人體活動辨識模組
Human activity recognition module

國立台灣科技大學電子系

Department of Electronic and Computer Engineering, NTUST

單元一：Cat & Dog分類CNN模型實驗

Unit 1: Cat & Dog classification and CNN model experiment

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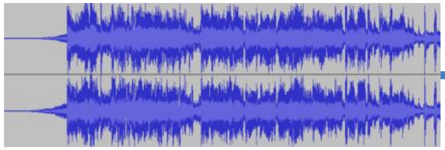
Unit 1: Cat & Dog classification and CNN model experiment

- What is machine learning?
- Perceptron
- Fully connected layer
- Convolution
- Transfer learning
- Lab 1

What is machine learning?

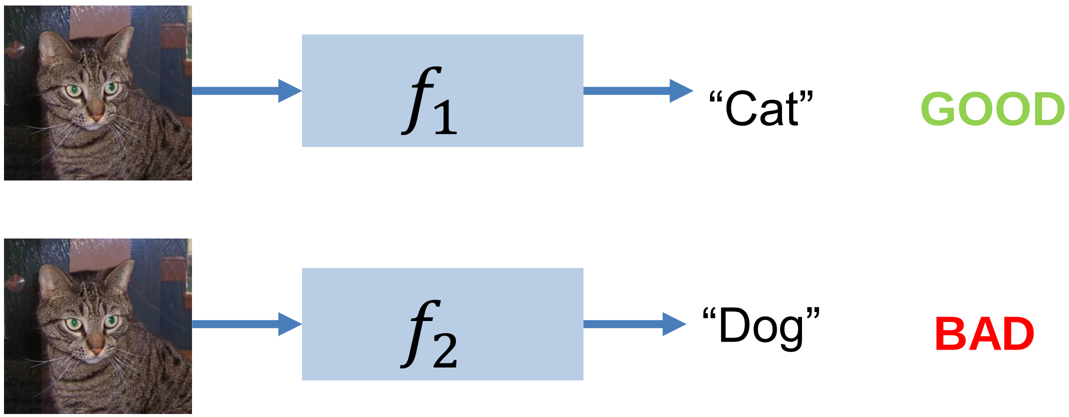
"Machine Learning" → f → "機器學習"

 → f → "Hello world"

 → f → "Cat"

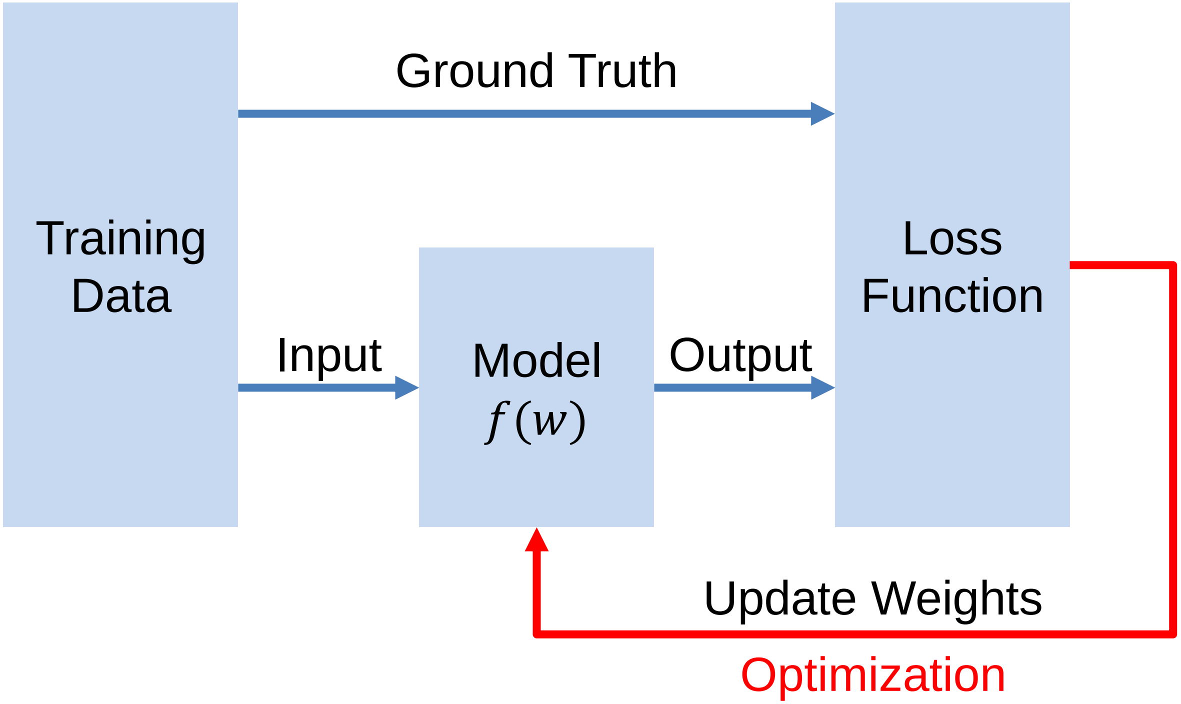
What is machine learning?

- Define a set of function $f(w_1, w_2, \ldots, w_n)$.
- Get a best function $f(0,1,\ldots,0)$.



Training

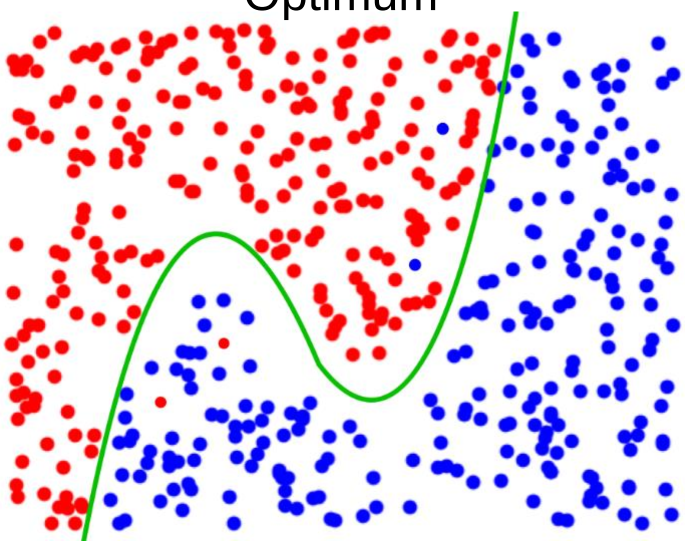
- Loss Function: Measure the difference between ground truth and model output.
- Optimization: Try to get better weights for the model.



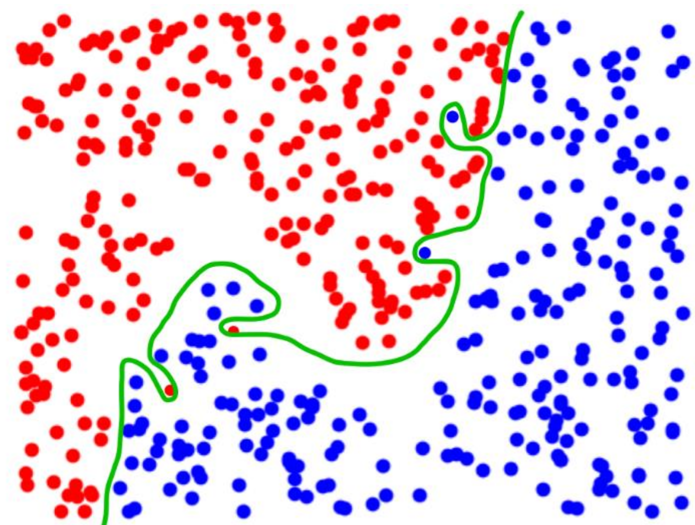
Overfitting

- Overfitting means that prediction is too close to the training data.
- It may get a bad accuracy at unseen data.

