

Deep Learning Workshop:

Concepts & Experiments

MSBD 5001 Fall 2019

Outline

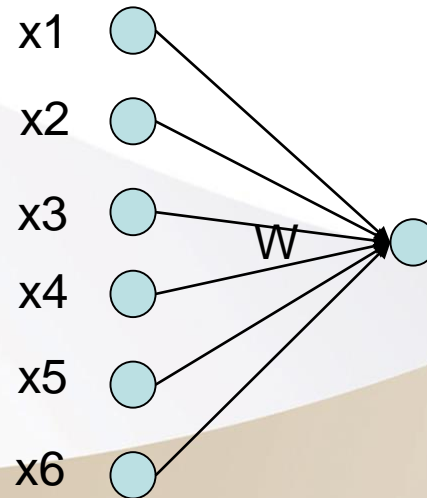
- The basics of fully connected neural network
- The basics of convolutional neural network
- The basics of deep learning
- The tutorial of Tensorflow 2.0.
- Use Tensorflow 2.0 beta to train, validate and test your own deep learning model

Install Tensorflow 2.0

- `pip install -U gast==0.2.2`
- `pip install tensorflow==2.0.0-beta0`
- `pip install pillow`
- Open python and run the following codes:
 - `from tensorflow import keras`
 - `keras.datasets.mnist.load_data()`
 - `keras.applications.VGG16(input_shape=(224,224,3),
weights='imagenet',include_top=False)`

Logistic Regression

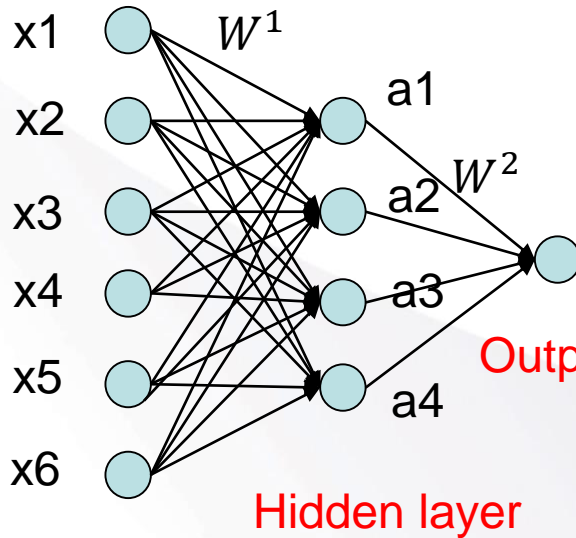
- $L = \sum(\text{Error}(y, \sigma(x^T w)))$ #make a swap of x/w .
- Apply a non-linear function (E.g. sigmoid) on $(x^T w)$ to fit the target value.
- We can use graph to represent the process.



$$\begin{aligned} \text{output} = & \sigma(x_1 * w_1 \\ & + x_2 * w_2 \\ & + x_3 * w_3 \\ & + x_4 * w_4 \\ & + x_5 * w_5 \\ & + x_6 * w_6) \end{aligned}$$

A Simple Fully Connected Feedforward Neural Network

Input layer



Hidden layer

W^1 : 6*4 matrix.

W^2 : 4*1 matrix. (So transposition is not needed)

W_{ij}^1 : The weight connecting x_i and a_j .

$$a = \sigma(xW^1)$$

$$output = aW^2 = \sigma(xW^1)W^2$$

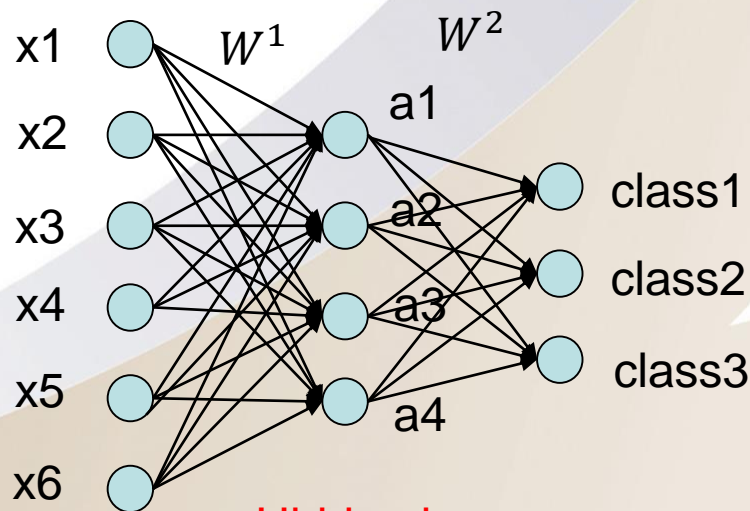
More complex neural networks could be extended based on this with more hidden layers.

