LECTURE 10
OBJECT RECOGNITION

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OBJECTIVES

- Understand and be able to describe fundamental workflows of object recognition using traditional approach and modern approach

TODAY'S CONTENT

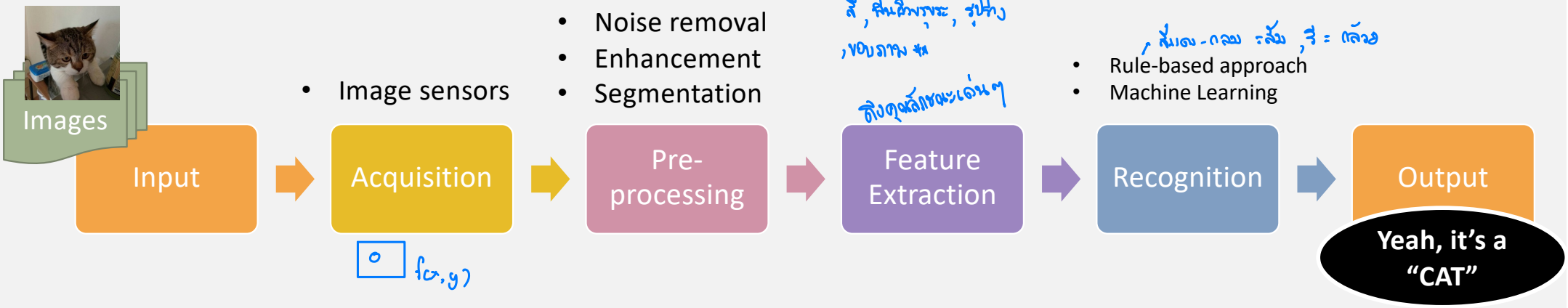
- Introduction
- Features – Histogram of oriented gradients
- Neural networks
- Convolutional Neural networks
- Demo: handwritten digits recognition
  - Traditional approach
  - Modern approach

boltplusbumblebee

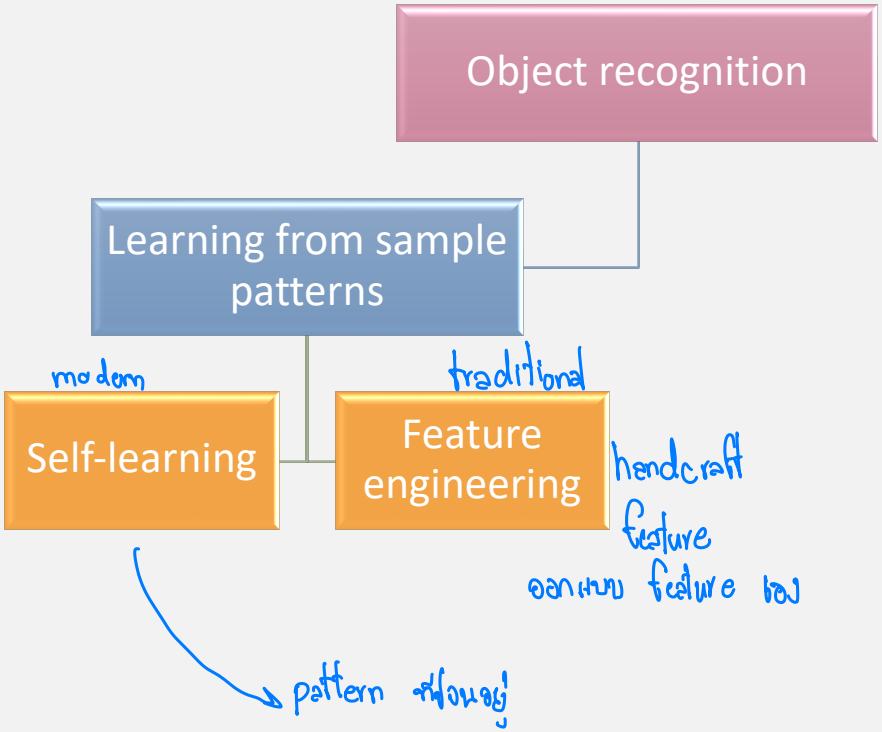
Britannica : Lion

Amazon : cat hat

OBJECT RECOGNITION FLOW



INTRODUCTION



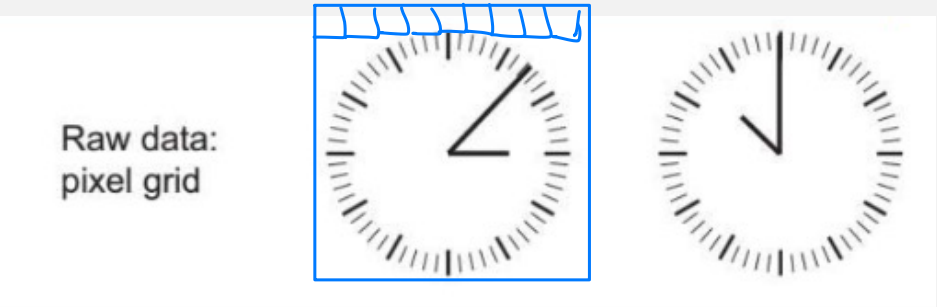
- Patterns – arrangements of descriptors
- Features – used in pattern recognition literature
- Pattern arrangements used in practices are vectors

$$\boldsymbol{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ \cdot \\ \cdot \end{bmatrix}$$

FEATURES

key info
└ compact แทน ,ข้อมูลตามจริง

- Feature Engineering
  - process of selecting and transforming raw data into a format that is suitable for machine learning algorithms
  - making a problem easier by expressing it in a simpler way. It usually requires understanding the problem in depth.
  - Colour is powerful
    - RGB colour model, HSV, CIELAB, YCbCr
  - Texture
    - Co-occurrence matrix
    - Tamura's textural features
  - Shape
    - Region properties
  - Edge detection (human-perception)
    - First / second derivatives – sobel, prewitt, canny



How to read the time?

FEATURES

- Feature Engineering
  - making a problem easier by expressing it in a simpler way. It usually requires understanding the problem in depth.
  - Colour is powerful
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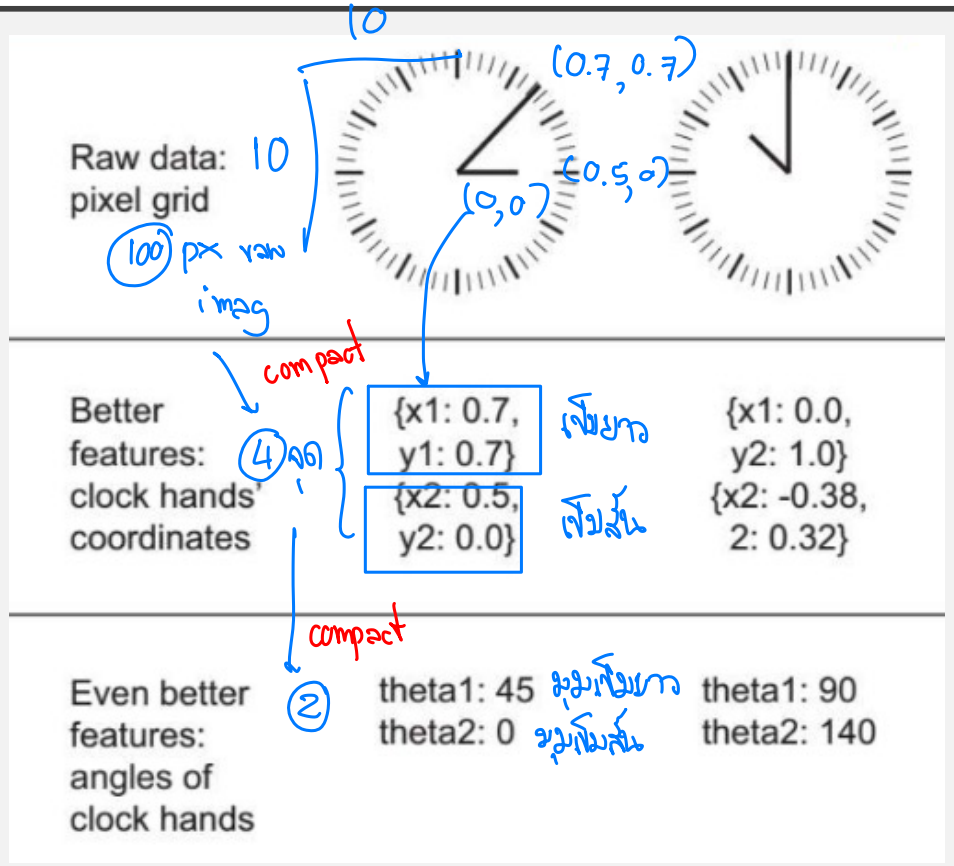


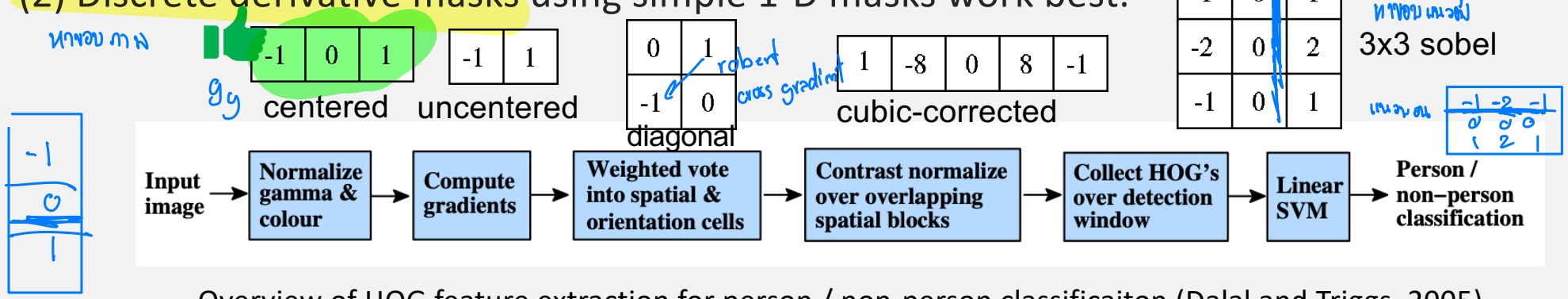
FEATURES

- Iris flowers has taxonomic problems, contains three plant species (setosa, virginica, versicolor) and four features measured for each sample

https://rpubs.com/yao33/611068

FEATURES - HOG

- Powerful features include histogram of oriented gradients (Dalal and Triggs, 2005) and scale-invariant feature transform (Lowe, 2004) both of which are based on gradients (edges) of the image
- HOG - (1) RGB and LAB colour spaces optionally with power law (gamma) equalization
- (2) Discrete derivative masks using simple 1-D masks work best.

