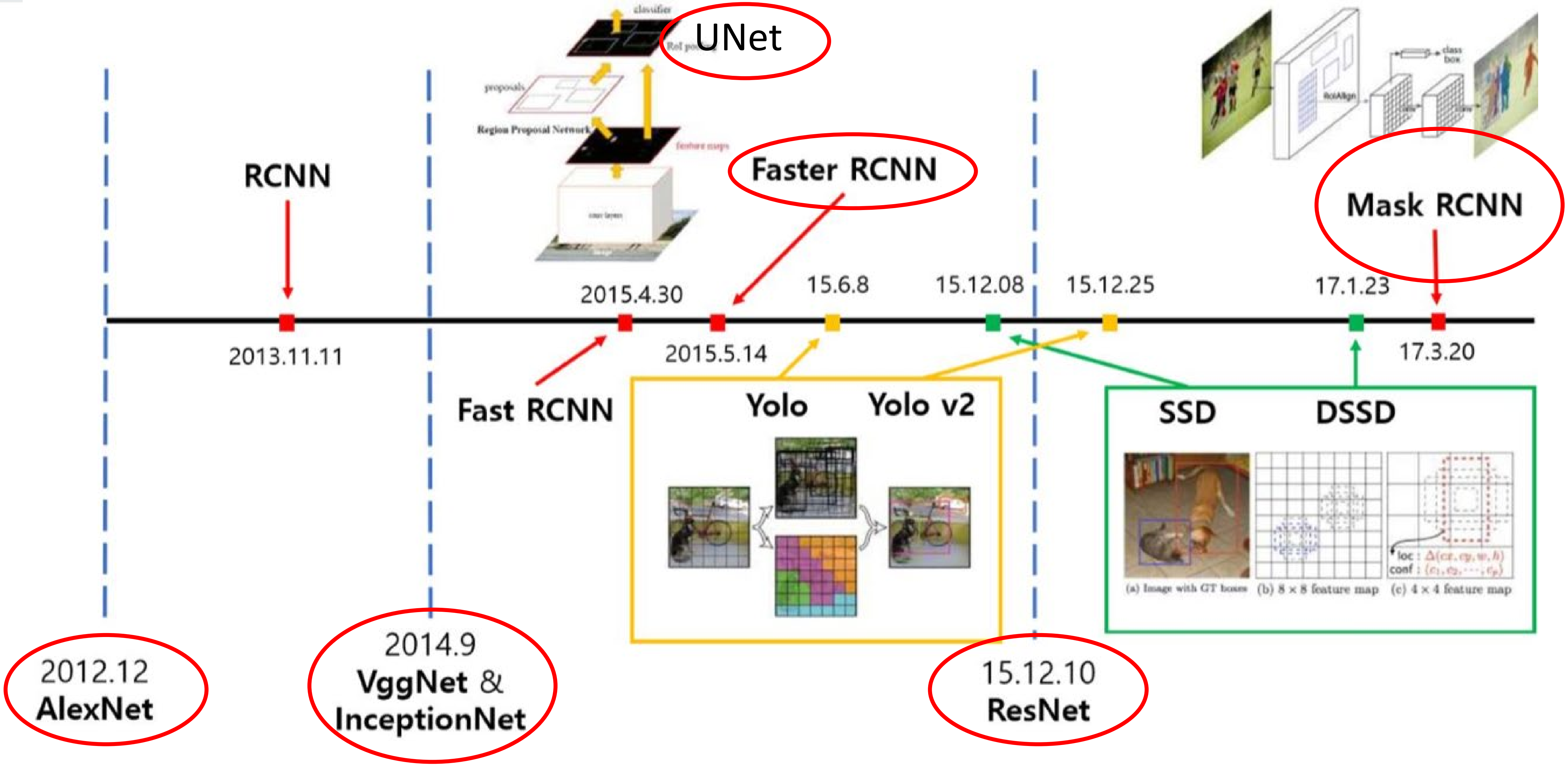
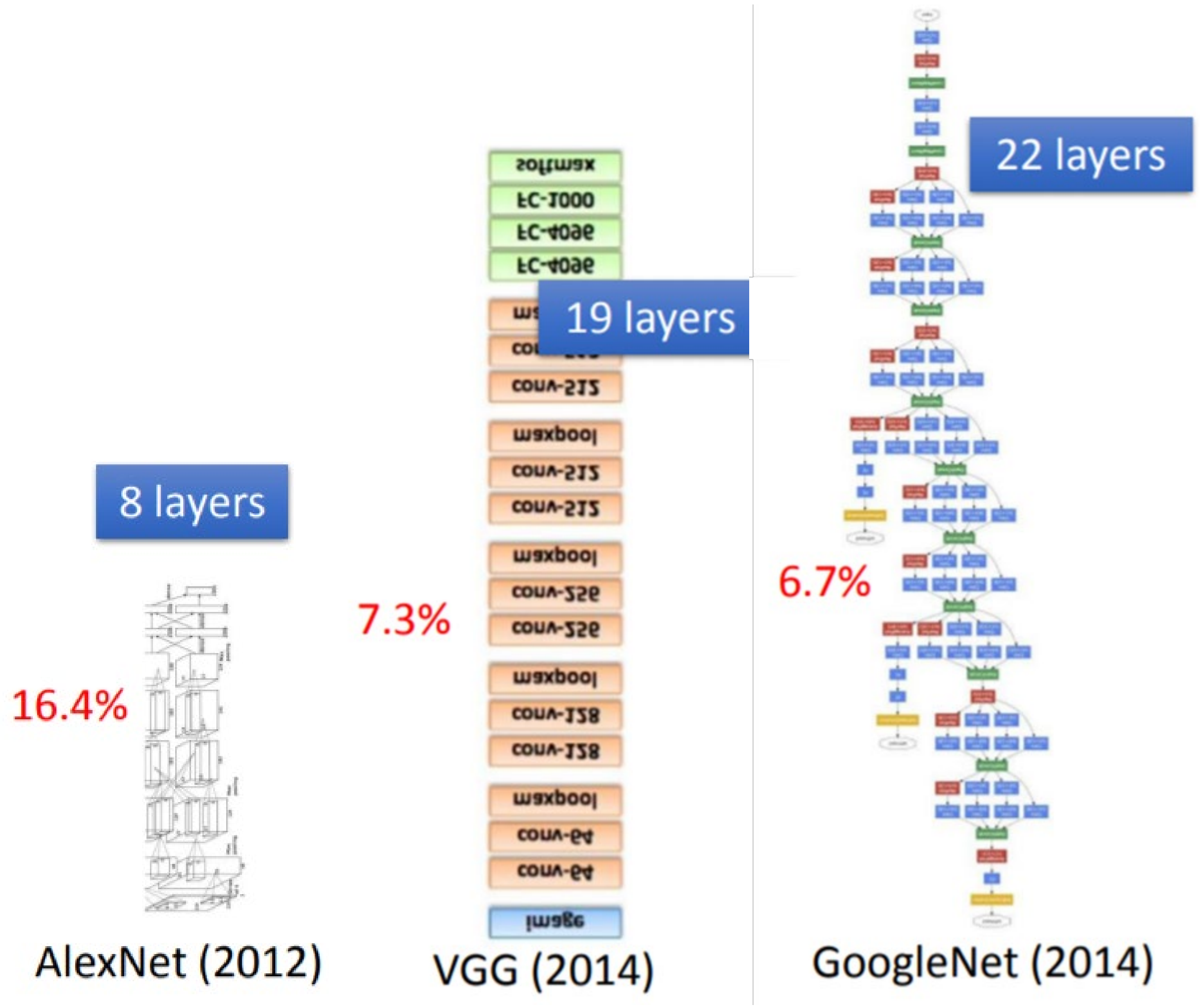
ResNet

