Introduction to Computer Vision

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Komatik UGM
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All of these materials are available at:
https://github.com/mdaniyalk/intro-comviz-komatik or link.enova.id/cv1-komatik

Prerequisite:
Python & little bit knowledge of calculus & linear algebra

Main Topics

- Why Deep Learning?
- Intro to Computer Vision: Classification
- Hands-on and Practice Lab: Image Classification
- Exploration: Advanced Image Processing & Computer Vision
- Q&A Session

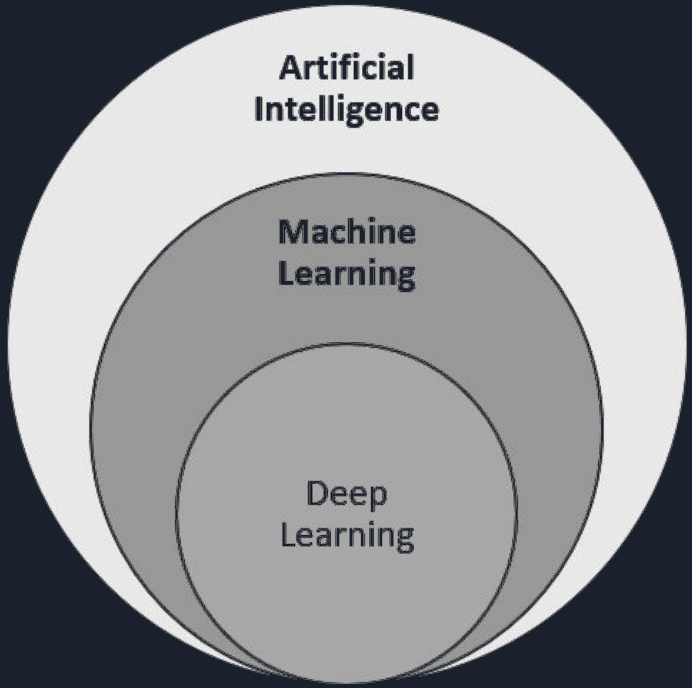
Why Deep Learning?

Deep Learning

Artificial Intelligence, any technique that enable computer to mimics human behavior.

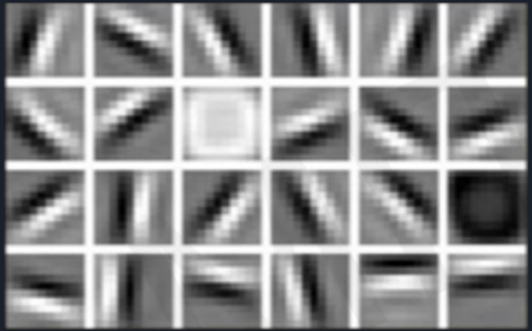
Machine Learning, ability to learn without explicitly being programmed.

Deep Learning, extract pattern from data using neural networks



Why deep learning?

Low level features



Lines & Edges

Mid level features

Eyes, Nose, & Ears

High level features

Facial Structures

Can we extract and hard coded a program to understand those features?

Why deep learning?

Can we extract and hard coded a program to understand those features?

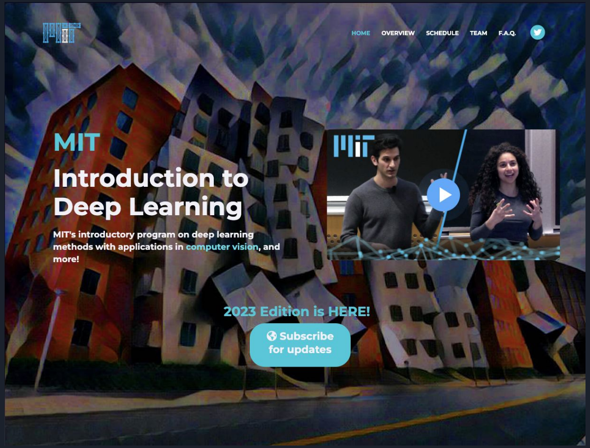
It's possible!

How about on this?

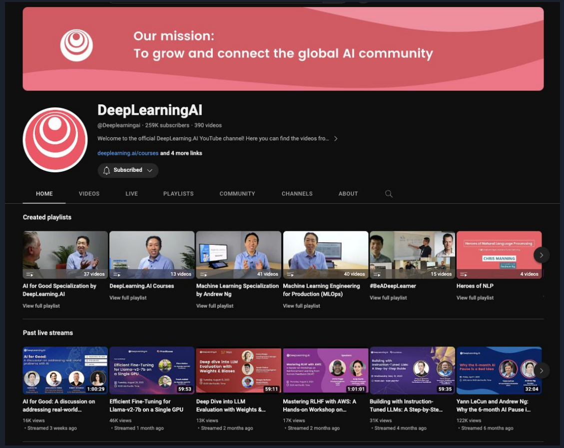
Or this?

You need to specify all of the possible pattern if using traditional image processing!

Where to learn deep learning



MIT Deep Learning 6.S191



DeepLearningAI

And others!

Foundational Deep Learning: Neural Nets

Introduction to Tensorflow API

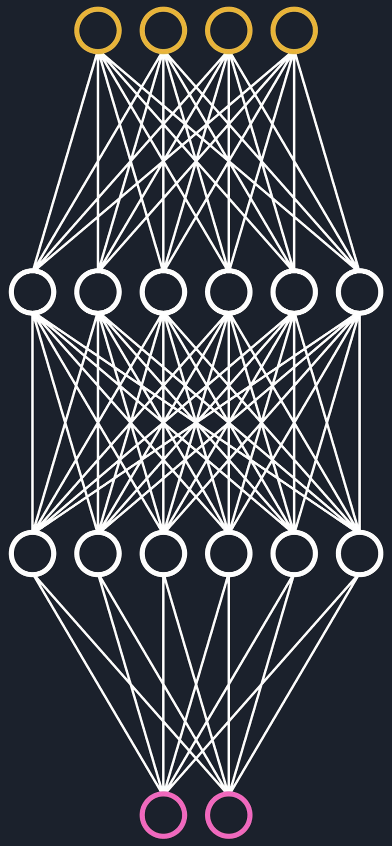
- Tensorflow is an open-source ML framework that develop by Google.
- It can be used in almost any devices, including microcontroller.
- Available in C++, **Python**, Java, Javascript, etc.
- Tensorflow offer two Model API. Functional and **Sequential API**.
- More on tensorflow at tensorflow.org

Neural Network

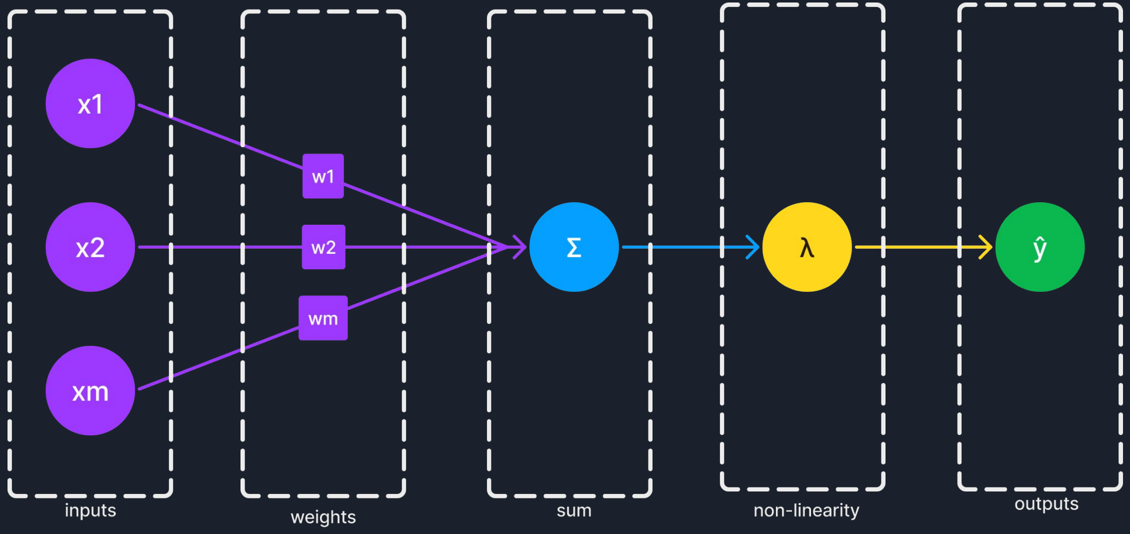
- Type of algorithm that inspired by human brain
- Consist of interconnected neurons
- Think of each neuron is a linear regression itself wrapped with non-linear function

```
outputs = activation(dot(input, weight) + bias)
```

- Use forward & back propagation to update it's weight and minimize loss on every iteration (epochs)