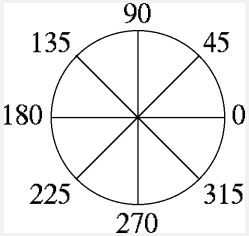


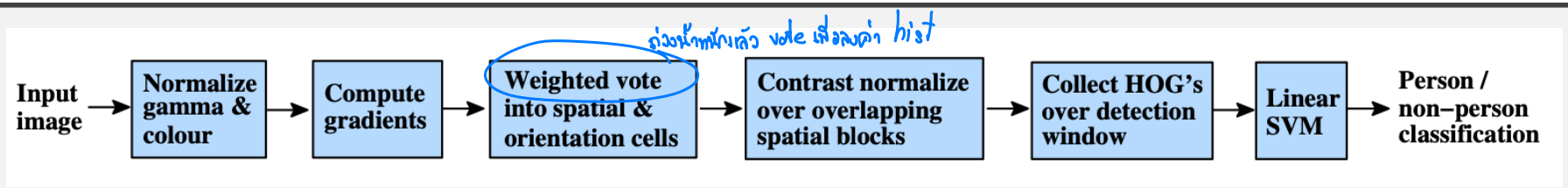
Overview of HOG feature extraction for person / non-person classificaiton (Dalal and Triggs, 2005)

Dalal and Triggs, 2005, Histograms of Oriented Gradients for Human Detection (CVPR'05)

D.G. Lowe, 2004, Distinctive Image Features from Scale-Invariant Keypoints (IJCV'04)

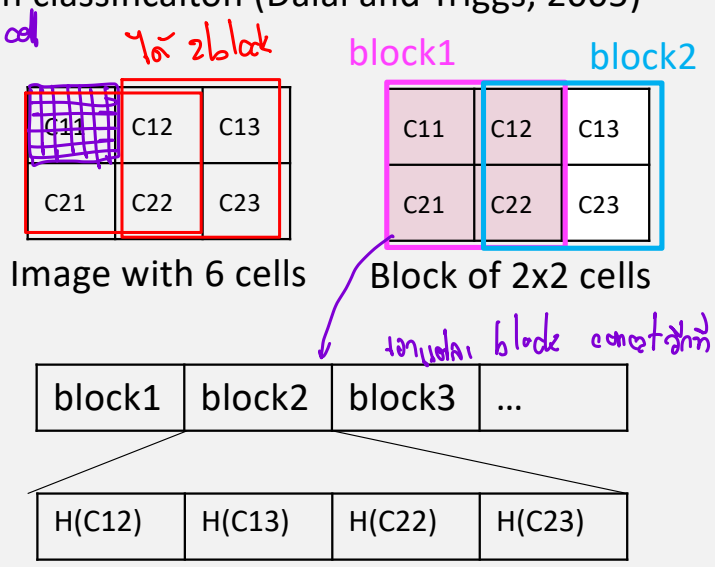
FEATURES - HOG





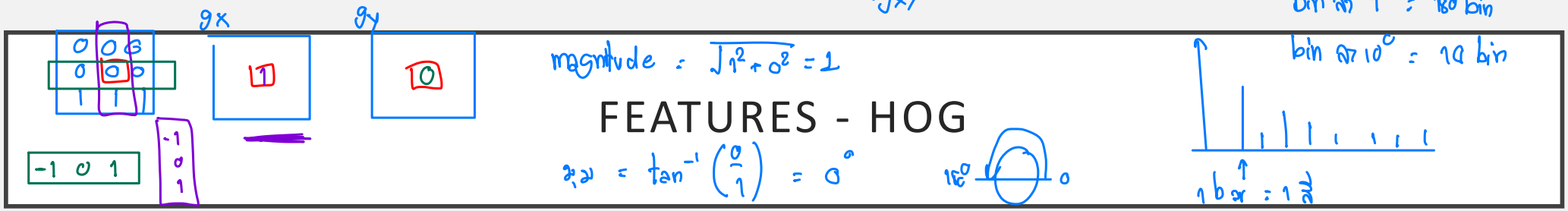
Overview of HOG feature extraction for person / non-person classificaiton (Dalal and Triggs, 2005)

- (3) Spatial and orientation binning
  - An image is partition into non-overlapping cells.
  - Each cell contains pixels which will be calculated using a weighted vote for an edge orientation histogram channel based on the orientation
  - Then construct blocks of cells, e.g., block size of 2x2 cells to create each HOG block.
  - Arrangement of Histograms in HOG Feature Vectors.
  - The HOG feature vector is arranged by HOG blocks. The cell histogram, H(Cxy), is 1-by-NumBins.



Gradient → gx — แนวนอน ① หาขนาดของขอบ (magnitude) $\sqrt{g_x^2+g_y^2}$ g_y = gradient แกน y

gy | แนวตั้ง ② มุม orientations $\tan^{-1}\left(\frac{g_y}{g_x}\right)$



Weighted vote for an edge orientation histogram

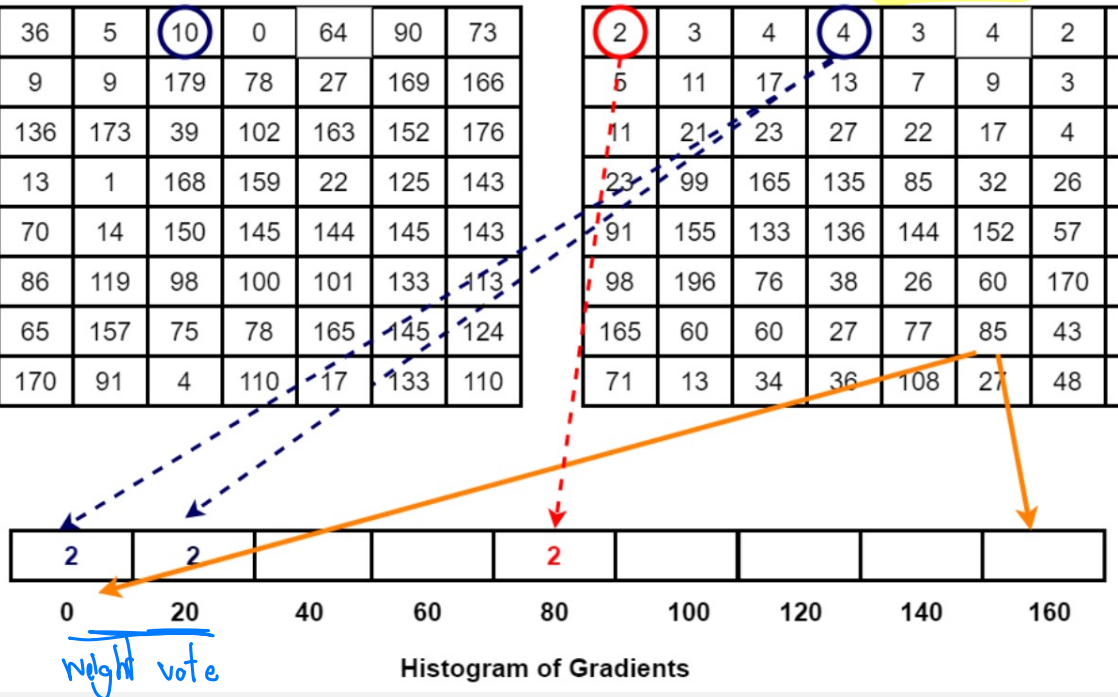
Gradient Direction

80	36	5	10	0	64	90	73
37	9	9	179	78	27	169	166
87	136	173	39	102	163	152	176
76	13	1	168	159	22	125	143
120	70	14	150	145	144	145	143
58	86	119	98	100	101	133	113
30	65	157	75	78	165	145	124
11	170	91	4	110	17	133	110

Gradient Magnitude

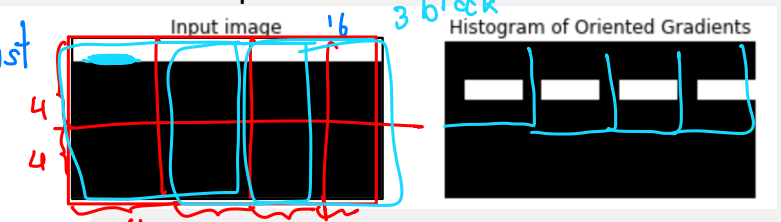
2	3	4	4	3	4	2	2
5	11	17	13	7	9	3	4
11	21	23	27	22	17	4	6
23	99	165	135	85	32	26	2
91	155	133	136	144	152	57	28
98	196	76	38	26	60	170	51
165	60	60	27	77	85	43	136
71	13	34	36	108	27	48	110

ใช้ค่าขนาดลง hist



เพราะ 10 อยู่ระหว่าง bin 0 กับ bin 20 ก็ทำ magnitude เท่าๆ กัน แล้วใส่ทั้งคู่

8 x 16 pixels



5 bins, 4 x 4 pixels per cell, 2 x 2 cells per block

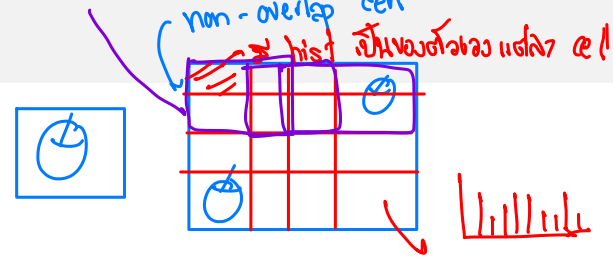
What is the size of the feature descriptor?

```
[0.  0.  0.70710678 0.  0.  0.  0.  0.70710678 0.  0.  0.  0.
 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.70710678 0.  0.  0.  0.
 0.70710678 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
 0.70710678 0.  0.  0.  0.  0.70710678 0.  0.  0.  0.  0.  0.
 0.  0.  0.  0.  0.  0. ]
```

Feature descriptor = 3 blocks × 4 cells × 5 bin : 60 ตัว

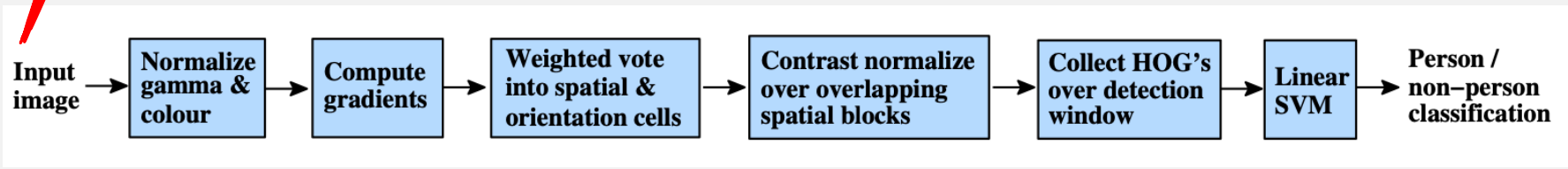
a bin = $\frac{180}{9}$ = 20° / bin

block → 2×2 cell overlap ได้



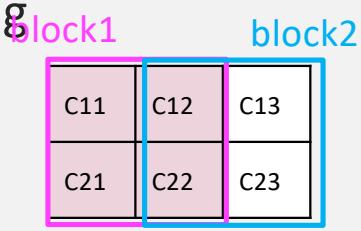
feature vector

FEATURES - HOG

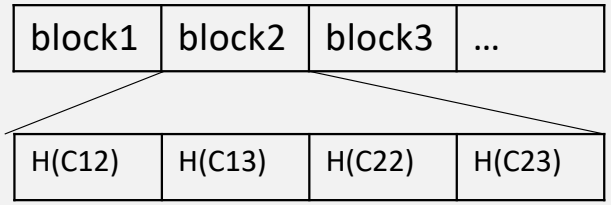


Overview of HOG feature extraction for person / non-person classificaiton (Dalal and Triggs, 2005)

- (4) Contrast normalize over the overlapping blocks
- (5) Collect HOG's over detection window
- (6) Classifier using Linear SVM



Block of 2x2 cells

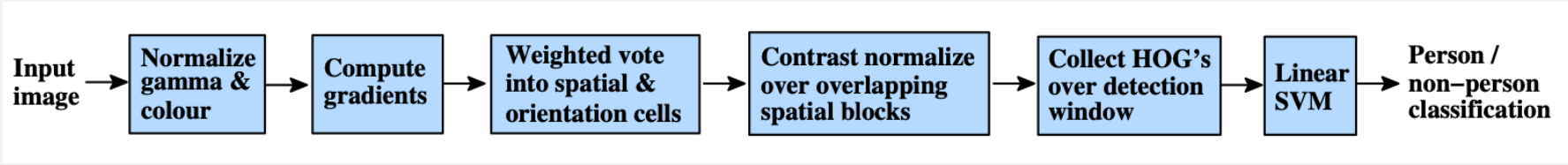


HOG Feature vector 1 x NumBin

H(C11)	H(C12)	HC(21)	HC(22)	H(C12)	H(C13)	H(C22)	H(C23)	....	...