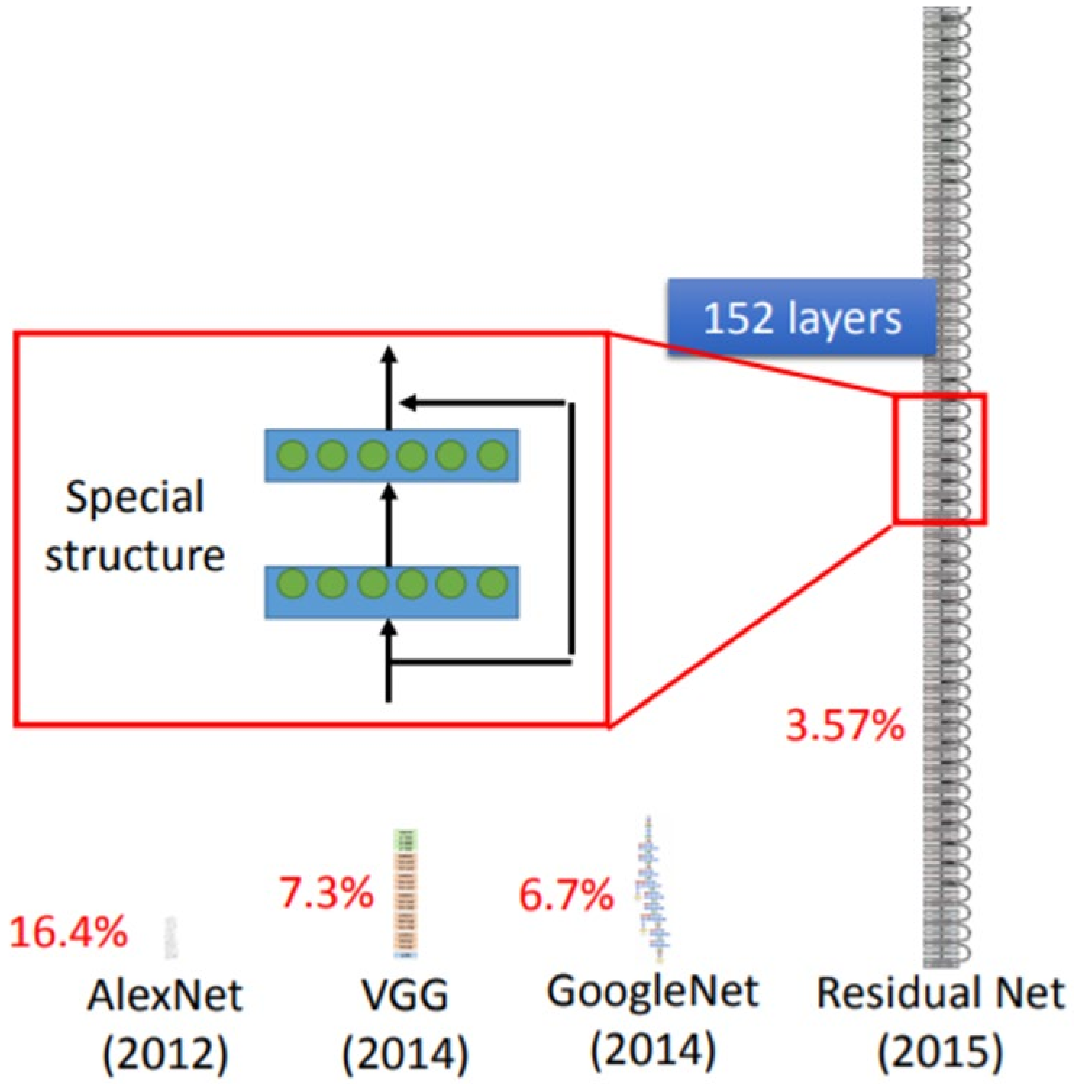
History of CNN families



圖來源: 李春煌 FasterRCNN講義 https://youtu.be/2i9CcmJp2yI

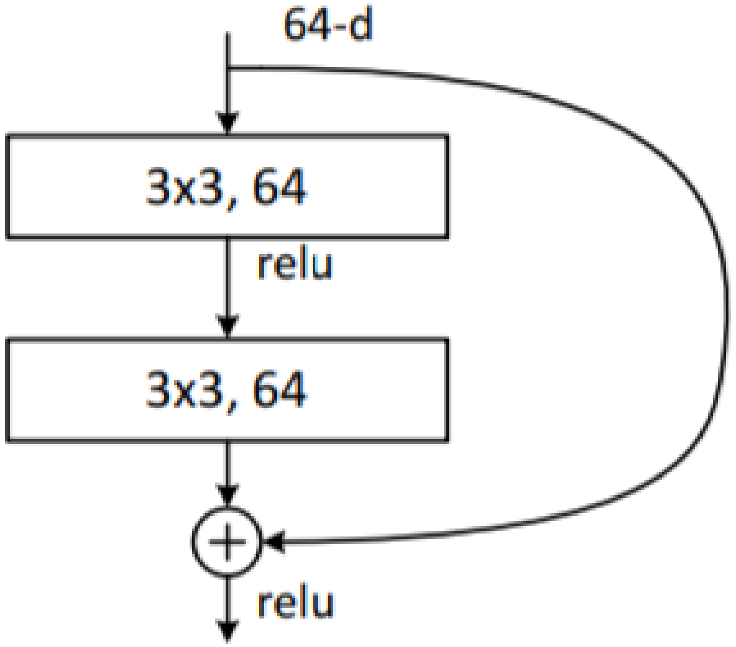
Going deeper and deeper…



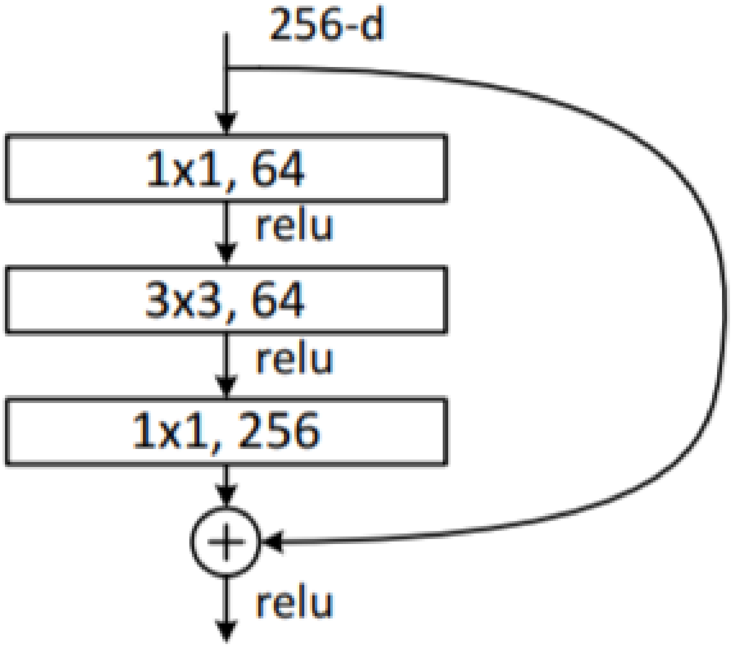


Reference: 李弘毅 ML Lecture 6 https://youtu.be/Dr-WRlEFefw

ResNet



Basic block



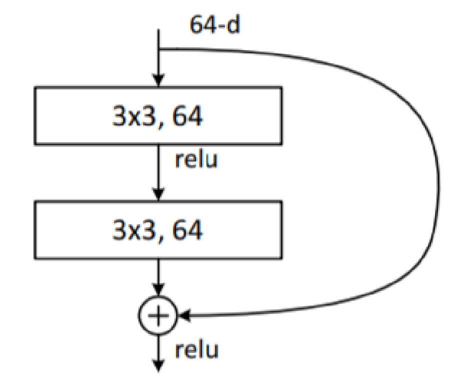
Bottleneck block

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).

Practice

6.4. Build my own ResNet.ipynb

Basic block




```python
class BasicBlock(nn.Module):
  expansion = 1
  def __init__(self, inplanes, planes, stride=1, downsample=None,)
    super(BasicBlock, self).__init__()
    self.conv1=conv3x3(inplanes,planes,stride)
    self.bn1=nn.BatchNorm2d(planes)
    self.relu=nn.ReLU(inplace=True)
    self.conv2=conv3x3(planes,planes)
    self.bn2=nn.BatchNorm2d(planes)
    self.downsample=downsample
    self.stride=stride

    if(stride!=1 or inplanes!=planes*self.expansion):
      self.downsample=nn.Sequential(
        nn.Conv2d(inplanes,planes*self.expansion,kernel_size=1,str
        nn.BatchNorm2d(planes*self.expansion),
      )
```

```python
def forward(self, x):
  residual = x
  out = self.conv1(x)
  out = self.bn1(out)
  out = self.relu(out)
  out = self.conv2(out)
  out = self.bn2(out)

  # Downsample:feature Map size/2 ||
  if (self.downsample is not None):
    residual = self.downsample(x)
  print("out= ", out.shape, "residua
  out+=residual
  out=self.relu(out)
  return out
```