Neural Networks: Neuron



Output

Linear combination of inputs

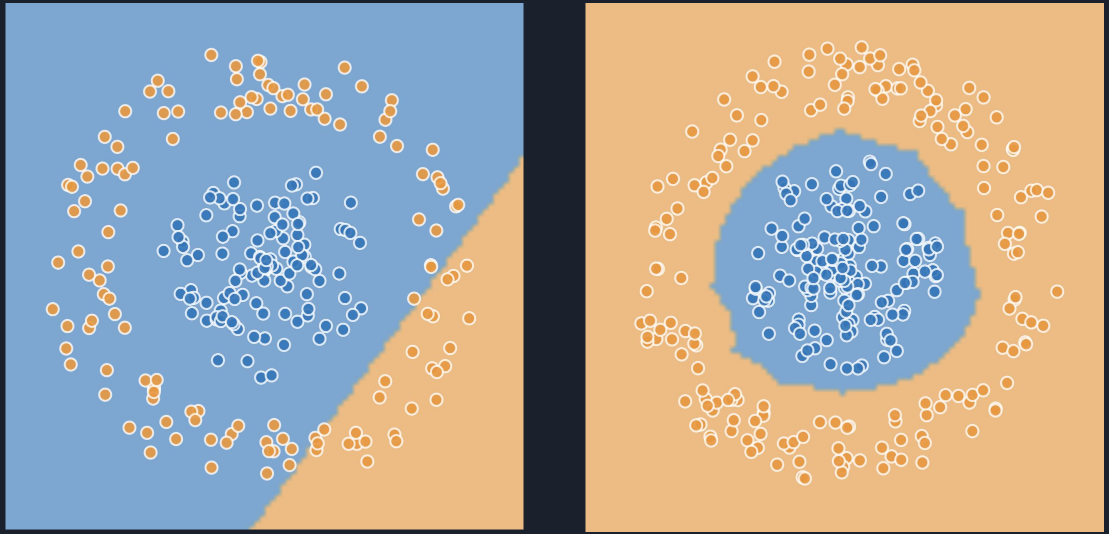
$$\hat{y} = g\left(\sum_{i=1}^{m} x_i \, w_i\right)$$

Non-linear activation function

$$\hat{y} = g\left(w_0 + \boldsymbol{X}^T \boldsymbol{W}\right)$$

where: $\boldsymbol{X} = \begin{bmatrix} x_1 \\ \vdots \\ x_m \end{bmatrix}$ and $\boldsymbol{W} = \begin{bmatrix} w_1 \\ \vdots \\ w_m \end{bmatrix}$

Neural Networks: Activation Function



Linear activation can't approximate complex functions

Non-linearities allow us to approximate complex functions

We have: $w_0 = 1$ and $\boldsymbol{W} = \begin{bmatrix} 3 \\ -2 \end{bmatrix}$

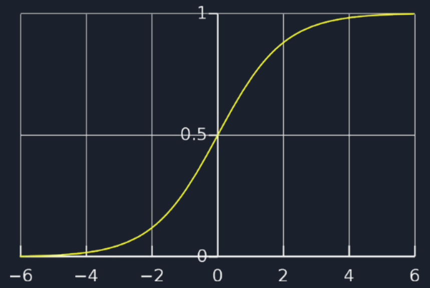
$$\hat{y} = g\left(w_0 + \boldsymbol{X}^T \boldsymbol{W}\right)$$

$$= g\left(1 + \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}^T \begin{bmatrix} 3 \\ -2 \end{bmatrix}\right)$$

$$\hat{y} = g(\underbrace{1 + 3x_1 - 2x_2}_{\text{This is just a line in 2D!}})$$

Neural Networks: Common Activation Function

Sigmoid Function

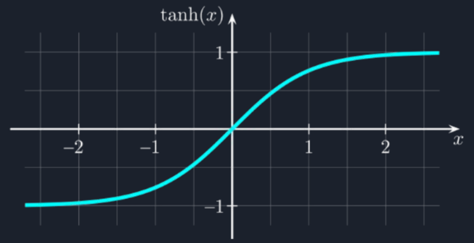


$$g(z) = \frac{1}{1 + e^{-z}}$$

$$g'(z) = g(z)(1 - g(z))$$

`tf.keras.activations.sigmoid(out)`

Hyperbolic Tangent

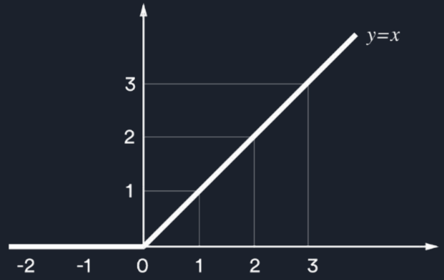


$$g(z) = \frac{e^{z} - e^{-z}}{e^{z} + e^{-z}}$$

$$g'(z) = 1 - g(z)^2$$

`tf.keras.activations.tanh(out)`

Rectified Linear Unit (ReLU)



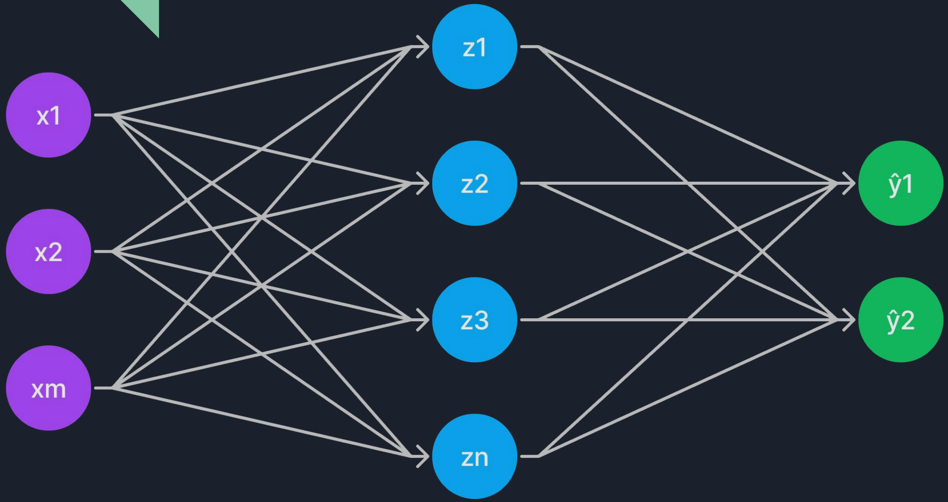
$$g(z) = \max(0, z)$$

$$g'(z) = \begin{cases} 1, & z > 0 \\ 0, & \text{otherwise} \end{cases}$$

`tf.keras.activations.relu(out)`

NOTE: Non-linear activation functions

Neural Networks: Single layer NN

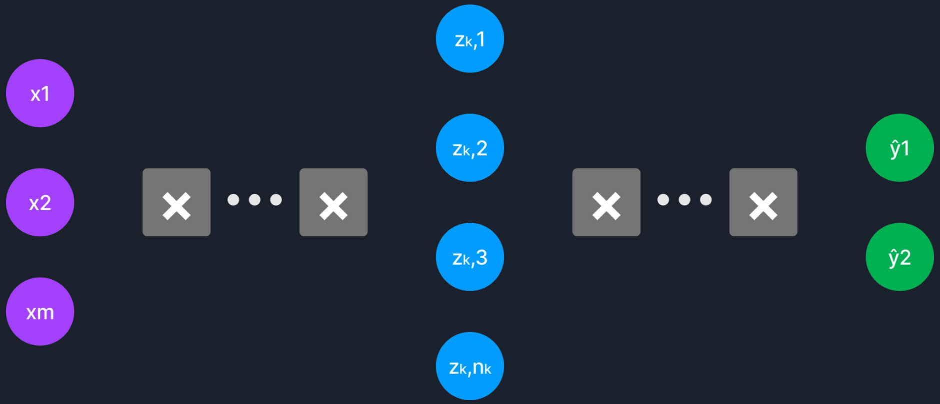



```python
import tensorflow as tf

model = tf.keras.Sequential([
    tf.keras.layers.Dense(n),
    tf.keras.layers.Dense(2)
])
```

$$z_{k,i} = w_{0,i}^{(k)} + \sum_{j=1}^{n_{k-1}} g(z_{k-1,j})\, w_{j,i}^{(k)}$$

Neural Networks: Deep NN



$$z_{k,i} = w_{0,i}^{(k)} + \sum_{j=1}^{n_{k-1}} g(z_{k-1,j})\, w_{j,i}^{(k)}$$

```python
import tensorflow as tf

model = tf.keras.Sequential([
    tf.keras.layers.Dense(n1),
    tf.keras.layers.Dense(n2),
    ...,
    tf.keras.layers.Dense(2)
])
```

Neural Networks: Loss Function

Loss measure the cost of incurred from incorrect predictions

$$\begin{array}{ccc} f(x) & & y \\ \begin{bmatrix} 0.1 \\ 0.8 \\ 0.6 \\ \vdots \end{bmatrix} & \begin{matrix} \times \\ \times \\ \checkmark \\ \end{matrix} & \begin{bmatrix} 1 \\ 0 \\ 1 \\ \vdots \end{bmatrix} \end{array}$$

$$\mathcal{L}\Big(\underbrace{f\big(x^{(i)}; \boldsymbol{W}\big)}_{\text{Predicted}}, \underbrace{y^{(i)}}_{\text{Actual}}\Big)$$

Neural Networks: Cross Entropy Loss

Cross-entropy is a measure of the difference between two probability distributions for a given random variable or set of events.