Optimum

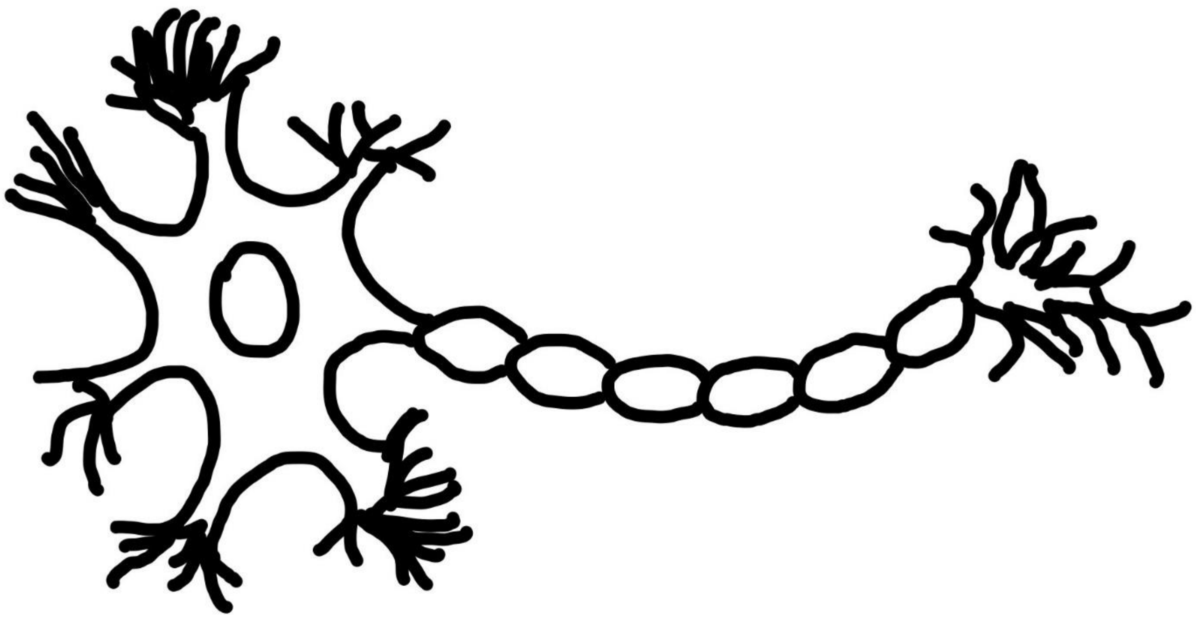


Overfitting



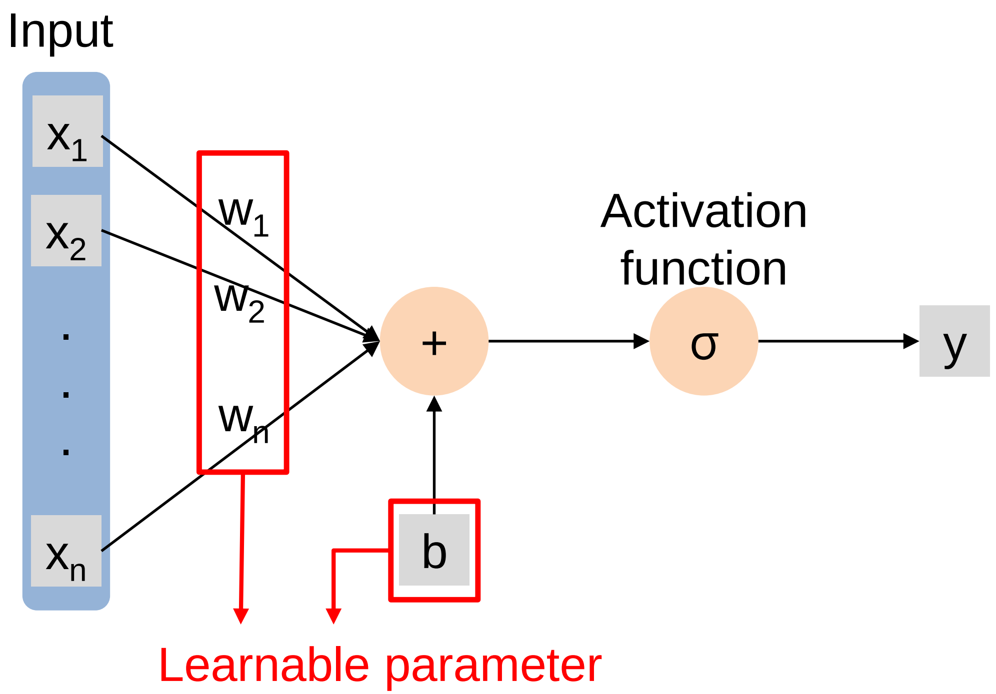
Perceptron

- Perceptron is a mathematical function modeled on the working of biological neurons.



Perceptron

- The output of perceptron is weighted sum of input and passed through a activation function.



$$y = \sigma\left(\sum_{i=1}^{n} w_i x_i + b\right)$$

Activation function

- Activation function is a nonlinear function that mapping the result value in a range.

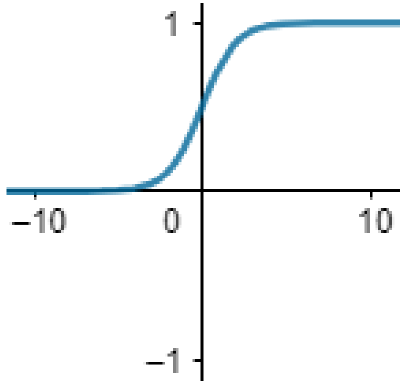
ex.

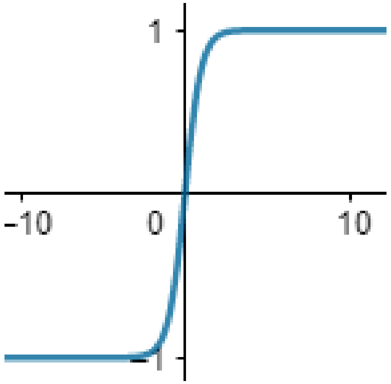
Sigmoid: $[-\infty, +\infty] \rightarrow [0, 1]$

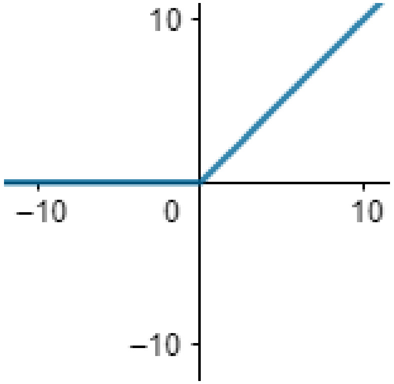
Tanh : $[-\infty, +\infty] \rightarrow [-1, 1]$

Activation function

- Common activation function







sigmoid : $\sigma = \frac{1}{1+e^{-x}}$

tanh : $\sigma = \tanh(x)$

ReLU : $\sigma = \begin{cases} 0 \; if \; x < 0 \\ x \; if \; x \geq 0 \end{cases}$

limit output value between 0 and 1

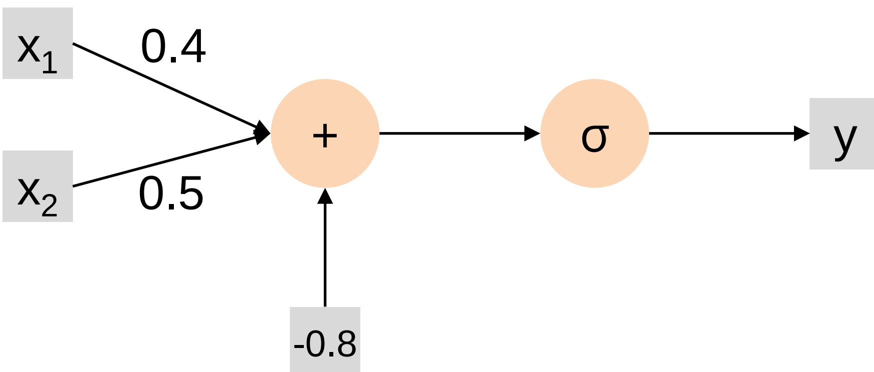
limit output value between -1 and 1

ignore negative output

Perceptron example

- AND gate

$$w = [0.4, 0.5], b = -0.8, \sigma(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{if } x \leq 0 \end{cases}$$



$$y = \sigma(0.4 * x_1 + 0.5 * x_2 - 0.8)$$

$$x = [0,0], y = \sigma(0.4 * 0 + 0.5 * 0 - 0.8) = \sigma(-0.8) = 0$$
$$x = [0,1], y = \sigma(0.4 * 0 + 0.5 * 1 - 0.8) = \sigma(-0.3) = 0$$
$$x = [1,0], y = \sigma(0.4 * 1 + 0.5 * 0 - 0.8) = \sigma(-0.4) = 0$$
$$x = [1,1], y = \sigma(0.4 * 1 + 0.5 * 1 - 0.8) = \sigma(+0.1) = 1$$

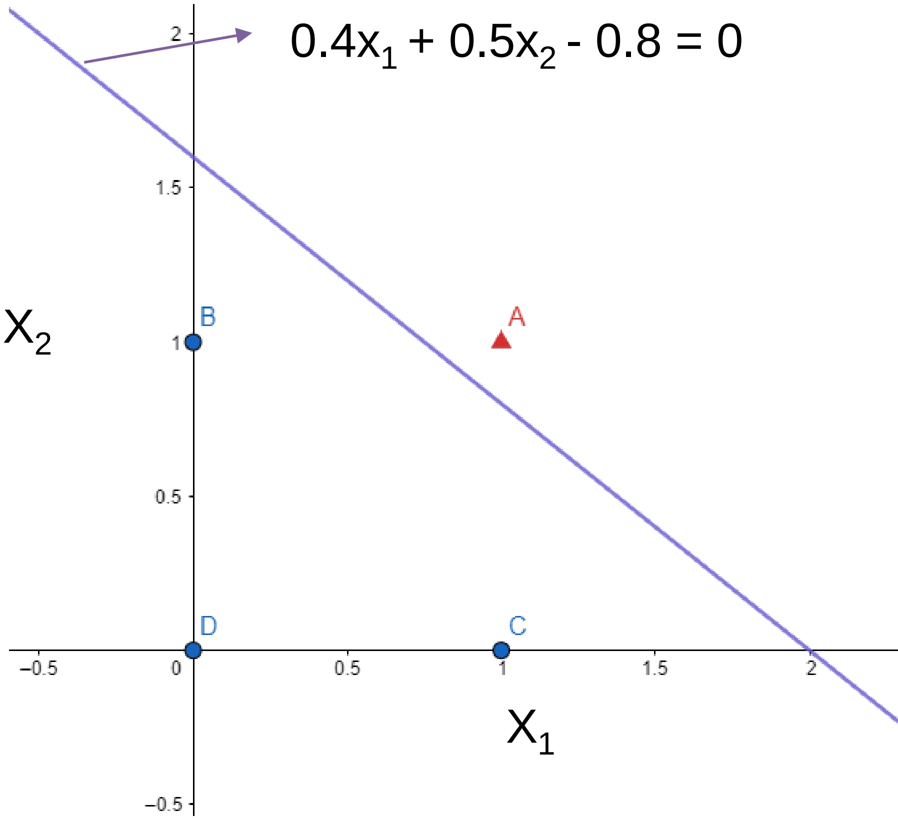
Perceptron example

- AND gate

$$w = [0.4, 0.5], b = -0.8, \sigma(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{if } x \leq 0 \end{cases}$$

Single level perceptron can learn only linearly separable patterns

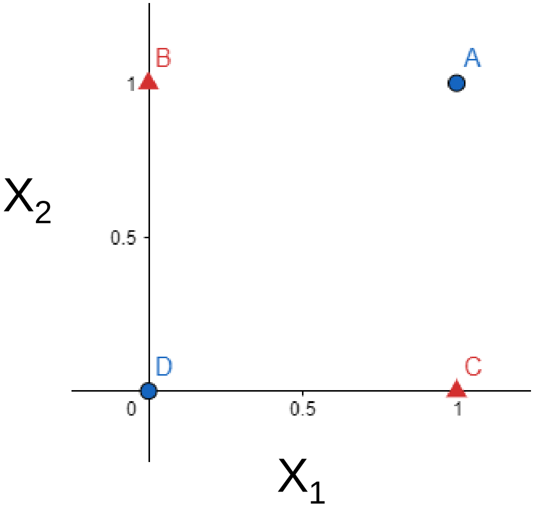
X_1	X_2	Q (label)
0	0	0
0	1	0
1	0	0
1	1	1



Perceptron example

- XOR gate
  - Cannot find a suitable parameter for simulating XOR gate.