Add batch normalization after convolution

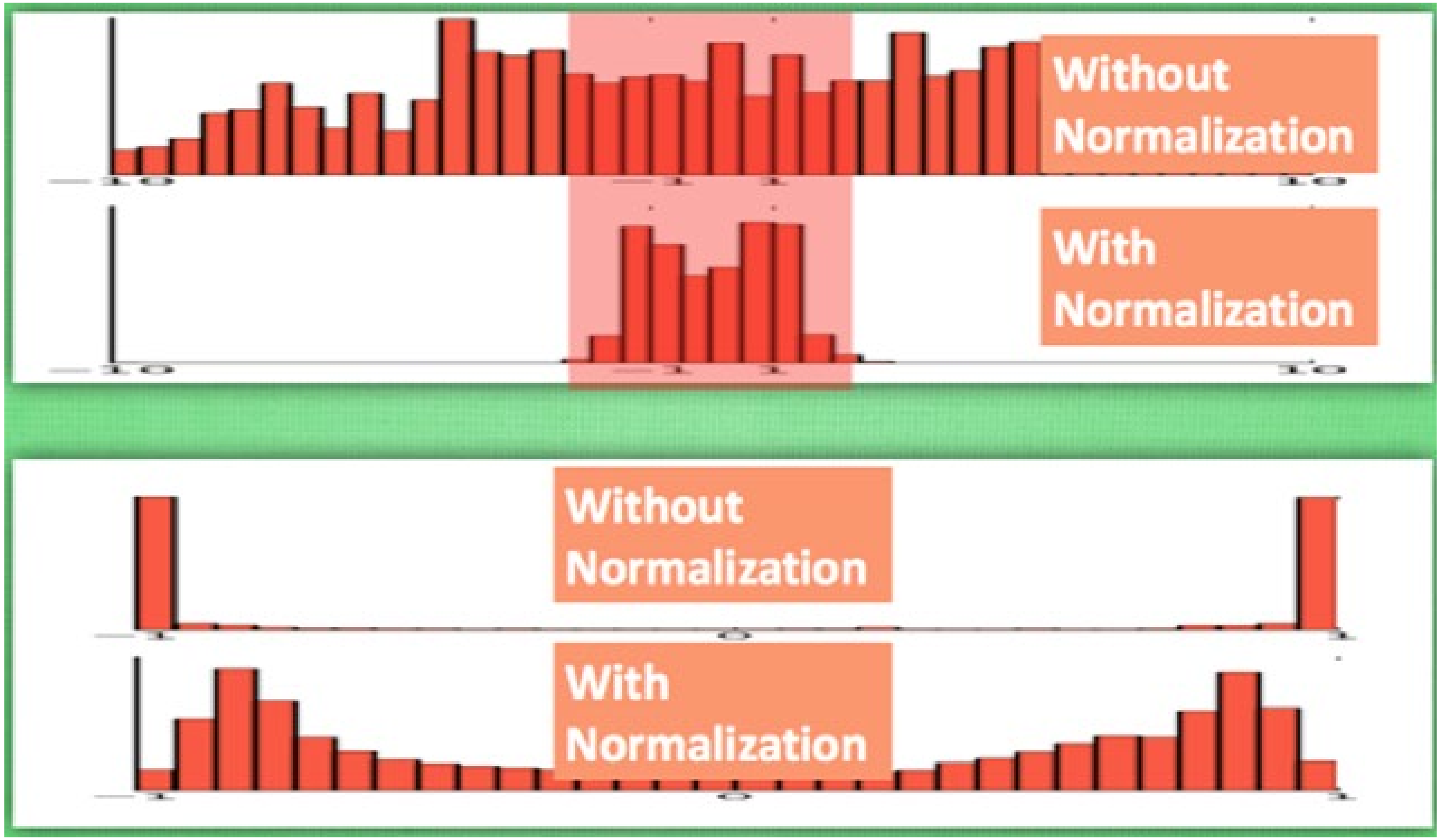
Applies Batch Normalization over a 4D input (a mini-batch of 2D inputs with additional channel dimension) as described in the paper Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift .

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

- The mean and standard-deviation are calculated per-dimension over the mini-batches.
- By default, the elements of γ are set to 1 and the elements of β are set to 0.

https://pytorch.org/docs/stable/generated/torch.nn.BatchNorm2d.html

batch normalization helps NN training



https://medium.com/ching-i/batch-normalization-%E4%BB%8B%E7%B4%B9-135a24928f12

My ResNet

```
class MyResNet(nn.Module):
  def __init__(self, block, layers, num_classes=2):
    super(MyResNet, self).__init__()
    self.inplanes = 64
    self.dilation = 1
    self.conv1=nn.Conv2d(3,self.inplanes,kernel_size
    self.maxpool=nn.MaxPool2d(kernel_size=3,stride=2
    self.layer1=self._make_layer(block,64,layers[0])
    self.layer2=self._make_layer(block,128,layers[1]
    self.avgpool=nn.AdaptiveAvgPool2d((1,1))
    self.fc=nn.Linear(128*block.expansion,num_classe
    self.linear=nn.Linear(128*block.expansion,num_cl
```

```
def _make_layer(self, block, planes, b
  layers=[]
  layers.append(block(self.inplanes,pl
  self.inplanes=planes*block.expansion

  for i in range(1,blocks):
    layers.append(block(self.inplanes,
  return nn.Sequential(*layers)
```

```
def forward(self, x):
  x=self.conv1(x)
  x=self.maxpool(x)
  x=self.layer1(x)
  x=self.layer2(x)
  x=self.avgpool(x)
  x=torch.flatten(x, 1)
  x=self.fc(x)
  return x
```

My ResNet

```
MyResNet(
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
  (layer1): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (layer2): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (downsample): Sequential(
        (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
  (fc): Linear(in_features=128, out_features=2, bias=True)
  (linear): Linear(in_features=128, out_features=2, bias=True)
)
```

Practice – Draw the structure of MyResNet

```
MyResNet(
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
```

```
[14]: out1=model.conv1(imageTensor.to(device))
      print(out1.shape)

      torch.Size([1, 64, 112, 112])

[15]: out2=model.maxpool(out1)
      print(out2.shape)

      torch.Size([1, 64, 56, 56])
```

Practice – Draw the structure of MyResNet

```
  (layer1): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
```

```
[16]: out3=model.layer1(out2)
```

```
out=  torch.Size([1, 64, 56, 56]) residual=  torch.Size([1, 64, 56, 56])
```

Practice – Draw the structure of MyResNet

```
(layer2): Sequential(
  (0): BasicBlock(
    (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
    (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace=True)
    (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (downsample): Sequential(
      (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
      (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
```

```
[17]: out4 = model.layer2(out3)
```

```
out=  torch.Size([1, 128, 28, 28]) residual=  torch.Size([1, 128, 28, 28])
```

Practice – Draw the structure of MyResNet

```
,
(avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
(fc): Linear(in_features=128, out_features=2, bias=True)
(linear): Linear(in_features=128, out_features=2, bias=True)
```

```
[18]: out5= model.avgpool(out4)
      print(out5.shape)

      torch.Size([1, 128, 1, 1])

[19]: out6=torch.flatten(out5,1)
      print(out6.shape)

      torch.Size([1, 128])

[20]: out7 = model.fc(out6)
      print(out7)

      tensor([[-0.0661, -0.1440]], device
```

Practice – Load pre-trained ResNet

```
In [2]: import torchvision
        model = torchvision.models.resnet18(pretrained=True)

Downloading: "https://download.pytorch.org/models/resnet18-5c106cde.pth" t

HBox(children=(FloatProgress(value=0.0, max=46827520.0), HTML(value='')))
```

ResNet

```
ResNet(
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
  (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (relu): ReLU(inplace=True)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
  (layer1): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
    (1): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
```

ResNet

```
(layer2): Sequential(
  (0): BasicBlock(
    (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
    (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace=True)
    (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (downsample): Sequential(
      (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
      (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (1): BasicBlock(
    (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace=True)
    (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  )
)
```

Why deep ?

With same number of parameters, deep is better

Layer X Size	Word Error Rate (%)	Layer X Size	Word Error Rate (%)
1 X 2k	24.2		
2 X 2k	20.4		
3 X 2k	18.4		
4 X 2k	17.8		
5 X 2k	17.2	1 X 3772	22.5
7 X 2k	17.1	1 X 4634	22.6
		1 X 16k	22.1

Why?

deep + thin

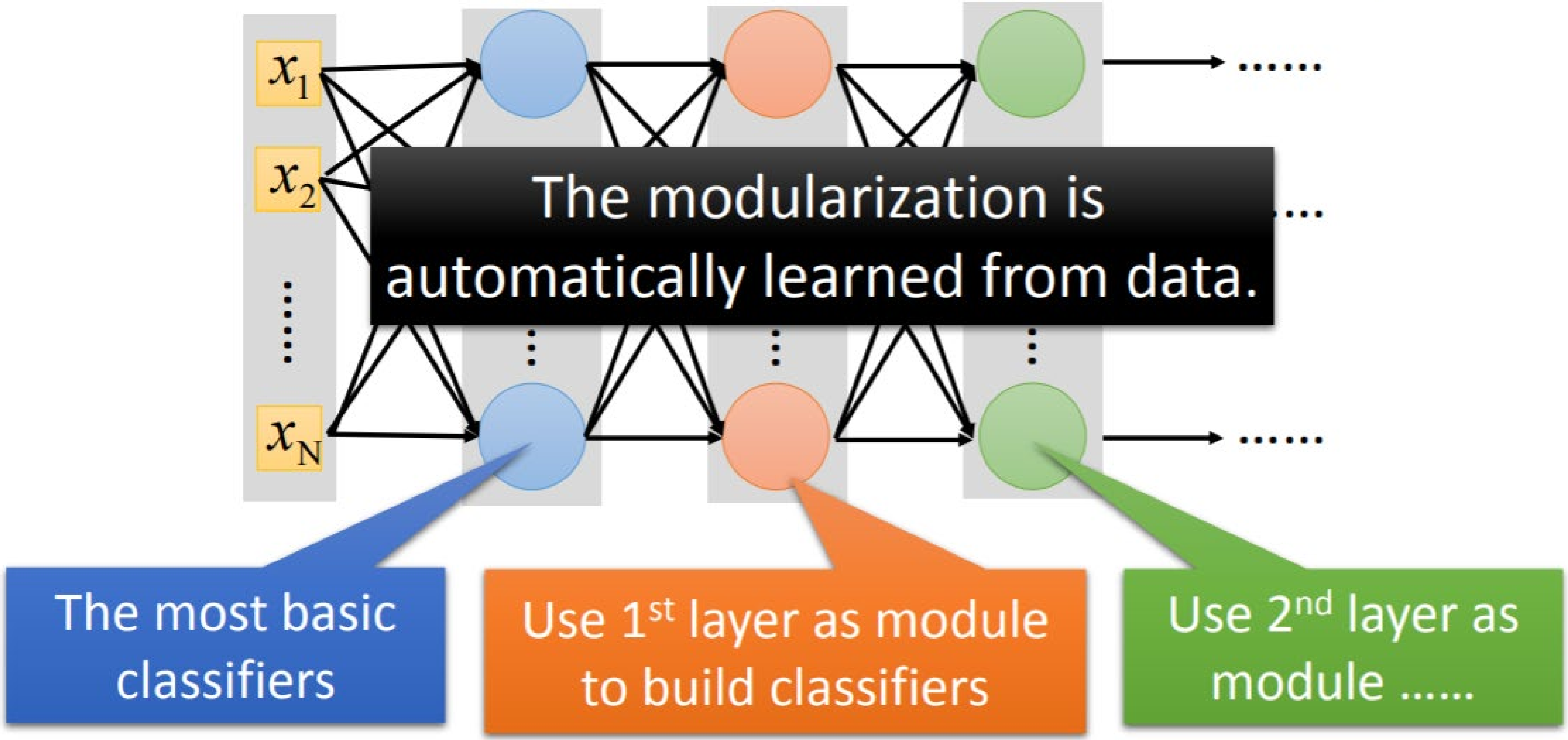
short + fat

Seide, Frank, Gang Li, and Dong Yu. "Conversational Speech Transcription Using Context-Dependent Deep Neural Networks." *Interspeech*. 2011.