HOG's feature vector over a window

FEATURES - HOG



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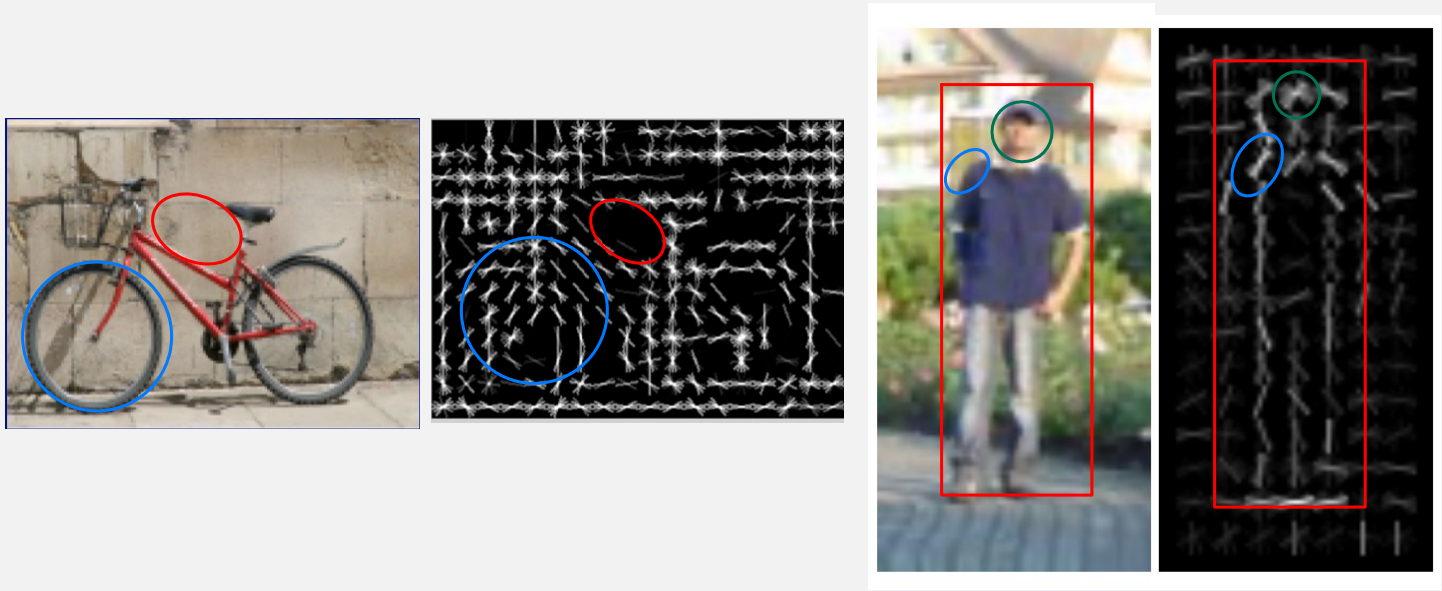
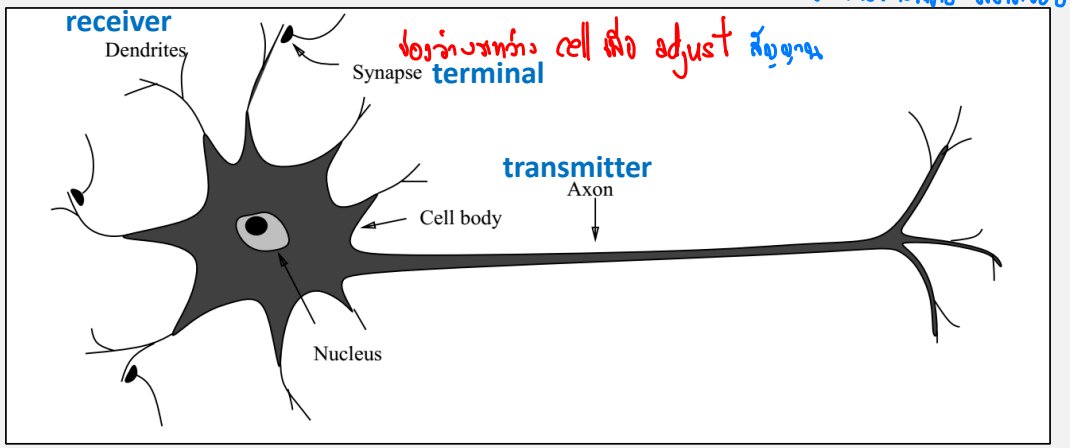


Dalal and Triggs, 2005, Histograms of Oriented Gradients for Human Detection (CVPR'05)

NEURAL NETWORKS

- A basic component in neural networks is **a neuron**, which imitates the biological neuron in the brain.
- **A neuron (or nerve cell)** is a special biological cell with information processing ability.



Brain neuron

The effectiveness of a synapse can be adjusted by the signals passing through it so that the synapses can learn from the activities in which they participate.

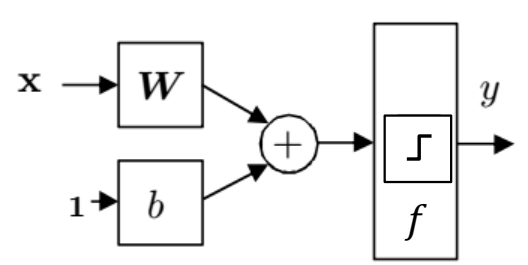
"human ability to remember"

w - learnable parameter

$y = f(W \cdot x + b)$

NEURAL NETWORKS

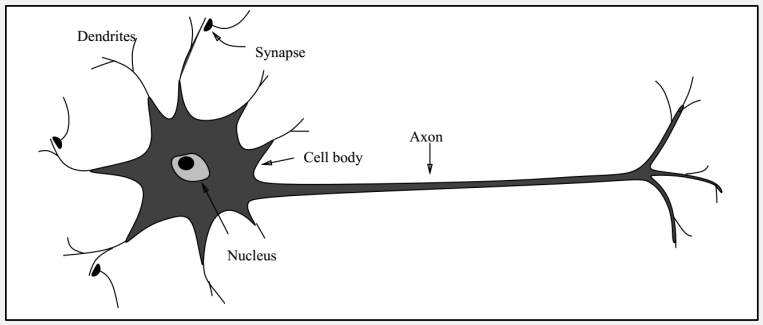
- Perceptron – learns a linear decision function with respect to the components of the pattern vectors.
- An input vector (x) weighted by a weight matrix (W) and the output (y) is the function (f) of the sum weighted input and the bias (b)
- The function (f) initially used a binary threshold unit as a computational model for a neuron. Function f is called activation function.



$$y = f(\mathbf{W}\mathbf{x} + b)$$

Perceptron

Perceptron – a simple model of the neuron

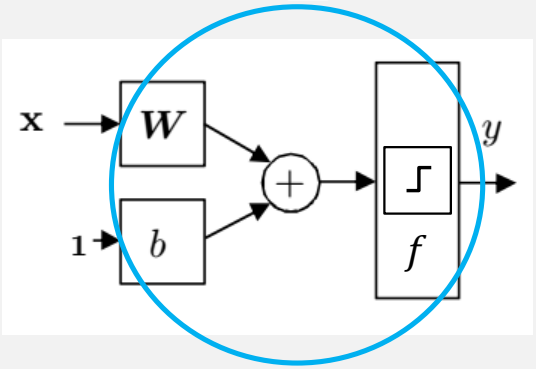


Brain neuron

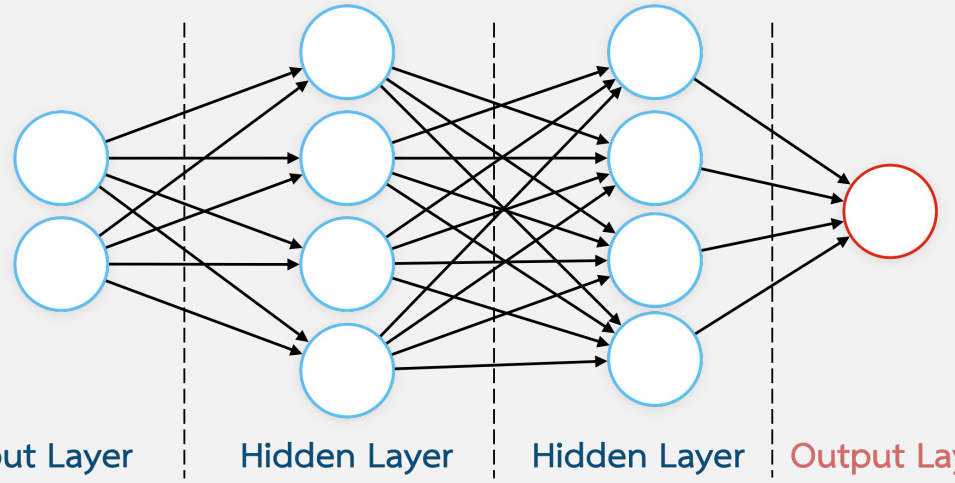
NEURAL NETWORKS

$y_{pred} \sim y_{true}$

=

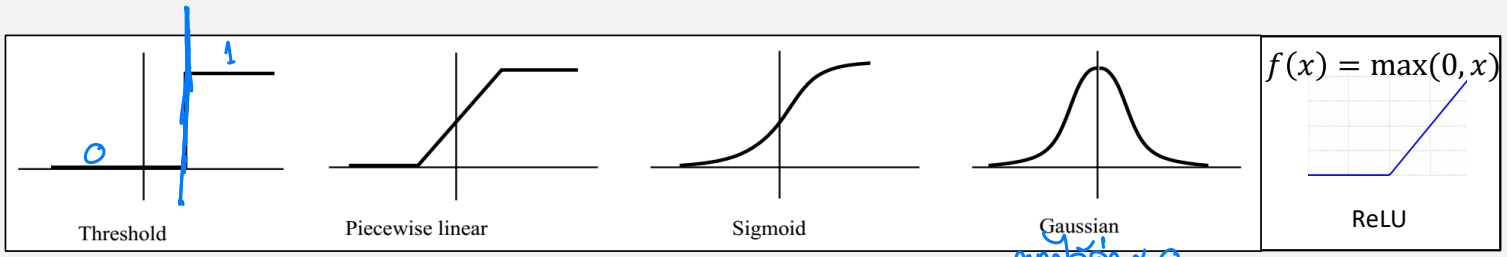


Perceptron



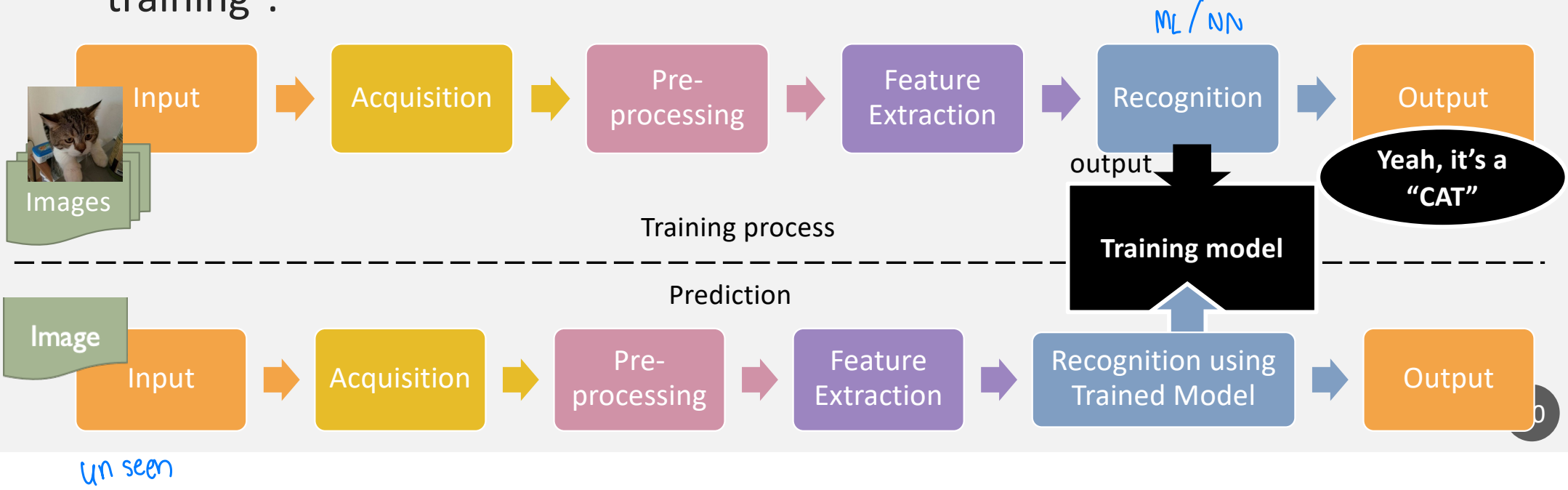
Multilayer Perceptron

To increase generalization is to use activation functions other than the threshold function, e.g., a piecewise linear, sigmoid, or Gaussian