Softmax: Classification

- N output nodes to represent the probability distribution over n different classes.
- W^2 : 4*3 matrix.
- $output = softmax(aW^2) = softmax(\sigma(xW^1)W^2)$
- Like logistic regression, use a non-linear function to transform output from $(-\infty, +\infty)$ to $[0, 1]$.
- Softmax is similar with sigmoid, supporting multiple outputs.

$$softmax(z)_i = \frac{\exp(z_i)}{\sum_j \exp(z_j)}$$

Input layer

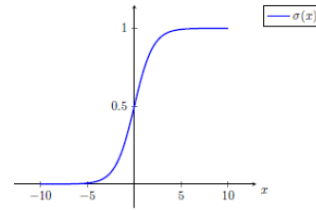


Hidden layer

Activation

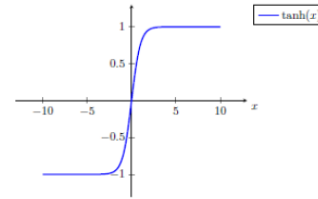
- Activation function is to transform the input signal into an output signal to model complex non-linear patterns.
- Without activation function, stacking linear layers is equivalent to a single linear layer.
- We can replace the sigmoid function in hidden layer with other non-linear functions!

Sigmoid



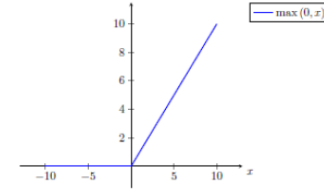
$$\sigma(x) = \frac{1}{1 + \exp(-x)}$$

tanh



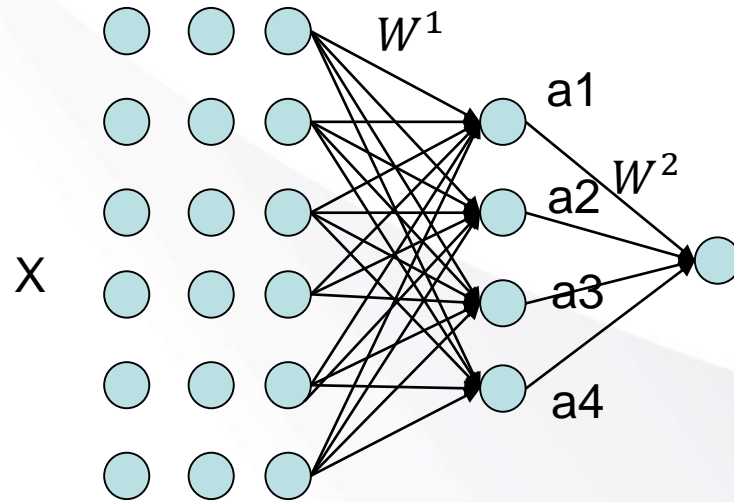
$$\tanh(x) = \frac{\exp(x) - \exp(-x)}{\exp(x) + \exp(-x)}$$

ReLu



$$\text{ReLu}(x) = \max(0, x)$$

Batch Forwarding



Batch size: 3

W^1 : 6*4 matrix.

W^2 : 4*1 matrix.

W_{ij}^1 : The weight connecting x_i and a_j .

X : 3*6 feature matrix (generally a row represents a sample)

X_{ij} : The j -th feature of the i -th sample.