X_1	X_2	Q (label)
0	0	0
0	1	1
1	0	1
1	1	0

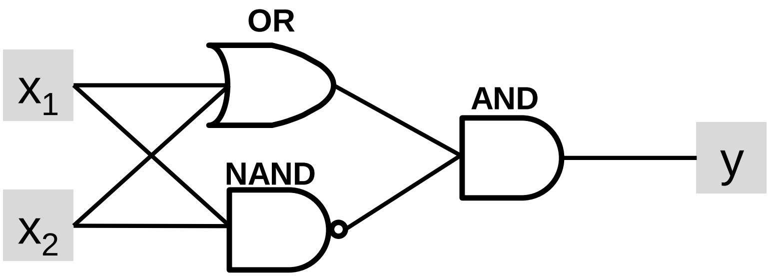


Perceptron example

- Single layer perceptron can learn only linear separable pattern.
- For more complicate problem, we need more perceptrons.

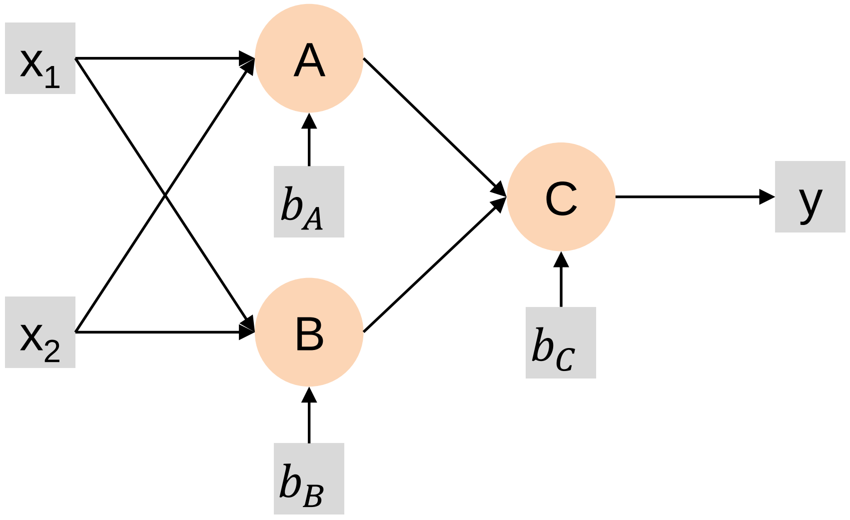
Perceptron example

- XOR gate
  - Idea: Combine more linear separable gates to perform XOR gate.



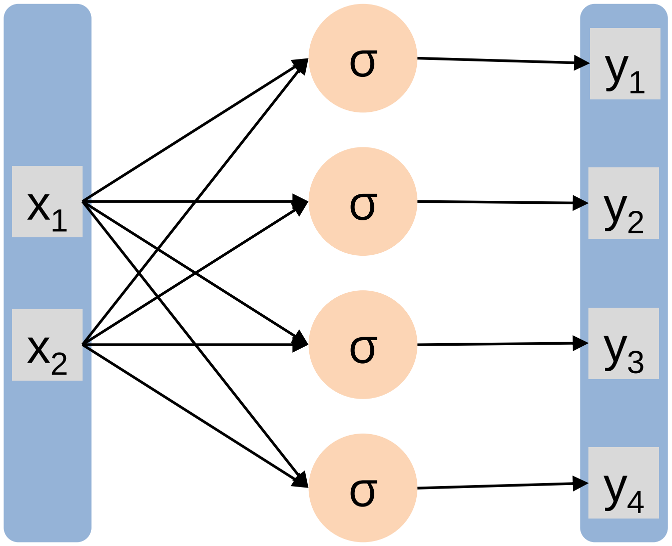
Perceptron example

- XOR gate



Fully connected layer

- Fully connected layer is a neuron network that all neurons are connected all the input neuron.



$$y_1 = \sigma(w_{11}x_1 + w_{21}x_2 + b_1)$$

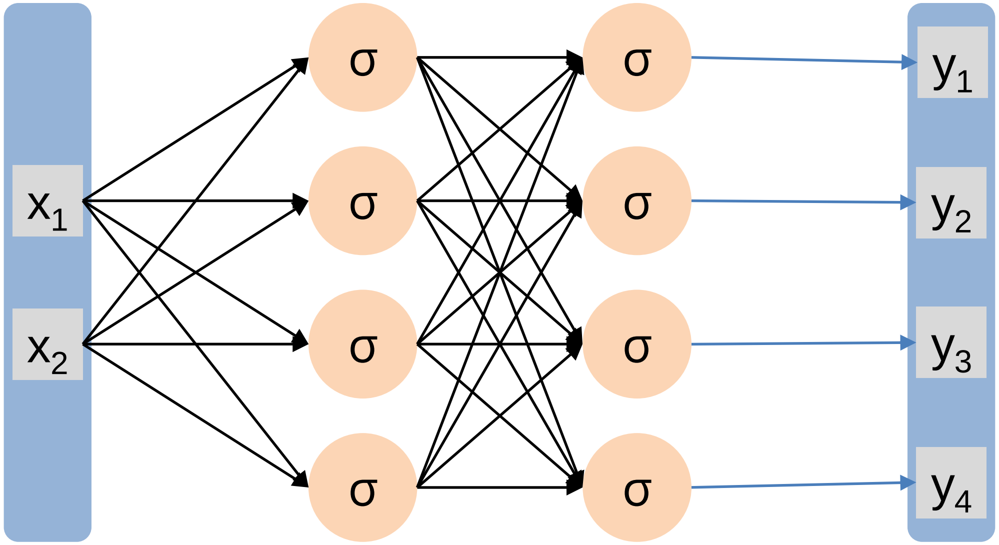
$$y_2 = \sigma(w_{12}x_1 + w_{22}x_2 + b_2)$$

$$y_3 = \sigma(w_{13}x_1 + w_{23}x_2 + b_3)$$

$$y_4 = \sigma(w_{14}x_1 + w_{24}x_2 + b_4)$$

Fully connected layer

- If we cannot classify the training data, we may need more layers.



Convolution

- If we want to find a pattern: Vertical line in a image, we can use the below kernel (filter) to calculate the convolution.

1*0 + 0*1 + 0*0 +
0*0 + 1*1 + 0*0 +
0*0 + 0*1 + 1*0

1	0	0	0	1
0	1	0	1	0
0	0	1	0	0
0	0	1	0	0
0	0	1	0	0

input

*

0	1	0
0	1	0
0	1	0

Kernel (filter)

=

1		

output

Convolution

- Then we slide window and calculate the next value.

0*0 + 0*1 + 0*0 +
1*0 + 0*1 + 1*0 +
0*0 + 1*1 + 0*0

1	0	0	0	1
0	1	0	1	0
0	0	1	0	0
0	0	1	0	0
0	0	1	0	0

input

*

0	1	0
0	1	0
0	1	0

Kernel (filter)

=

1	1	

output

Convolution

- Then we slide window and calculate the next value.

0*0 + 0*1 + 1*0 +
0*0 + 1*1 + 0*0 +
1*0 + 0*1 + 0*0

1	0	0	0	1
0	1	0	1	0
0	0	1	0	0
0	0	1	0	0
0	0	1	0	0

input

*

0	1	0
0	1	0
0	1	0

Kernel (filter)

=

1	1	1

output

Convolution

- Then we slide window and calculate the next value.

0*0 + 1*1 + 0*0 +
0*0 + 0*1 + 1*0 +
0*0 + 0*1 + 1*0

1	0	0	0	1
0	1	0	1	0
0	0	1	0	0
0	0	1	0	0
0	0	1	0	0

input

*

0	1	0
0	1	0
0	1	0

Kernel (filter)

=

1	1	1
1		

output

Convolution

1*0 + 0*1 + 0*0 +
1*0 + 0*1 + 0*0 +
1*0 + 0*1 + 0*0

1	0	0	0	1
0	1	0	1	0
0	0	1	0	0
0	0	1	0	0
0	0	1	0	0

input

*

Kernel (filter)

0	1	0
0	1	0
0	1	0

=

1	1	1
1	2	1
0	3	0

output

Convolution

- The output indicates how many (vertical line) features the input has.

vertical line feature

max value

input

1	0	0	0	1
0	1	0	1	0
0	0	1	0	0
0	0	1	0	0
0	0	1	0	0

*

Kernel (filter)