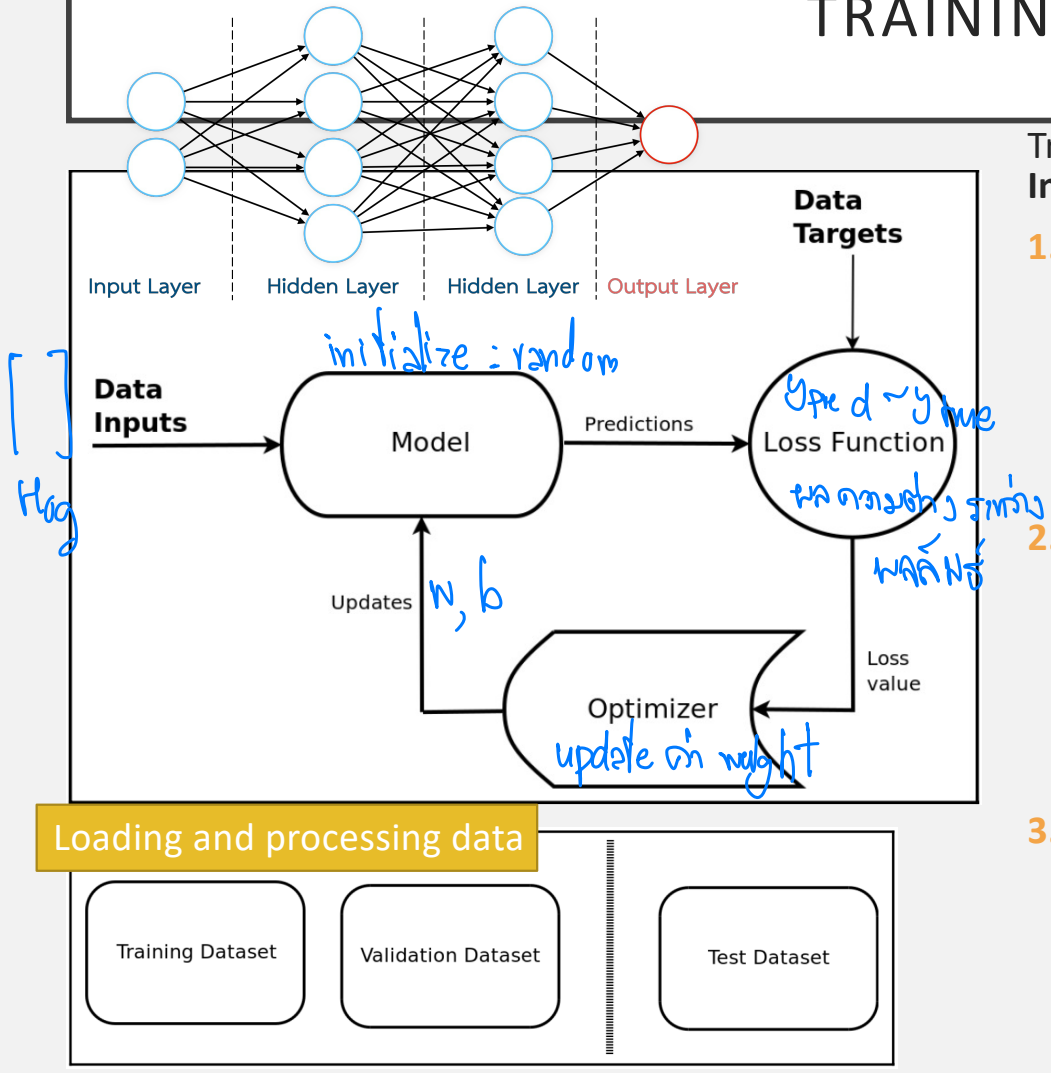


TRAINING PROCESS

- The patterns used to estimate these parameters usually are called “training patterns”, and a set of such patterns from each class is called a “traning set”. The process is used to obtain decision function is called “learning” or “training”.



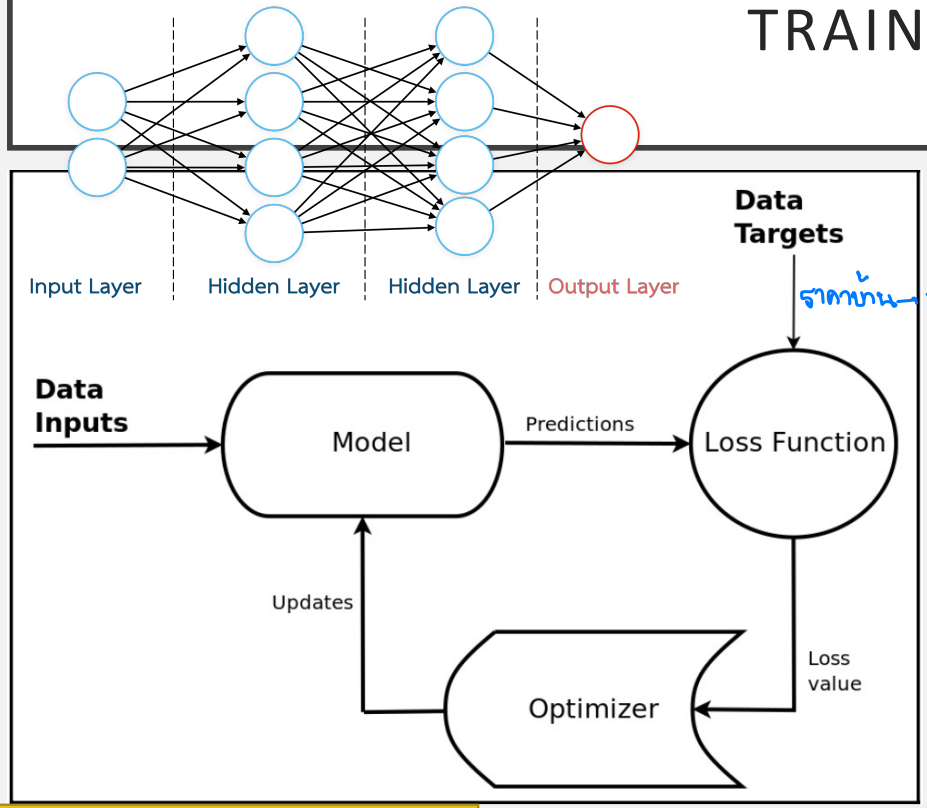
TRAINING PROCESS



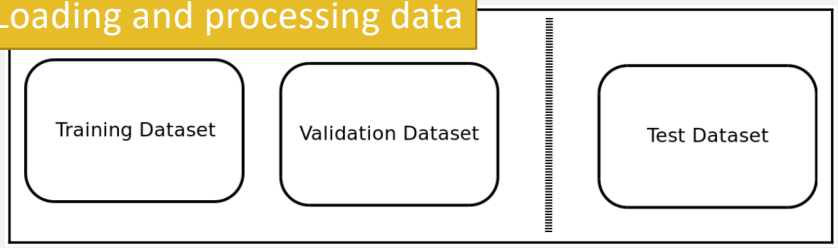
Training process is an iterative process. Processing data – **Inputs and targets** are divided into three main subsets:

1. **Training dataset**
   - 60-80% of the whole data
   - the model learns patterns, relationships, and features from this data to make predictions or classifications.
   - Used to adjust its internal parameters based on these examples to minimize the error or loss function.
2. **Validation dataset**
   - 10-20% of the whole data
   - used to fine-tune model hyperparameters and monitor its performance during training
   - helps in selecting the best hyperparameters and deciding when to stop training
3. **Testing dataset**
   - simulating how the model will perform in the real world
   - The model's performance metrics, such as accuracy, precision, recall, or F1-score, are computed to assess its generalization ability.
   - should be large enough to provide statistically significant results but should not overlap with the training or validation datasets

TRAINING PROCESS



Loading and processing data



Loss function - known as a cost function or objective function

- to measure how well or poorly a model is performing, with the goal of minimizing this function during the training process.
- to serve as a guide for optimization algorithms
- These optimized parameters make the model's predictions as close as possible to the true target values

Examples of Loss Functions

- Mean Squared Error (MSE)

$$loss = \frac{1}{n}\sum^{n}(y_{true} - y_{pred})^2$$

- Binary Cross-Entropy

$$loss = -y_i \log(p_i) - (1 - y_i)\log(1 - p_i)$$

y_i is class indicator and p_i is probability of of the sample i.

- Categorical Cross-Entropy

$$loss = \sum_{c=1}^{M} -y_{i,c}\log(p_{i,c})$$

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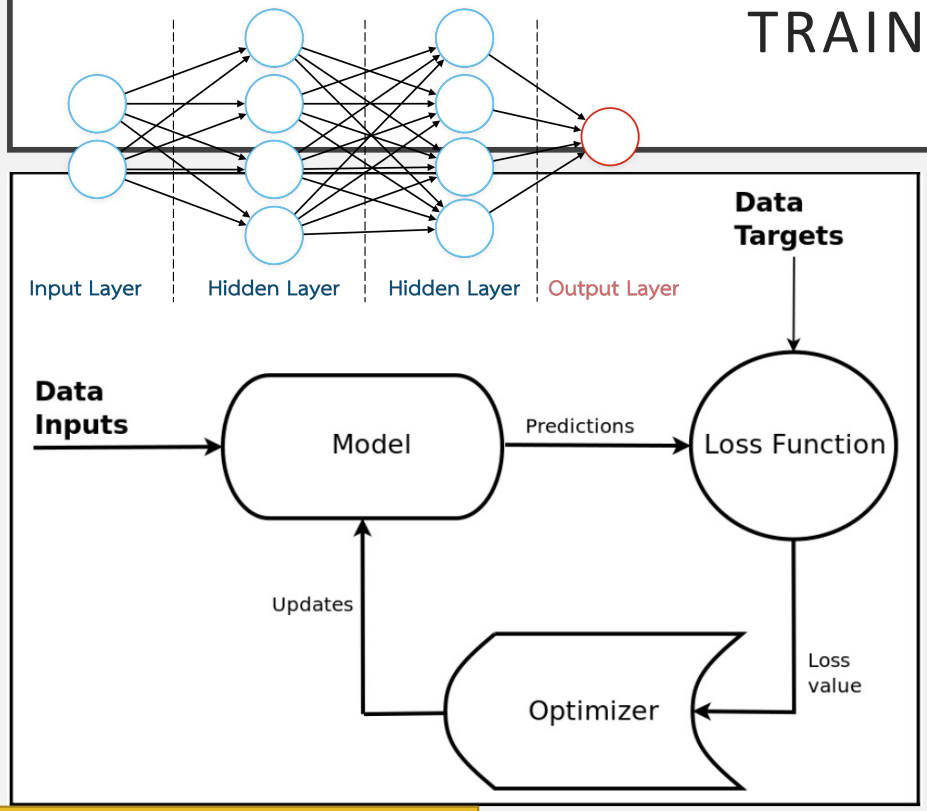
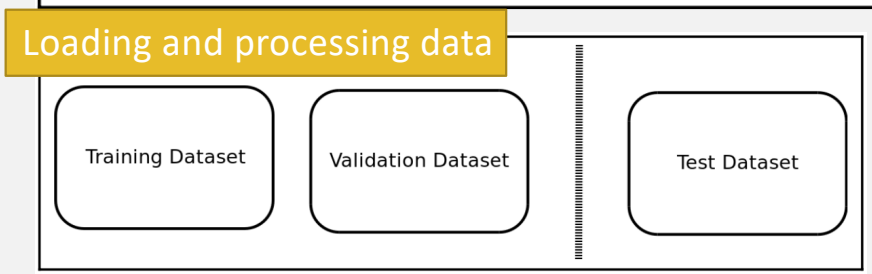
TRAINING PROCESS