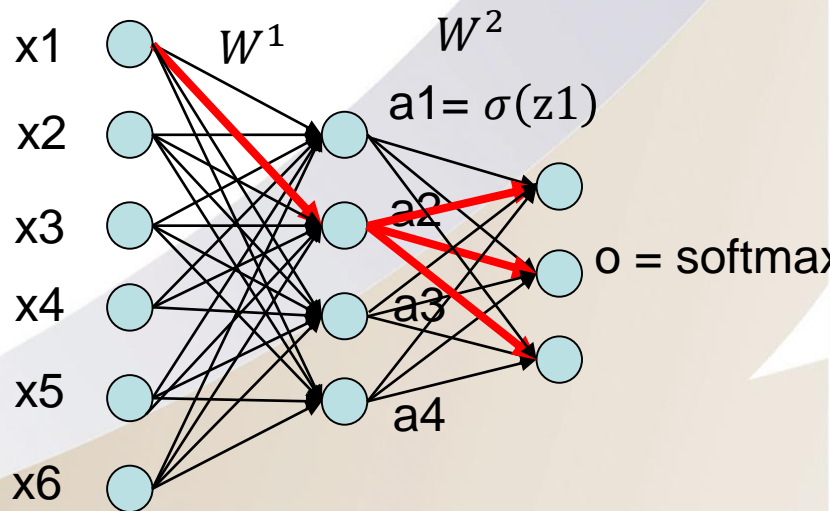
$$A = \sigma(XW^1)$$

$$\text{output} = AW^2 = \sigma(XW^1)W^2$$

Output: 3*1 matrix.

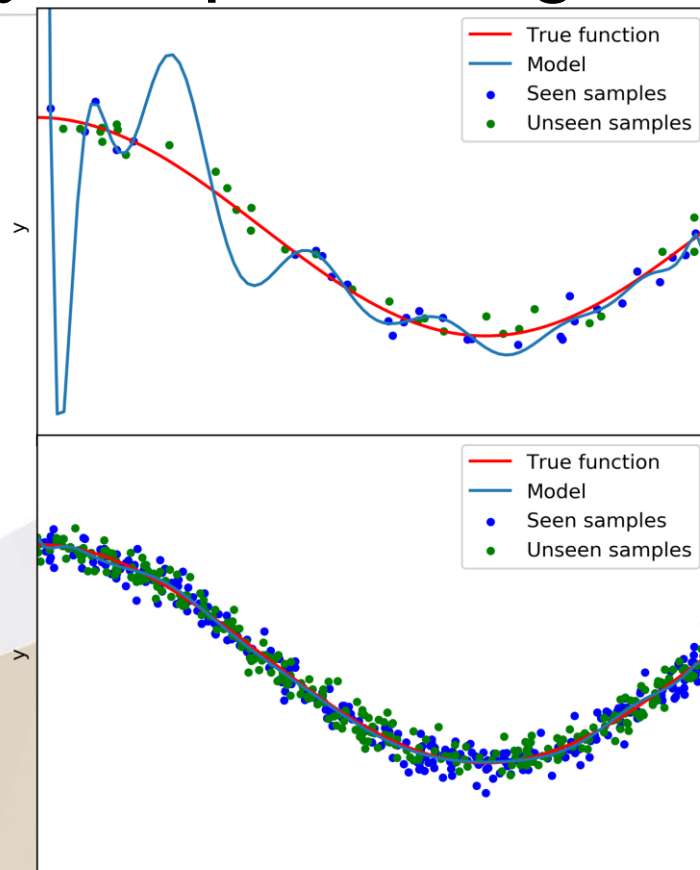
Back-propagation

- Chain Rule of Calculus:
- $z = f(g_1(x) + g_2(x))$
- $\frac{\partial z}{\partial x} = \frac{\partial z}{\partial g_1} \frac{\partial g_1}{\partial x} + \frac{\partial z}{\partial g_2} \frac{\partial g_2}{\partial x}$
- $loss = L(\text{softmax}(aW^2))$
- $= L(\text{softmax}(\sigma(xW^1)W^2))$
- For W_{12}^1 , $\frac{\partial L}{\partial W_{12}^1} = \sum_k \frac{\partial L}{\partial o_k} (\frac{\partial o_k}{\partial s_k} \frac{\partial s_k}{\partial a_2} \frac{\partial a_2}{\partial z_2} \frac{\partial z_2}{\partial W_{12}^1})$
- Accelerated by matrix multiplication.