Reference: 李弘毅 ML Lecture 11 https://youtu.be/XsC9byQkUH8

Reason 1 – Modularization

- Deep → Modularization → Less training data?



Reference: 李弘毅 ML Lecture 11 https://youtu.be/XsC9byQkUH8

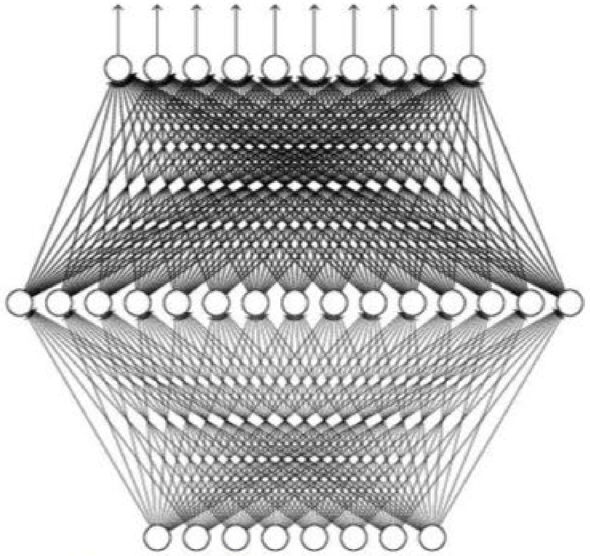
Universality theorem

Any continuous function f

$$f : R^N \rightarrow R^M$$

Can be realized by a network with one hidden layer

(given **enough** hidden neurons)



Reference for the reason: http://neuralnetworksanddeeplearning.com/chap4.html

Yes, shallow network can represent any function.

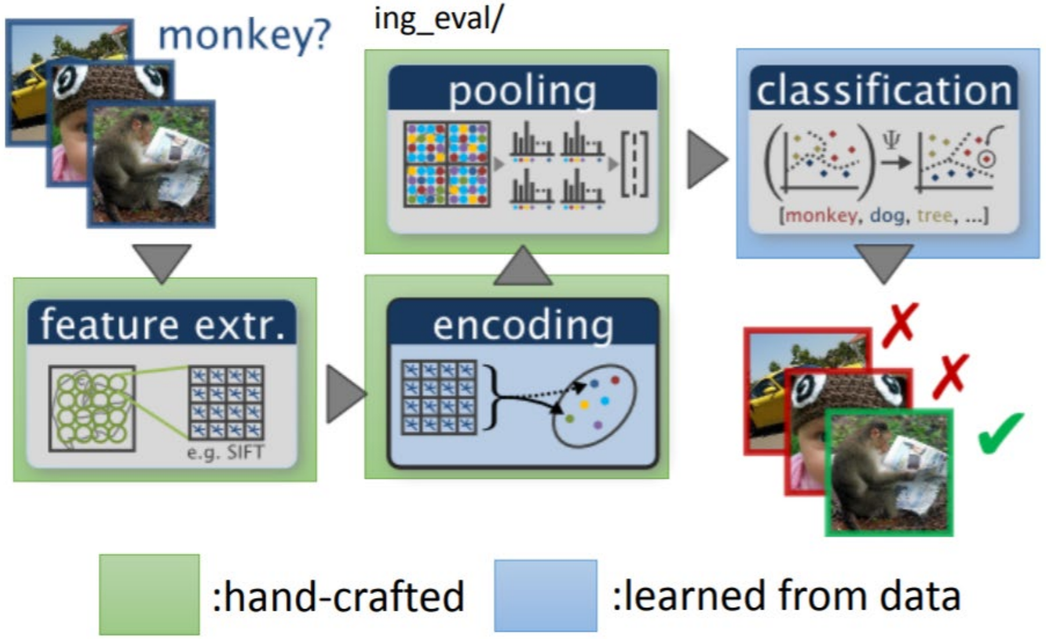
However, using deep structure is more effective.