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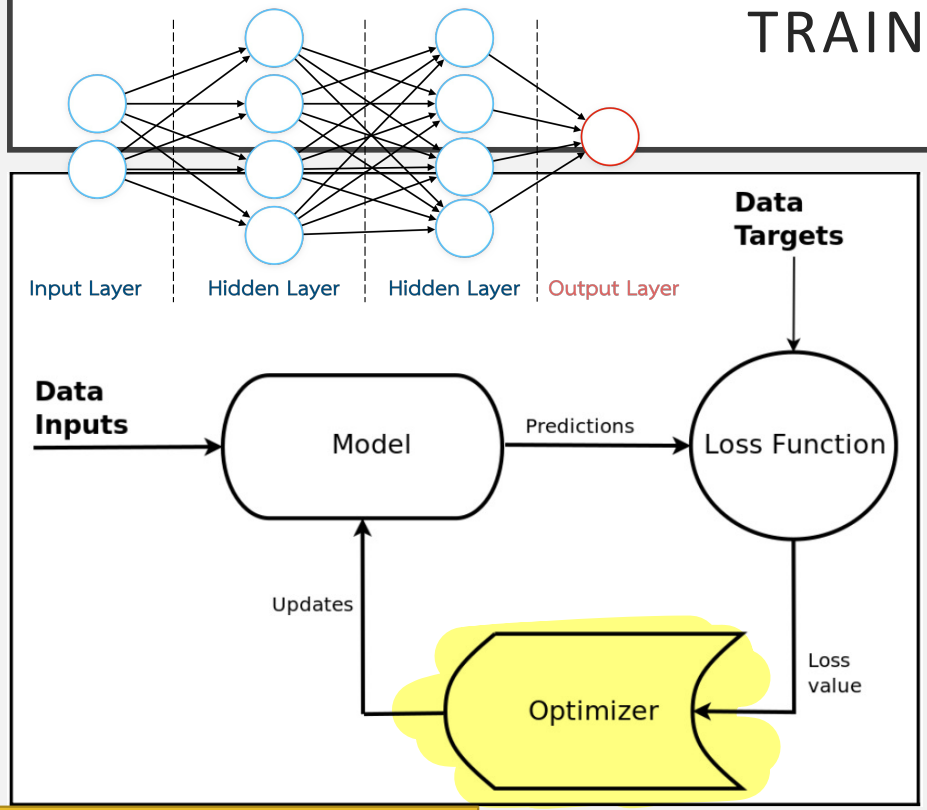
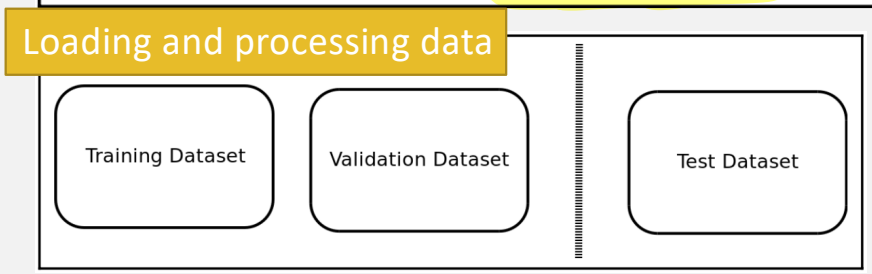
TRAINING PROCESS





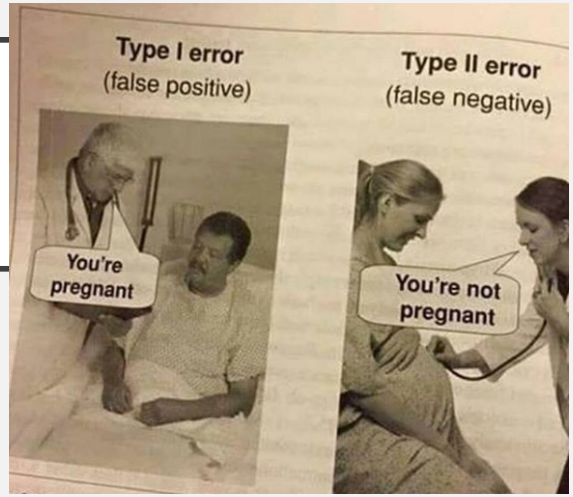
Optimizer - an algorithm that adjusts the weights and biases of the network to minimize the loss function

- aims to find the **minimum** of the loss function. By doing so, it improves the model's predictions using **gradient** of the loss function

Examples of Optimizers:

- Gradient Descent - GD uses the entire dataset to calculate the gradient of the cost function for each iteration
- Stochastic Gradient Descent (SGD) - updates weights by considering one data point at a time batch (subset data)
- Momentum - considers the previous gradients to keep the momentum พิจารณา gradient ของก่อนหน้าด้วย
- RMSprop - adapts the learning rates during training ปรับ lr ระหว่าง train ให้เหมาะสม
- Adam - adjusts the learning rates which is the size of the steps that the optimizer takes while updating the weights of each parameter, benefiting from adaptive learning rates. base on gradient

PERFORMANCE EVALUATION (IMAGE CLASSIFICATION)



- **Performance evaluation**:
  - counts of test records correctly and incorrectly predicted by the model using "**confusion matrix**"

Confusion matrix for a 2-class problem.

		Predicted Class	
	CANCER	$Class = 1$	$Class = 0$
Actual Class	$Class = 1$	f_{11} TP	f_{10} FN
	$Class = 0$	f_{01} FP	f_{00} TN

True positive (TP)
True negative (TN)
False positive (FP) – false alarm – Type I
False negative (FN) – Type II miss case

- the total number of correct predictions made by the model is $(f_{11} + f_{00})$ = **TP+TN**
- the total number of incorrect predictions is $(f_{10} + f_{01})$ = **FN+FP**

PERFORMANCE EVALUATION (IMAGE CLASSIFICATION)

- Accuracy

$$\text{Accuracy} = \frac{\#\ of\ correct\ predictions}{total\ \#\ of\ predictions} = \frac{f_{11}+f_{00}}{f_{11}+f_{10}+f_{01}+f_{00}} = \frac{TP+TN}{ALL}$$

- Precision

$$\text{Precision} = \frac{TP}{TP+FP}$$ ↑

- Recall

Recall สูง FN น้อย

$$\text{Recall} = \frac{TP}{TP+FN}$$ ↑

- F-measure

$$\text{F-score} = 2 \cdot \frac{precision \cdot recall}{precision + recall}$$

เฉลี่ยเลข harmonic
ถ้าตัวใดตัวหนึ่งต่ำ
F1 จะต่ำ

- Others: ROC curve, PR curve

Confusion matrix for a 2-class problem.

		Predicted Class	
		$Class = 1$	$Class = 0$
Actual Class	$Class = 1$	f_{11} TP	f_{10} FN
	$Class = 0$	f_{01} FP	f_{00} TN

embryo selection เด็กหลอดแก้ว
- Recall ↑ FP ตรวจเพิ่มได้ (ตัวอ่อนไม่เกิดบุตร)
แต่ embryo FP ก็สำคัญด้วย Precision ก็สำคัญ
เลยเลือก F1 แทน recall

CASE STUDY: MNIST DATASET

- **MNIST** - a database of handwritten digits made up of a training set of 60,000 examples and a test set of 10,000 examples.
  - Apply HOG features and use neural networks for classification and visualization
- Load data

```
import numpy as np
from skimage.feature import hog
from sklearn import preprocessing

(X_train, y_train), (X_test, y_test) = mnist.load_data()
```

```
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(60000, 28, 28)
(10000, 28, 28)
(60000,)
(10000,)
```

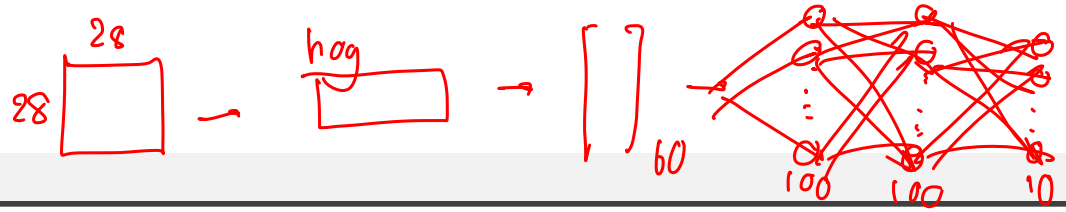
CASE STUDY: MNIST DATASET

- Data Normalization

```
X_train = X_train.astype('float32')
X_test = X_test.astype('float32')
X_train /= 255 # 0 - 1
X_test /= 255
```

- Feature Extraction

```
list_hog = []
for feature in X_train:
    fd = hog(feature.reshape((28,28)), orientations=9,
            pixels_per_cell=(14,14),cells_per_block=(1,1))
list_hog.append(fd)

hog_features_train = np.array(list_hog, 'float64')
```



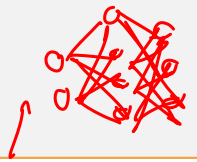
CASE STUDY: MNIST DATASET

- Feature normalization

Scale each feature by its maximum absolute value. The maximal absolute value of each feature in the training set will be 1.0

```
preProcess = preprocessing.MaxAbsScaler().fit(hog_features_train)
hog_features_transformed_train = preProcess.transform(hog_features_train)
```

- Training model



Currently, MLPClassifier supports only the Cross-Entropy loss function for **classification** task.

```
model_hog_mlp = MLPClassifier(activation='relu', hidden_layer_sizes=(100, 100),
verbose=1,max_iter=20)
model_hog_mlp.fit(hog_features_transformed_train, y_train)
print("Training accuracy ::
{}\n".format(model_hog_mlp.score(hog_features_transformed_train, y_train)))
```

https://scikit-learn.org/stable/modules/neural_networks_supervised.html
https://scikit-learn.org/stable/modules/generated/sklearn.neural_network.MLPClassifier.html

CASE STUDY: MNIST DATASET

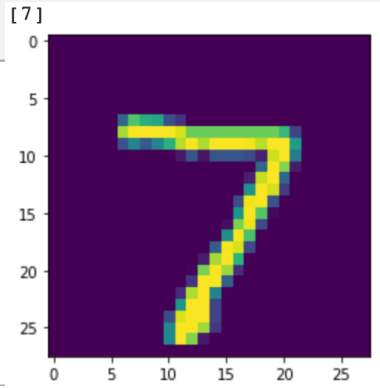
- Testing

```
Testing Score :: 0.8922
```

```
list_hog_test = []
for feature in X_test:
    fd = hog(feature.reshape((28,28)), orientations=9, pixels_per_cell=(14,14),cells_per_block=(1,1) )
    list_hog_test.append(fd)
hog_features_test = np.array(list_hog_test, 'float64')

hog_features_transformed_test = preProcess.transform(hog_features_test)

print("Testing Score :: {}\n".format(model_hog_mlp.score(hog_features_transformed_test, y_test)))
```

- Deployment

```
fd_test = hog(X_test[0].reshape((28,28)), orientations=9,
pixels_per_cell=(14,14),cells_per_block=(1,1))
hog_features_transformed_test =
                preProcess.transform(fd_test.reshape((1,hog_features_test.shape[1])))
print(model_hog_mlp.predict(hog_features_transformed_test))

plt.imshow(X_test[0])
plt.show()
```



OBJECT RECOGNITION FLOW

Input → Acquisition → Pre-processing → Feature Extraction → Recognition → Output

- Image sources
- Noise removal
- Enhancement
- Segmentation

HOG

NN

- Rule-based approach
- Machine Learning

Yeah, it's a "CAT"

Traditional Approach

hidden feature ?

Input → Acquisition → Pre-processing → Deep Learning → Output

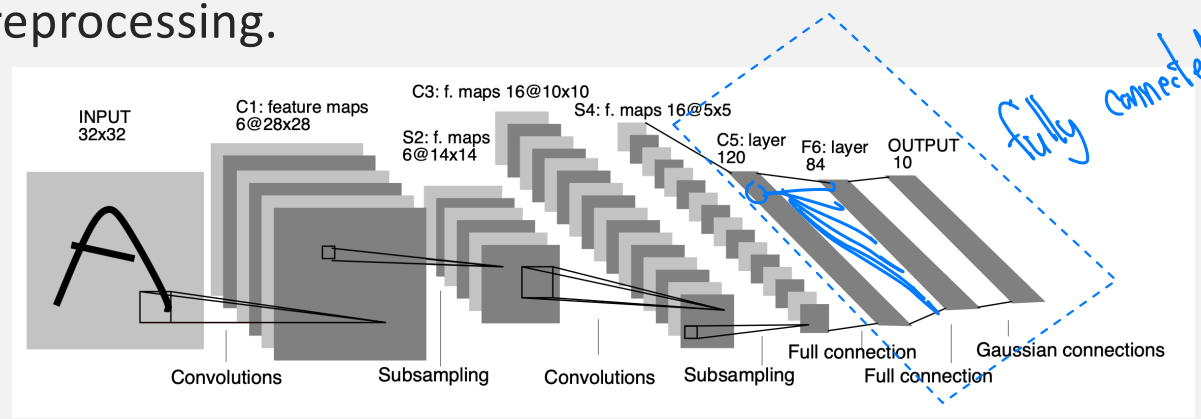
CNN

Yeah, it's a "CAT"

Modern Approach

CONVOLUTIONAL NEURAL NETWORKS

- Deep learning uses neural networks to learn useful representations of features directly from data.
- The state-of-the-art **convolutional neural networks (CNNs or ConvNets)** is used for classification and regression. A Convolutional Neural Network (CNN, or ConvNet) designed to recognize visual patterns directly from pixel images with **minimal** preprocessing.