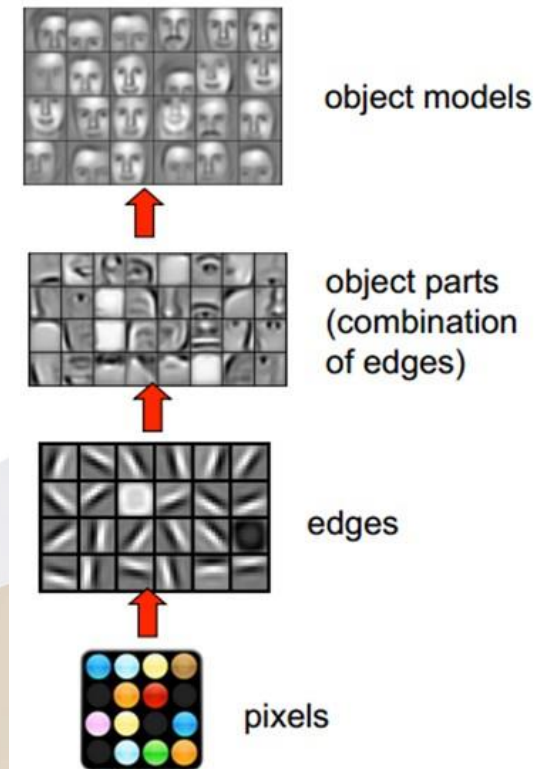
Why deep learning?

- Why neural network?
 - **Universal approximation theorem** (Hornik et al., 1989; Cybenko 1989) states that a feedforward network with a linear output layer and at least one hidden layer can approximate almost any function, given enough hidden units.
 - Huge amount of data lowers the possibility of overfitting.



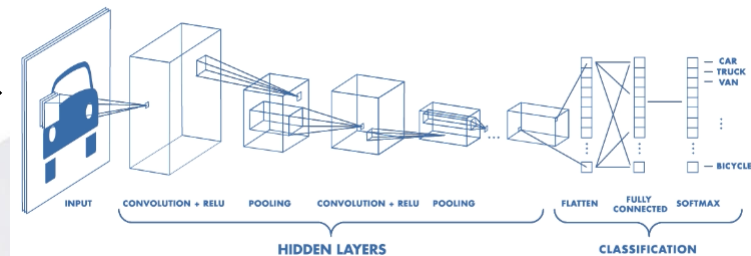
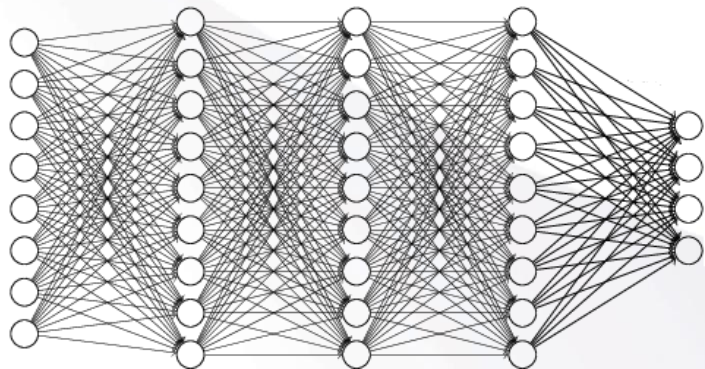
Why deep learning?

- Why deep?
 - Deeper models reduce the number of units required to represent the function involving composition of simpler functions.



ConVnet for Image Feature Extraction

- Convolutional neural network for images



ConVnet for Image Feature Extraction

- What makes image different with other machine learning training data?



$64*64=4096$ pixels
 $4096*3=12288$ dimensions



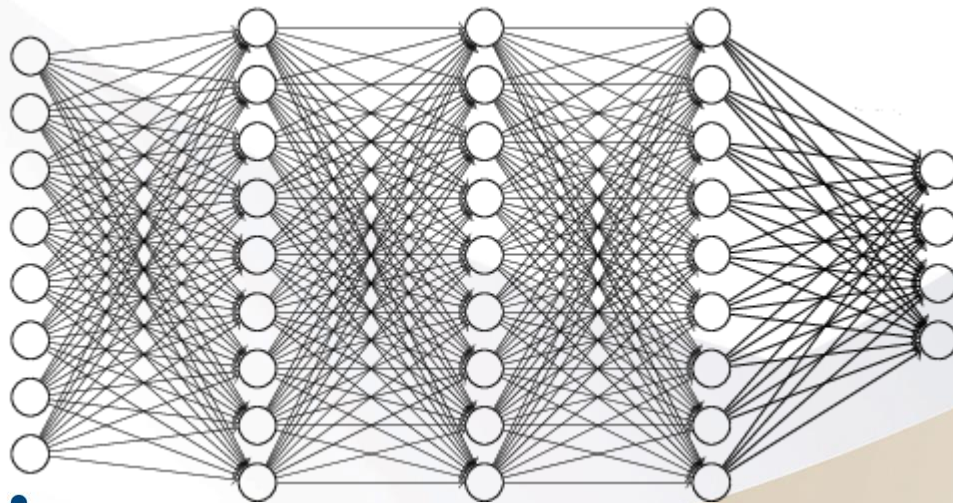
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$1000*1000*3=3$ million!