Reference: 李弘毅 ML Lecture 11 https://youtu.be/XsC9byQkUH8

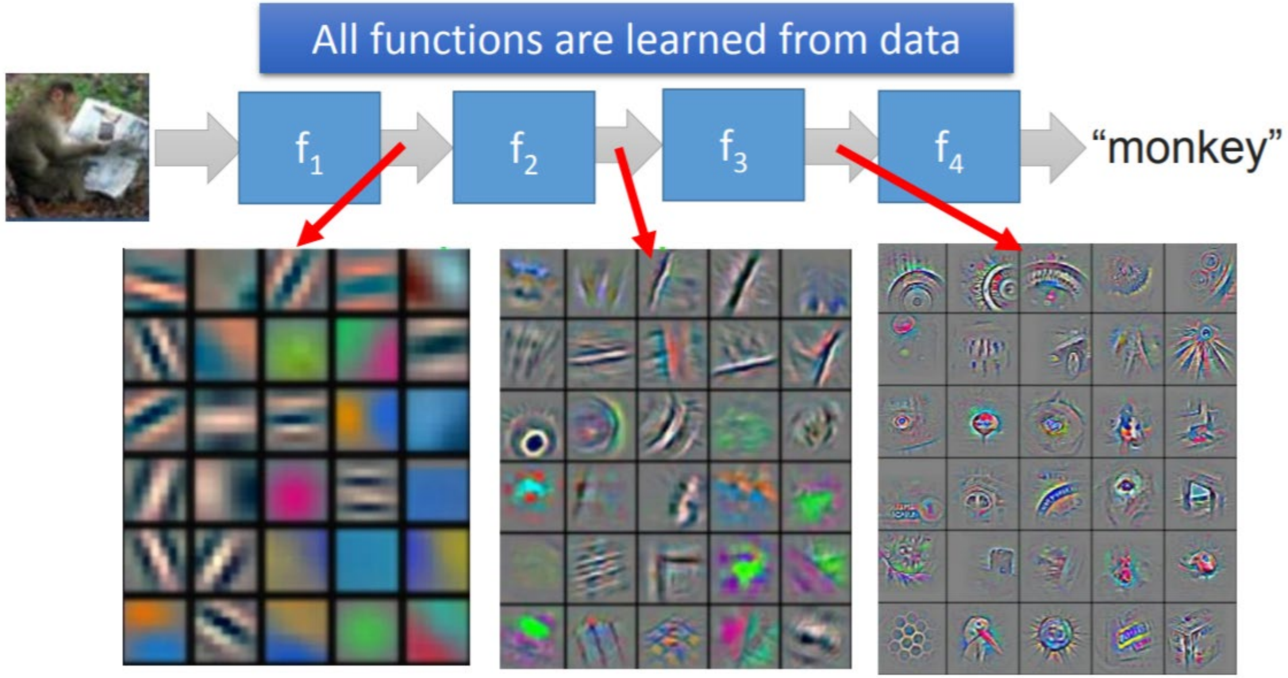
Reason 2: End-to-end learning

- Shallow Approach

http://www.robots.ox.ac.uk/~vgg/research/encoding_eval/



- Deep Learning

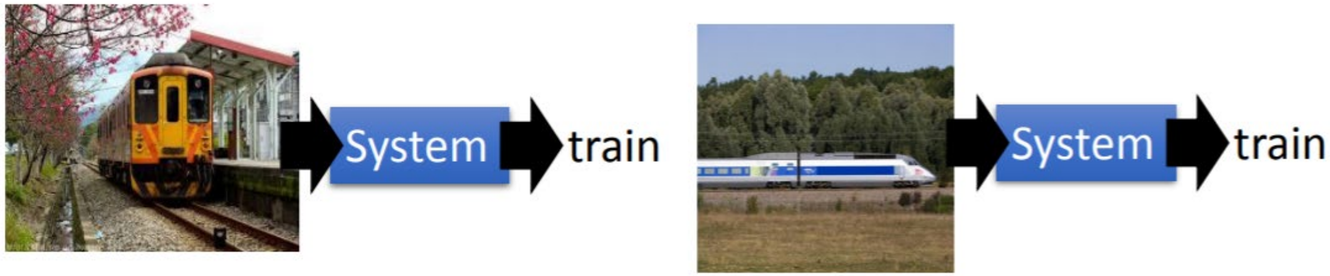


Reference: 李弘毅 ML Lecture 11 https://youtu.be/XsC9byQkUH8

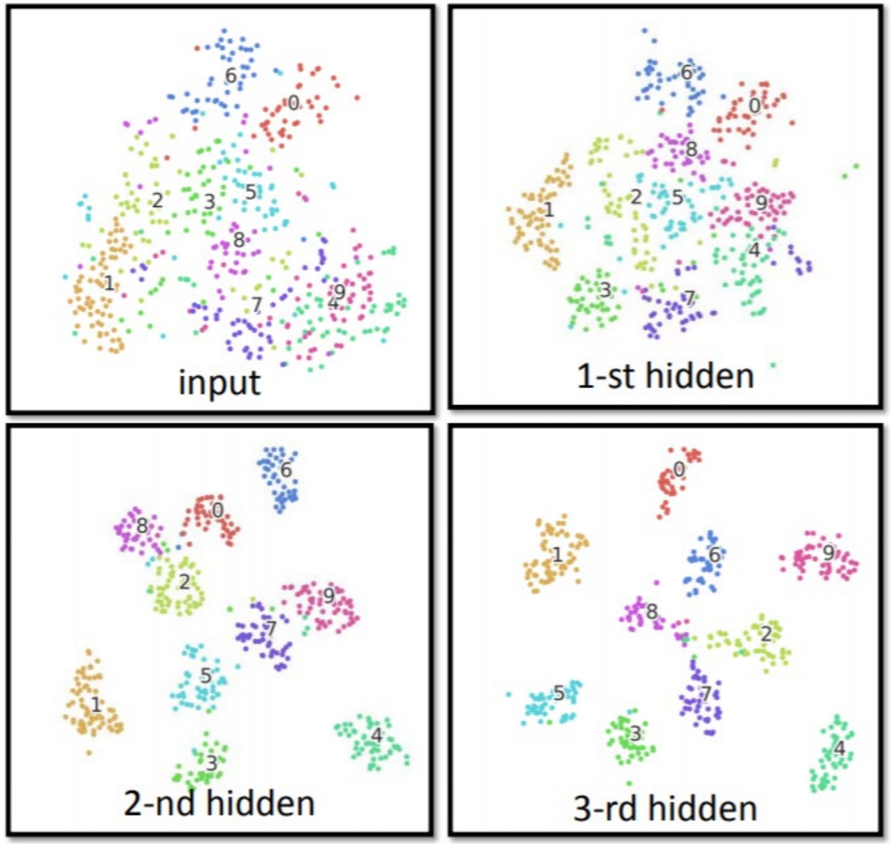
Reason 3 - Easier to handle complex task

- Very similar input, different output

- Very different input, similar output



MNIST



Reference: 李弘毅 ML Lecture 11 https://youtu.be/XsC9byQkUH8

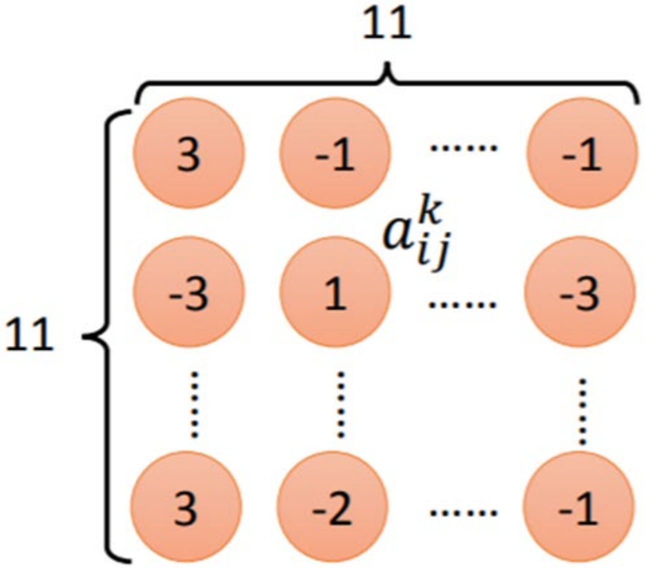
What does CNN learn?

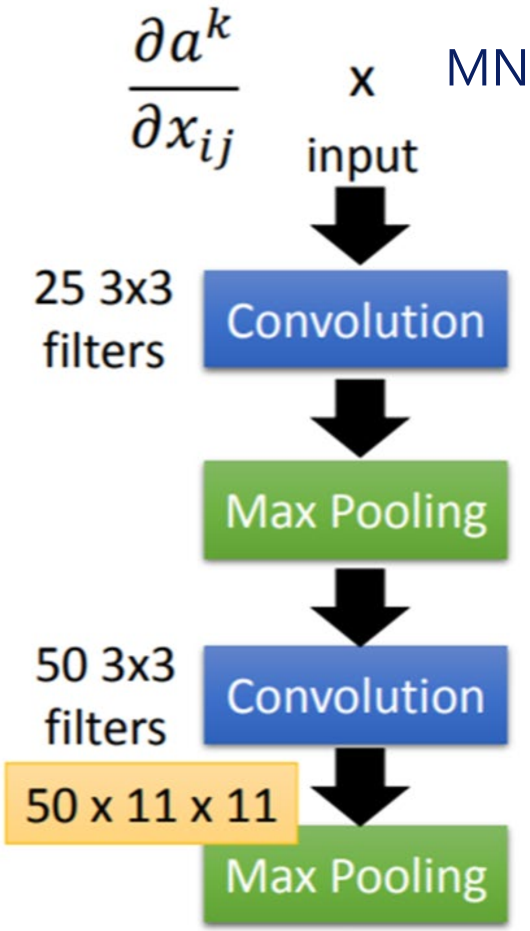
Find input images that make the k^{th} filter activate more

The output of the k-th filter is a 11 x 11 matrix.

Degree of the activation of the k-th filter: $a^k = \sum_{i=1}^{11}\sum_{j=1}^{11} a_{ij}^k$

$x^* = arg\max_x a^k$ (gradient ascent)





MNIST images

Reference: 李弘毅 ML Lecture 10 https://youtu.be/FrKWiRv254g

Input images that make the k^{th} filter activate more

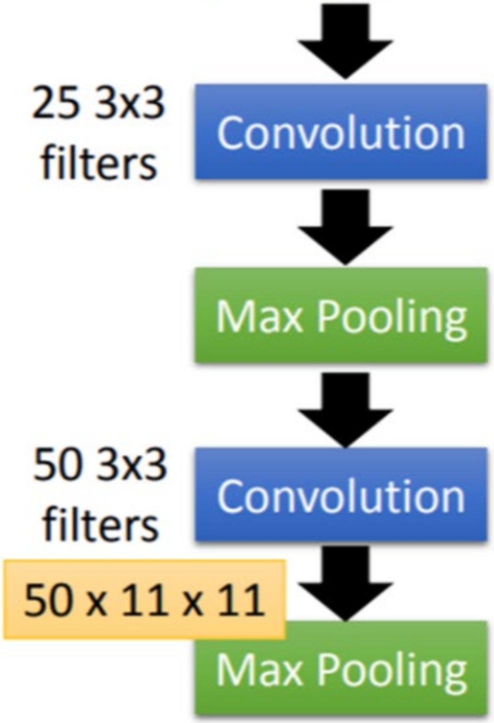
The output of the k-th filter is a 11 x 11 matrix.

Degree of the activation of the k-th filter: $a^k = \sum_{i=1}^{11} \sum_{j=1}^{11} a_{ij}^k$

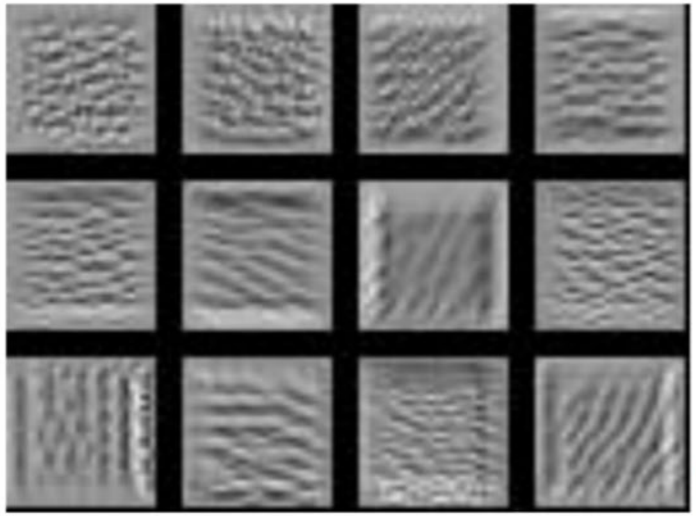
$x^* = arg \max_x a^k$ (gradient ascent)