Can be used for models that outputs a probability between 0 and 1

Binary for two classes

Multi-class for more than two classes

$$\begin{array}{ccc} f(x) & & y \\ \begin{bmatrix} 0.1 \\ 0.8 \\ 0.6 \\ \vdots \end{bmatrix} & \begin{matrix} \times \\ \times \\ \checkmark \\ \\ \end{matrix} & \begin{bmatrix} 1 \\ 0 \\ 1 \\ \vdots \end{bmatrix} \end{array}$$

$$J(\boldsymbol{W}) = -\frac{1}{n}\sum_{i=1}^{n} \underbrace{y^{(i)}}_{\text{Actual}} \log\Big(\underbrace{f\big(x^{(i)};\boldsymbol{W}\big)}_{\text{Predicted}}\Big) + (1-\underbrace{y^{(i)}}_{\text{Actual}}) \log\Big(1-\underbrace{f\big(x^{(i)};\boldsymbol{W}\big)}_{\text{Predicted}}\Big)$$

```
loss = tf.keras.losses.BinaryCrossentropy()
```

Neural Networks: Mean Squared Error (MSE) Loss

MSE is a measure of average squared distances of predicted and actual value.

Can be used with regression models that output continuous value.

$$
\begin{array}{ccc}
f(x) & & y \\
\begin{bmatrix} 30 \\ 80 \\ 85 \\ \vdots \end{bmatrix} & \begin{matrix} \times \\ \times \\ \checkmark \\ \end{matrix} & \begin{bmatrix} 90 \\ 20 \\ 95 \\ \vdots \end{bmatrix}
\end{array}
$$

$$
J(\boldsymbol{W}) = \frac{1}{n}\sum_{i=1}^{n}\Big(\underbrace{y^{(i)}}_{\text{Actual}} - \underbrace{f\big(x^{(i)};\boldsymbol{W}\big)}_{\text{Predicted}}\Big)^2
$$

```
loss = tf.keras.losses.MeanSquaredError()
```

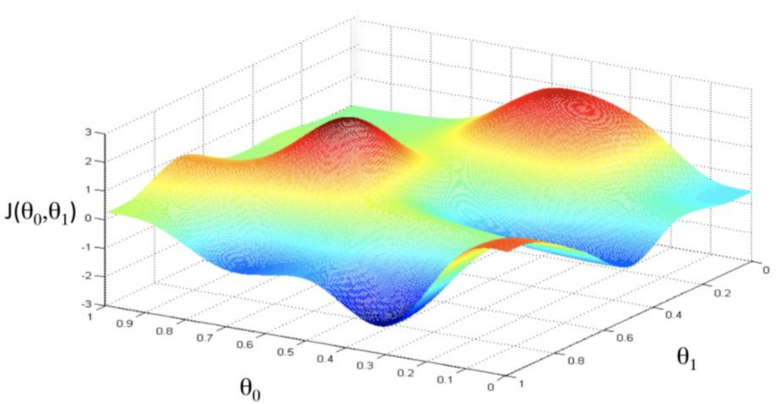
Training Neural Nets

Neural Networks: Loss Optimization

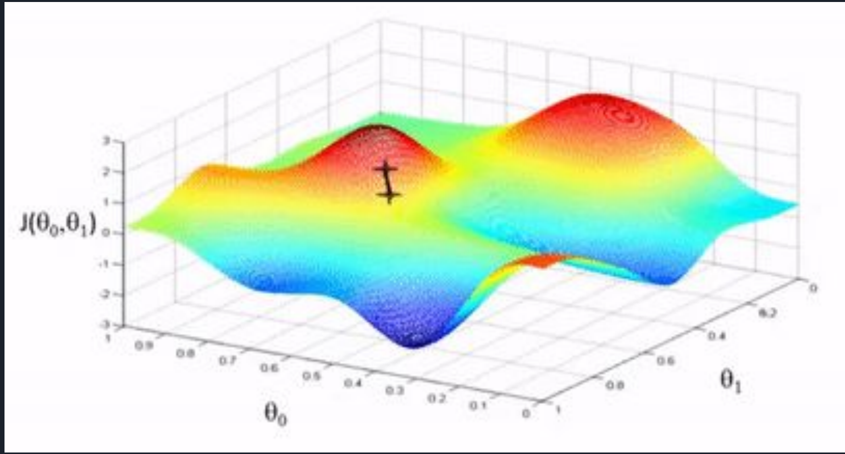
We want to find the network weights that achieve the lowest loss

$$W^* = \underset{W}{\operatorname{argmin}} \frac{1}{n}\sum_{i=1}^{n} \mathcal{L}\left(f\left(x^{(i)}; W\right), y^{(i)}\right)$$

$$W^* = \underset{W}{\operatorname{argmin}}\, J(W)$$



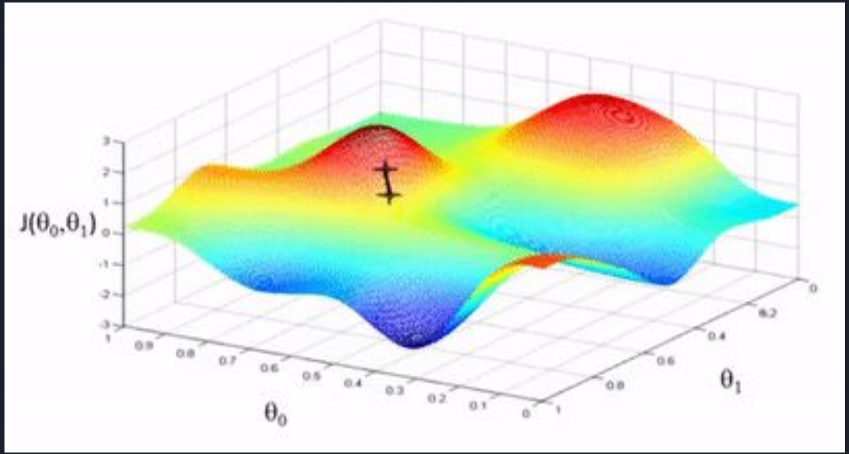
Neural Networks: Gradient Descent



Algorithm

1. Initialize weights randomly $\sim\mathcal{N}(0, \sigma^2)$
2. Loop until convergence:
3. Compute gradient, $\frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}}$
4. Update weights, $\boldsymbol{W} \leftarrow \boldsymbol{W} - \eta \frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}}$
5. Return weights

Neural Networks: Gradient Descent



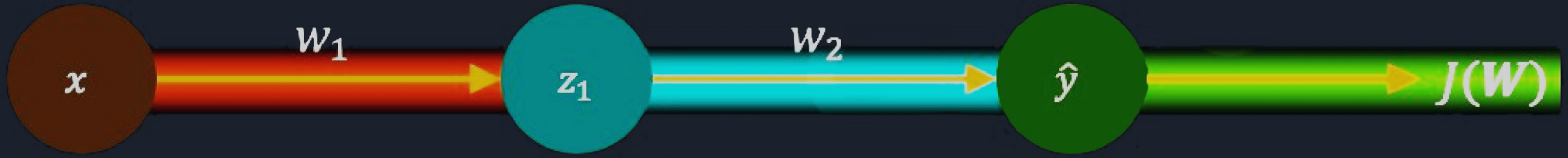

```
import tensorflow as tf

weight = tf.Variable([tf.random.normal()])

while True:
   with tf.GradientTape() as grad:
       loss = compute_loss(weight)
       gradient = grad.gradient(loss,
weight)

   weight = weight - lr *  gradient
```

Neural Networks: Backpropagation

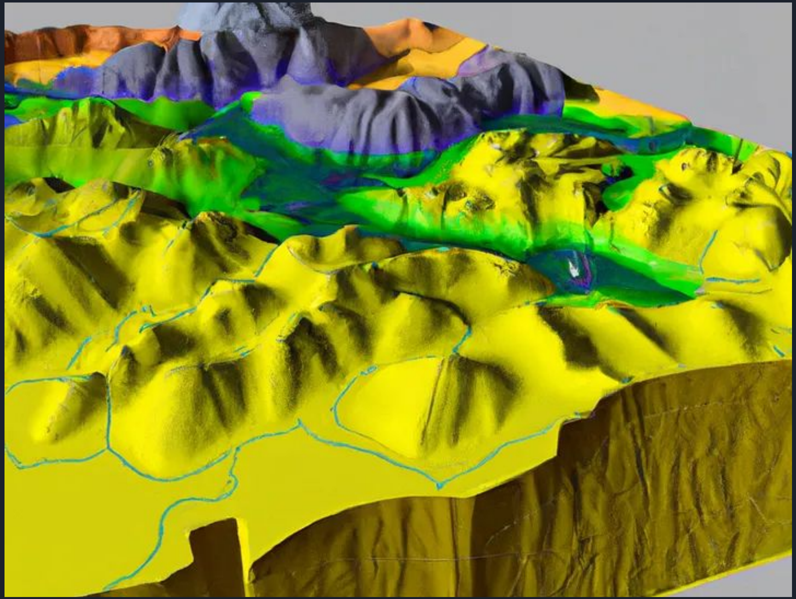


$$\frac{\partial J(\boldsymbol{W})}{\partial w_1} = \frac{\partial J(\boldsymbol{W})}{\partial \hat{y}} * \frac{\partial \hat{y}}{\partial z_1} * \frac{\partial z_1}{\partial w_1}$$