Architecture of LENET-5

Three main layers

- Convolution Layer
- Pooling
- Fully Connected → NN

Y. Lecun, et al, 1998, Gradient-based learning applied to document recognition

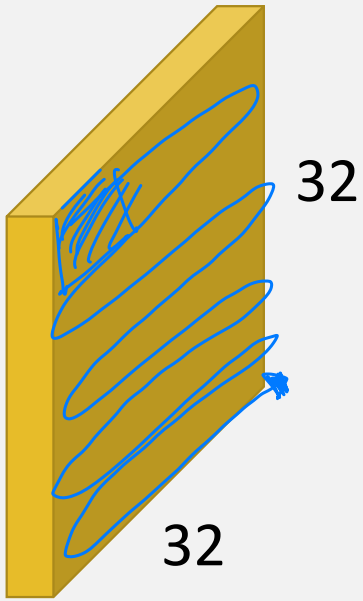
CONVOLUTIONAL NEURAL NETWORKS

filter / kernel → learnable parameter → model ตัวแรกที่เรียนรู้

- Convolution layer

1 filter = 1 pattern

A 32x32x3 image

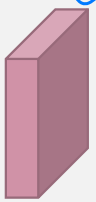


9 channel → rgb

A 5x5x3 filter

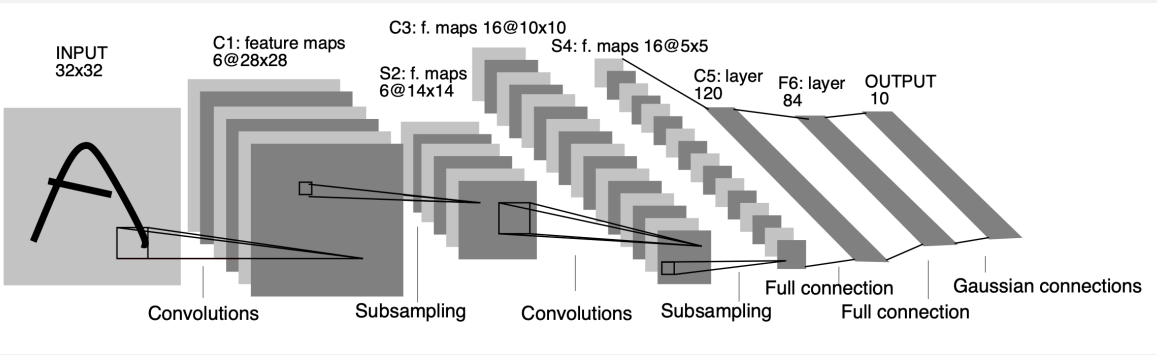
พื้นที่ channel

input โดยตัวในสีเขียว

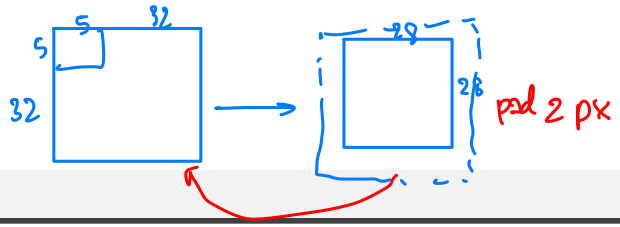


flip แล้ว apply

Convolve the filter with the image
i.e. “slide over the image spatially,
computing dot products”



Architecture of LENET-5



CONVOLUTIONAL NEURAL NETWORKS

- Convolution layer

A 32x32x3 image

A 5x5x3 filter

32

32

3

An output
=Activation map

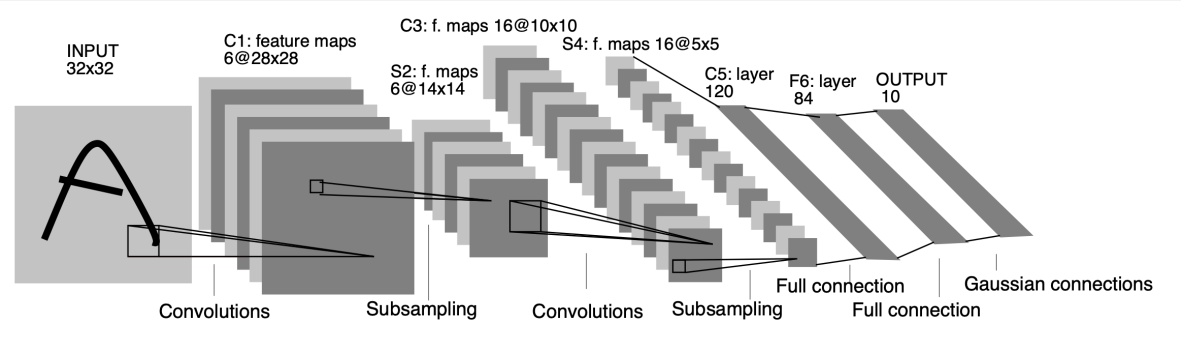
28

28

1

Stride = 1, no padding

stride =2 → skip 1 px



Architecture of LENET-5

1 filter = 5×5×3 = 75 ตัว × 6 filter } convo parameter = (5×5×3+1) × 6 = 456 parameter

bias 1 ตัว / 1 filter

bias

CONVOLUTIONAL NEURAL NETWORKS

- Convolution layer

A 32x32x3 image

A 5x5x3 filter

32

32

3

An output
=Activation map

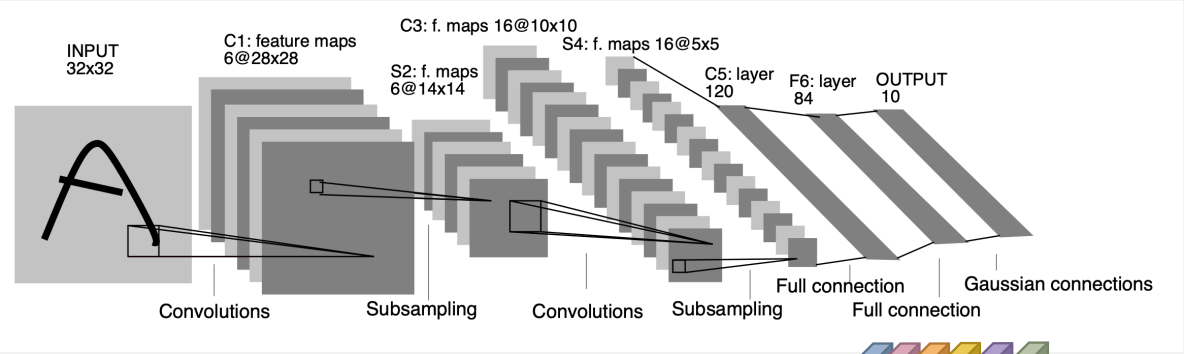
28

28

1 channel / 1 filter

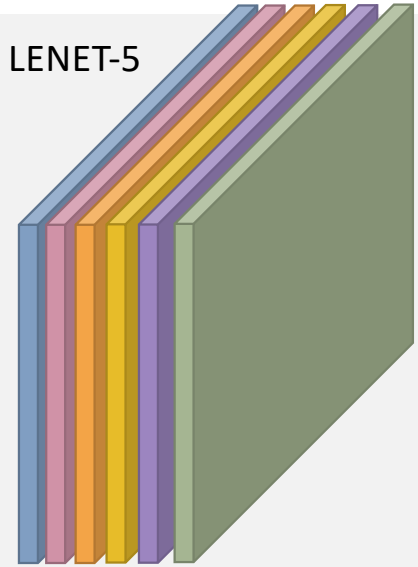
feature map

Stride = 1, no padding



Architecture of LENET-5

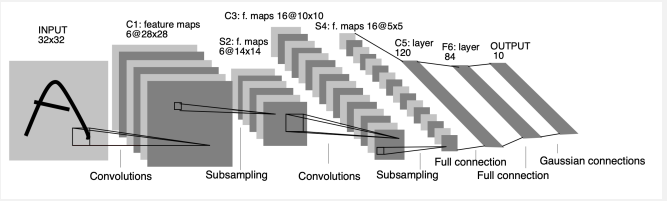
For 6 5x5 filters, we get the activation maps
6x28x28