$\frac{\partial a^k}{\partial x_{ij}}$

MNIST images



Input images that make the first 14 filters activate most



For each filter

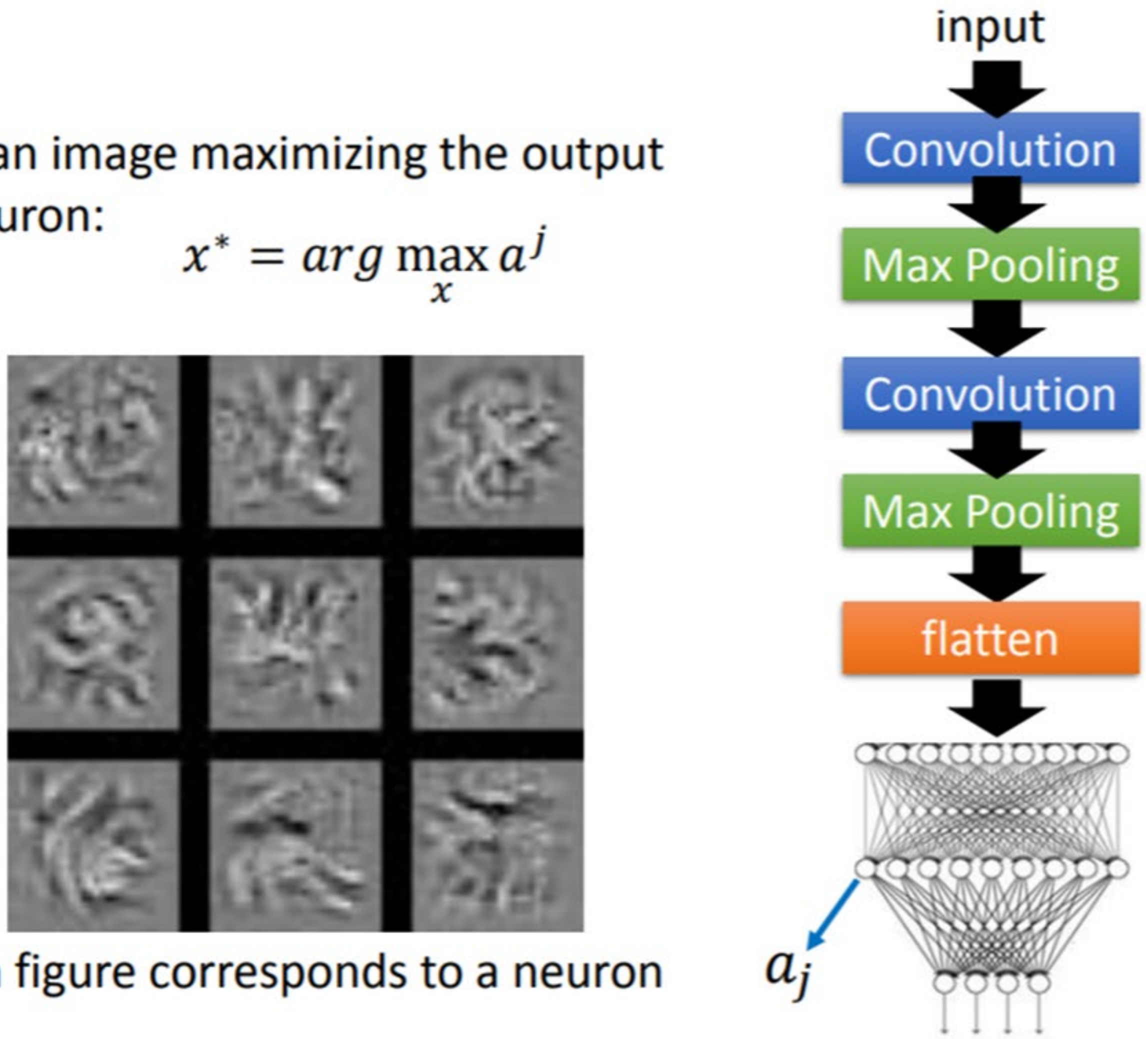
Reference: 李弘毅 ML Lecture 10 https://youtu.be/FrKWiRv254g

Input images that make the nodes in fully connected layer activate more

Input images that make the first 9 nodes in the fully connected layer activate the most

Find an image maximizing the output of neuron:

