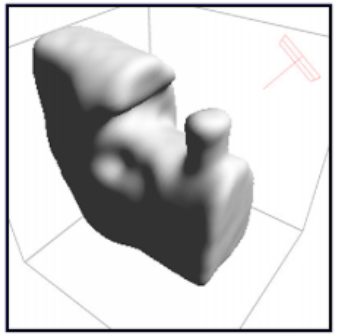
- Nov. 13, 2002, a Russian mathematician, **Grigori Perelman**, proved the Poincaré conjecture.
  - Poincaré Conjecture is one of Millennium Prize Problems
  - Prize: $1 million
  - But Perelman rejected that prize

3D Modeling and AI

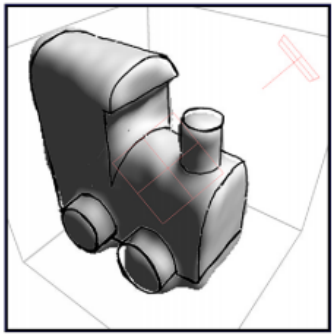
- J. Delanoy, M. Aubry, P. Isola, A. A. Efros, and A. Bousseau, "**3D Sketching using Multi-View Deep Volumetric Prediction**," *Proc. ACM Comput. Graph. Interact. Tech*. 1, 1, Article 21, July 2018.



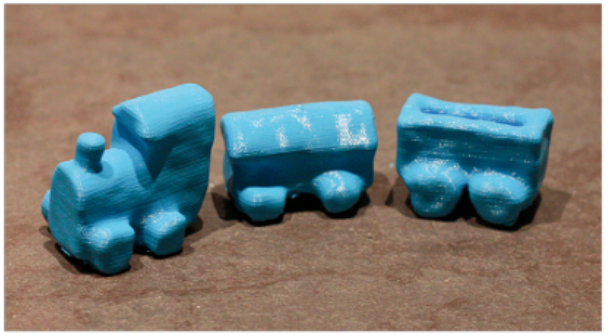
a) Initial drawing



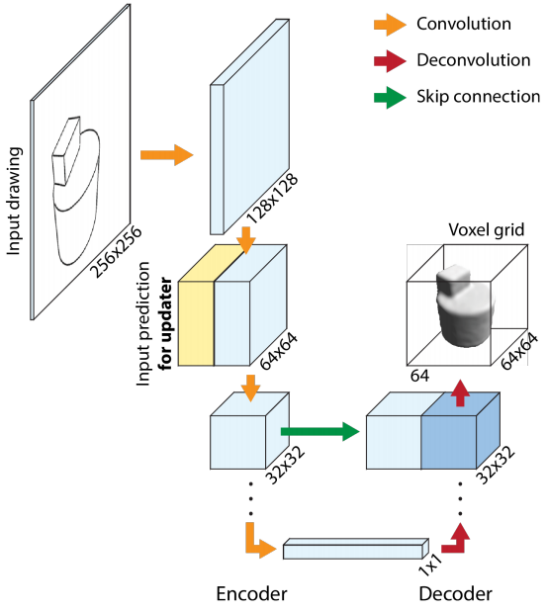
b) 3D prediction seen from another viewpoint



