深度學習
-補充範例
-卷積神經網路在看什麼?

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Outline

- 補充說明

1. Iteration or Epoch
2. MNIST實例: Batch normalization and ReLU 對模型影響
3. MNIST實例: Residual Block對模型影響

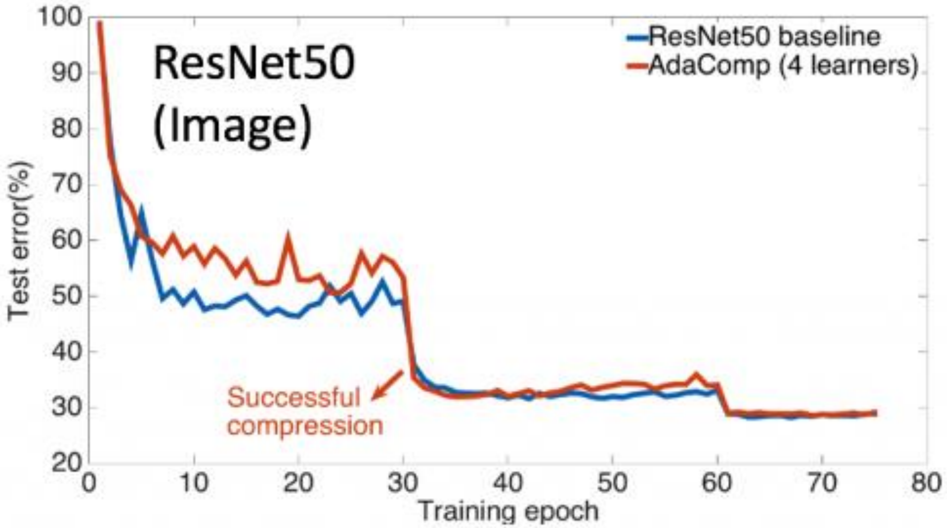
- CNN取什麼特徵?