$$x^* = arg\max_x a^j$$

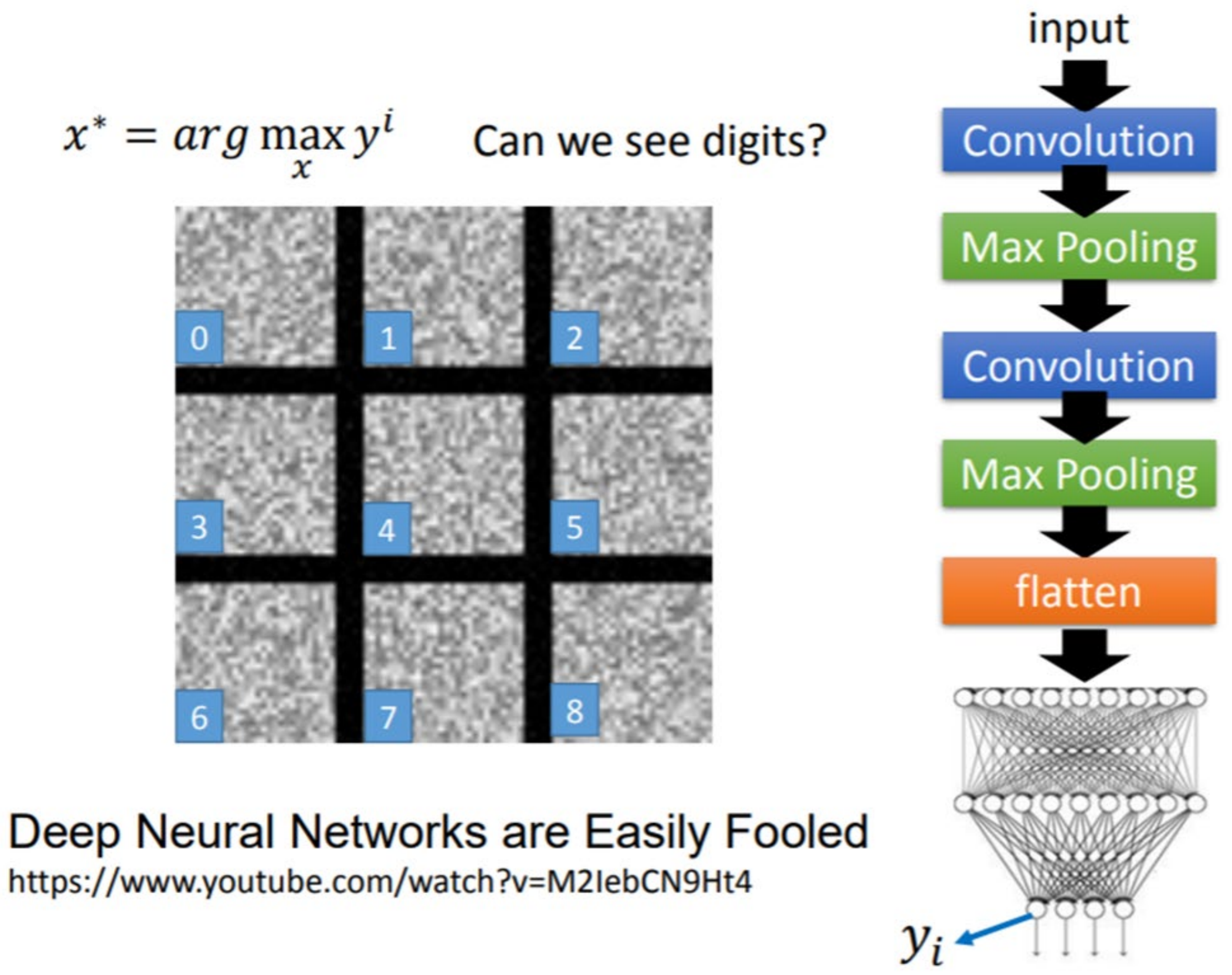


Each figure corresponds to a neuron

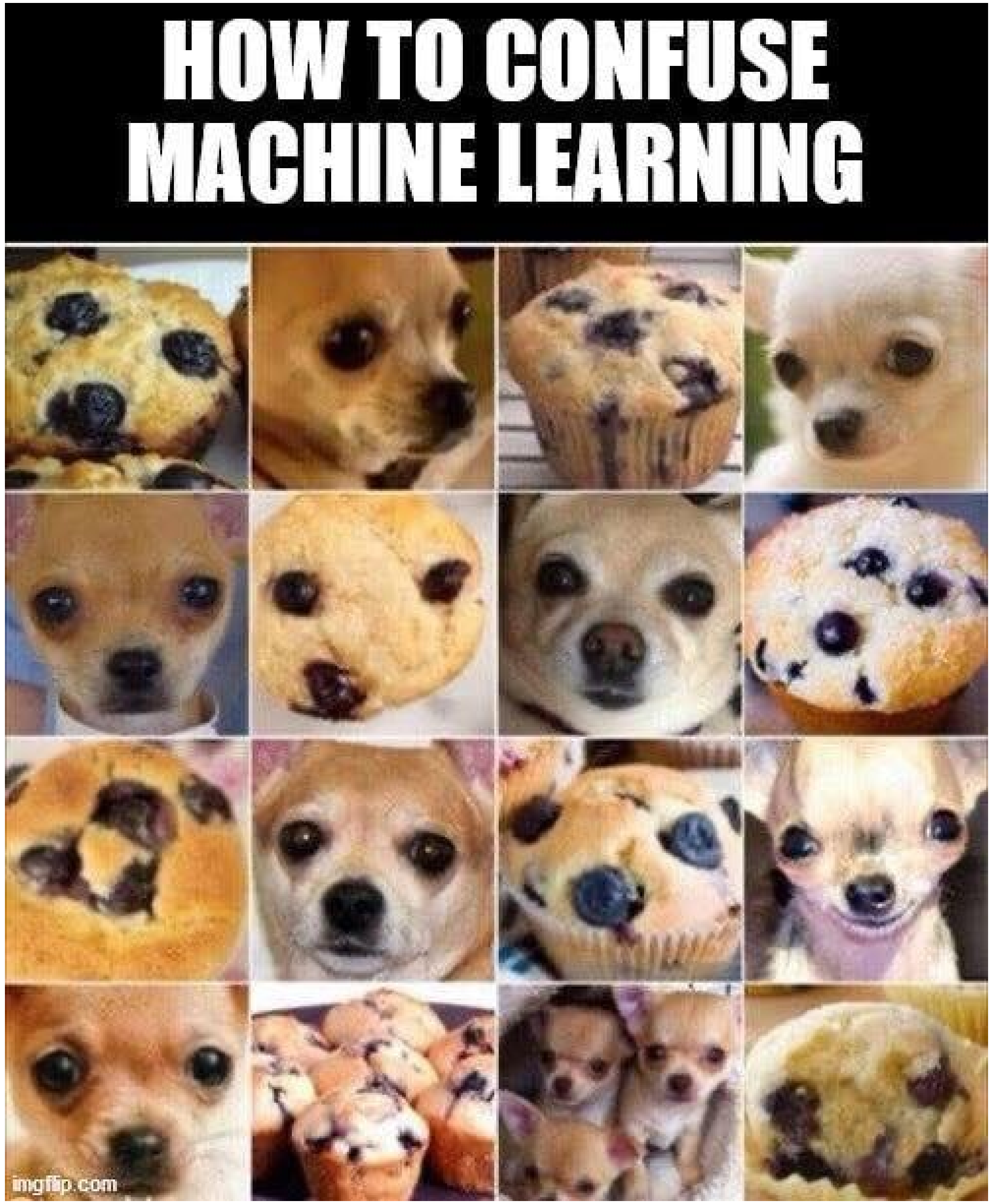
Reference: 李弘毅 ML Lecture 10 https://youtu.be/FrKWiRv254g

Input images that make the output nodes activate more

Input images that make the 9 output classes activate the most



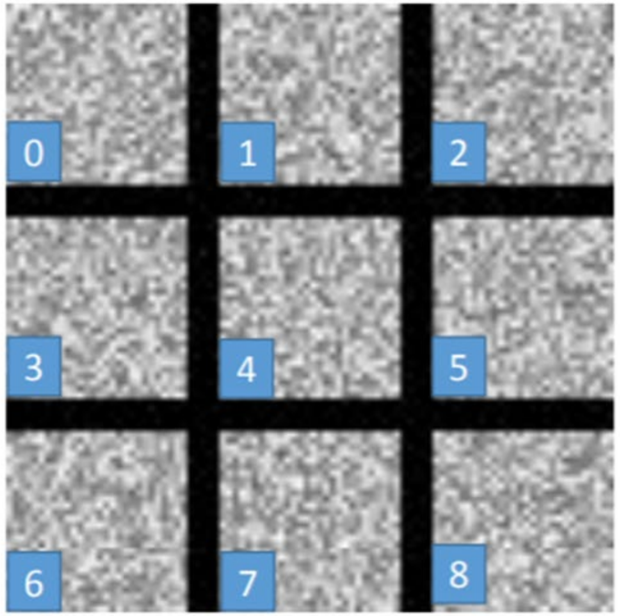
Reference: 李弘毅 ML Lecture 10 https://youtu.be/FrKWiRv254g



https://www.facebook.com/105366834575253/photos/a.106433371135266/217334733378462/

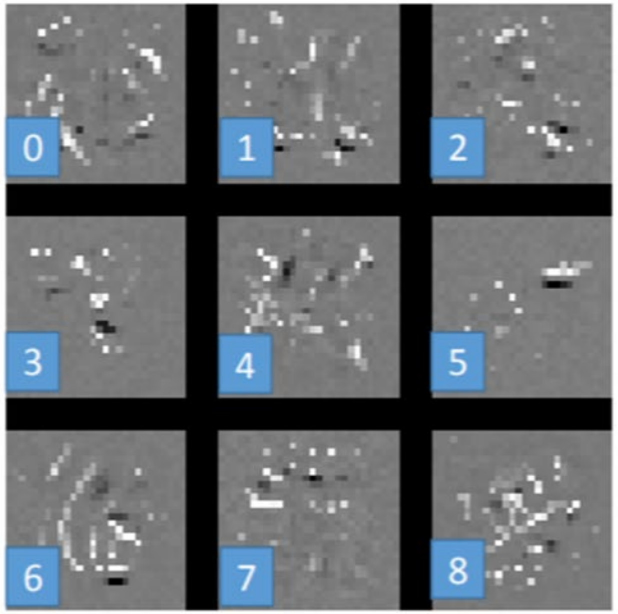
Input images that make the output nodes activate more

$$x^* = arg\max_x y^i$$



Over all pixel values

$$x^* = arg\max_x \left(y^i - \boxed{\sum_{i,j} |x_{ij}|} \right)$$

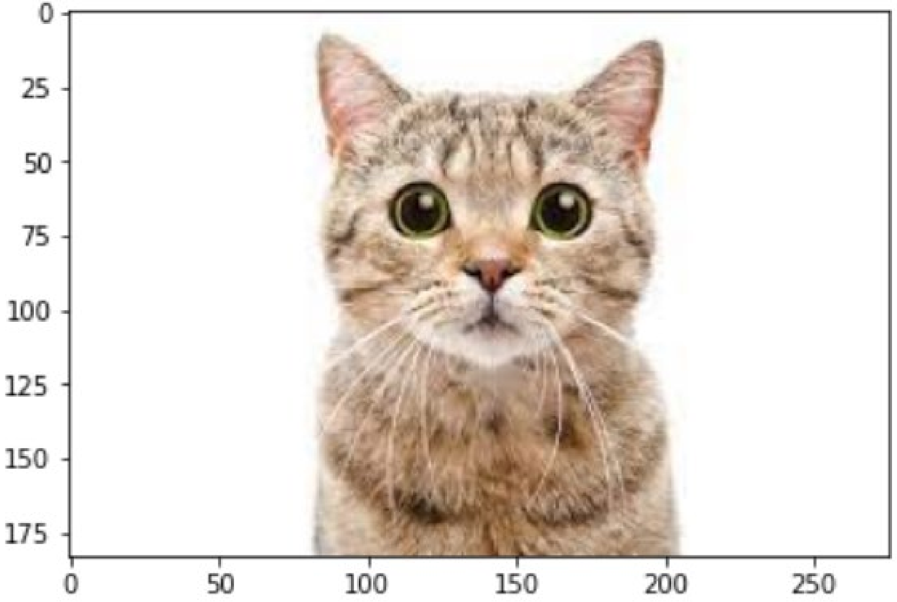


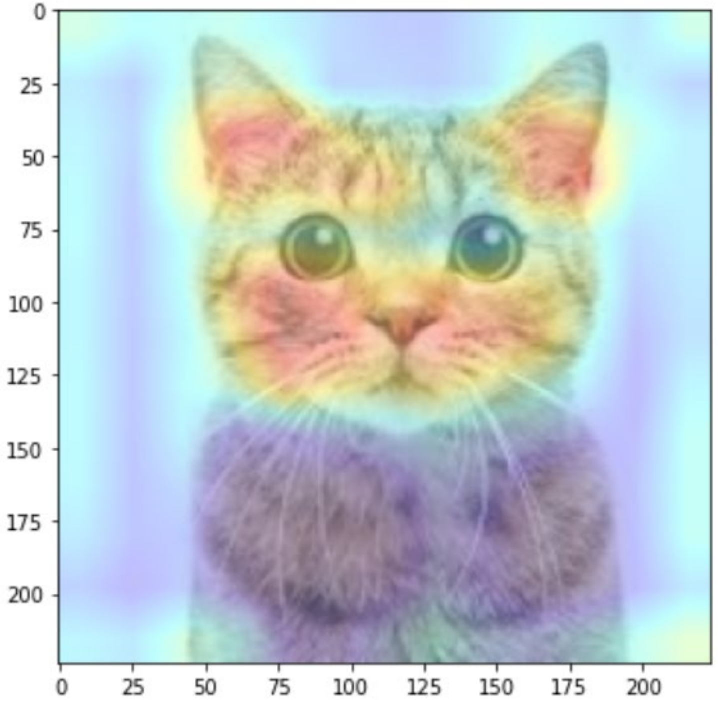
Force x_{ij}=0, i.e., force most pixels to NO INK (as only small part of the image has ink)