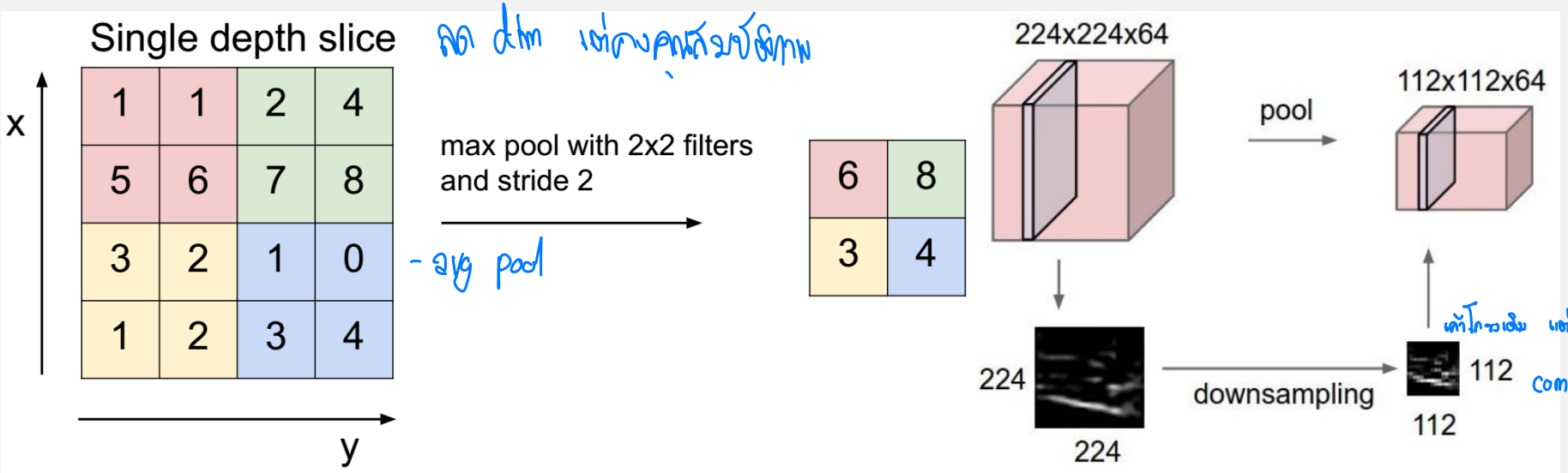
6 #filter

ไม่มี parameter เลย

CONVOLUTIONAL NEURAL NETWORKS

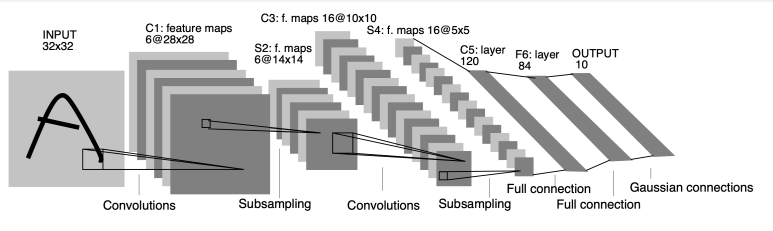


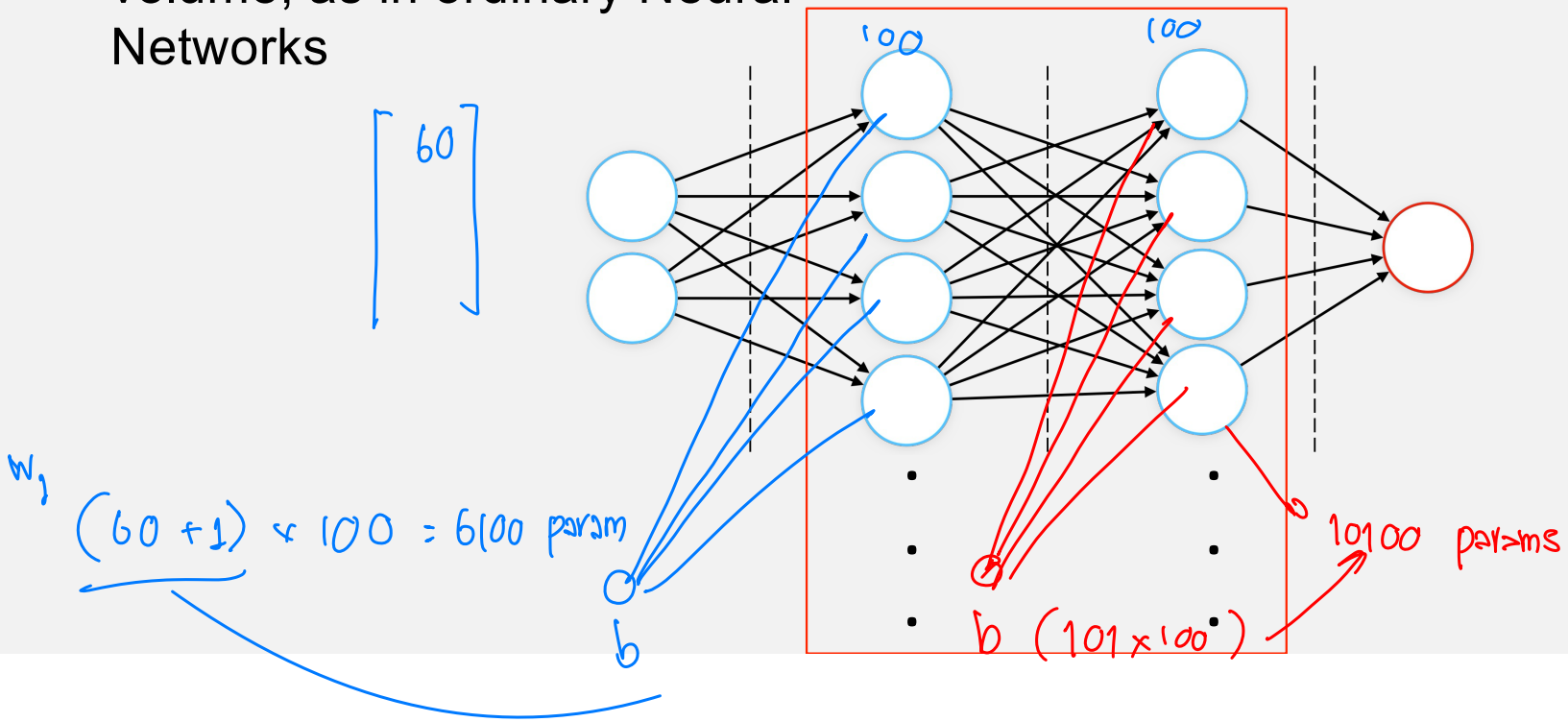
- Pooling layer
  - makes the representations smaller and more manageable
  - operates over each activation map independently



CONVOLUTIONAL NEURAL NETWORKS

- Fully Connection layer / Dense / Linear
  - Contains neurons that connect to the entire input volume, as in ordinary Neural Networks





CONVOLUTIONAL NEURAL NETWORKS

Key parameters / functions

- **Losses functions** or objective functions, or optimization score function
  - **Class loss** - used to calculate the cross-entropy for classification problems. Multiple versions include binary cross-entropy, $loss = -y_i \log(p_i) - (1 - y_i) \log(1 - p_i)$; y_i is class indicator and p_i is probability of of sample i.
  - categorical cross-entropy , $loss = \sum_{c=1}^{M} -y_{i,c} \log(p_{i,c})$; $y_{i,c}$ is class indicator and $p_{i,c}$ is the probability of sample i in class c
- **A metric function** is the results from evaluating a metric are not used when training the model, e.g., 'accuracy'
- **An epoch** is one complete pass through the whole training set
- **Batch size** is the number of training instances observed before optimization performs update

Reference: https://pytorch.org/tutorials/

DEEP LEARNING FRAMEWORK

Everyone's situation and needs are different, so it boils down to which features matter the most for your AI project. For easy reference, here's a chart that breaks down the features of Keras vs PyTorch vs TensorFlow.

	Keras	PyTorch	TensorFlow
API Level	High	Low	High and Low
Architecture	Simple, concise, readable	Complex, less readable	Not easy to use
Datasets	Smaller datasets	Large datasets, high performance	Large datasets, high performance
Debugging	Simple network, so debugging is not often needed	Good debugging capabilities	Difficult to conduct debugging
Does It Have Trained Models?	Yes	Yes	Yes

	Keras	PyTorch	TensorFlow
Popularity	Most popular	Third most popular	Second most popular
Speed	Slow, low performance	Fast, high-performance	Fast, high-performance
Written In	Python	Lua	C++, CUDA, Python

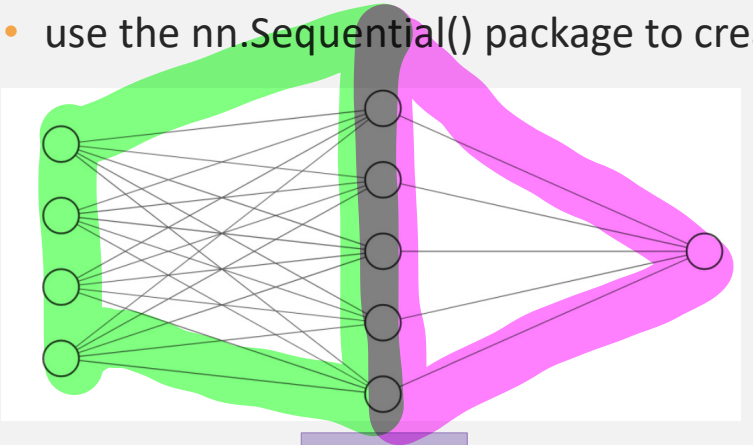
https://www.simplilearn.com/keras-vs-tensorflow-vs-pytorch-article

TRADITIONAL VS. MODERN
CASE STUDY: MNIST DATASET

- Apply a simple convolutional neural networks and compared the results with previous approach

CREATING A MODEL USING PYTORCH

- Implementing a sequential model
  - use the nn.Sequential() package to create a deep learning model by passing layers in order



```
from torch import nn
# define a two-layer model
model = nn.Sequential(
      nn.Linear(4, 5),
      nn.ReLU(),
      nn.Linear(5, 1),
      )
print(model)
```

Output:

```
Sequential(
      (0): Linear(in_features=4, out_features=5, bias=True)
      (1): ReLU()
      (2): Linear(in_features=5, out_features=1, bias=True) )
```


Reference: https://pytorch.org/tutorials/beginner/basics/quickstart_tutorial.html

CREATING A MODEL USING PYTORCH

- Defining models using nn.Module
  - specify the layers in the `__init__` method of the class
  - In `forward` method, we apply the layers to inputs
  - This method provides better flexibility for building customized models.
  - To accelerate operations in the neural network, we move it to the GPU if available.

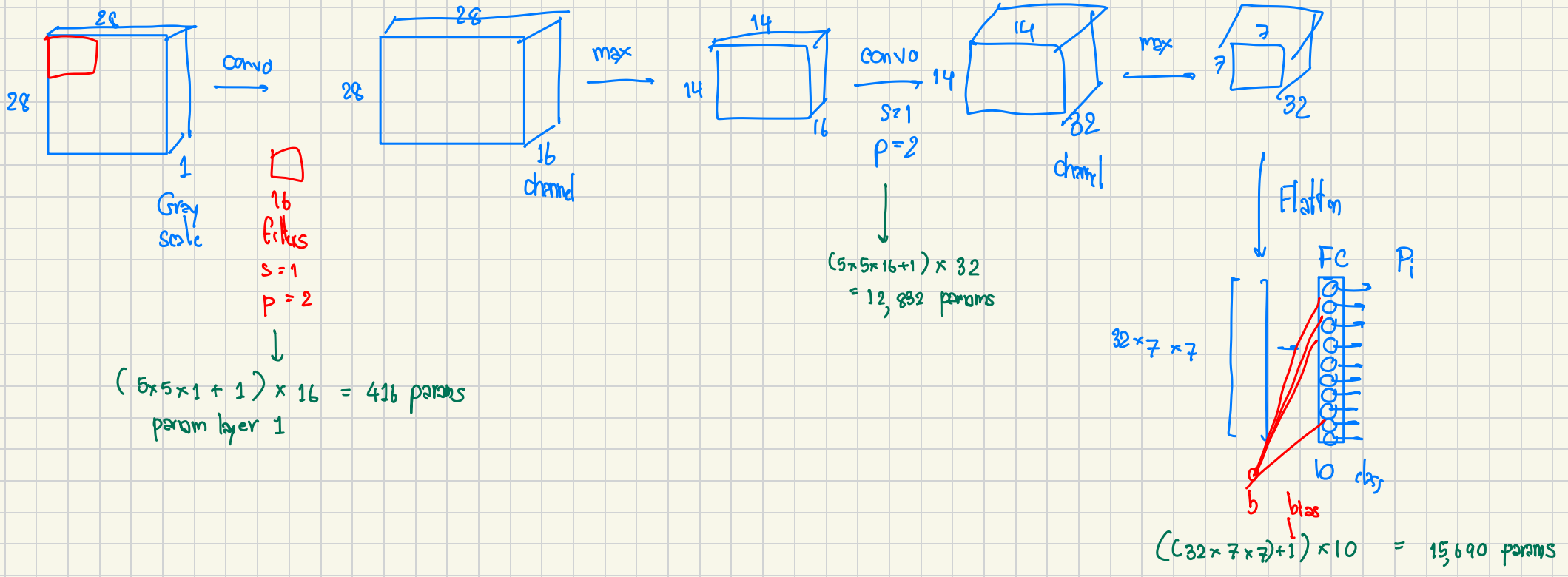
```
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Sequential(
            nn.Conv2d(
                in_channels=1,
                out_channels=16,
                kernel_size=5,
                stride=1,
                padding=2,
            ),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2),
        )
        self.conv2 = nn.Sequential(
            nn.Conv2d(16, 32, 5, 1, 2),
            nn.ReLU(),
            nn.MaxPool2d(2),
        )
        # fully connected layer, output 10 classes
        self.out = nn.Linear(32 * 7 * 7, 10)
    def forward(self, x):
        x = self.conv1(x)
        x = self.conv2(x)

        # flatten the output of conv2 to (batch_size, 32 * 7 *
        x = x.view(x.size(0), -1)
        output = F.log_softmax(self.out(x), dim=1)
        return output
model = Net().to(device)
print(model)
```

The use of log probabilities improves numerical stability, when the probabilities are very small,

Output:

```
Net(
      (conv1): Sequential(
            (0): Conv2d(1, 16, kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))
            (1): ReLU()
            (2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False) )
      (conv2): Sequential(
            (0): Conv2d(16, 32, kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))
            (1): ReLU()
            (2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False) )
            (out): Linear(in_features=1568, out_features=10, bias=True)
      )
```

Reference: https://pytorch.org/tutorials/beginner/basics/quickstart_tutorial.html

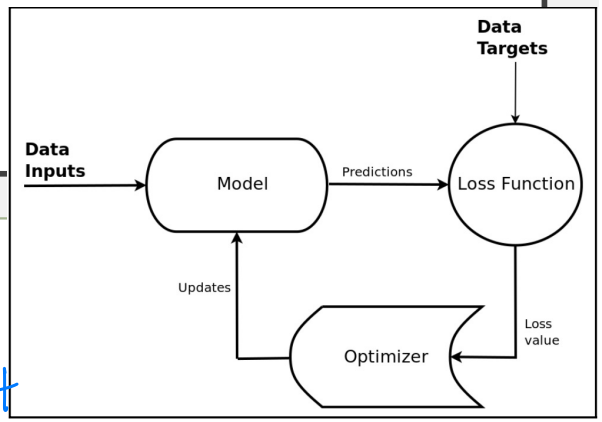

28
28
1
Gray scale
conv
16 filtros
s = 1
p = 2
(5x5x1 + 1) x 16 = 416 params
param layer 1
28
28
16 channel
max
14
14
16
conv
s=1
p=2
(5x5x16+1) x 32
= 12,832 params
14
14
32 channel
max
7
7
32
Flatten
32x7x7
FC
Pi
10 class
b
bias
((32x7x7)+1) x10 = 15,690 params