0	1	0
0	1	0
0	1	0

=

output

1	1	1
1	2	1
0	3	0

Convolution

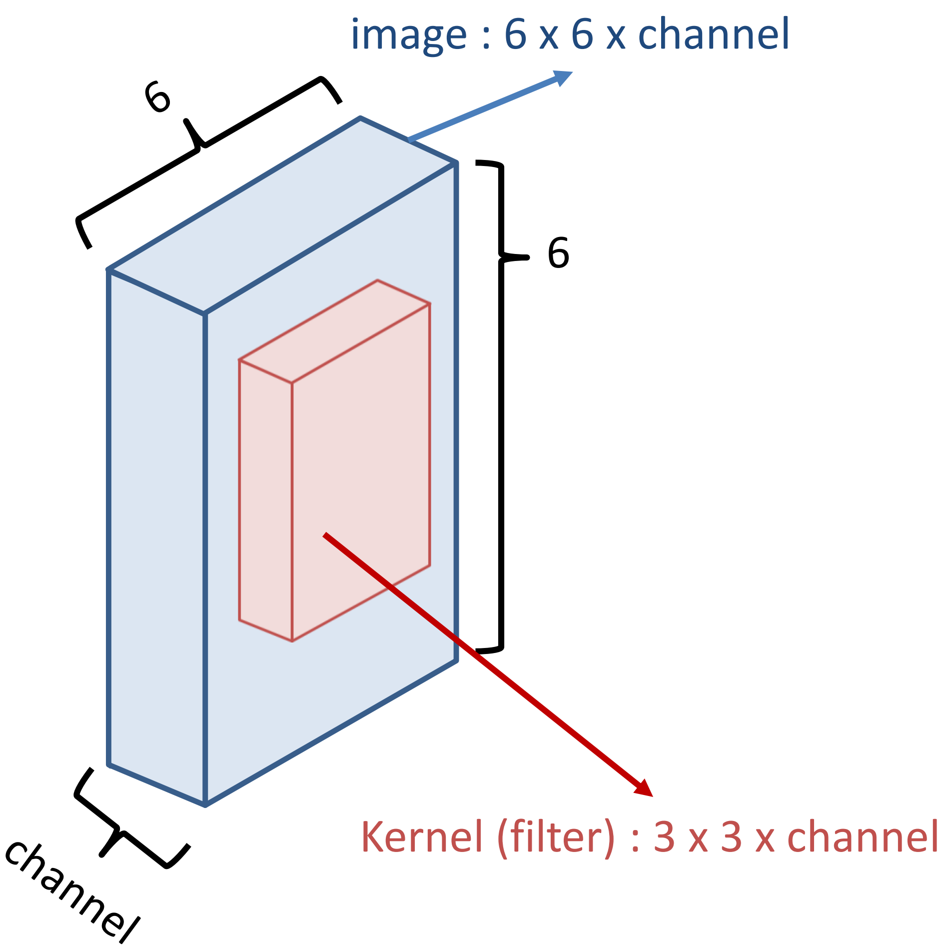
- Convolution operation can extract features on the image.
- But handicraft kernel is not efficient.
- So we use training data to train the kernel parameters.

w_{11}	w_{12}	w_{13}
w_{21}	w_{22}	w_{23}
w_{31}	w_{32}	w_{33}

Kernel (filter)

Learnable parameter

Convolution

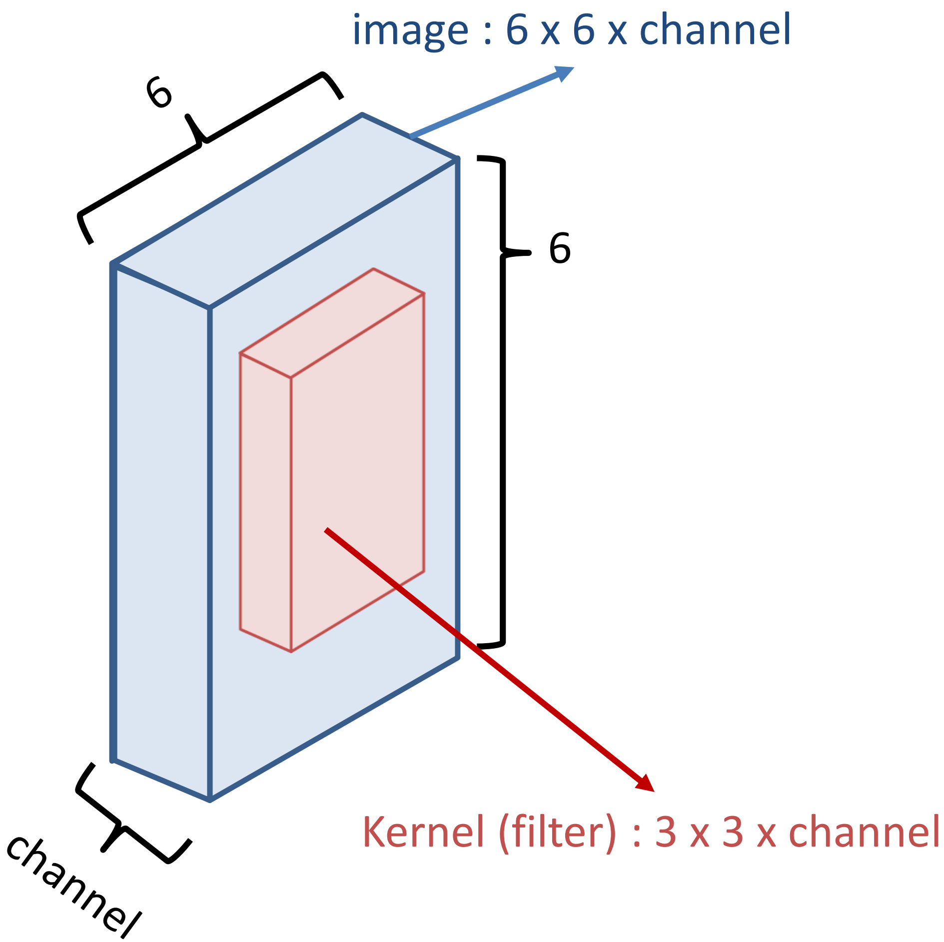


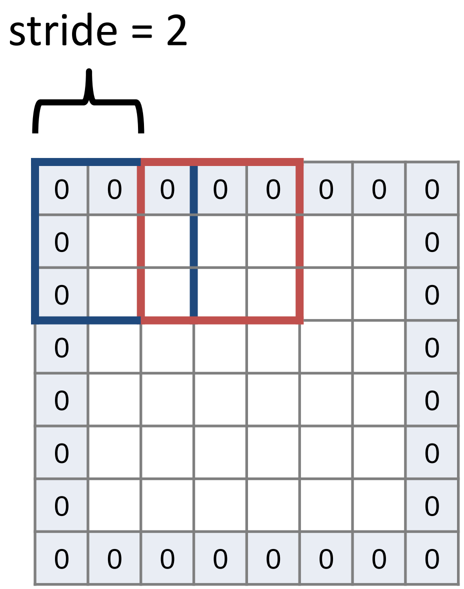
0	0	0	0	0	0	0	0
0							0
0							0
0							0
0							0
0							0
0							0
0	0	0	0	0	0	0	0

image with padding zero

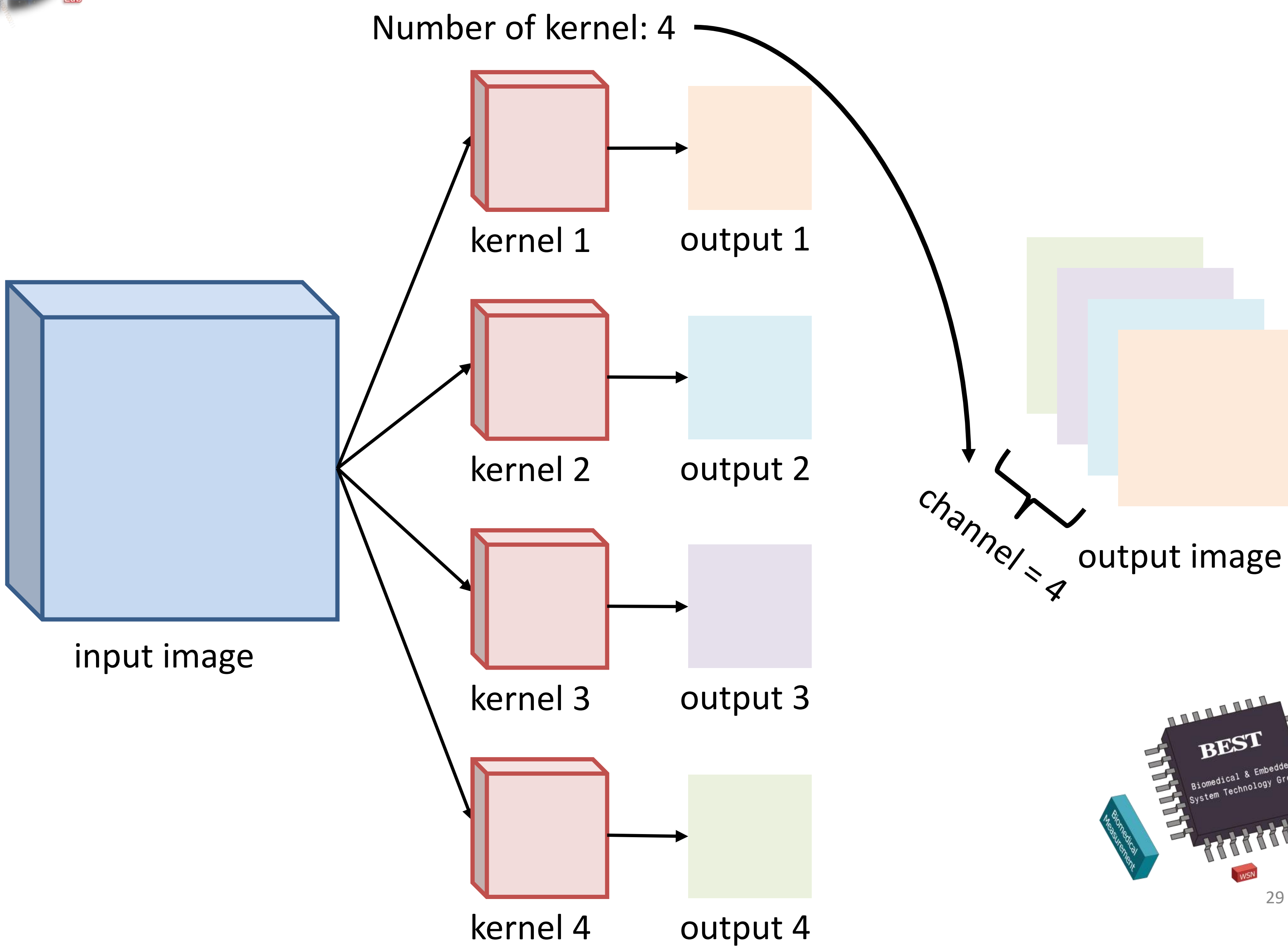
image without padding zero

Convolution



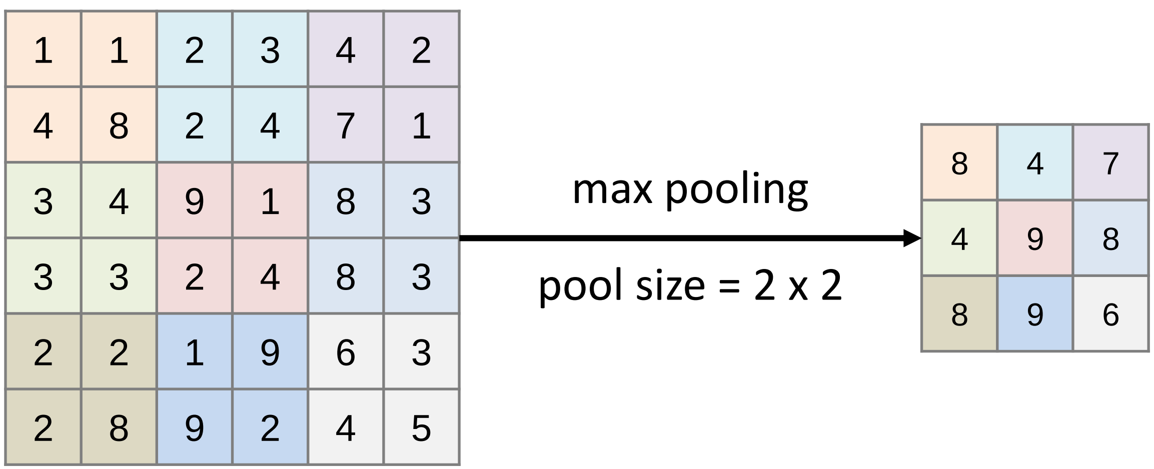


Convolution



Pooling

- Downsample the image to reduce the calculated complexity.