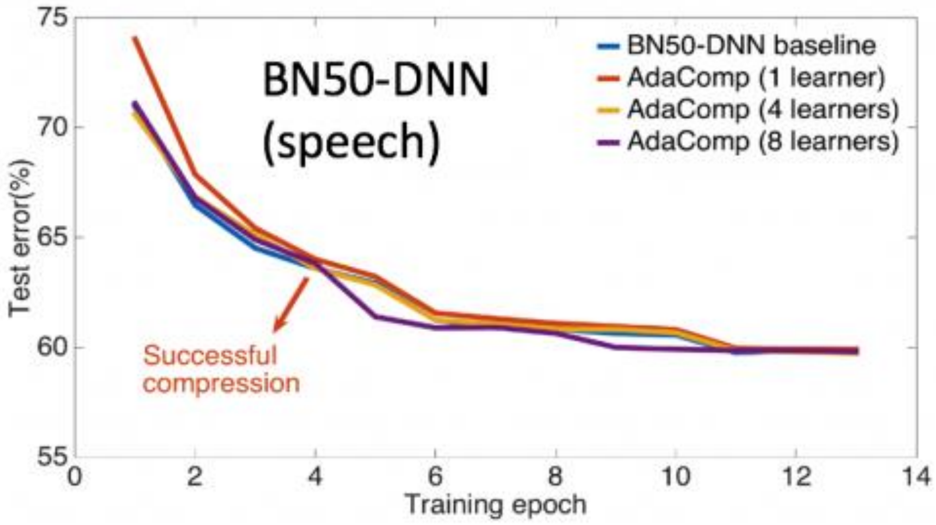
補充說明

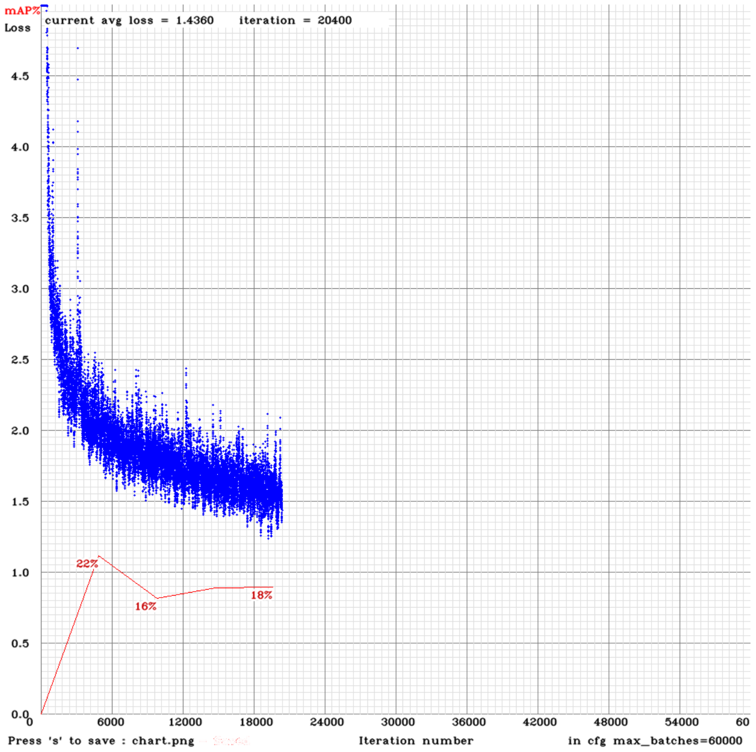
- 訓練模型名稱說明

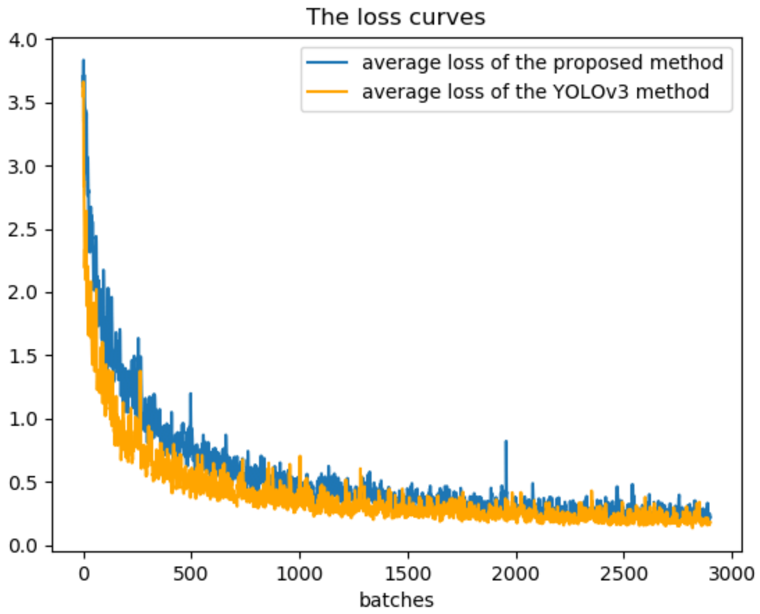
Learning iteration

Learning Epoch



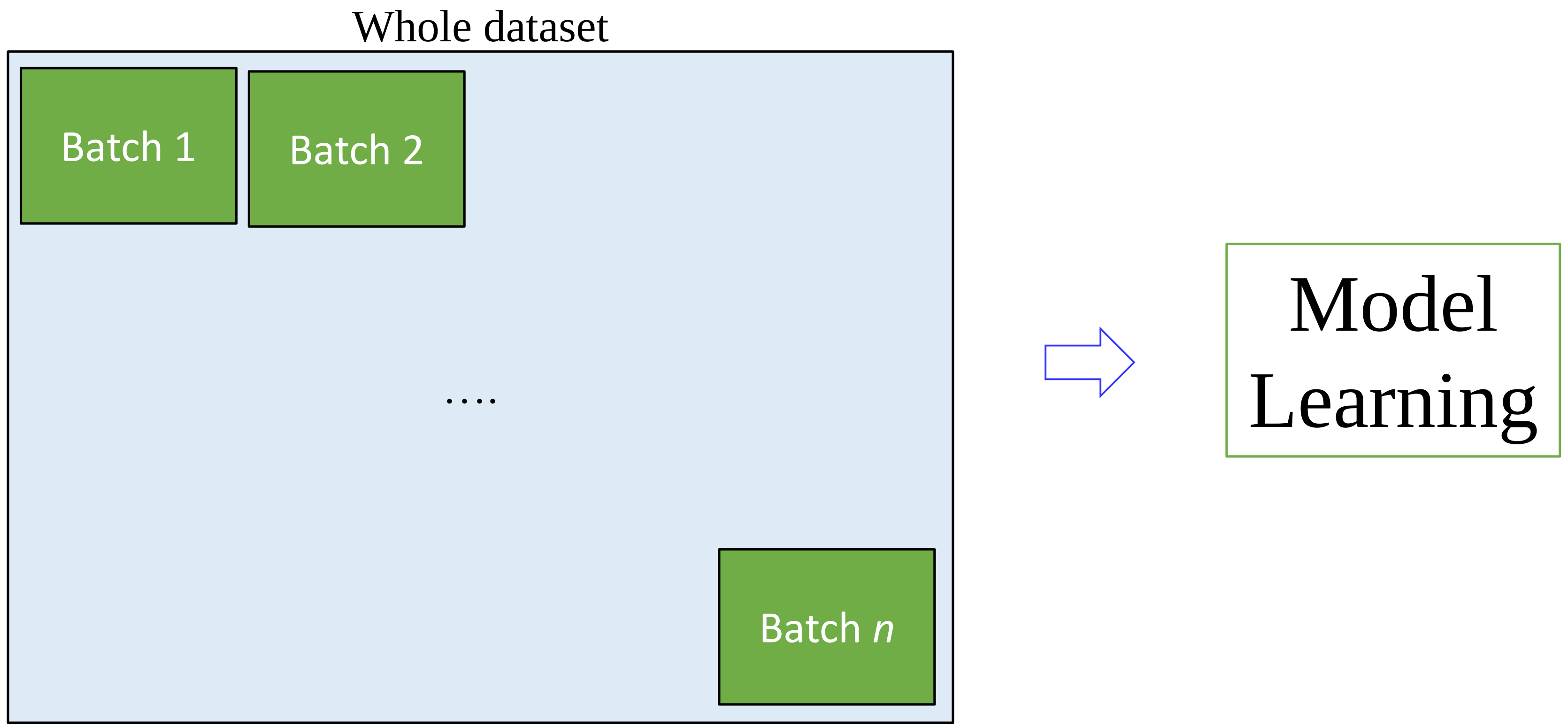






補充說明

- 學習深度學習模型，因為倒傳遞需要特徵圖、權重和Gradients(當前和上一次的)等，因此需要大量記憶體，因此不可能一次全部的資料都到記憶體，所以採用batch-learning。



一次batch進去做完訓練模型稱為一個iteration。

所有的資料(Whole dataset)都學過一次稱為一個epoch。

Batch normalization and ReLU 對模型影響

- 上週提到Sigmoid和BN，測試看看當模型深層採用Sigmoid和BN的影響

- MNIST: 建立一個10層Conv層和一個FC層的神經網路

CONV層

- 1. Conv. + Sigmoid
- 2. Conv. + ReLU
- 3. Conv. + Sigmoid + BN
- 4. Conv. + ReLU + BN

```
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = Conv(1, 32, 3, 1)
        self.conv2 = nn.Sequential(
            Conv(32, 32, 3, 1),
            Conv(32, 32, 3, 1),
            Conv(32, 32, 3, 1),
            Conv(32, 32, 3, 1),
            Conv(32, 32, 3, 1),
            Conv(32, 32, 3, 1),
            Conv(32, 32, 3, 1),
            Conv(32, 32, 3, 1),
            Conv(32, 32, 3, 1)
        )
        self.fc = nn.Linear(32, 10)
```

Batch normalization and ReLU 對模型影響

- 1. Conv. + Sigmoid
- 2. Conv. + ReLU

```
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = Conv(1, 32, 3, 1)
        self.conv2 = nn.Sequential(
            Conv(32, 32, 3, 1),
            Conv(32, 32, 3, 1),
            Conv(32, 32, 3, 1),
            Conv(32, 32, 3, 1),
            Conv(32, 32, 3, 1),
            Conv(32, 32, 3, 1),
            Conv(32, 32, 3, 1),
            Conv(32, 32, 3, 1),
            Conv(32, 32, 3, 1)
        )
        self.fc = nn.Linear(32, 10)
```

	Sigmoid	ReLU
Epoch	acc	acc
1	10.09	11.35
2	9.82	11.35
3	11.35	11.35
4	11.35	11.35
5	11.35	11.35
6	11.35	11.35
7	11.35	11.35
8	11.35	11.35
9	11.35	11.35
10	11.35	11.35
11	11.35	11.35
12	11.35	11.35
13	11.35	11.35
14	11.35	11.35
15	11.35	11.35

- 沒有BN，不論用Sigmoid或是ReLU都無法將模型訓練起來。

Batch normalization and ReLU 對模型影響

- 3. Conv. + Sigmoid + BN
- 4. Conv. + ReLU + BN

```
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = Conv(1, 32, 3, 1)
        self.conv2 = nn.Sequential(
            Conv(32, 32, 3, 1),
            Conv(32, 32, 3, 1),
            Conv(32, 32, 3, 1),
            Conv(32, 32, 3, 1),
            Conv(32, 32, 3, 1),
            Conv(32, 32, 3, 1),
            Conv(32, 32, 3, 1),
            Conv(32, 32, 3, 1),
            Conv(32, 32, 3, 1)
        )
        self.fc = nn.Linear(32, 10)
```

	BN+Sigmoid	BN+ReLU
Epoch	acc	acc
1	9.48	69.62
2	9.8	93.4
3	10.1	90.89
4	22.84	98.08
5	41.51	99.15
6	69.51	98.91
7	41.2	99.16
8	46.54	99.2
9	66.63	99.28
10	51.88	99.29
11	86.88	99.27
12	77.89	99.31
13	86.72	99.3
14	90.74	99.3
15	89.56	99.27

- 有BN
- ReLu比Sigmoid好。

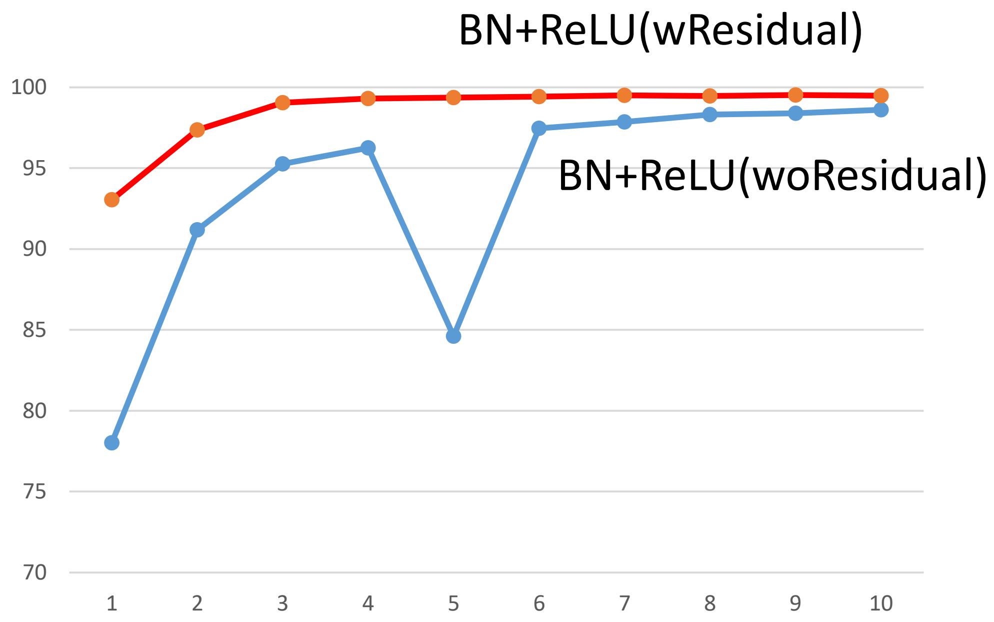
Residual Block對模型影響

- 建立一個４２層的卷積神經網路，每一個Residual block有兩個Conv.。
- 用MNIST資料庫測試。

```
class ResidualBlock(nn.Module):
    def __init__(self, in_channels,
out_channels, kernel_size=3, stride=1,
groups=1):
        padding = (kernel_size - 1) // 2
        super().__init__()
        self.conv1 = nn.Conv2d(in_channels,
out_channels, kernel_size, stride, padding,
groups=groups, bias=False)
        self.conv2 = nn.Conv2d(out_channels,
out_channels, kernel_size, stride, padding,
groups=groups, bias=False)
        self.bn1 = nn.BatchNorm2d(out_channels)
        self.bn2 = nn.BatchNorm2d(out_channels)
        self.relu = nn.ReLU()

    def forward(self, x):
        residual = x
        x = self.conv1(x)
        x = self.bn1(x)
        x = self.relu(x)

        x = self.conv2(x)
        x = self.bn2(x)

        x += residual
        x = self.relu(x)
        return x
```

```
self.conv1 = Conv(1, 32, 3, 1)
self.conv2 = nn.Sequential(
    ResidualBlock(32, 32, 3, 1), #1
    ResidualBlock(32, 32, 3, 1), #2
    ResidualBlock(32, 32, 3, 1), #3
    ResidualBlock(32, 32, 3, 1), #4
    ResidualBlock(32, 32, 3, 1), #5
    ResidualBlock(32, 32, 3, 1), #6
    ResidualBlock(32, 32, 3, 1), #7
    ResidualBlock(32, 32, 3, 1), #8
    ResidualBlock(32, 32, 3, 1), #9
    ResidualBlock(32, 32, 3, 1), #10
    ResidualBlock(32, 32, 3, 1), #11
    ResidualBlock(32, 32, 3, 1), #12
    ResidualBlock(32, 32, 3, 1), #13
    ResidualBlock(32, 32, 3, 1), #14
    ResidualBlock(32, 32, 3, 1), #15
    ResidualBlock(32, 32, 3, 1), #16
    ResidualBlock(32, 32, 3, 1), #17
    ResidualBlock(32, 32, 3, 1), #18
    ResidualBlock(32, 32, 3, 1), #19
    ResidualBlock(32, 32, 3, 1), #20
    ResidualBlock(32, 32, 3, 1),  # 21
    ResidualBlock(32, 32, 3, 1),  # 22
    ResidualBlock(32, 32, 3, 1),  # 23
    ResidualBlock(32, 32, 3, 1),  # 24
    ResidualBlock(32, 32, 3, 1),  # 25
    ResidualBlock(32, 32, 3, 1),  # 26
    ResidualBlock(32, 32, 3, 1),  # 27
    ResidualBlock(32, 32, 3, 1),  # 28
    ResidualBlock(32, 32, 3, 1),  # 29
    ResidualBlock(32, 32, 3, 1),  # 30
    ResidualBlock(32, 32, 3, 1),  # 31
    ResidualBlock(32, 32, 3, 1),  # 32
    ResidualBlock(32, 32, 3, 1),  # 33
    ResidualBlock(32, 32, 3, 1),  # 34
    ResidualBlock(32, 32, 3, 1),  # 35
    ResidualBlock(32, 32, 3, 1),  # 36
    ResidualBlock(32, 32, 3, 1),  # 37
    ResidualBlock(32, 32, 3, 1),  # 38
    ResidualBlock(32, 32, 3, 1),  # 39
    ResidualBlock(32, 32, 3, 1),  # 40
)
self.fc = nn.Linear(32, 10)
```