TRAINING PROCESS

In a single training loop, the model makes predictions on the training dataset (fed to it in batches), and backpropagates the prediction error to adjust the model's parameters.

```
def train(dataloader, model, loss_fn, optimizer):
    size = len(dataloader.dataset)
    model.train()
    for batch, (X, y) in enumerate(dataloader):
        X, y = X.to(device), y.to(device)

        # Compute prediction error
        pred = model(X)
        loss = loss_fn(pred, y)

        # Backpropagation
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        if batch % 100 == 0:
            loss, current = loss.item(), batch * len(X)
            print(f"loss: {loss:>7f}  [{current:>5d}/{size:>5d}]")
```

```
def val(dataloader, model, loss_fn):
    size = len(dataloader.dataset)
    num_batches = len(dataloader)
    model.eval()
    test_loss, correct = 0, 0
    with torch.no_grad():
        for X, y in dataloader:
            X, y = X.to(device), y.to(device)
            pred = model(X)
            test_loss += loss_fn(pred, y).item()
            correct += (pred.argmax(1) == y).type(torch.float).sum().item()
    test_loss /= num_batches
    correct /= size
    print(f"Val Accuracy: {(100*correct):>0.1f}%,  Avg loss: {test_loss:>8
```



Sets the gradients of all optimized torch.Tensor s to zero.

compute the gradients with respect to the model parameters

update the model parameters

Context-manager that disabled gradient calculation / not update internal weights

Loading and processing data

Reference: https://pytorch.org/tutorials/beginner/basics/quickstart_tutorial.html

TRAINING PROCESS

```
def test(dataloader, model, loss_fn):
    size = len(dataloader.dataset)
    num_batches = len(dataloader)
    model.eval()
    test_loss, correct = 0, 0
    with torch.no_grad():
        for X, y in dataloader:
            X, y = X.to(device), y.to(device)
            pred = model(X)
            test_loss += loss_fn(pred, y).item()
            correct += (pred.argmax(1) == y).type(torch.float).sum().item()
    test_loss /= num_batches
    correct /= size
    print(f"Test Accuracy: {(100*correct):>0.1f}%,  Avg loss: {test_loss:>8f} \n")

epochs = 5
for t in range(epochs):
    print(f"Epoch {t+1}\n-------------------------------")
    train(train_dataloader, model, loss_fn, optimizer)
    val(val_dataloader, model, loss_fn)
print("Done!")
```

ไม่ compute gradient เหมือน val แต่ต่างที่ ... seen

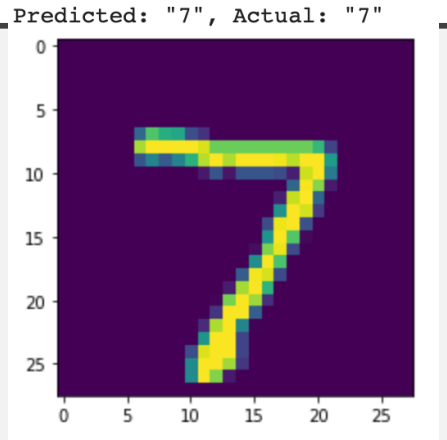
Reference: https://pytorch.org/tutorials/beginner/basics/quickstart_tutorial.html

CREATING A MODEL USING PYTORCH

- Save model (for later use) and load model

```
torch.save(model.state_dict(), "model.pth")
print("Saved PyTorch Model State to model.pth")
```

```
model = Net().to(device)
model.load_state_dict(torch.load("model.pth"))
```



- Evaluation

```
model.eval()
x, y = test_data[0][0], test_data[0][1]
print(x.shape)
with torch.no_grad():
    pred = model(x.unsqueeze(0).to(device))
    predicted, actual = pred[0].argmax(0), y
    print(f'Predicted: "{predicted}", Actual: "{actual}"')

plt.imshow(x[0])
plt.show()
```

model.eval() is a kind of switch for some specific layers/parts of the model that behave differently during training and inference (evaluating) time.

- For example, Dropouts Layers, BatchNorm Layers etc. You need to turn off them during model evaluation, and .eval() will do it for you.
- In addition, the common practice for evaluating/validation is using torch.no_grad()in pair with model.eval() to turn off gradients computation:

Reference: https://pytorch.org/tutorials/beginner/basics/quickstart_tutorial.html

IMPROVING MODEL GENERIZATION

- Dropout is a technique where you remove (or "drop out") units in a neural net to simulate training large numbers of architectures simultaneously. Importantly, dropout can drastically reduce the chance of overfitting during training.
- Number of layers / epoch /
- Number of filters
- Batch normalization

```
self.conv2 = nn.Sequential(
            nn.Conv2d(16, 32, 5, 1, 2),
            nn.BatchNorm2d(32),
            nn.Dropout(0.25),
            nn.ReLU(),
            nn.MaxPool2d(2),
        )
```

normalize ค่าใน feature map ก่อน 4D

set zero บาง layer ลดการ fitting

  - Applies Batch Normalization over a 4D input (a mini-batch of 2D inputs with additional channel dimension)

CH, W, H, จำนวน

  - The mean and standard-deviation are calculated per-dimension over the mini-batches and γ and β are learnable parameter vectors of size *C* (where *C* is the input size)

$$y = \frac{x - \mathrm{E}[x]}{\sqrt{\mathrm{Var}[x] + \epsilon}} * \gamma + \beta$$

γ, β ไม่ได้กำหนดเอง

RECOGNITION PERFORMANCE

Input → Acquisition → Pre-processing → Feature Extraction → Recognition → Output

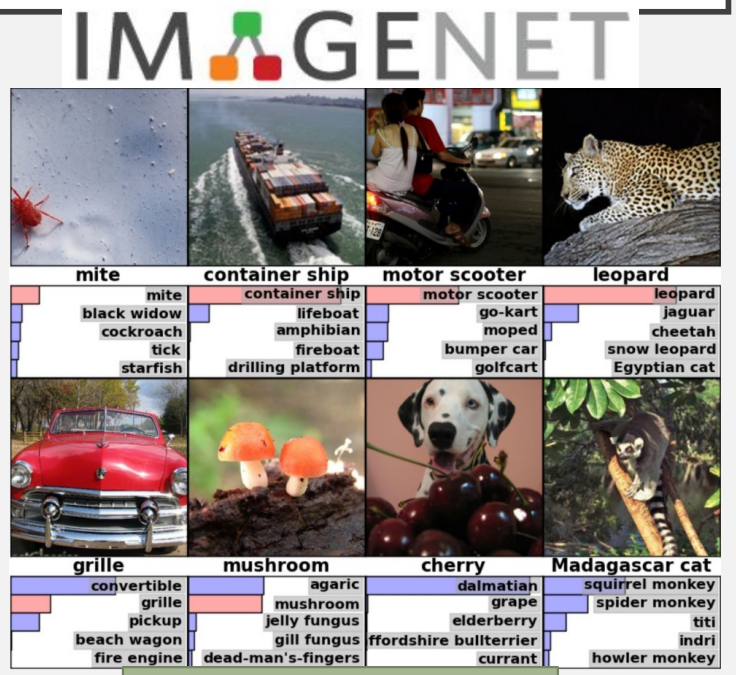
- Image sensors
- Noise removal
- Enhancement
- Segmentation
- Rule-based approach
- Machine Learning

Yeah, it's a "CAT"

- Specific to problems
- Feature Selection / Self learning features
- Dataset Quality and Quantity
  - Data augmentation
- Error analysis + Literature review
- Improve current model (parameters, and architecture) or use alternative models

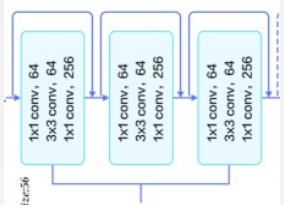
IMAGE CLASSIFICATION ADVANCEMENT

- **ImageNet** project is a large visual database
  - 1,000 object classes (categories).
  - > 1M train labeled high resolution images
- Deeper, wider or more flexible layers, introducing dropout, data augmentation, GPU parallel computation
  - AlexNet, ZFNet, GoogLeNet and VGG were the winner and runner-up of the ILSVRC-2014, ResNet,
  - EfficientNet (Scaling CNNs)
- Transfer learning concept



ILSVRC - Challenge 2010-2017

Residual learning blocks

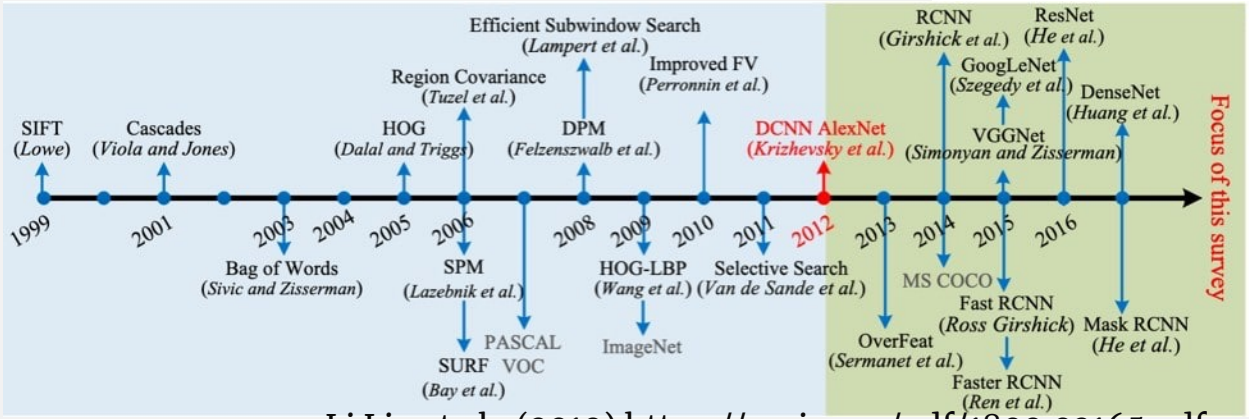


Challenge 2017

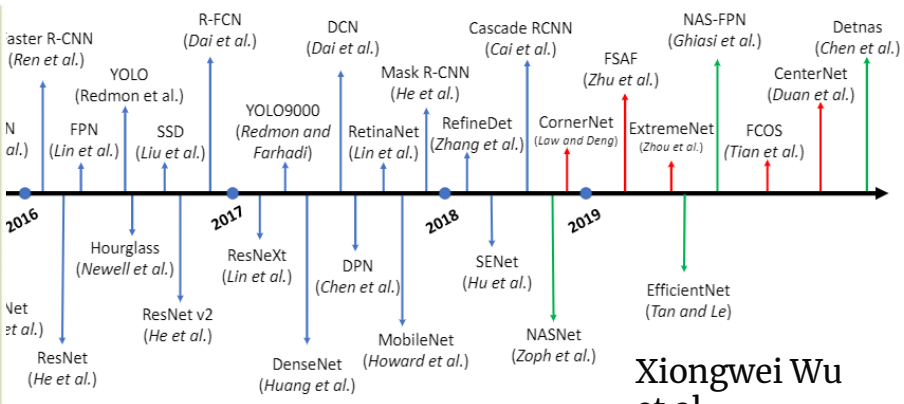
I. Object localization for 1000 categories.
II. Object detection for 200 fully labeled categories.
III. Object detection from video for 30 fully labeled categories.

OBJECT RECOGNITION TRENDS

- Deeper, wider or more flexible layers, introducing dropout, data augmentation, GPU parallel computation
  - AlexNet, ZFNet, GoogLeNet and VGG were the winner and runner-up of the ILSVRC-2014, ResNet,
  - EfficientNet (Scaling CNNs)
- Transfer learning concept
- More work on object detection / segmentation



Li Liu et al., (2019) https://arxiv.org/pdf/1809.02165.pdf



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