Transfer learning

- A pre-trained model is a saved network that was previously trained on a large dataset.

- You can customize the pre-trained model for your task.

Transfer learning

- VGG-16
  - The model accuracy is 92.7% on top-5 test of ImageNet, which is a dataset of over 14 million images belonging to 1000 classes.

Image
Conv 64
Conv 64
Max pooling
Conv 128
Conv 128
Max pooling
Conv 256
Conv 256
Max pooling
Conv 512
Conv 512
Conv 512
Max pooling
Conv 512
Conv 512
Conv 512
Max pooling
FC 4096
FC 4096
FC 1000

Transfer learning

- Task :
  - classify dog and cat
- Idea :
  - change last FC layer

Image	Image
Conv 64	Conv 64
Conv 64	Conv 64
Max pooling	Max pooling
Conv 128	Conv 128
Conv 128	Conv 128
Max pooling	Max pooling
Conv 256	Conv 256
Conv 256	Conv 256
Max pooling	Max pooling
Conv 512	Conv 512
Conv 512	Conv 512
Conv 512	Conv 512
Max pooling	Max pooling
Conv 512	Conv 512
Conv 512	Conv 512
Conv 512	Conv 512
Max pooling	Max pooling
FC 4096	FC 4096
FC 4096	FC 4096
FC 1000	**FC 2**

Transfer learning

- Try to use pre-trained weights when training in a small dataset.

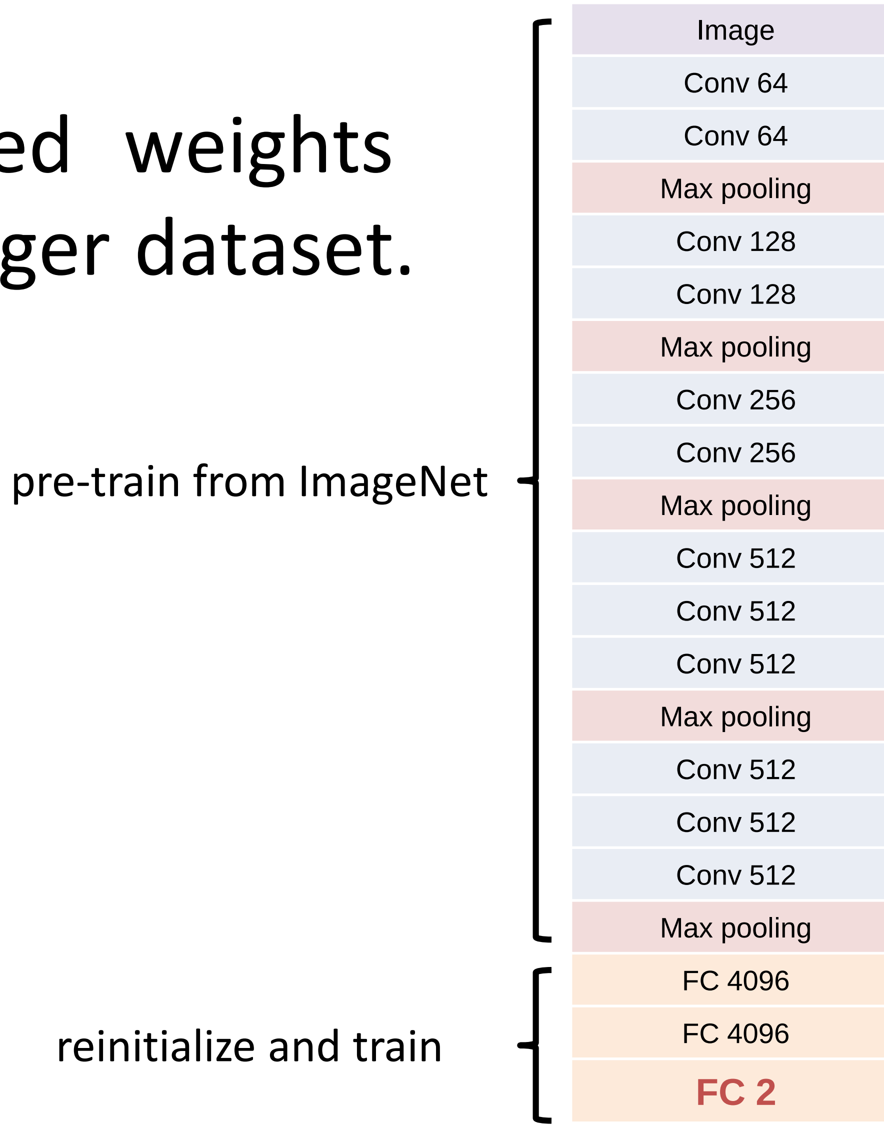
Image
Conv 64
Conv 64
Max pooling
Conv 128
Conv 128
Max pooling
Conv 256
Conv 256
Max pooling
Conv 512
Conv 512
Conv 512
Max pooling
Conv 512
Conv 512
Conv 512
Max pooling
FC 4096
FC 4096
FC 2

pre-train from ImageNet

reinitialize and train

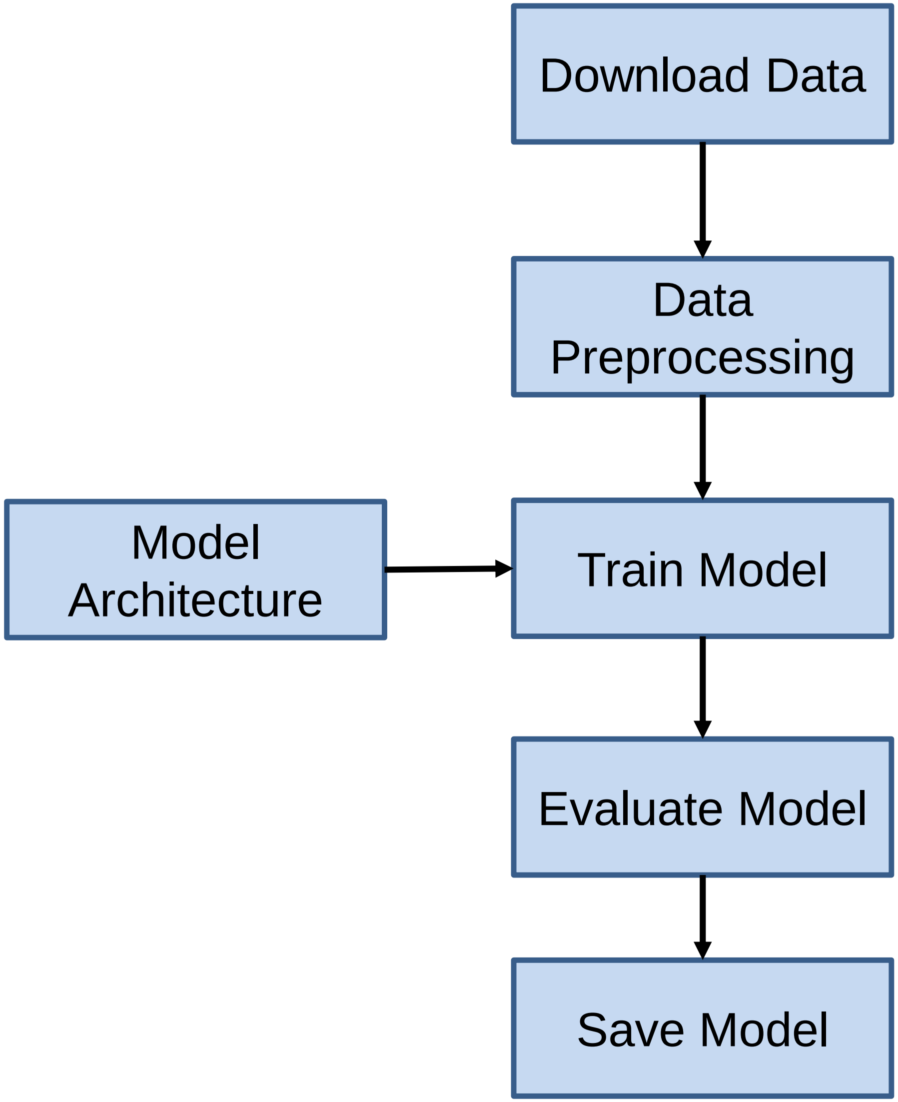
Transfer learning

- Use fewer pre-trained weights when training in a larger dataset.