Residual Block對模型影響




```
self.conv1 = Conv(1, 32, 3, 1)
self.conv2 = nn.Sequential(
    ResidualBlock(32, 32, 3, 1), #1
    ResidualBlock(32, 32, 3, 1), #2
    ResidualBlock(32, 32, 3, 1), #3
    ResidualBlock(32, 32, 3, 1), #4
    ResidualBlock(32, 32, 3, 1), #5
    ResidualBlock(32, 32, 3, 1), #6
    ResidualBlock(32, 32, 3, 1), #7
    ResidualBlock(32, 32, 3, 1), #8
    ResidualBlock(32, 32, 3, 1), #9
    ResidualBlock(32, 32, 3, 1), #10
    ResidualBlock(32, 32, 3, 1), #11
    ResidualBlock(32, 32, 3, 1), #12
    ResidualBlock(32, 32, 3, 1), #13
    ResidualBlock(32, 32, 3, 1), #14
    ResidualBlock(32, 32, 3, 1), #15
    ResidualBlock(32, 32, 3, 1), #16
    ResidualBlock(32, 32, 3, 1), #17
    ResidualBlock(32, 32, 3, 1), #18
    ResidualBlock(32, 32, 3, 1), #19
    ResidualBlock(32, 32, 3, 1), #20
    ResidualBlock(32, 32, 3, 1),  # 21
    ResidualBlock(32, 32, 3, 1),  # 22
    ResidualBlock(32, 32, 3, 1),  # 23
    ResidualBlock(32, 32, 3, 1),  # 24
    ResidualBlock(32, 32, 3, 1),  # 25
    ResidualBlock(32, 32, 3, 1),  # 26
    ResidualBlock(32, 32, 3, 1),  # 27
    ResidualBlock(32, 32, 3, 1),  # 28
    ResidualBlock(32, 32, 3, 1),  # 29
    ResidualBlock(32, 32, 3, 1),  # 30
    ResidualBlock(32, 32, 3, 1),  # 31
    ResidualBlock(32, 32, 3, 1),  # 32
    ResidualBlock(32, 32, 3, 1),  # 33
    ResidualBlock(32, 32, 3, 1),  # 34
    ResidualBlock(32, 32, 3, 1),  # 35
    ResidualBlock(32, 32, 3, 1),  # 36
    ResidualBlock(32, 32, 3, 1),  # 37
    ResidualBlock(32, 32, 3, 1),  # 38
    ResidualBlock(32, 32, 3, 1),  # 39
    ResidualBlock(32, 32, 3, 1),  # 40
)
self.fc = nn.Linear(32, 10)
```

Outline

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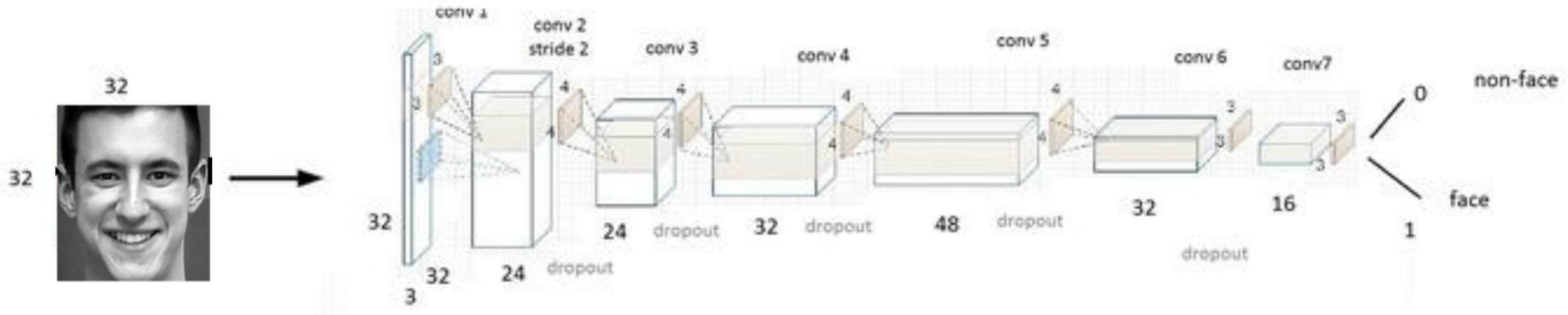
1. Iteration or Epoch
2. MNIST實例: Batch normalization and ReLU 對模型影響
3. MNIST實例: Residual Block對模型影響

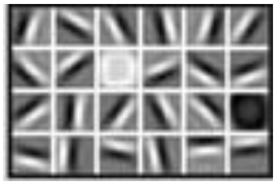
- CNN取什麼特徵?

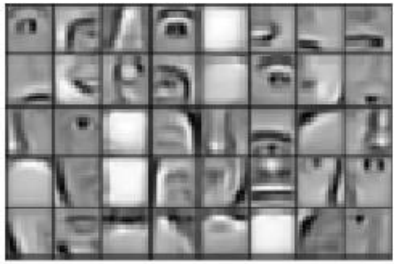
以CNN(Convolutional Neural Network)做人臉影像識別



Source: Face detection based on deep convolutional neural networks exploiting incremental facial part learning (Dec 2016)

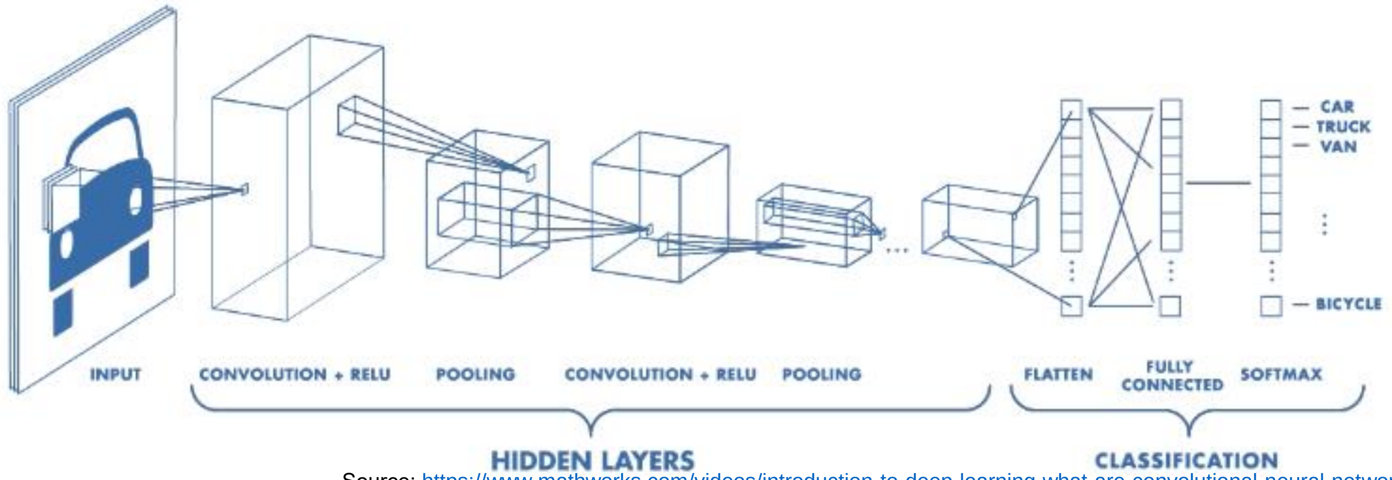
Low-Level Feature → Middle-Level Feature → High-Level Feature → Trainable Classifier