ConVnet for Image Feature Extraction

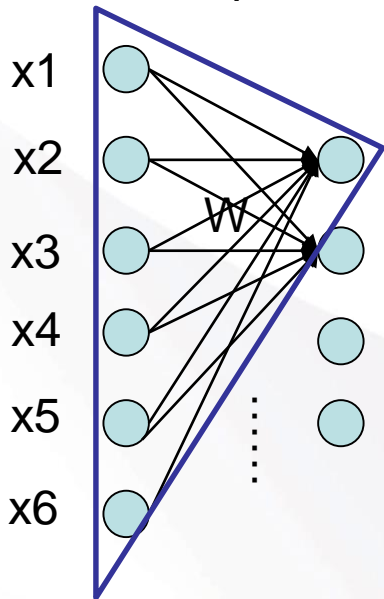
Full connected neural network



Just for the first layer:
 $3 \text{ million} * \#(\text{first hidden layer nodes})$ parameters!!

ConVnet for Image Feature Extraction

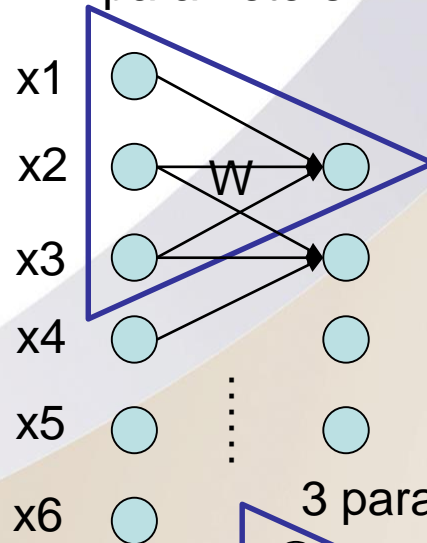
$W: 6 \times 4 = 24$ parameters



$$h1 = x1 \cdot w_{11} + x2 \cdot w_{12} + x3 \cdot w_{13} + x4 \cdot w_{14} + x5 \cdot w_{15} + x6 \cdot w_{16}$$