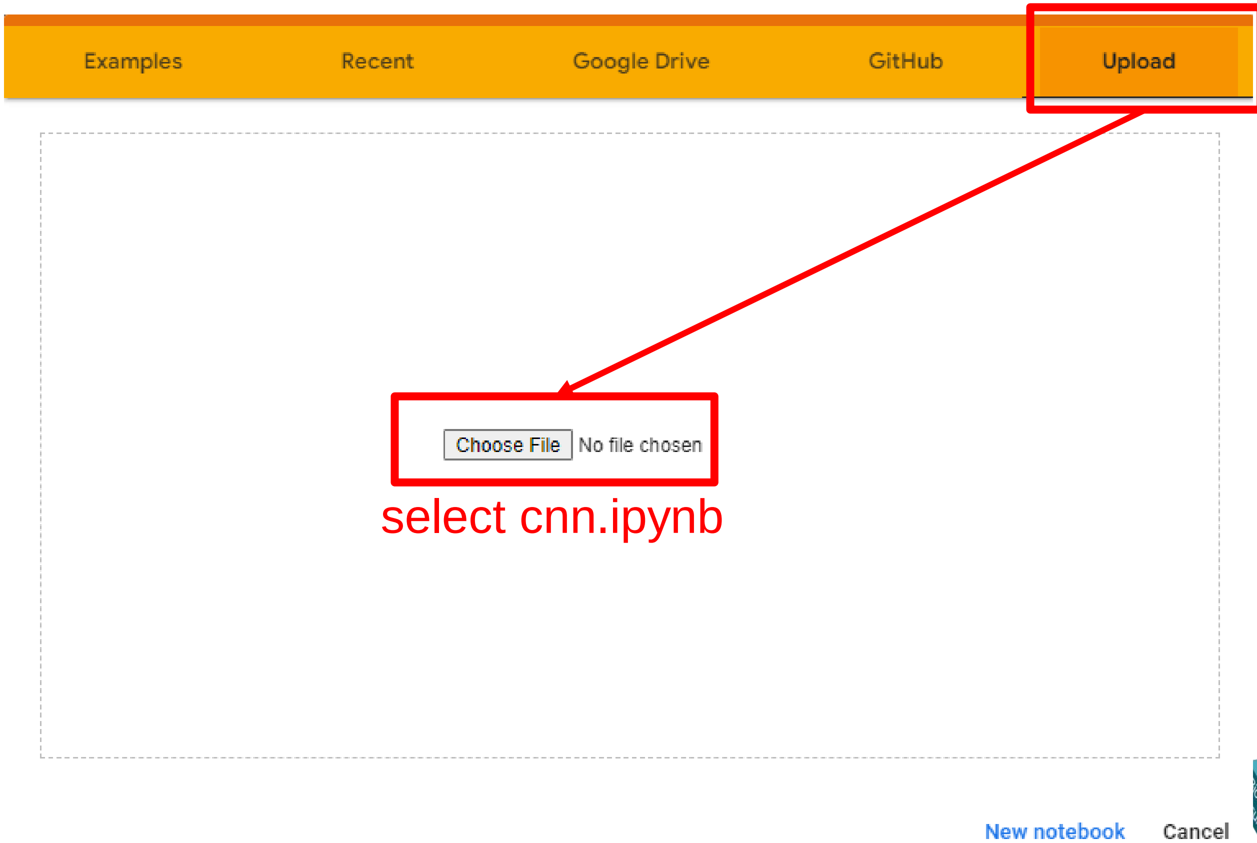
Lab 1
Cat & Dog classification and CNN model experiment

Flowchart


Download Data
Data Preprocessing
Model Architecture
Train Model
Evaluate Model
Save Model

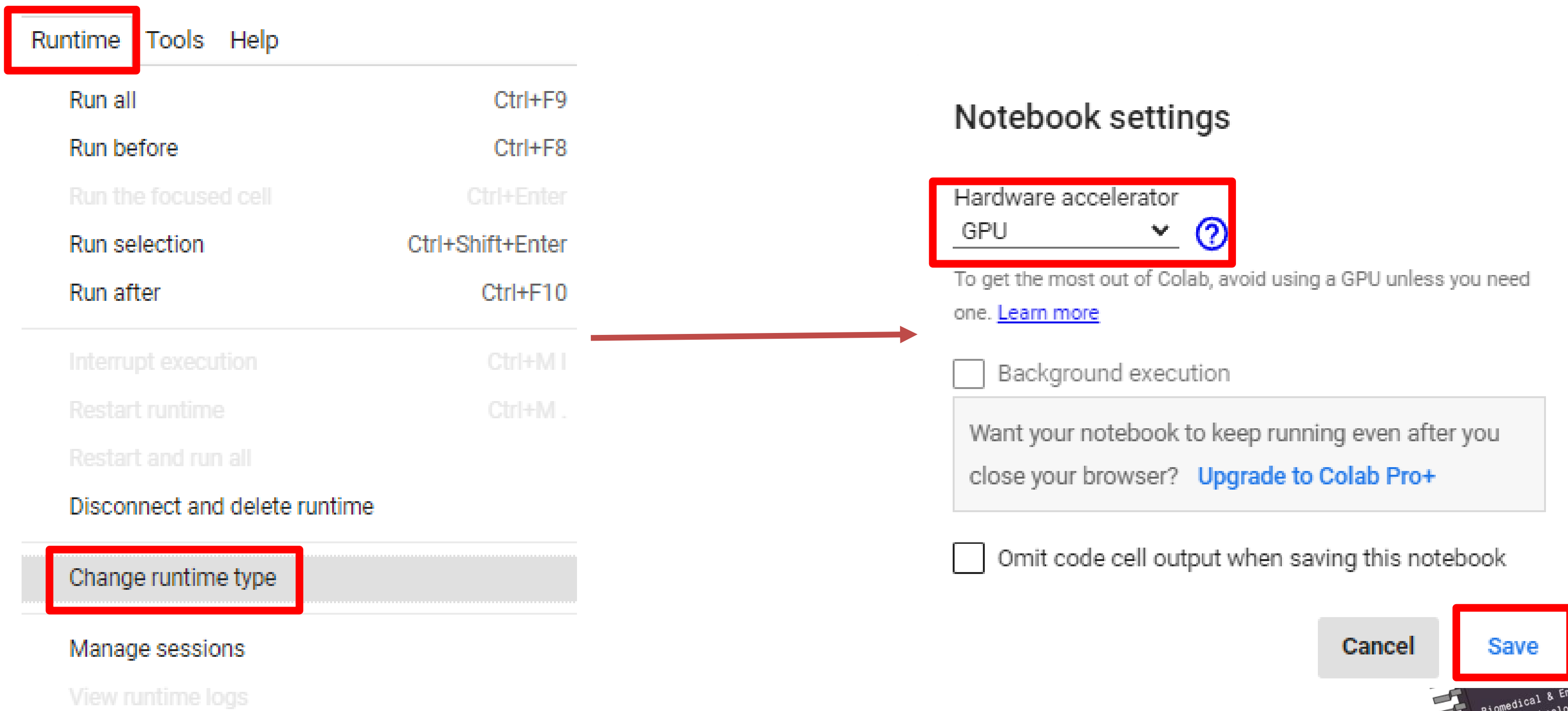
Open Colab

https://colab.research.google.com/?utm_source=scs-index



Colab setting

- Computing on a GPU in Colab.



Download dataset

- The dataset is excerpted from the
”Dogs vs. Cats” dataset on Kaggle.

- Train data : 2000 JPG of cats and dogs
- Validation data : 1000 JPG of cats and dogs

```
!wget --no-check-certificate \
    https://storage.googleapis.com/mledu-datasets/cats_and_dogs_filtered.zip \
    -O /tmp/cats_and_dogs_filtered.zip
```

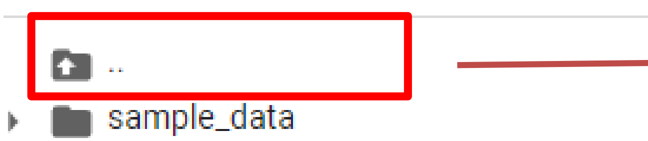
Download dataset

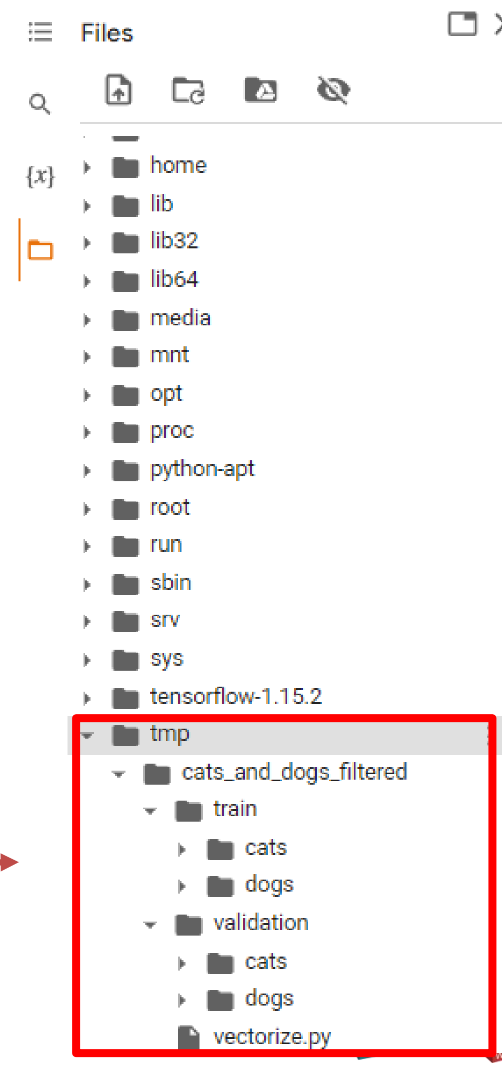
- Unzip the file.

```
import zipfile

local_zip = '/tmp/cats_and_dogs_filtered.zip'
zip_ref = zipfile.ZipFile(local_zip, 'r')
zip_ref.extractall('/tmp')
zip_ref.close()
```

Download dataset

- Check the file hierarchy.
  - Go to the parent directory and check tmp/cats_and_dogs_filtered.