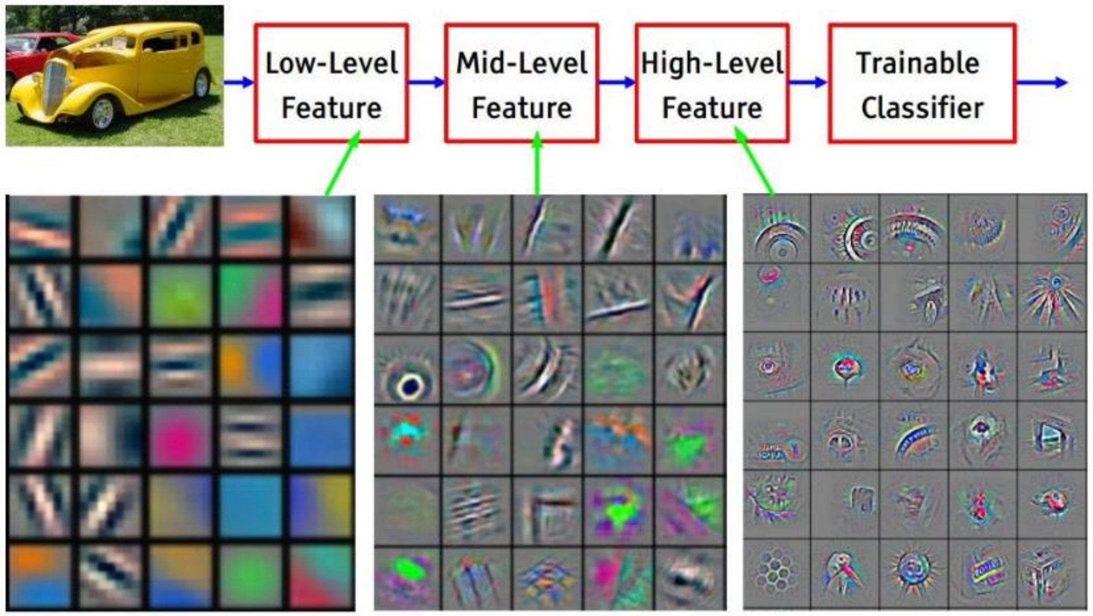


Source: Feature Visualization of Convnet trained on ImageNet from [Zeiler & Fergus 2013]

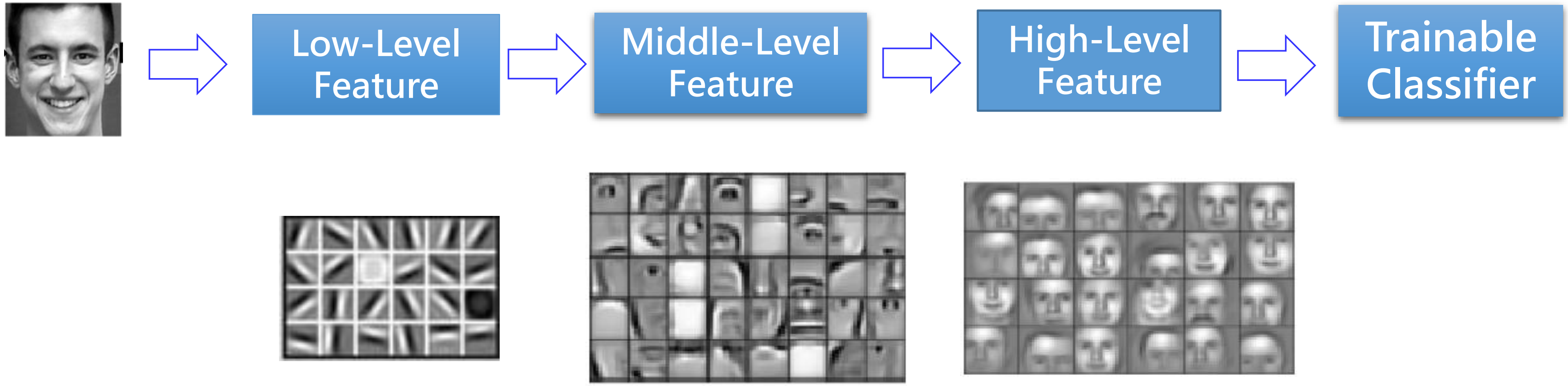
CNN (Convolutional Neural Network) Vehicle Classification

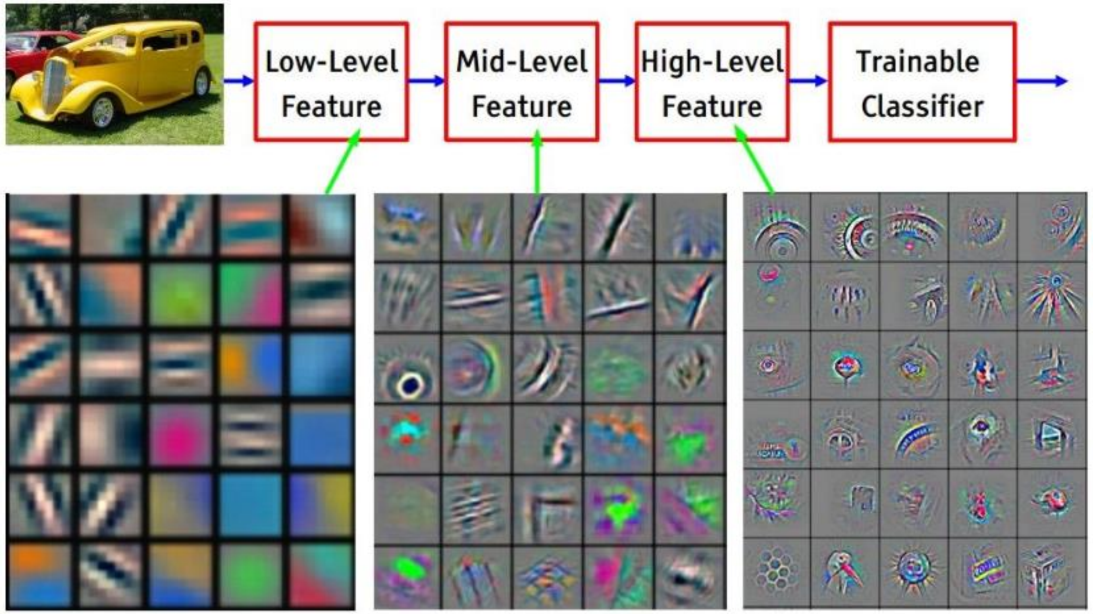


Source: https://www.mathworks.com/videos/introduction-to-deep-learning-what-are-convolutional-neural-networks--1489512765771.html



CNN取什麼特徵?


Low-Level Feature
Middle-Level Feature
High-Level Feature
Trainable Classifier


Low-Level Feature
Mid-Level Feature
High-Level Feature
Trainable Classifier

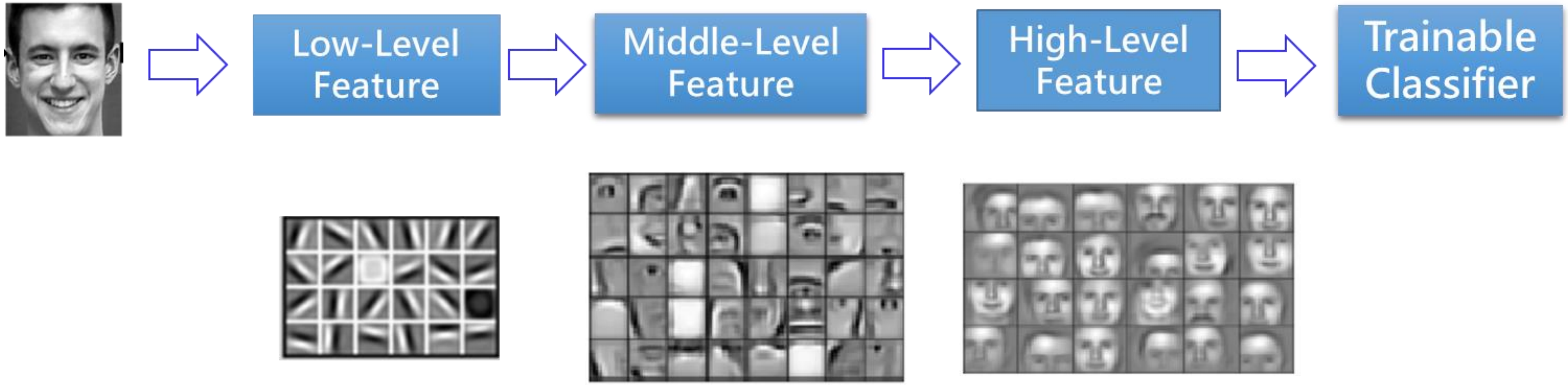
CNN取什麼特徵?