c) New drawing and updated prediction



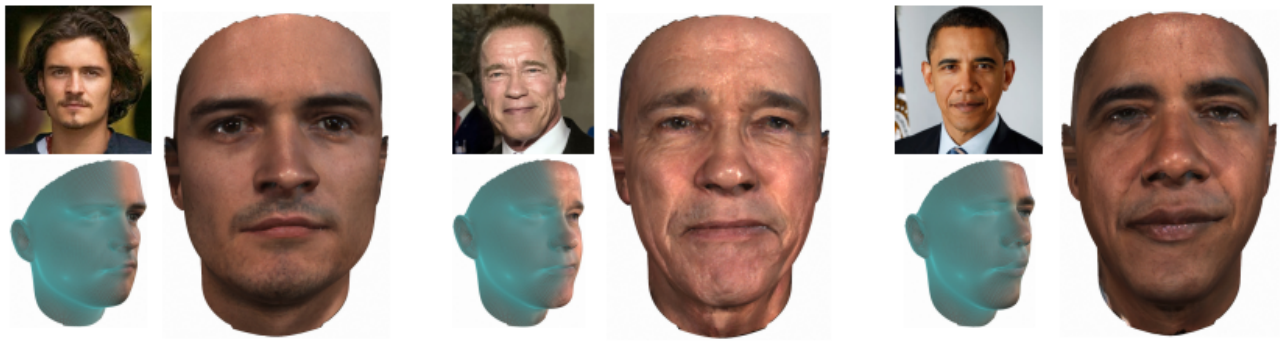
d) 3D printed objects

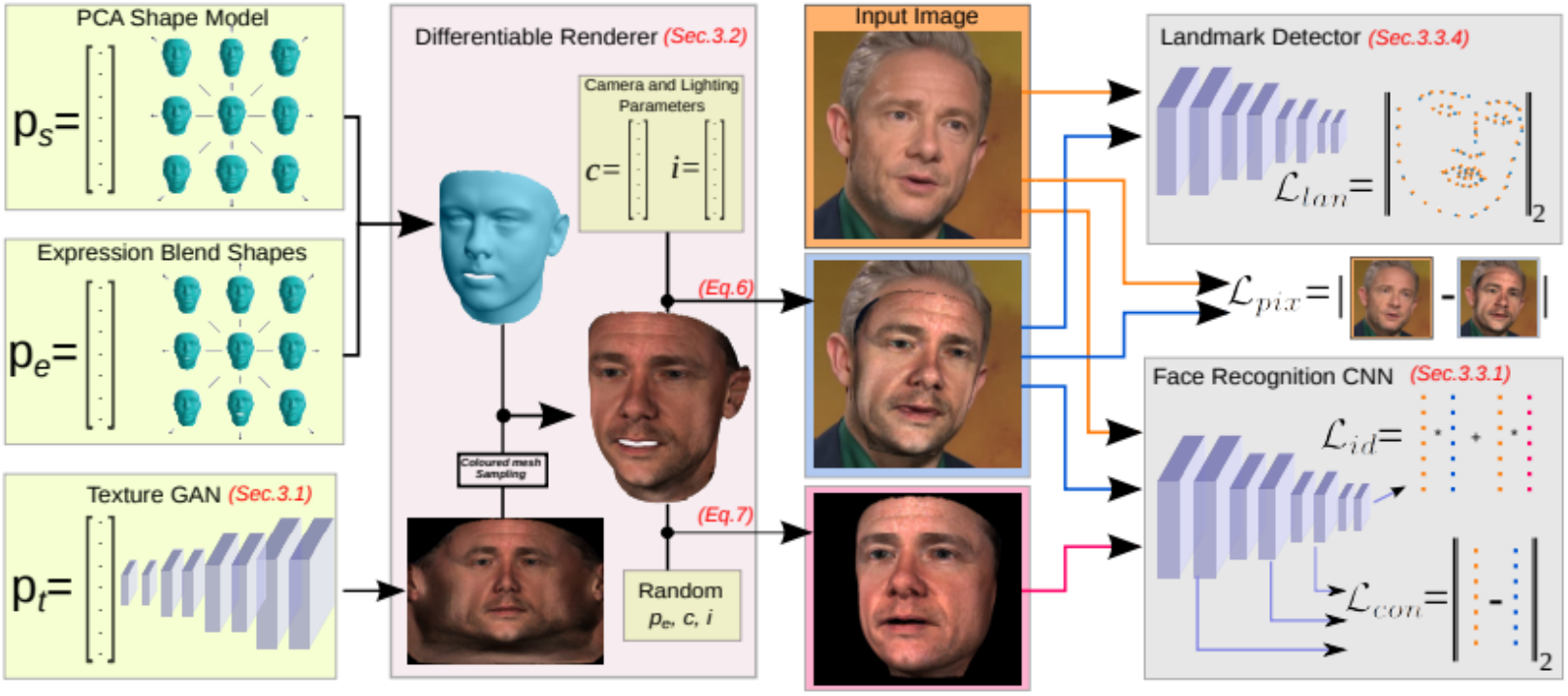


https://www.youtube.com/watch?time_continue=354&v=DGIYzmlm2pQ

3D Modeling and AI

- B. Gecer et al, "GANFIT: Generative Adversarial Network Fitting for High Fidelity 3D Face Reconstruction, " CVPR 2019





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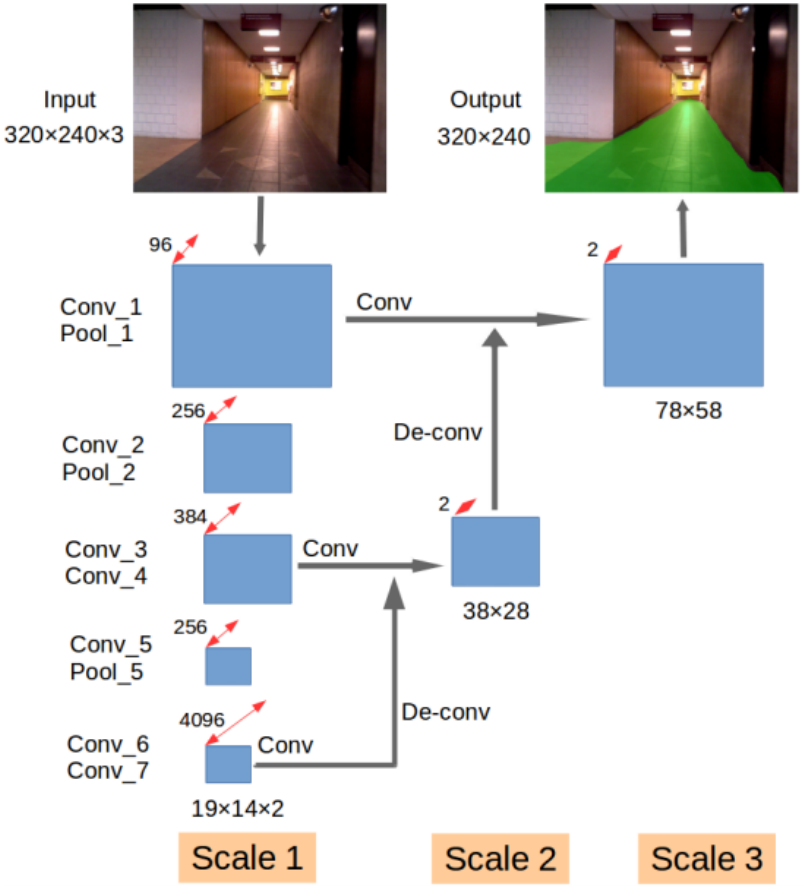

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