Repeat for every weight in the network using gradient from later layers

Optimizing Neural Nets & Problems

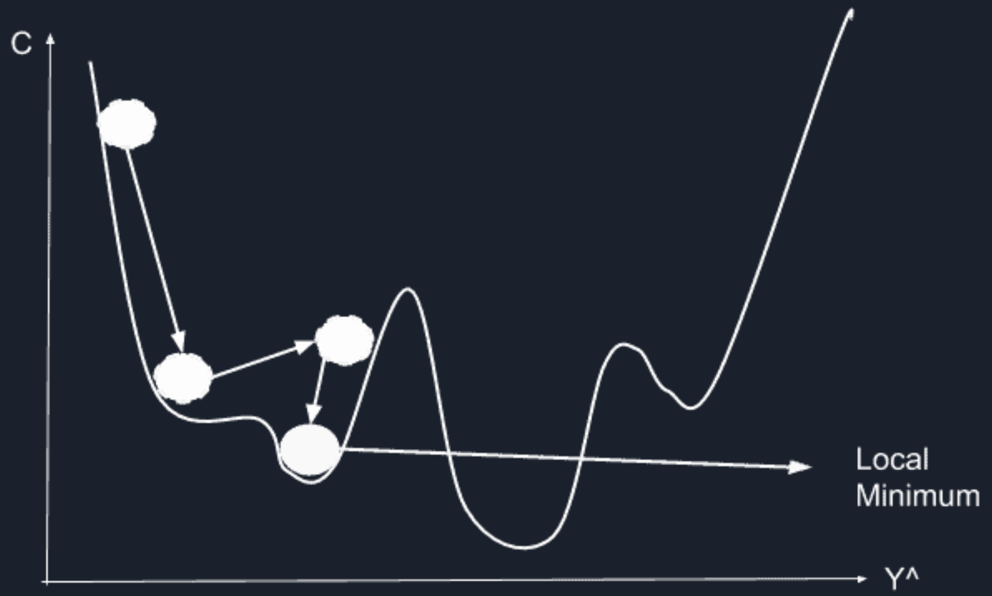
Neural Networks: Finding Learning Rate



Optimizing and finding best learning rate is difficult

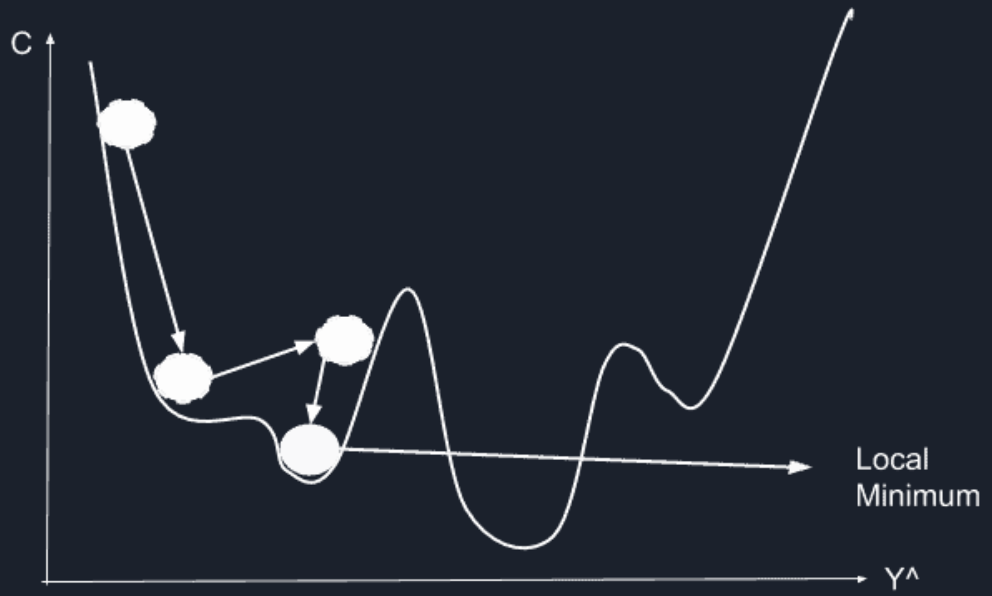
Neural Networks: Finding Learning Rate

- Large learning rate = Overshoot, Unstable, and Diverge
- Small learning rate = Slow to Converge, and Stuck in local minima
- Stable learning rate = Converge Smoothly, and avoid local minima



Neural Networks: Finding Learning Rate

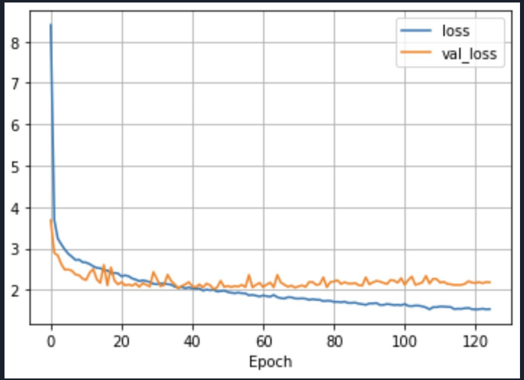
- Method 1: Brute force the learning rate and find what is work
- Method 2: Use mini batches
- Method 3: Adaptive learning rate; not fixed learning rate



Neural Networks: Gradient Descent Algorithms

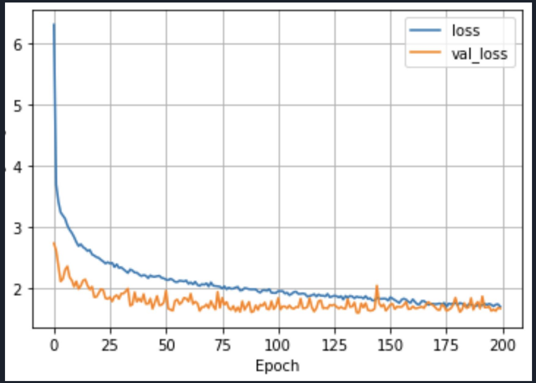
- SGD (Stochastic Gradient Descent) `tf.keras.optimizer.SGD`
- Adam `tf.keras.optimizer.Adam`
- Adadelta `tf.keras.optimizer.Adadelta`
- Adagrad `tf.keras.optimizer.Adagrad`
- RMSProp `tf.keras.optimizer.RMSProp`