MNIST 手寫數字資料庫

訓練一個五層的CNN

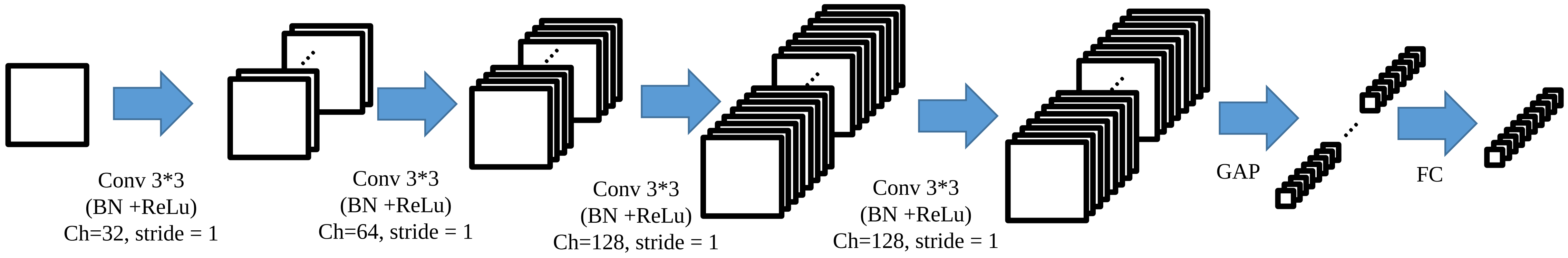
我們觀察一下這個模型的特徵圖。

```
self.conv1 =ConvBNReLU(1, 32, 3, 1)
self.conv2 =ConvBNReLU(32, 64, 3, 1)
self.conv3 =ConvBNReLU(64, 128, 3, 1)
self.conv4 =ConvBNReLU(128, 128, 3, 1)
self.fc = nn.Linear(128, 10)
```

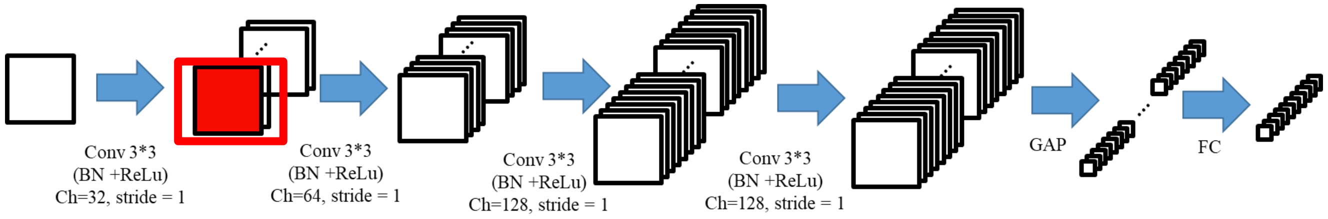


CNN取什麼特徵?

```
self.conv1 =ConvBNReLU(1, 32, 3, 1)
self.conv2 =ConvBNReLU(32, 64, 3, 1)
self.conv3 =ConvBNReLU(64, 128, 3, 1)
self.conv4 =ConvBNReLU(128, 128, 3, 1)
self.fc = nn.Linear(128, 10)
```

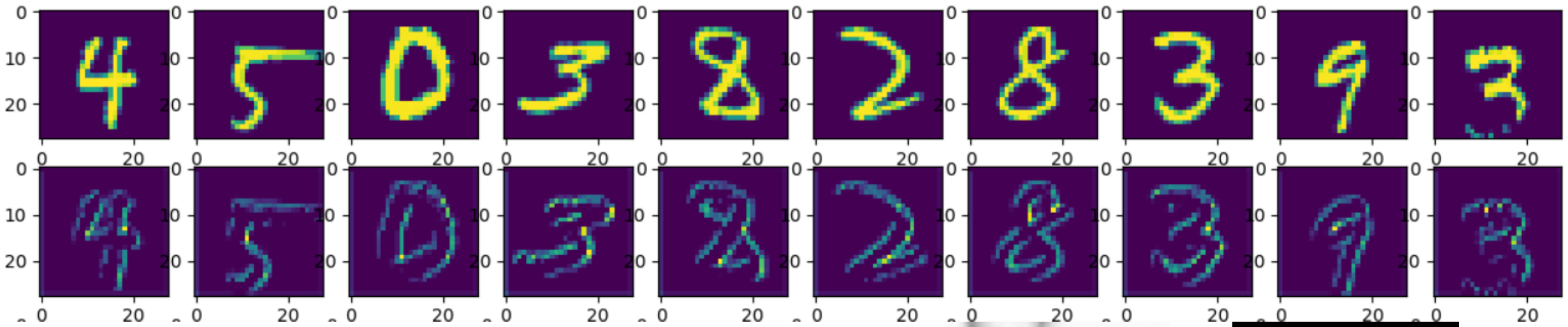


CNN取什麼特徵?

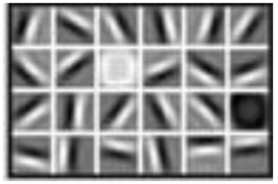


輸入圖

徵圖都只取第一張
第一層卷積
輸出特徵圖



Low-Level Feature



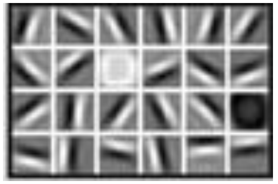
Low-level Feature只取邊的特徵
就如同Canny Edge Detection

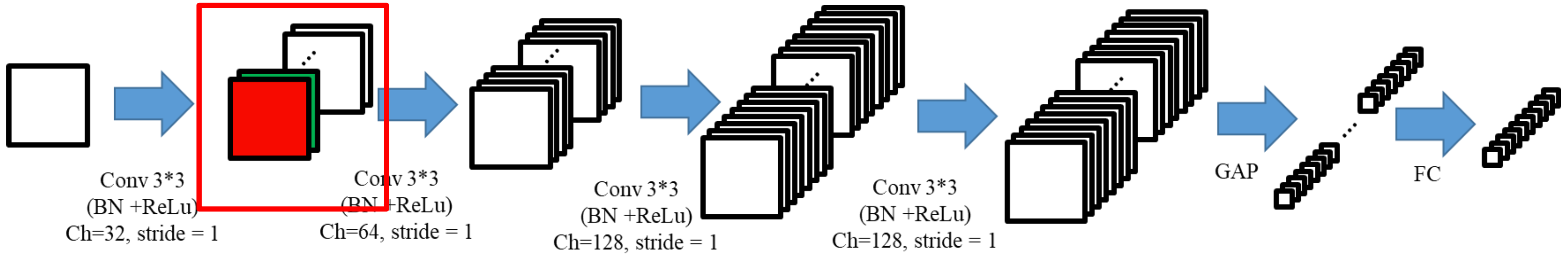
一兩層簡單的卷積就只保留圖像的邊

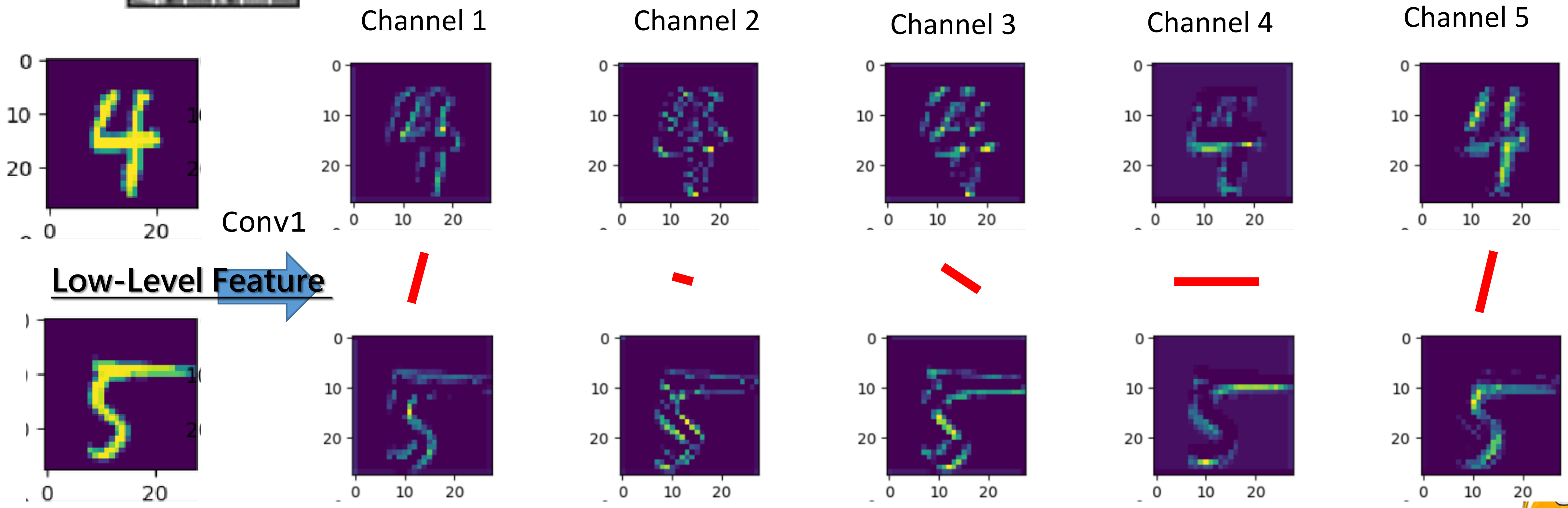
在卷積神經網路的Low-level Feature
則是讓 "邊的部分被強化"，所以可
以發現上圖的邊顏色變強了。

第一層卷積輸出特徵圖，取不同channel特徵圖

Low-Level Feature

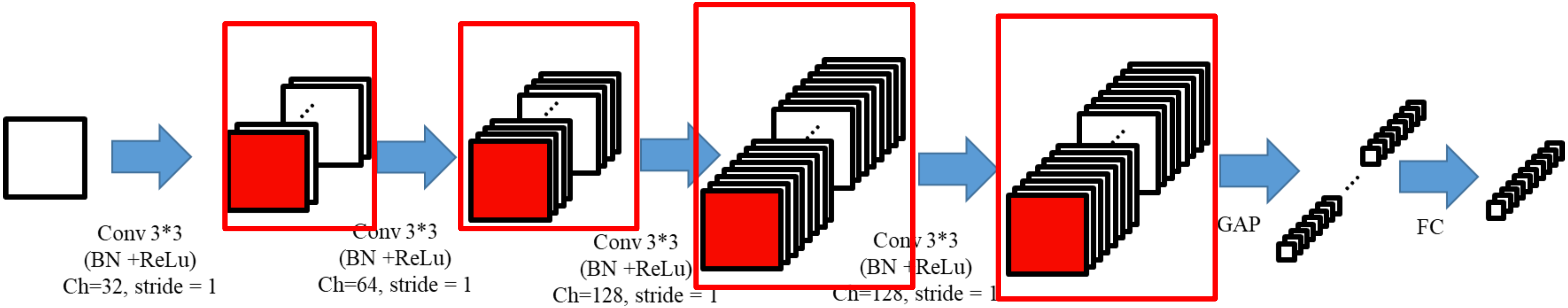






CNN取什麼特徵?