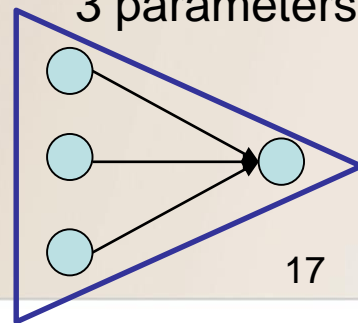


$3 \times 4 = 12$ parameters



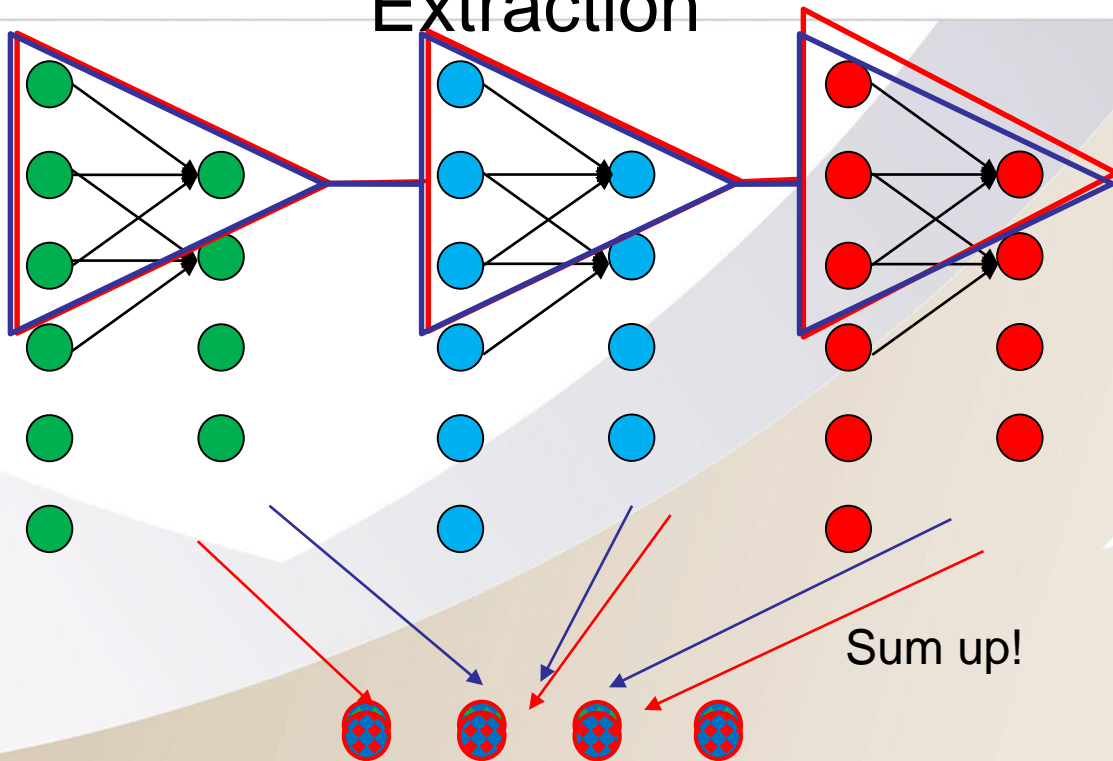
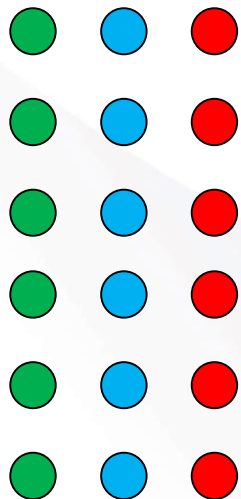
$$h1 = x1 \cdot w_{11} + x2 \cdot w_{12} + x3 \cdot w_{13}$$

3 parameters!

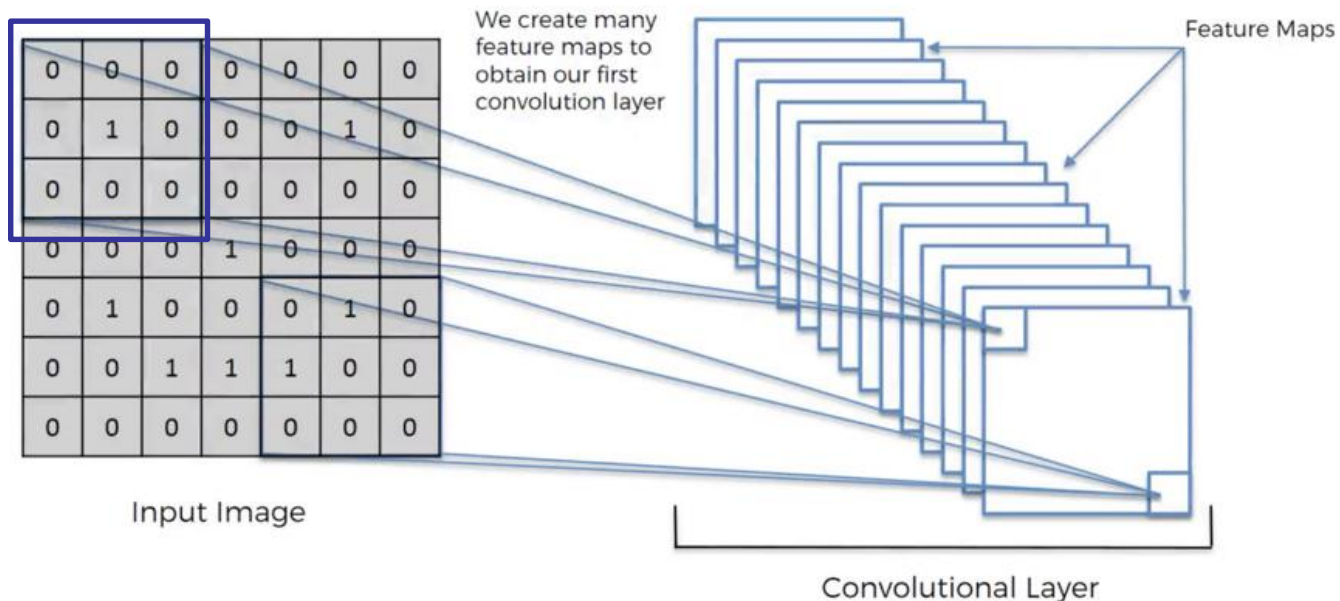
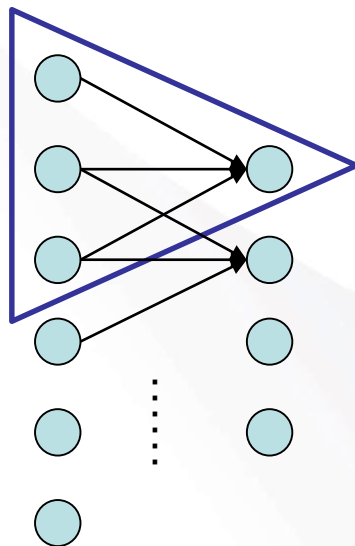