Neural Networks: Learning Curve & Overfitting Problem

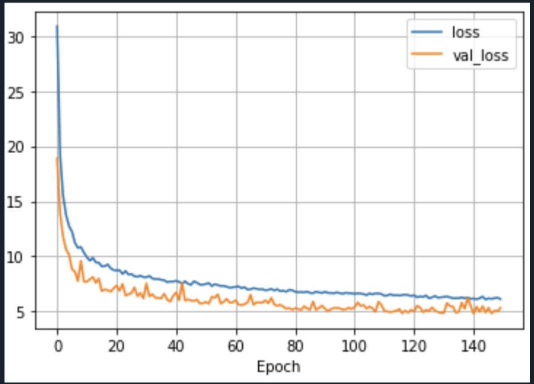


Overfitted model

Our model can’t generalize well



Fitted model



Underfitted model

Our model can’t fully understand the data

Neural Networks: Regularization

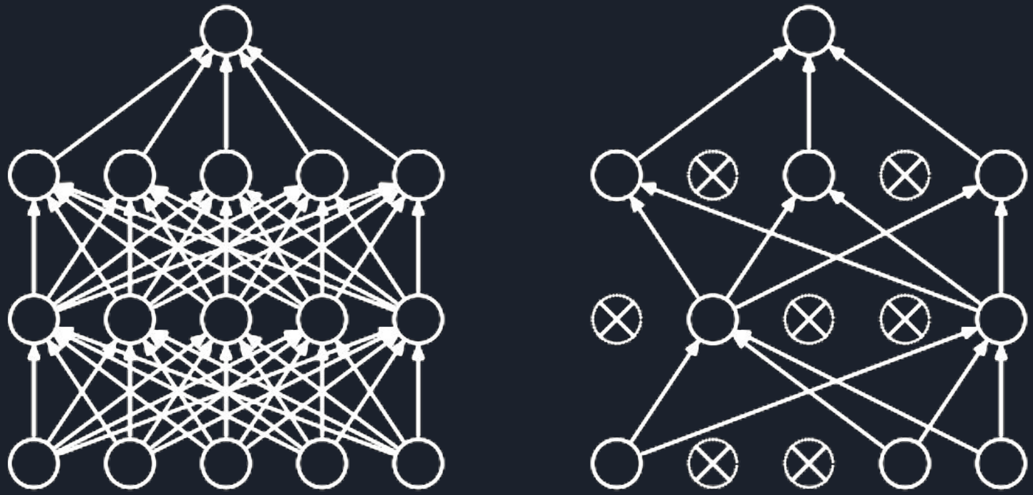
Technique to prevent overfitting

1. Droupout
2. Early stopping
3. BatchNormalization
4. etc.

Dropout

`tf.keras.layers.Dropout`

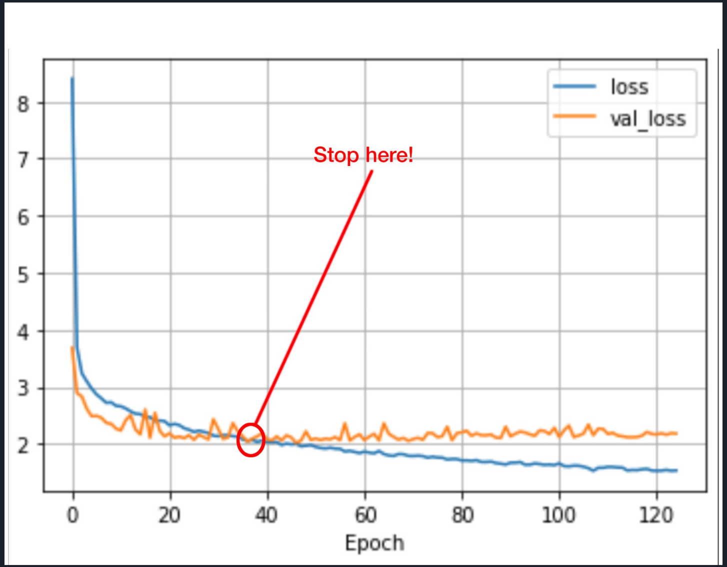
Dropout refers to dropping out the nodes (input and hidden layer) in a neural network with probability of *p*.



(a) Standard Neural Net (b) After applying dropout.

Early Stopping

`tf.keras.callbacks.EarlyStopping`

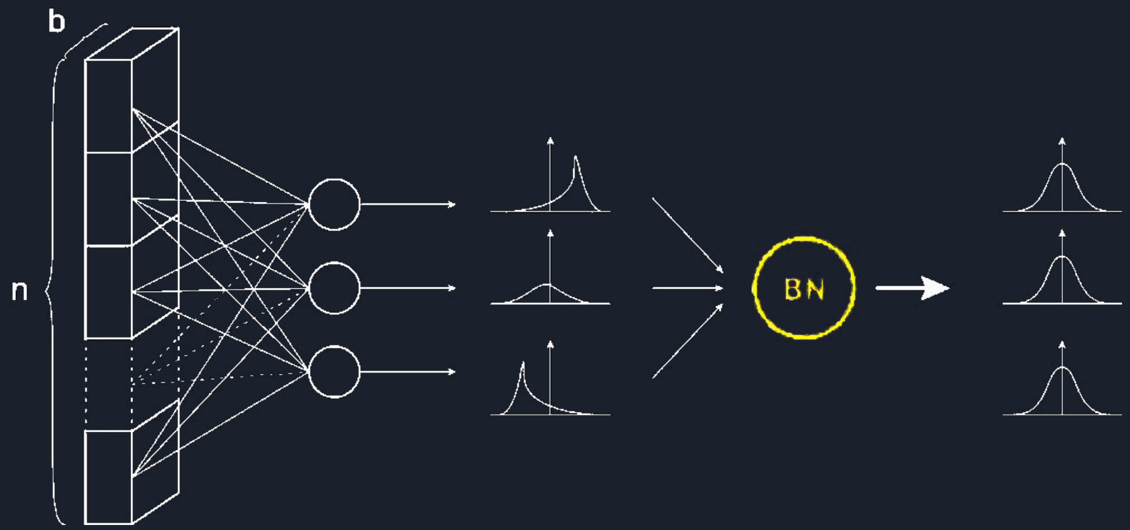


Stop the training before the model overfit

BatchNormalization

`tf.keras.layers.BatchNormalization`

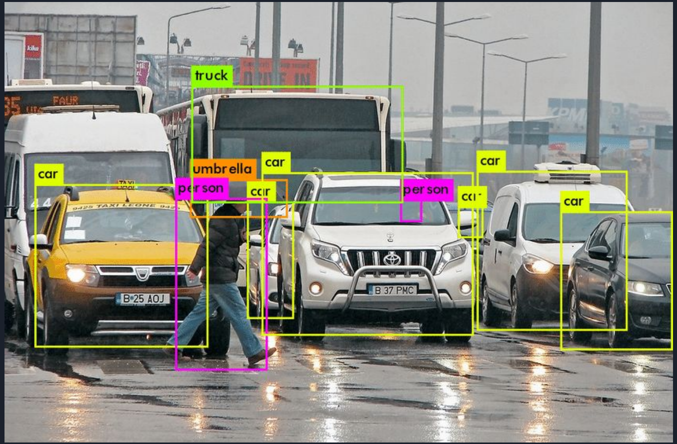
Batch normalization applies a transformation that maintains the mean output close to 0 and the output standard deviation close to 1.



Intro to Computer Vision: Classification

Example Use Case of Computer Vision

Regression: output variable takes continuous value. E.g. bounding box.



Object Detection

Object Segmentation

Example Use Case of Computer Vision

Classification: output variable takes class label.

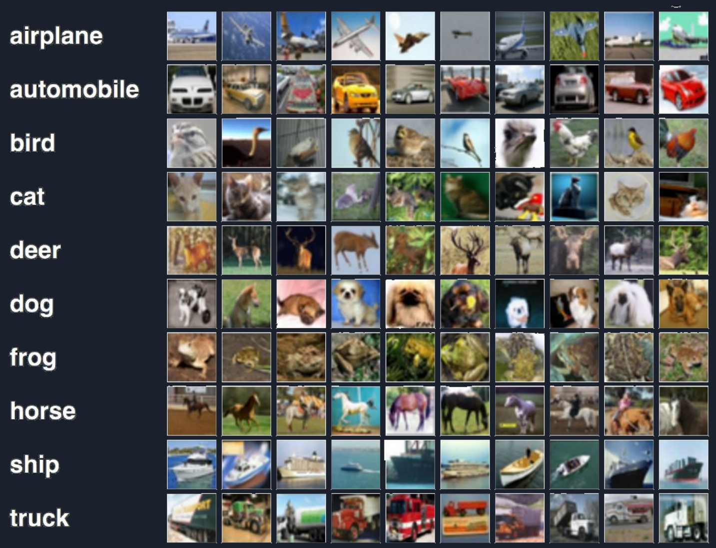
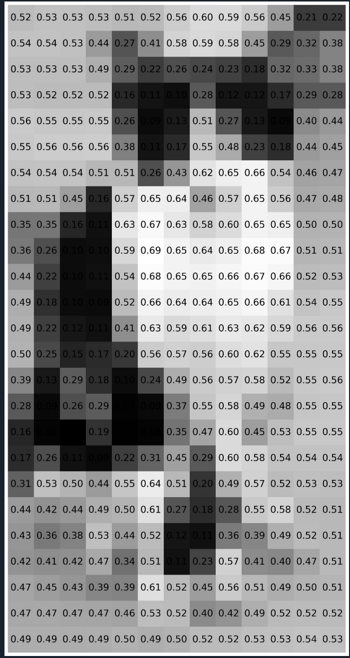