- 每一層卷積輸出特徵圖，取不同channel特徵圖



每一層卷積輸出特徵圖
取不同channel特徵圖

範例:數字4

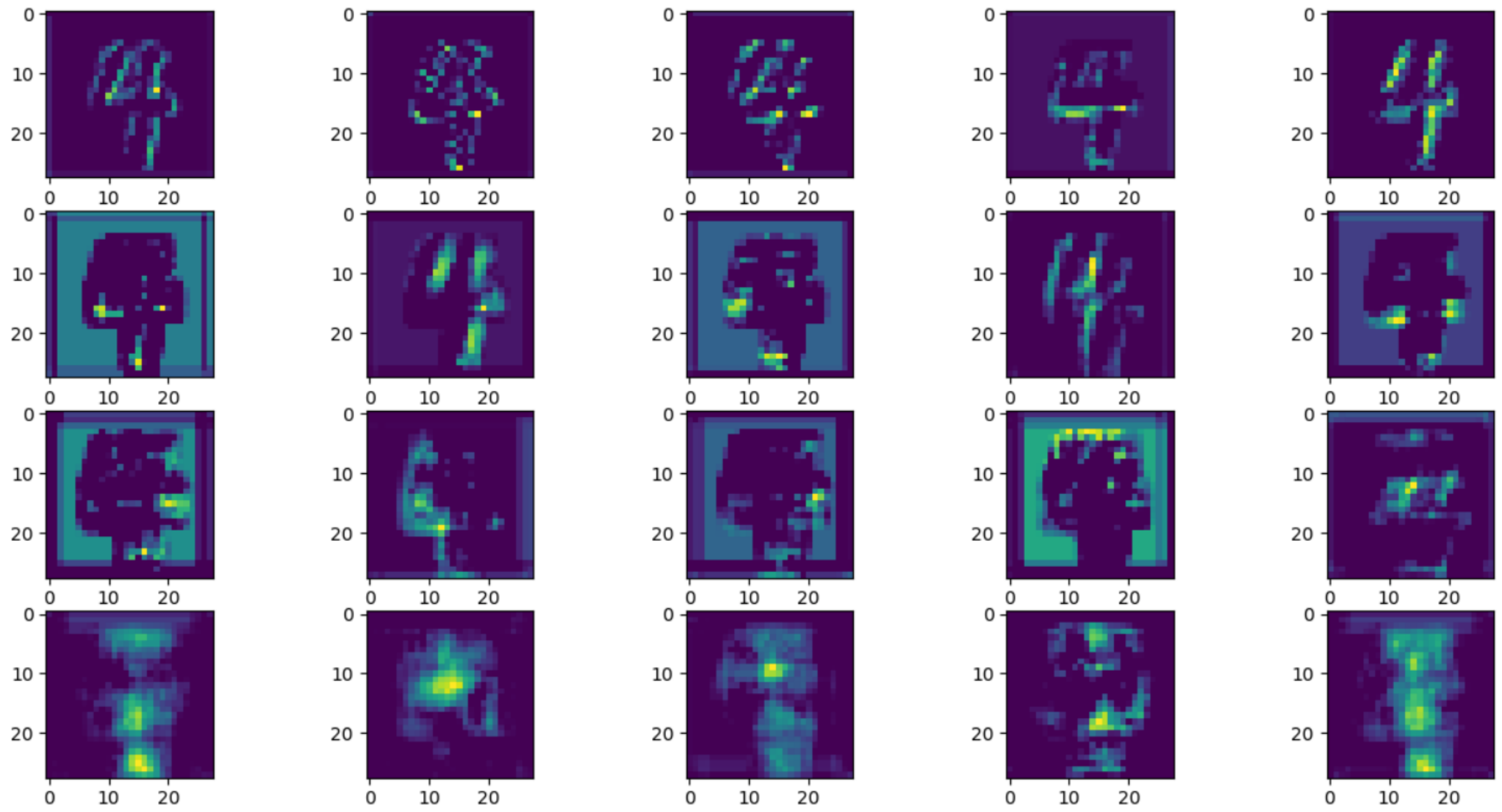
Channel 1 | Channel 2 | Channel 3 | Channel 4 | Channel 5

Conv1輸出

Conv2輸出

Conv3輸出

Conv4輸出



Low-Level Feature

Middle-Level Feature

High-Level Feature

每一層卷積輸出特徵圖
取不同channel特徵圖

範例:數字5

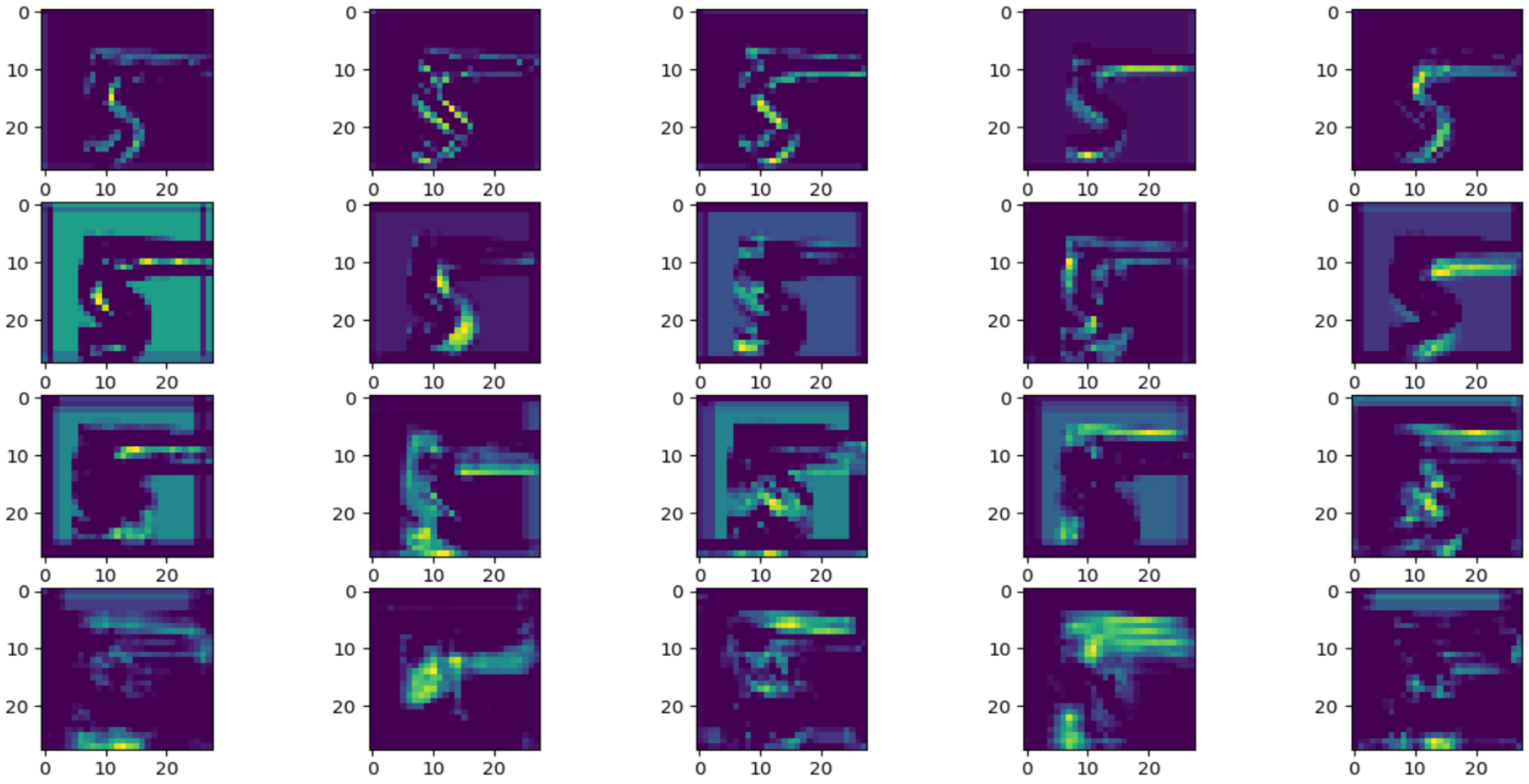
Channel 1 Channel 2 Channel 3 Channel 4 Channel 5

Conv1輸出

Conv2輸出

Conv3輸出

Conv4輸出



Low-Level Feature

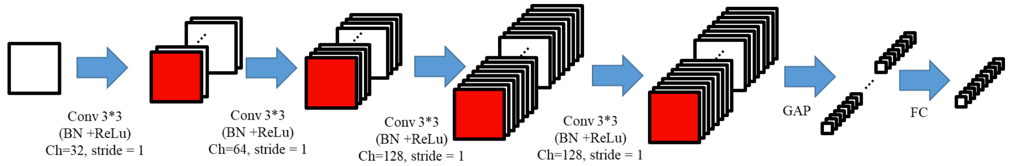
↓

Middle-Level Feature

↓

High-Level Feature

CNN不同層取什麼特徵?