Local receptive field
Shared weights and biases

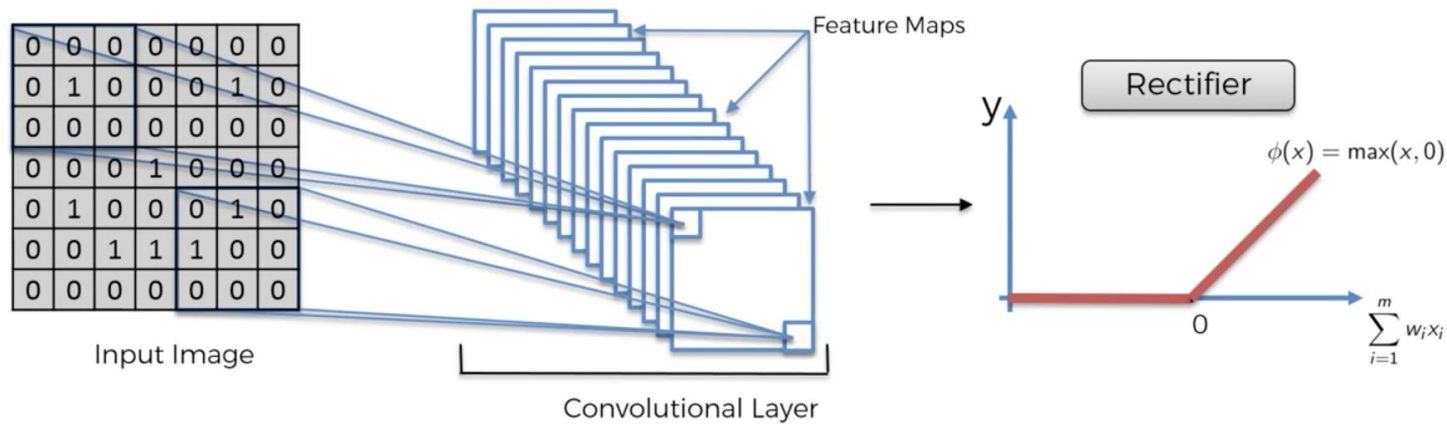
ConVnet for Image Feature Extraction



ConVnet for Image Feature Extraction

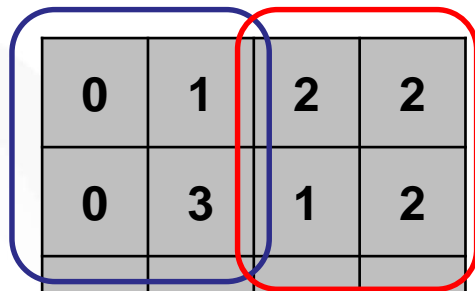


ConVnet for Image Feature Extraction



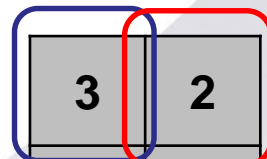
Activation: make the function non-linear