Image classification

How computers see images?




```
[[0.52 0.53 0.53 0.53 0.51 0.52 0.56 0.6  0.59 0.56 0.45 0.21 0.22]
 [0.54 0.54 0.53 0.44 0.27 0.41 0.58 0.59 0.58 0.45 0.29 0.32 0.38]
 [0.53 0.53 0.53 0.49 0.29 0.22 0.26 0.24 0.23 0.18 0.32 0.33 0.38]
 [0.53 0.52 0.52 0.52 0.16 0.11 0.1  0.28 0.12 0.12 0.17 0.29 0.28]
 [0.56 0.55 0.55 0.55 0.26 0.09 0.13 0.51 0.27 0.13 0.09 0.4  0.44]
 [0.55 0.56 0.56 0.56 0.38 0.11 0.17 0.55 0.48 0.23 0.18 0.44 0.45]
 [0.54 0.54 0.54 0.51 0.51 0.26 0.43 0.62 0.65 0.66 0.54 0.46 0.47]
 [0.51 0.51 0.45 0.16 0.57 0.65 0.64 0.46 0.57 0.65 0.56 0.47 0.48]
 [0.35 0.35 0.16 0.11 0.63 0.67 0.63 0.58 0.6  0.65 0.65 0.5  0.5 ]
 [0.36 0.26 0.1  0.1  0.59 0.69 0.65 0.64 0.65 0.68 0.67 0.51 0.51]
 [0.44 0.22 0.1  0.11 0.54 0.68 0.65 0.65 0.66 0.67 0.66 0.52 0.53]
 [0.49 0.18 0.1  0.09 0.52 0.66 0.64 0.64 0.65 0.66 0.61 0.54 0.55]
 [0.49 0.22 0.12 0.11 0.41 0.63 0.59 0.61 0.63 0.62 0.59 0.56 0.56]
 [0.5  0.25 0.15 0.17 0.2  0.56 0.57 0.56 0.6  0.62 0.55 0.55 0.55]
 [0.39 0.13 0.29 0.18 0.1  0.24 0.49 0.56 0.57 0.58 0.52 0.55 0.56]
 [0.28 0.09 0.26 0.29 0.07 0.09 0.37 0.55 0.58 0.49 0.48 0.55 0.55]
 [0.16 0.08 0.07 0.19 0.07 0.08 0.35 0.47 0.6  0.45 0.53 0.55 0.55]
 [0.17 0.26 0.11 0.09 0.22 0.31 0.45 0.29 0.6  0.58 0.54 0.54 0.54]
 [0.31 0.53 0.5  0.44 0.55 0.64 0.51 0.2  0.49 0.57 0.52 0.53 0.53]
 [0.44 0.42 0.44 0.49 0.5  0.61 0.27 0.18 0.28 0.55 0.58 0.52 0.51]
 [0.43 0.36 0.38 0.53 0.44 0.52 0.12 0.11 0.36 0.39 0.49 0.52 0.51]
 [0.42 0.41 0.42 0.47 0.34 0.51 0.11 0.23 0.57 0.41 0.4  0.47 0.51]
 [0.47 0.45 0.43 0.39 0.39 0.61 0.52 0.45 0.56 0.51 0.49 0.5  0.51]
 [0.47 0.47 0.47 0.47 0.46 0.53 0.52 0.4  0.42 0.49 0.52 0.52 0.52]
 [0.49 0.49 0.49 0.49 0.5  0.49 0.5  0.52 0.52 0.53 0.53 0.54 0.53]]
```

Image is just array of brightness value from each color channel!

How we see images?

Wheels
Glass
Tailgate
Doors

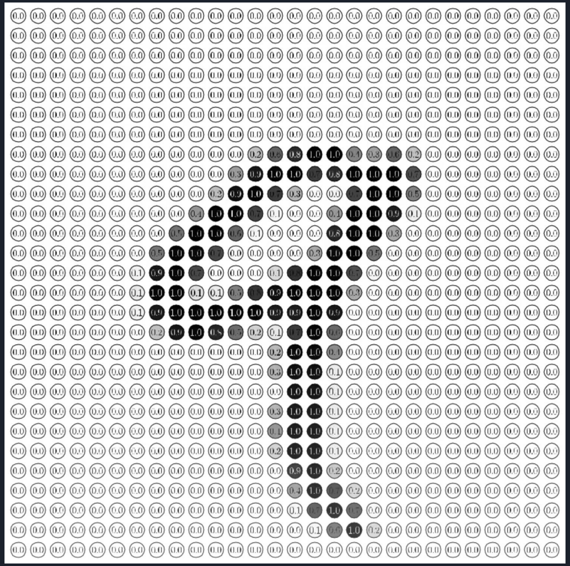
Ears
Mouth
Eyes
Nose

Ears
Mouth
Eyes
Nose

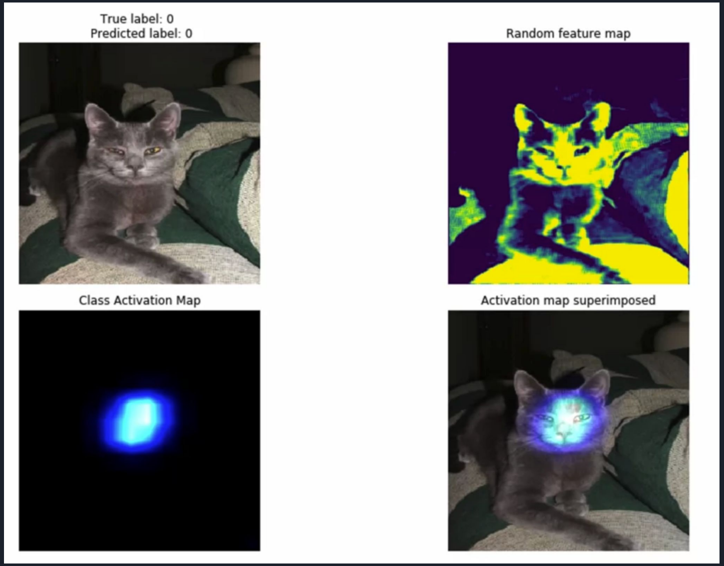
Different object have different feature.

Similar object have similar feature but different pattern.

What should computers see?



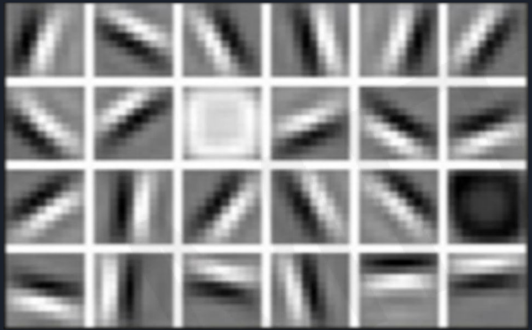
Array representation of image



Class activation map

What should computers do to understand?

Low level features



Lines & Edges

Mid level features

Eyes, Nose, & Ears

High level features

Facial Structures

Learning feature representations directly from data!

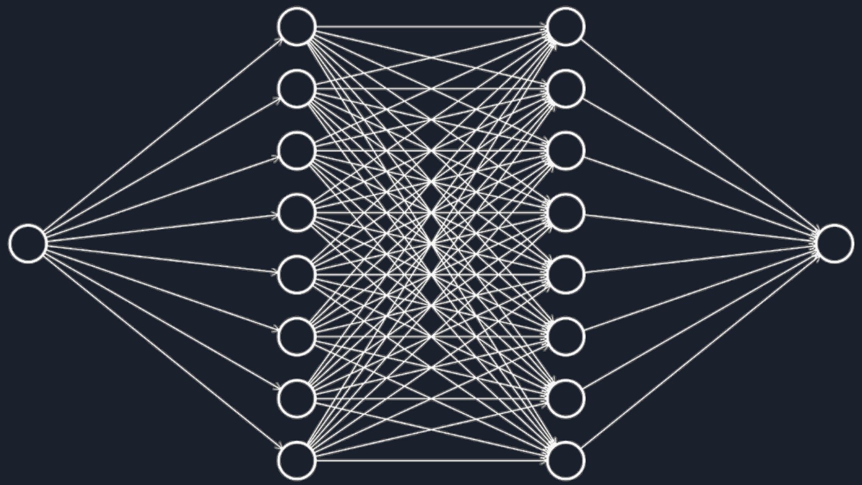
So, how can we make computer learning visual representation of images?

So, how can we make computer learning visual representation of images?

1. Feed-Forward Neural Network (FFN)
2. Convolutional Neural Network (CNN)
3. Transformer (*Next meeting*)

Feed-Forward Neural Network

Feed-Forward Neural Network

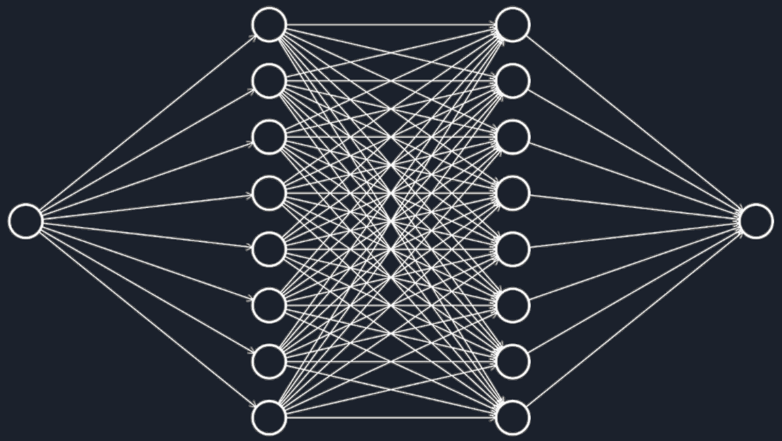


```
import tensorflow as tf


model = tf.keras.Sequential([
    tf.keras.layers.Dense(n1),
    tf.keras.layers.Dense(n2),
    ...,
    tf.keras.layers.Dense(2)
])
```

Feed-Forward Neural Network: Disadvantages

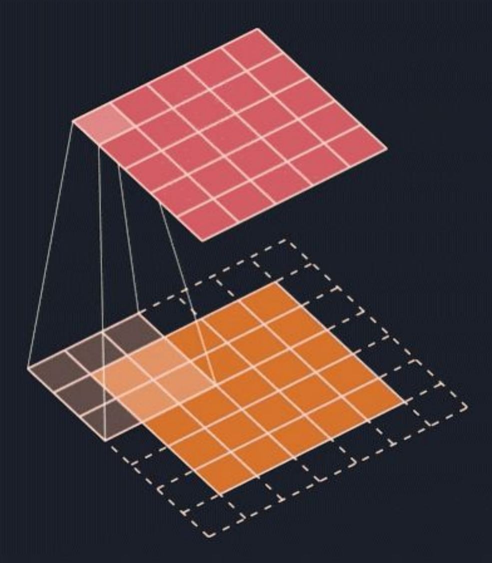
- No spatial information!
- 2D image input will be flatten out to 1D
- Lots of trainable parameters! (imagine a 100x100 px RGB image = more than 30k trainable parameter on neuron in first layer!)