範例: 不同數字在不同層的第一個特徵圖。

輸入圖

特徵圖都只取第一張

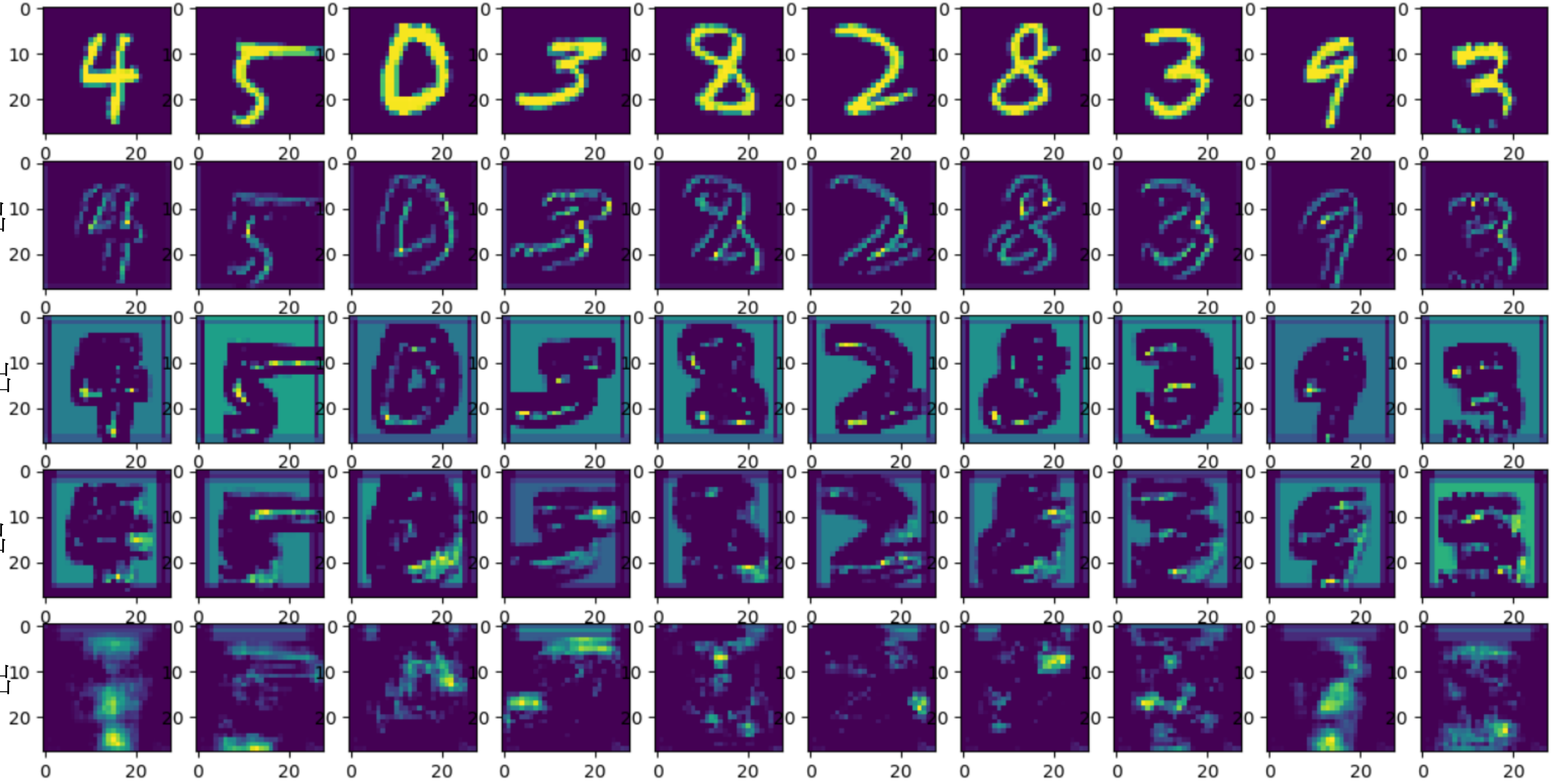
Low-Level Feature → Middle-Level Feature → High-Level Feature

Conv1輸出

Conv2輸出

Conv3輸出

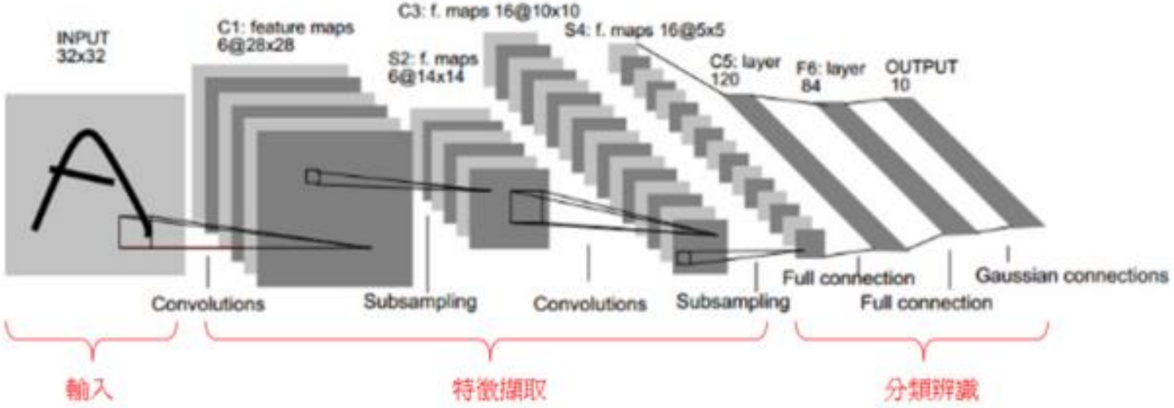
Conv4輸出

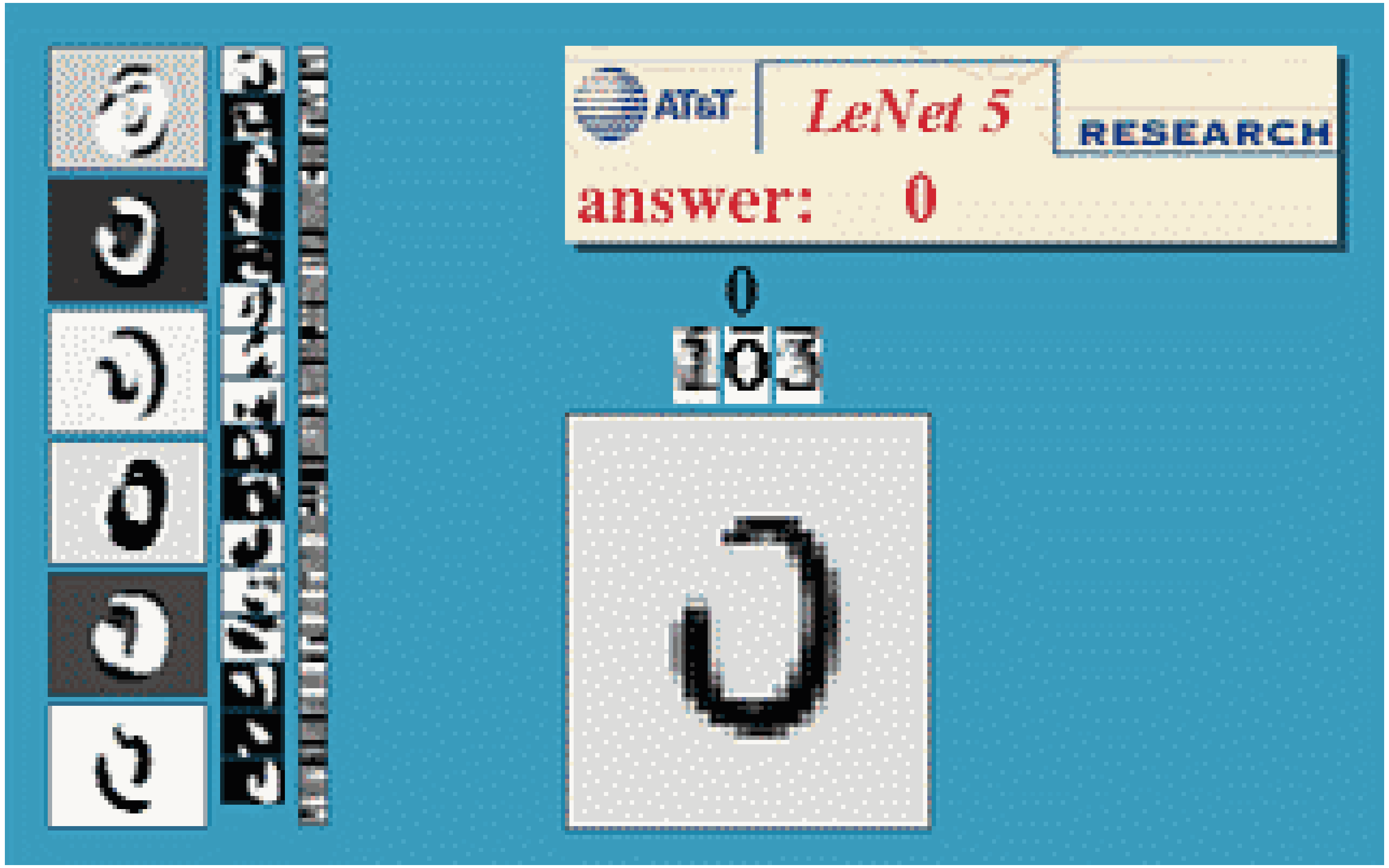


Conv4的第一個特徵圖，看的是垂直線的特徵，所以只有4和9會有反應。

CNN不同層取什麼特徵?