Reference: 李弘毅 ML Lecture 10 https://youtu.be/FrKWiRv254g

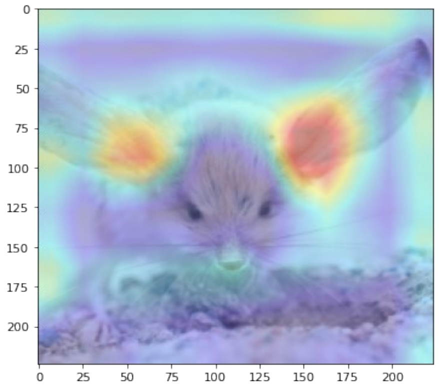
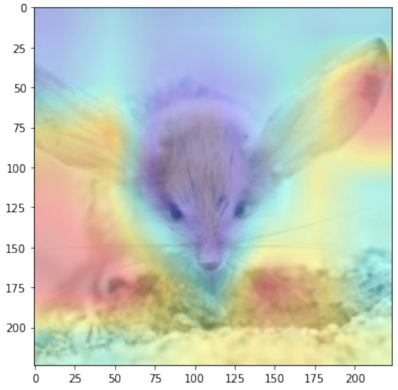
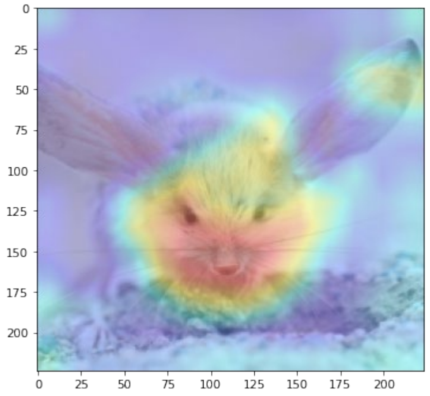
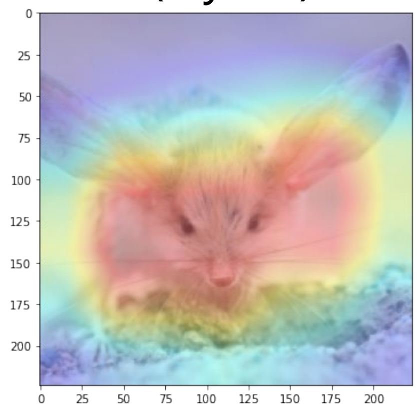
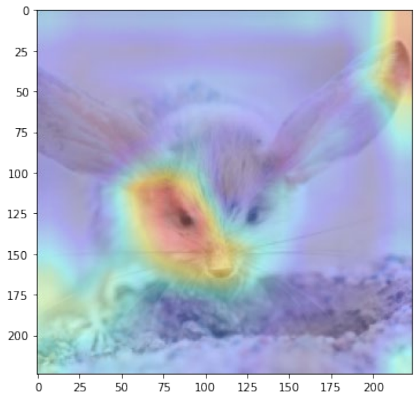
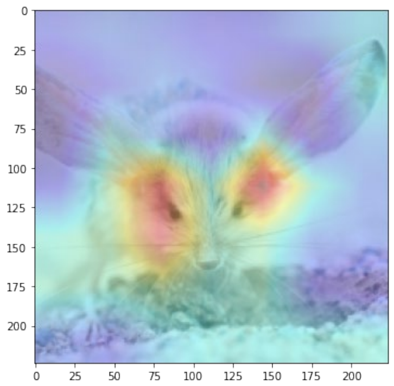
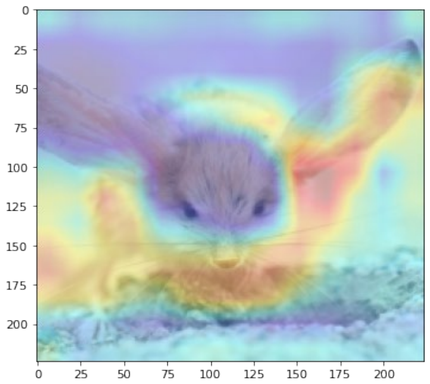
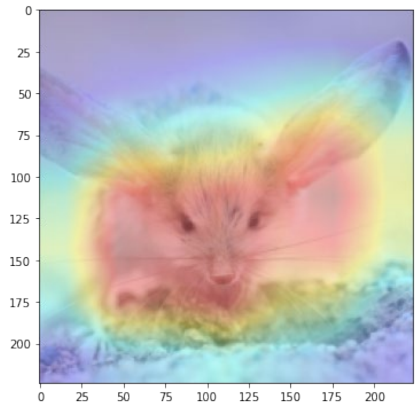
Practice – What does CNN learn?

- Run “6.5 GradCAM.ipynb"





Use GradCAM to visualize focused area

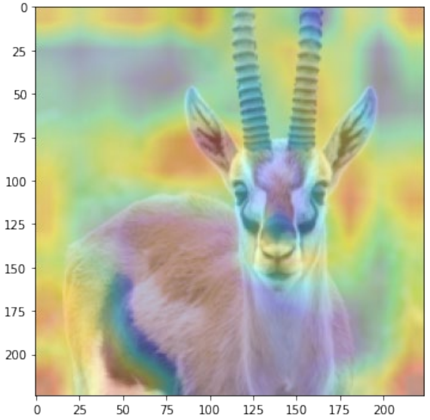
	AlexNet (features_11)	VGG16 (features_30)	VGG19 (features_35)	ResNet18 (layer4)
Class predicted by NN	 (墨西哥鈍口螈 29)	 (野兔 331)	 (333 倉鼠)	 (330棉尾兔)
Class manually assigned	 (野兔 331)	 (333 倉鼠)	 (野兔 331)	 (野兔 331)

Ref: 1061307林家禾 (2021)

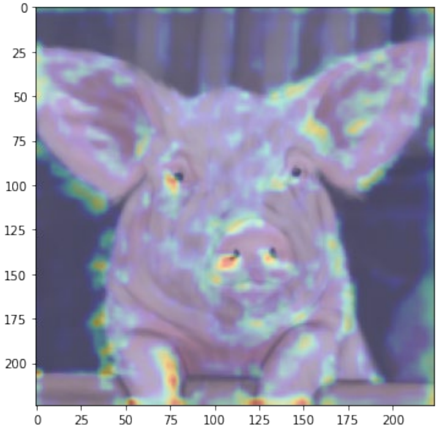
Use GradCAM to visualize focused area

AlexNet | VGG16 | ResNet101

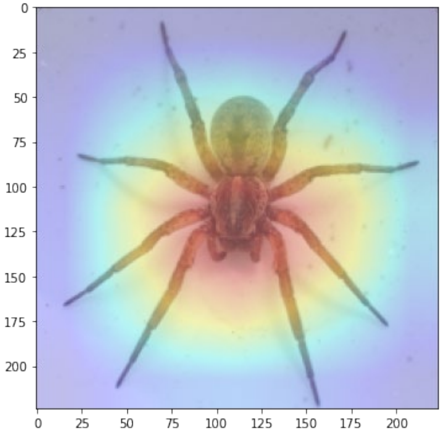
Class predicted by NN



353:gazelle(瞪羚)

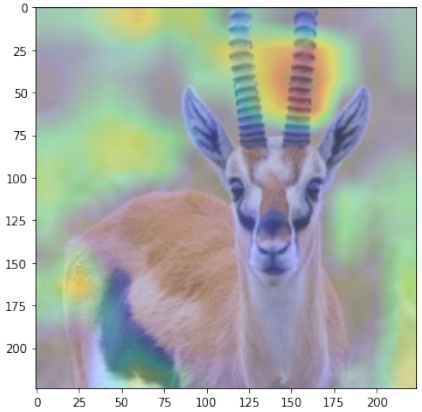


332: Rabbit

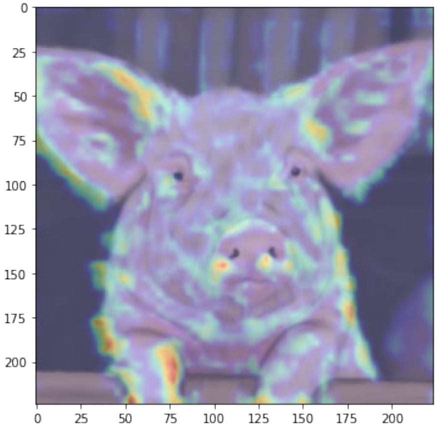


77: wolf spider

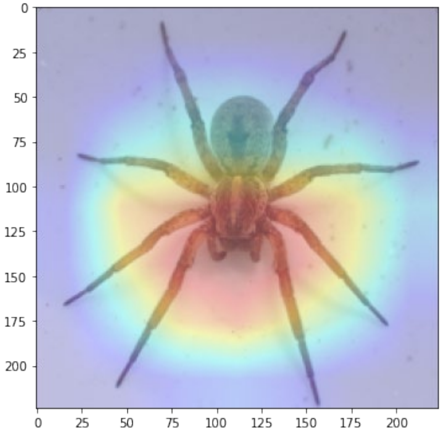
Class manually assigned

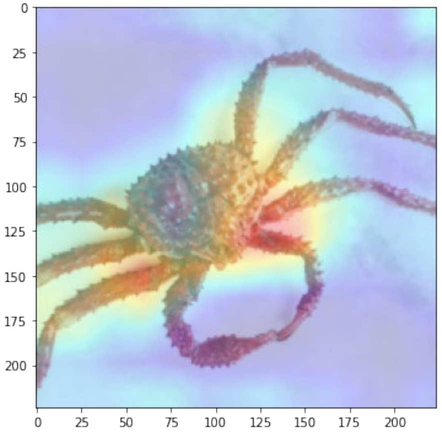


349：bighorn(大角羊)



豬338





121:帝王蟹

Ref: 1071346 吳挺維 (2021)