Convolutional Neural Network (CNN)

Convolution Layer

a Deep Learning algorithm that can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image, and be able to differentiate one from the other.



Convolution Layer

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

?

=

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	1	-1	-1	-1
-1	-1	1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	1	-1	-1
-1	-1	-1	1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

Are they both the same?

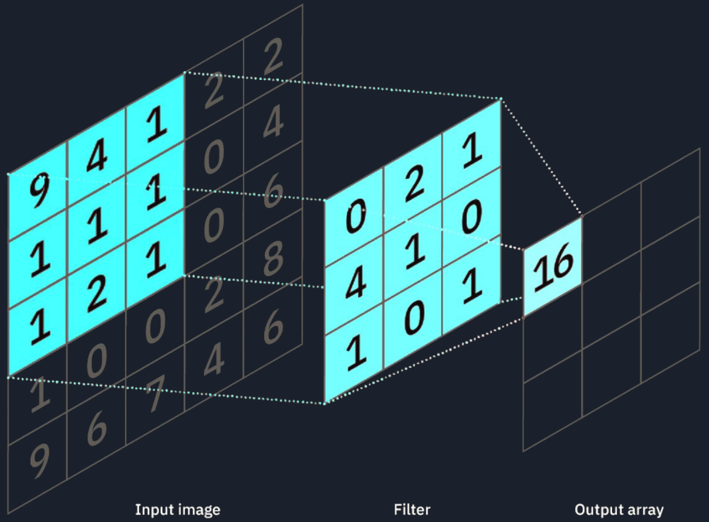
Convolution Layer

Yes. Both have the same features!

Thus, spatial information is very important!

Convolution Layer: Convolution Operation

`tf.keras.layers.Conv2D`



It's a dot product operation of given input image and it's filters.

Convolution: Feature Map

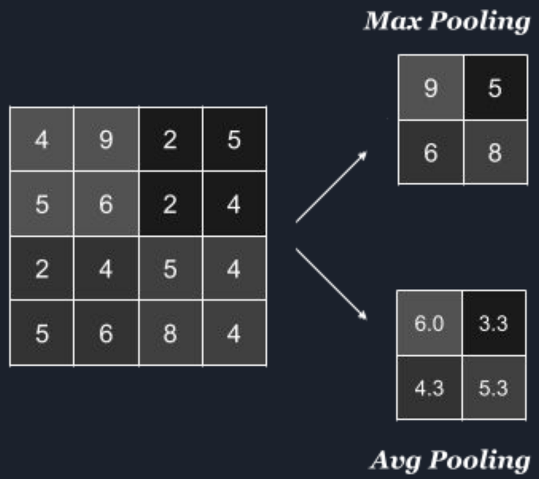
Original

Sharpen

Edge Detect

Pooling Layer

A common down-sampling technique in CNN




```
tf.keras.layers.MaxPool2D(pool_size=(2,2)
,
                               stride=2)
tf.keras.layers.AveragePooling2D(
                             pool_size=(2, 2),
                             stride=2)
```

CNN for Classification

CNN for Classification

1. Feature Extractor:

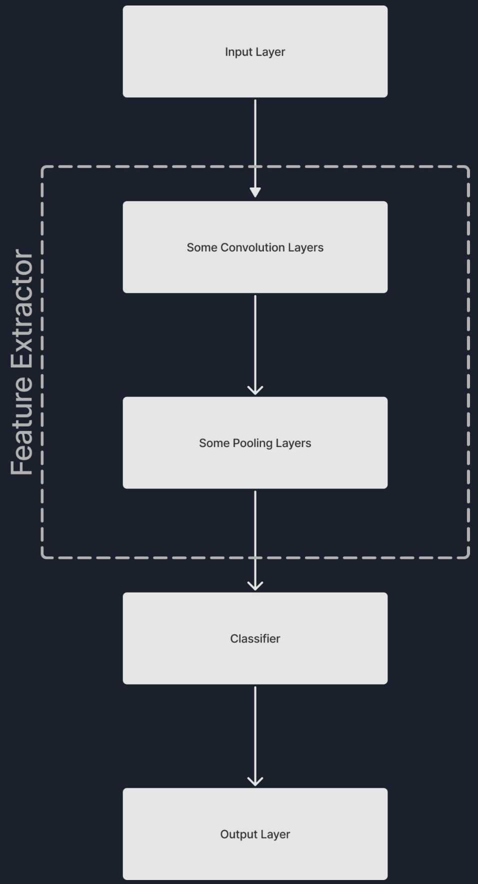
   Conv. Layer and Pooling Layer

2. Classifier:

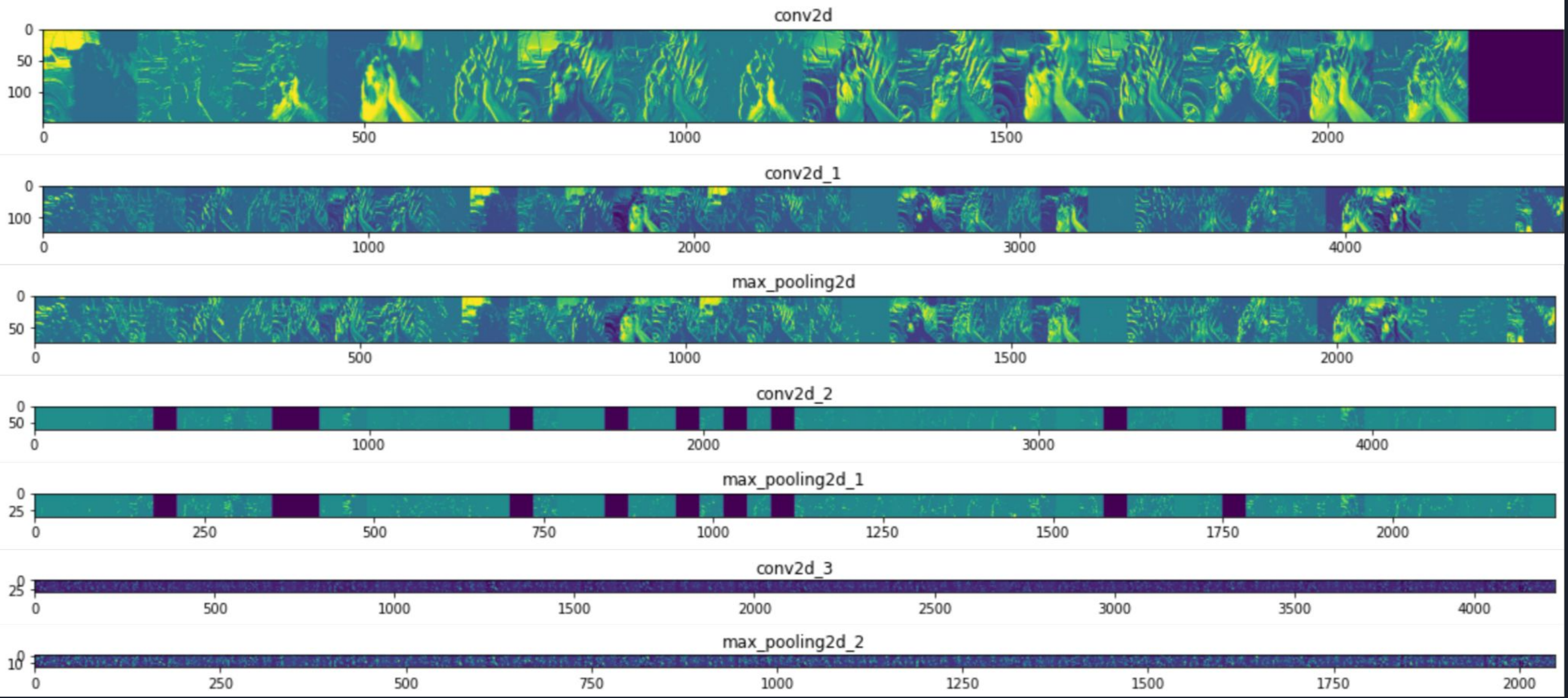
   Dense Layer with n neuron

3. Additional Layer:

   Dropout or Batch Normalization (to prevent overfitting)



CNN: Feature Extractor



CNN for Classification in Tensorflow

```
import tensorflow as tf
model = tf.keras.models.Sequential([
    tf.keras.layers.Conv2D(filters, kernel_size, padding,
activation='relu', input_shape=(image_shape)),
    ...,
    tf.keras.layers.MaxPooling2D(pool_size, strides),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(256, activation='relu'),
    tf.keras.layers.Dense(num_class, activation='softmax')
])
```

Hands-on: Cat vs Dog Image Classification

Colab : https://link.enova.id/lab1-cv1

Transfer Learning

Transfer Learning

Transfering the knowledge of one model to perform a new task.