Data preprocessing

- Use image_dataset_from_directory to load image.

```
image_size = (224,224)
train_ds = tf.keras.preprocessing.image_dataset_from_directory(
        "/tmp/cats_and_dogs_filtered/train",
        seed=1337,
        image_size=image_size,
        label_mode="binary",
        batch_size=20
)
val_ds = tf.keras.preprocessing.image_dataset_from_directory(
        "/tmp/cats_and_dogs_filtered/validation",
        seed=1337,
        image_size=image_size,
        label_mode="binary",
        batch_size=20
)
```

Data preprocessing

- Seed : random seed for shuffling data.
- Label_mode : ‘binary’ means that the labels are encoded as scalars with values 0 or 1.
- Image_size : resize the image.

```
image_size = (224,224)
train_ds = tf.keras.preprocessing.image_dataset_from_directory(
        "/tmp/cats_and_dogs_filtered/train",
        seed=1337,
        image_size=image_size,
        label_mode="binary",
        batch_size=20
)
```

Data preprocessing

- Rescale an input in the [0, 255] range to be in the [0, 1] range.

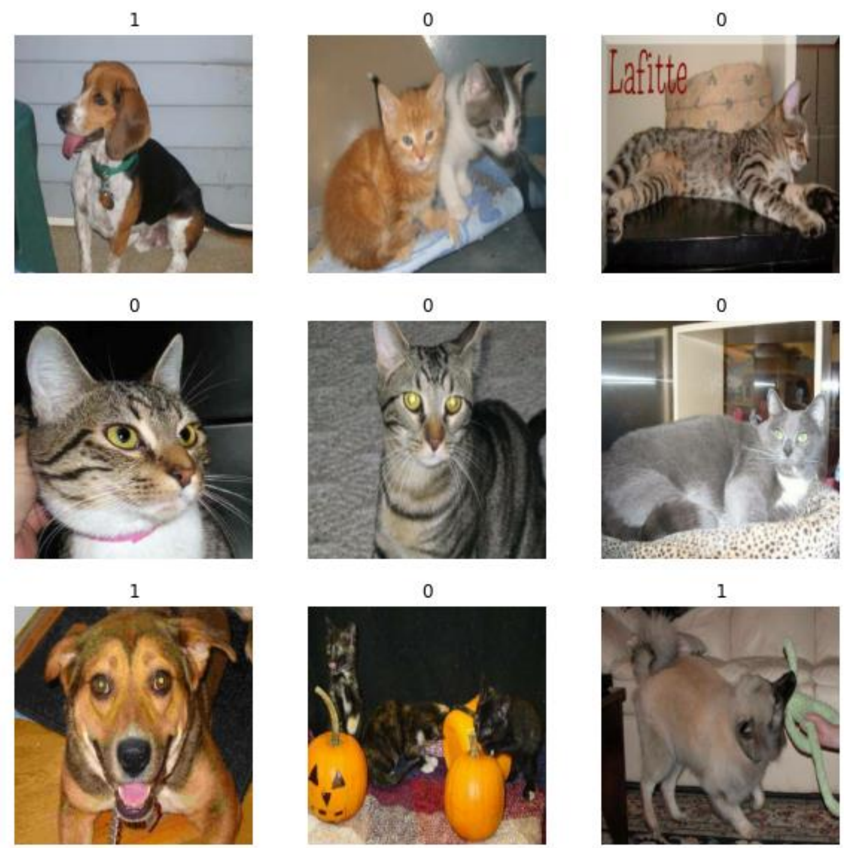
```
normalization_layer = tf.keras.layers.Rescaling(1./255)
train_ds = train_ds.map(lambda x, y: (normalization_layer(x), y))
val_ds = val_ds.map(lambda x, y: (normalization_layer(x), y))
```

- Check the value.

```
image_batch, labels_batch = next(iter(train_ds))
first_image = image_batch[0]
print(np.min(first_image), np.max(first_image))
```

Show image with label

```python
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 10))
for images, labels in train_ds.take(1):
    for i in range(9):
        ax = plt.subplot(3, 3, i + 1)
        plt.imshow((images[i].numpy()*255).astype("uint8"))
        plt.title(int(labels[i]))
        plt.axis("off")
```



0 : cat
1 : dog

Model architecture

- Import the layers you need.

```
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Dense
from tensorflow.keras.layers import Activation, Flatten, Input
```

- Define input layer.

```
input_tensor=Input(shape=(224,224,3))
```

The shape of image

Model architecture

- Forward propagation the value by cascade layer.

```
input_tensor=Input(shape=(224,224,3))

x  =  Conv2D(64,(3,3),activation='relu',padding='same')(input_tensor)
x  =  Conv2D(32,(3,3),activation='relu',padding='same')(x)
x  =  MaxPooling2D((2,2),strides=(2,2))(x)

x  =  Conv2D(16,(3,3),activation='relu',padding='same')(x)
x  =  Conv2D(16,(3,3),activation='relu',padding='same')(x)
x  =  MaxPooling2D((2,2),strides=(2,2))(x)

x  =  Flatten()(x)
x  =  Dense(128,activation='relu')(x)
output_tensor  =  Dense(1,activation='sigmoid')(x)
model  =  Model(input_tensor,output_tensor)
```

Model architecture

```
x  =  Conv2D(16,(3,3),activation='relu',padding='same')(x)
```

Number of kernel

Kernel size

One of “valid” or “same”.
“valid” means no padding.
“same” padding with zero.

Commonly used ‘relu’, ‘sigmoid’, ‘softmax’, ‘tanh’

Model architecture

```
x = MaxPooling2D((2,2),strides=(2,2))(x)
```

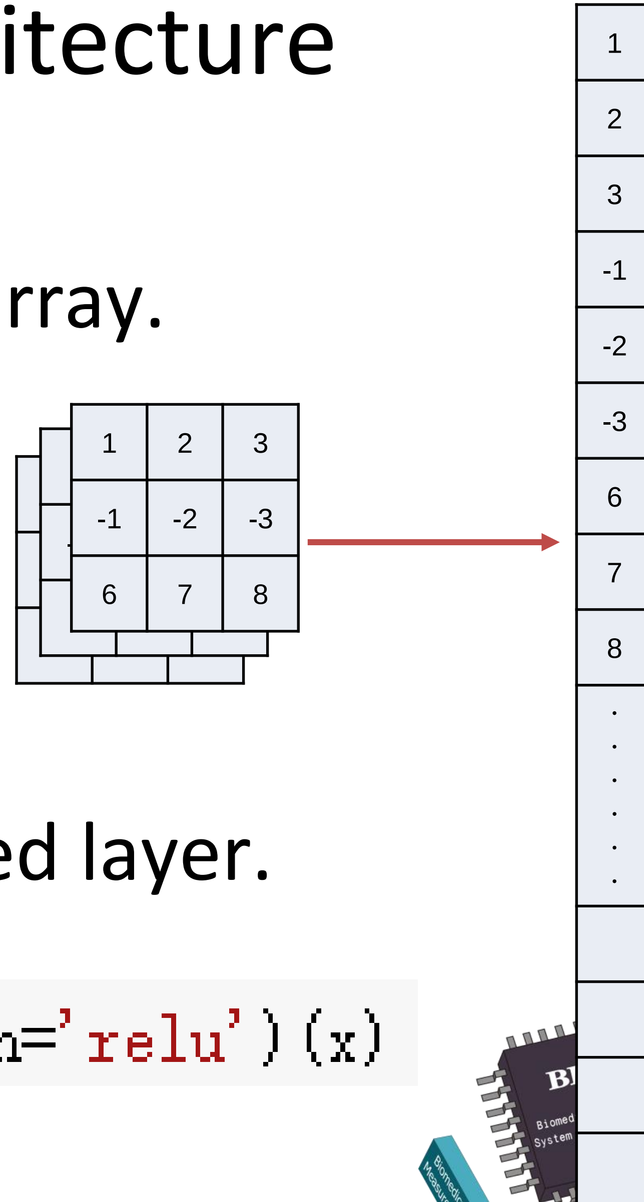
Pool size

Specifies how far the pooling window moves for each pooling step.

Model architecture

- Change the 3d array to 1d array.

```
x = Flatten()(x)
```



- Dense means fully connected layer.

```
x = Dense(128,activation='relu')(x)
```

Number of neuron

Check your model

```
model.summary()
```

Layer (type)	Output Shape	Param #
input_11 (InputLayer)	[(None, 224, 224, 3)]	0
conv2d_25 (Conv2D)	(None, 224, 224, 64)	1792
conv2d_26 (Conv2D)	(None, 224, 224, 32)	18464
max_pooling2d_11 (MaxPooling2D)	(None, 112, 112, 32)	0
conv2d_27 (Conv2D)	(None, 112, 112, 16)	4624
conv2d_28 (Conv2D)	(None, 112, 112, 16)	2320
max_pooling2d_12 (MaxPooling2D)	(None, 56, 56, 16)	0
flatten_9 (Flatten)	(None, 50176)	0
dense_18 (Dense)	(None, 128)	6422656
dense_19 (Dense)	(None, 1)	129

Total params: 6,449,985
Trainable params: 6,449,985
Non-trainable params: 0

Train model

- Configure the model, set optimizer and loss function.

```
adam = tf.keras.optimizers.Adam(learning_rate=0.001)
momentum = tf.keras.optimizers.SGD(learning_rate=0.001, momentum=0.9)

model.compile(optimizer=momentum, loss='binary_crossentropy', metrics=['accuracy'])
```

Now is “momentum”

Train model

- Train the model and store record of training loss values and metrics values.

- Epochs : Number of epochs to train the model.