ConVnet for Image Feature Extraction



0	1	2	2
0	3	1	2
3	2	4	2
0	1	1	0

Max pooling

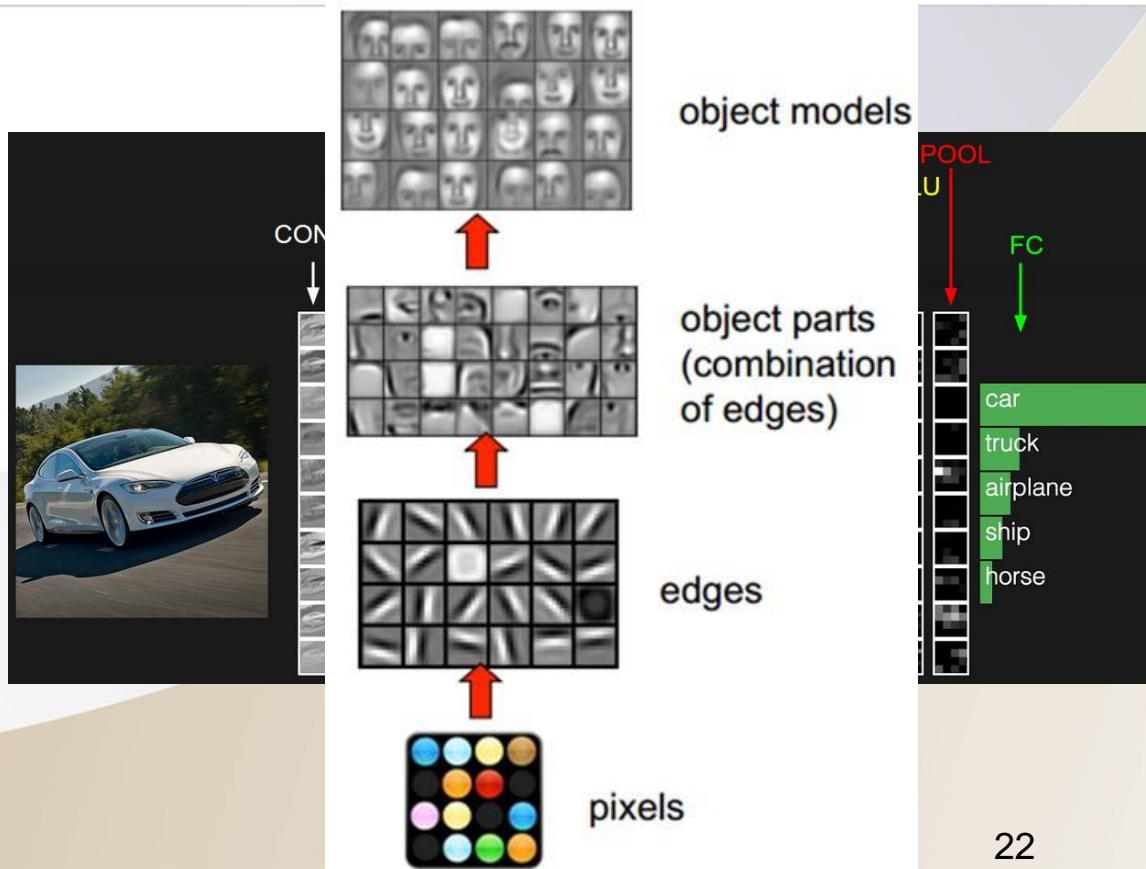


3	2
3	4

Pooling: reduce the dimension

CNN for Image Feature Extraction

- Local receptive field
- Shared weights and biases
- Activation
- Pooling



Tensorflow 2.0 features



Eager

Keras



Machine Learning Components

Data

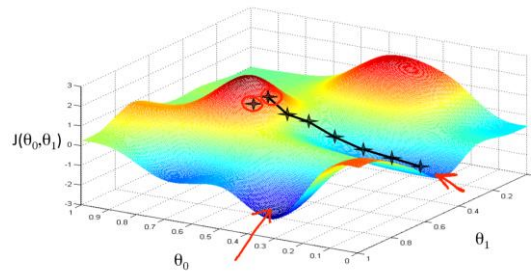
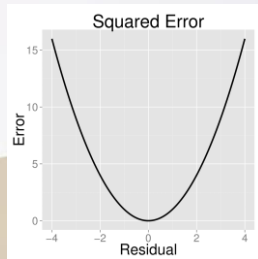
Model
parameters

Loss

$$Loss = \sum_{i=1}^n (\text{predicted} - \text{truth})^2$$

$$= \text{Squared Error}$$

$$\frac{\partial \text{loss}}{\partial \text{parameters}}$$



Optimizer

Metric

Thanks

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