Transfer Learning: Motivation

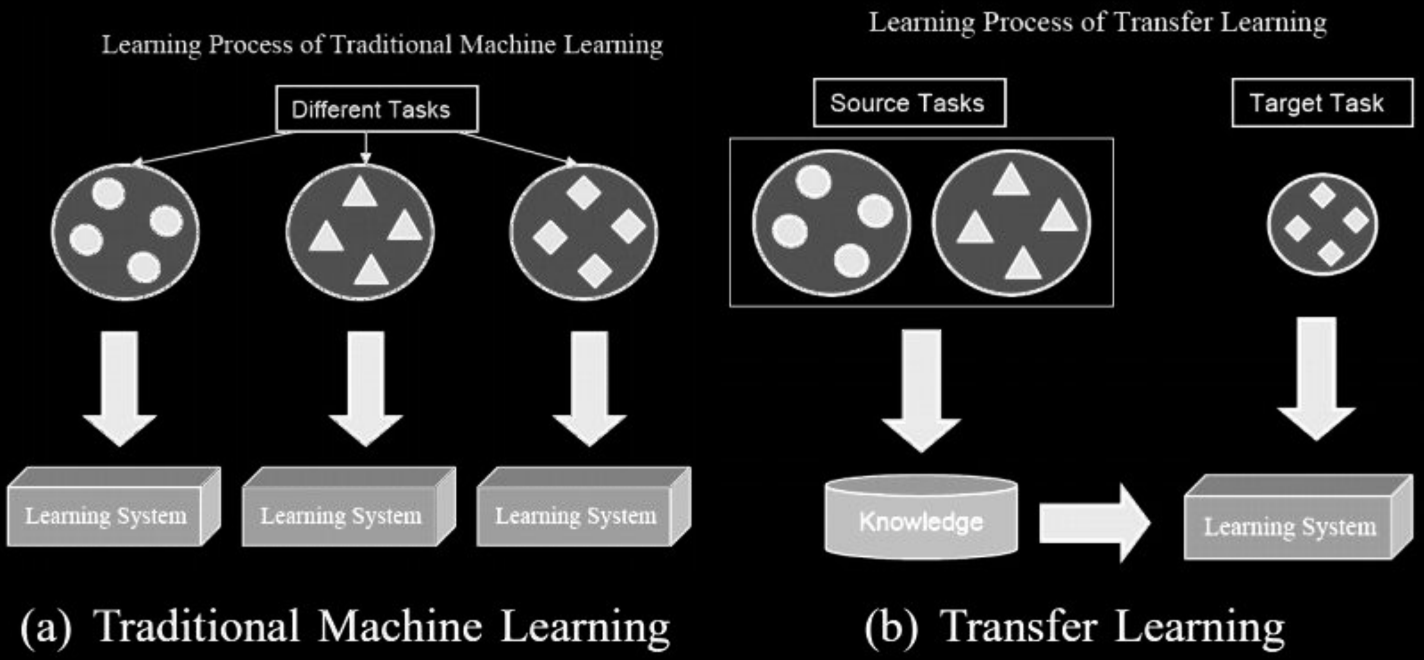
- Lots of data, time, resources needed to train and tune a neural network from scratch

    An ImageNet deep neural net can take weeks to train and fine-tune from scratch.

    Unless you have 256 GPUs, possible to achieve in 1 hour

- Cheaper, faster way of adapting a neural network by exploiting their generalization properties

Traditional Learning vs Transfer Learning



Transfer Learning in Neural Networks

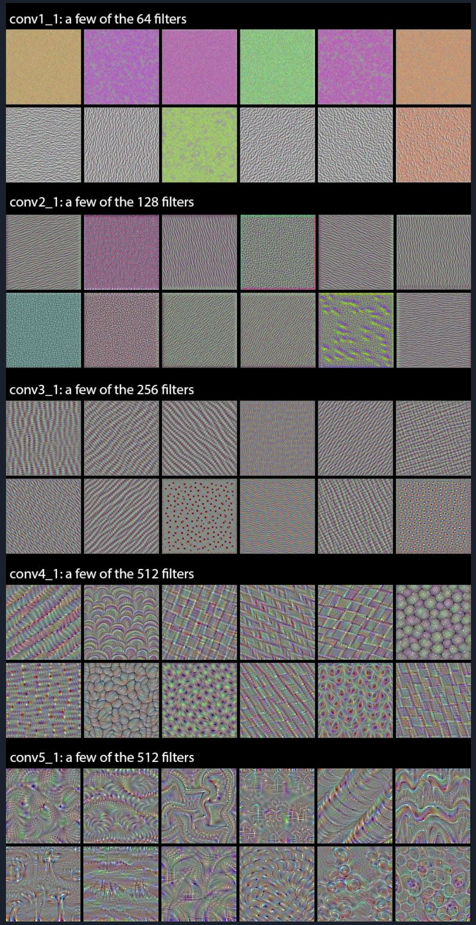
Neural Network Layers: General to Specific

- Bottom/first/earlier layers: general learners

    Low-level notions of edges, visual shapes

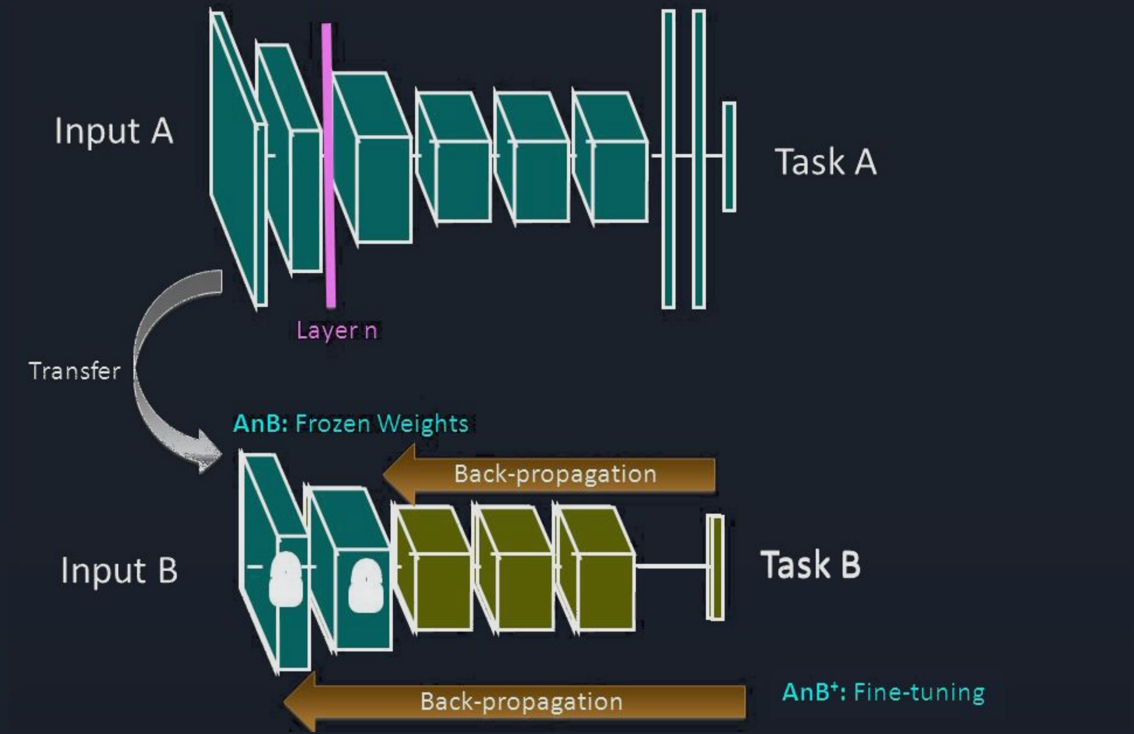
- Top/last/later layers: specific learners

    High-level features such as eyes, feathers



VGG16 Filters

Transfer Learning in Neural Networks



Practice Lab: Chest Cancer Detection

Colab : https://link.enova.id/lab2-cv1

Exploration: Advanced Computer Vision

Crowd Counting (Object Detection)
Combined CSRNet & mobilenetv3_ssdlite

Human Pose, Face Landmarks, and Hand Tracking
Mediapipe API

Exploration: Advanced Computer Vision

Style Transfer (GANs)
Fast Neural Style Transfer

Image to Video (GANs)
NeRF: Neural Radiance Fields

Exploration: Advanced Computer Vision

You can explore more on this area from this topic:

- Advances Computer Vision using Tensorflow Functional API
- Generative Deep Learning
- Transfer Learning Techniques
- etc.

Next Week: Advanced Computer Vision

- Tensorflow Functional API
- Transformer for Image
- Methods for Object Detection
- Overview of Image Segmentation

Q&A Session

Thank You

For further questions, contact me at daniyal.kausar@gmail.com

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