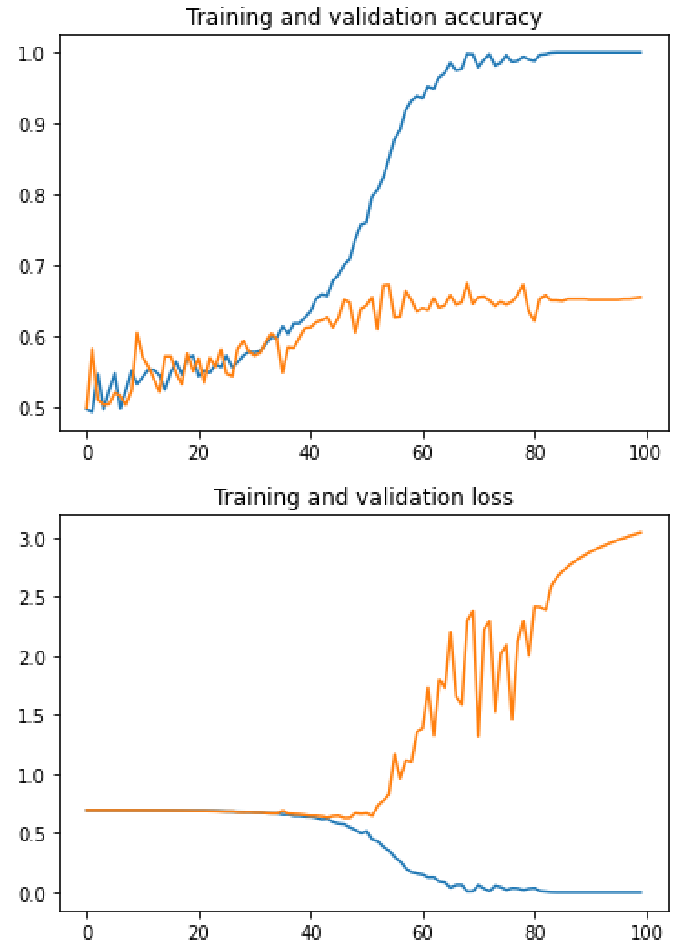
```
hist = model.fit(train_ds,
                 epochs=100,
                 validation_data=val_ds,
                 verbose=1)
```

Train model

```
Epoch 1/100
100/100 [==============================] - 111s 709ms/step - loss: 0.6932 - accuracy: 0.4975 - val_loss: 0.6931 - val_accuracy: 0.5000
Epoch 2/100
100/100 [==============================] - 71s 707ms/step - loss: 0.6931 - accuracy: 0.4935 - val_loss: 0.6930 - val_accuracy: 0.5830
Epoch 3/100
100/100 [==============================] - 71s 708ms/step - loss: 0.6930 - accuracy: 0.5470 - val_loss: 0.6929 - val_accuracy: 0.5110
Epoch 4/100
100/100 [==============================] - 71s 707ms/step - loss: 0.6931 - accuracy: 0.4970 - val_loss: 0.6929 - val_accuracy: 0.5040
Epoch 5/100
100/100 [==============================] - 71s 708ms/step - loss: 0.6929 - accuracy: 0.5245 - val_loss: 0.6928 - val_accuracy: 0.5050
Epoch 6/100
100/100 [==============================] - 71s 707ms/step - loss: 0.6928 - accuracy: 0.5485 - val_loss: 0.6927 - val_accuracy: 0.5210
Epoch 7/100
100/100 [==============================] - 71s 708ms/step - loss: 0.6929 - accuracy: 0.4985 - val_loss: 0.6926 - val_accuracy: 0.5160
Epoch 8/100
100/100 [==============================] - 71s 708ms/step - loss: 0.6928 - accuracy: 0.5240 - val_loss: 0.6926 - val_accuracy: 0.5040
Epoch 9/100
100/100 [==============================] - 71s 708ms/step - loss: 0.6926 - accuracy: 0.5520 - val_loss: 0.6924 - val_accuracy: 0.5240
Epoch 10/100
100/100 [==============================] - 71s 707ms/step - loss: 0.6926 - accuracy: 0.5330 - val_loss: 0.6923 - val_accuracy: 0.6050
Epoch 11/100
100/100 [==============================] - 71s 708ms/step - loss: 0.6926 - accuracy: 0.5430 - val_loss: 0.6922 - val_accuracy: 0.5710
Epoch 12/100
100/100 [==============================] - 71s 707ms/step - loss: 0.6923 - accuracy: 0.5530 - val_loss: 0.6920 - val_accuracy: 0.5580
Epoch 13/100
100/100 [==============================] - 71s 708ms/step - loss: 0.6921 - accuracy: 0.5530 - val_loss: 0.6918 - val_accuracy: 0.5400
Epoch 14/100
100/100 [==============================] - 71s 707ms/step - loss: 0.6921 - accuracy: 0.5455 - val_loss: 0.6917 - val_accuracy: 0.5220
Epoch 15/100
100/100 [==============================] - 71s 708ms/step - loss: 0.6920 - accuracy: 0.5250 - val_loss: 0.6913 - val_accuracy: 0.5720
Epoch 16/100
100/100 [==============================] - 71s 708ms/step - loss: 0.6916 - accuracy: 0.5495 - val_loss: 0.6910 - val_accuracy: 0.5720
Epoch 17/100
100/100 [==============================] - 71s 708ms/step - loss: 0.6911 - accuracy: 0.5645 - val_loss: 0.6907 - val_accuracy: 0.5480
Epoch 18/100
100/100 [==============================] - 71s 708ms/step - loss: 0.6911 - accuracy: 0.5465 - val_loss: 0.6905 - val_accuracy: 0.5330
```

Evaluate model

```
import matplotlib.pyplot as plt
from keras.preprocessing.image import img_to_array, load_img

# Retrieve a list of accuracy results on training and test data
# sets for each training epoch
acc = hist.history['accuracy']
val_acc = hist.history['val_accuracy']

# Retrieve a list of list results on training and test data
# sets for each training epoch
loss = hist.history['loss']
val_loss = hist.history['val_loss']

# Get number of epochs
epochs = range(len(acc))

# Plot training and validation accuracy per epoch
plt.plot(epochs, acc)
plt.plot(epochs, val_acc)
plt.title('Training and validation accuracy')

plt.figure()

# Plot training and validation loss per epoch
plt.plot(epochs, loss)
plt.plot(epochs, val_loss)
plt.title('Training and validation loss')
```



Evaluate model

- As you can see, the model is overfitting.

- Our training accuracy gets close to 100%, but validation accuracy stalls at 60%.

Overfitting

- Overfitting is a tough problem when we train the model.
- Overfitting happens when a model learns the detail and noise in the training data to the extent that it negatively impacts the performance of the model on new data.

Save / load model

- Save your model to deploy on different platform.
- You can find your file in /content/myModel.h5.

```
model.save("myModel.h5")

new_model = tf.keras.models.load_model('myModel.h5')

new_model.evaluate(val_ds,verbose=1)
```

```
50/50 [==============================] - 11s 214ms/step - loss: 0.0730 - accuracy: 0.9770
[0.07302631437778473, 0.9769999980926514]
```

Inference

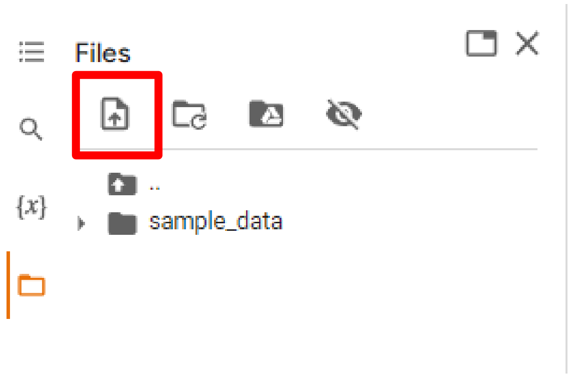
```python
animal = "cat" # cat or dog
index = 2222 # 2000-2499
img_path = f"/tmp/cats_and_dogs_filtered/validation/{animal}s/{animal}.{index}.jpg"
img = load_img(img_path, target_size=(224, 224))  # this is a PIL image
plt.title(img_path)
plt.axis("off")
plt.imshow(img)

x = img_to_array(img)  # Numpy array with shape (224, 224, 3)
x = x.reshape((1,) + x.shape)  # Numpy array with shape (1, 224, 224, 3)
x /= 255 # Rescale by 1/255

import time
start = time.time() # record start time

result = new_model.predict(x) # inference(predict)
if result < 0.5:
  print("It is a cat.")
else:
  print("It is a dog.")
finish = time.time() # record finish time

print ("Result = %f" %result)
print("Test time :%f second." %(finish-start))
```

```
It is a cat.
Result = 0.004889
Test time :0.167567 second.
```

/tmp/cats_and_dogs_filtered/validation/cats/cat.2222.jpg

Upload/load model

- Upload pre-trained model and evaluate the model.




```
model = tf.keras.models.load_model("myModel.h5")

model.evaluate(val_ds,verbose=1)
```

```
50/50 [==============================] - 494s 10s/step - loss: 0.0730 - accuracy: 0.9770
[0.07302630692720413, 0.9769999980926514]
```

Assignment 1

- Select two of the models in the right chart.
- Implement and compare their accuracies.

<table>
<tr><th>A</th><th>B</th><th>C</th><th>D</th><th>E</th></tr>
<tr><td>conv3-4</td><td>conv3-4
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conv3-4</td></tr>
<tr><td colspan="5">maxpool(size=(2,2),strides=(2,2))</td></tr>
<tr><td>conv3-8</td><td>conv3-8
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<tr><td colspan="5">maxpool(size=(2,2),strides=(2,2))</td></tr>
<tr><td>conv3-16
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<tr><td>conv3-32
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<tr><td>conv3-64
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conv3-64</td></tr>
<tr><td colspan="5">maxpool(size=(2,2),strides=(2,2))</td></tr>
<tr><td colspan="5">FC-128</td></tr>
<tr><td colspan="5">FC-64</td></tr>
<tr><td colspan="5">FC-1</td></tr>
<tr><td colspan="5">sigmoid</td></tr>
</table>

ConvA-B => kernel size: (A,A), number of the kernerl: B
FC-N => number of neuron: N

Assignment 1

- Finish a report.
  - What is observed & learned?
  - Screen dump:
    - Model.summary()
    - Plot training and validation accuracy
    - Plot training and validation loss

Submission

- Hierarchy:
  - Model_1.ipynb
  - Model_2.ipynb
  - Report.pdf

- Compress all above files in a single zip file named StudentID_lab1.zip.

References

- K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," arXiv:1409.1556, 2014.
- Stanford University CS231n, "Deep Learning for Computer Vision." [Online]. Available: http://cs231n.stanford.edu/.
- H. Y. Lee, "Hung-yi Lee youtube channel" [Online]. Available: https://www.youtube.com/c/HungyiLeeNTU.
- Kaggle, "Dogs vs. Cats." [Online]. Available: https://www.kaggle.com/c/dogs-vs-cats.