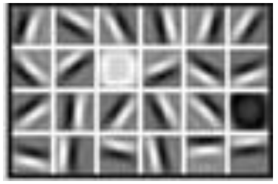
- LeNet5 from Yann LeCun

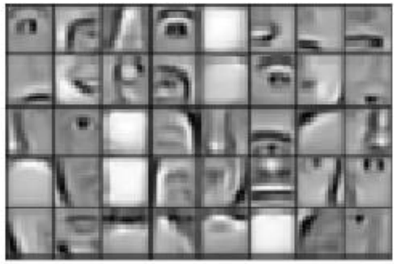




CNN取什麼特徵?

→ Low-Level Feature → Middle-Level Feature → High-Level Feature → Trainable Classifier



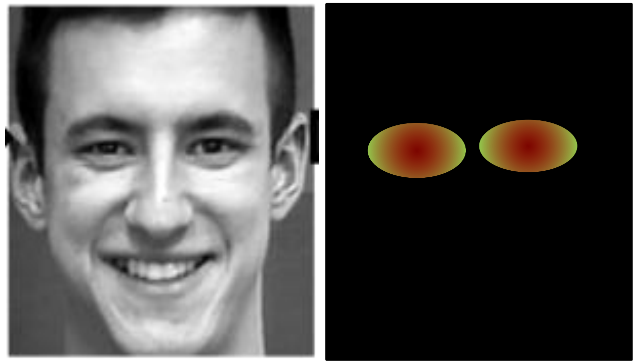


Low-level Feature
看到的是邊的部分會被強化，邊在特徵圖上的輸出值較大。

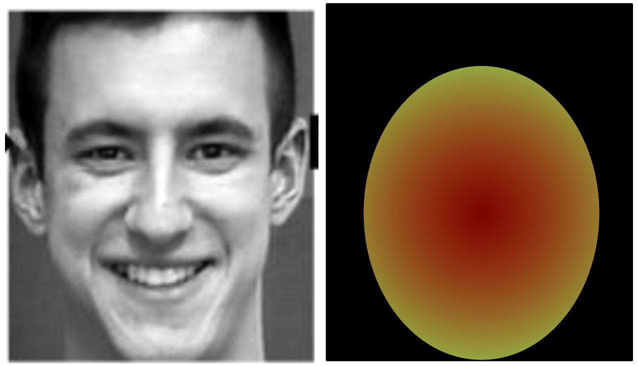
Middle-Level Feature
看到的是圖上器官的在feature map的輸出值較大。

High-Level Feature
看到的是圖上臉的在feature map的輸出值較大。

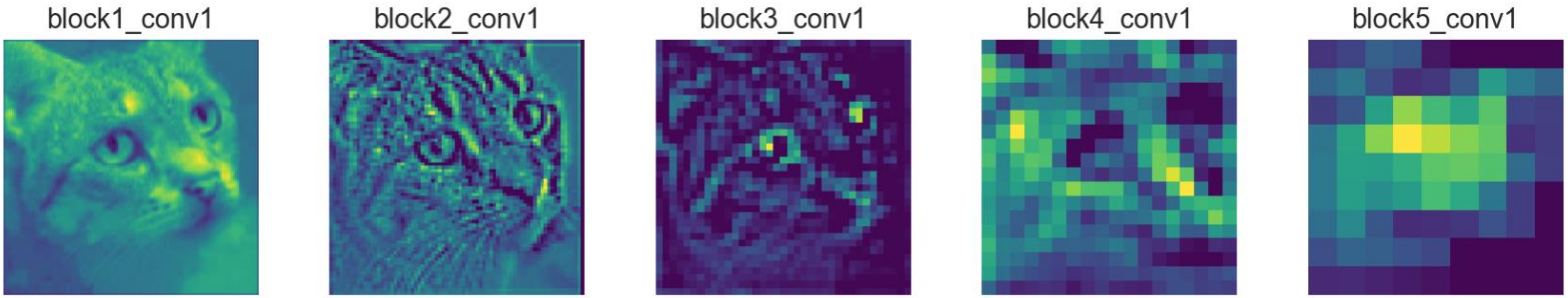
EX: 特徵圖(表示眼睛的反應)



EX: 特徵圖(表示臉的反應)



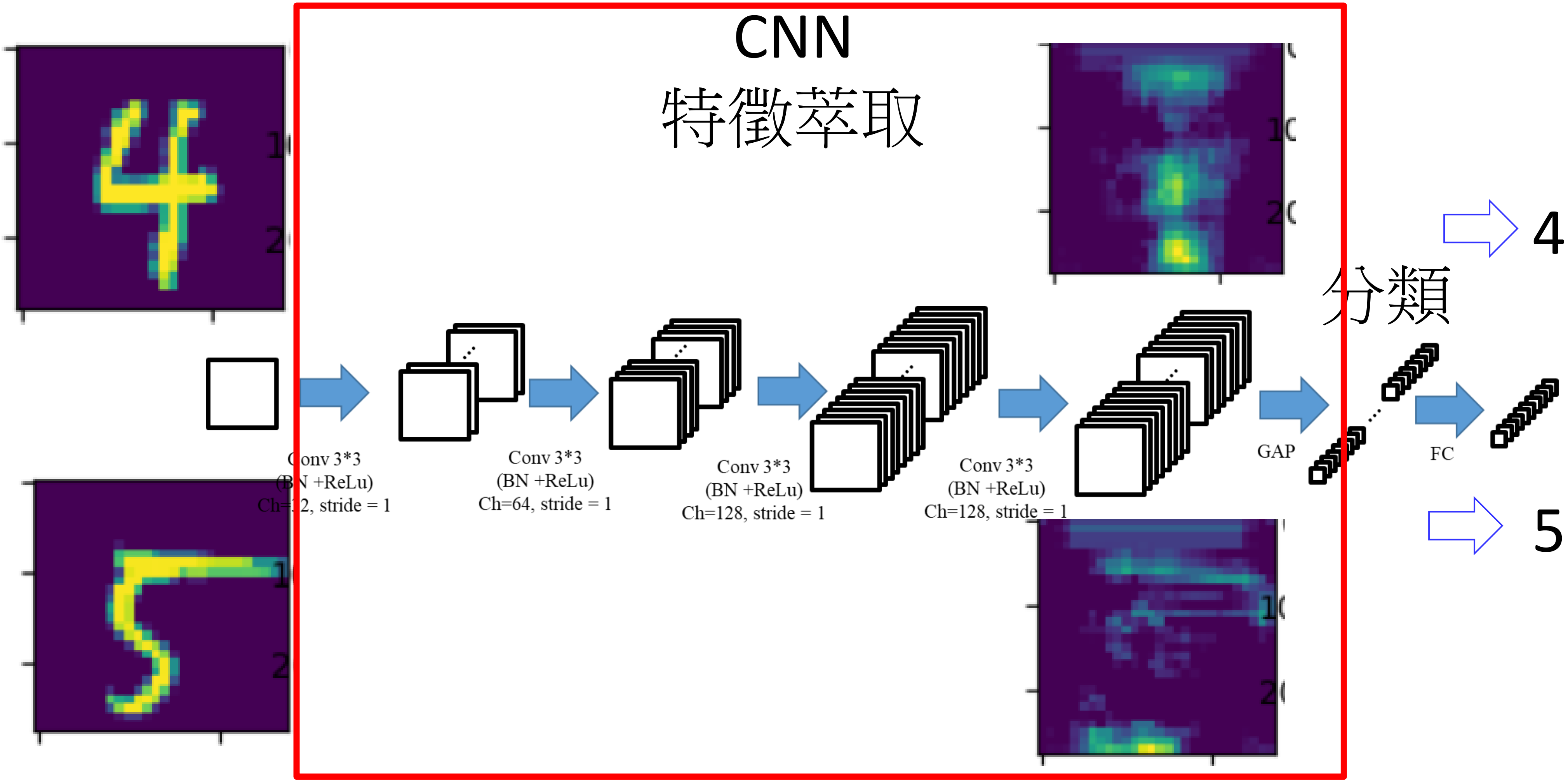
CNN取什麼特徵?



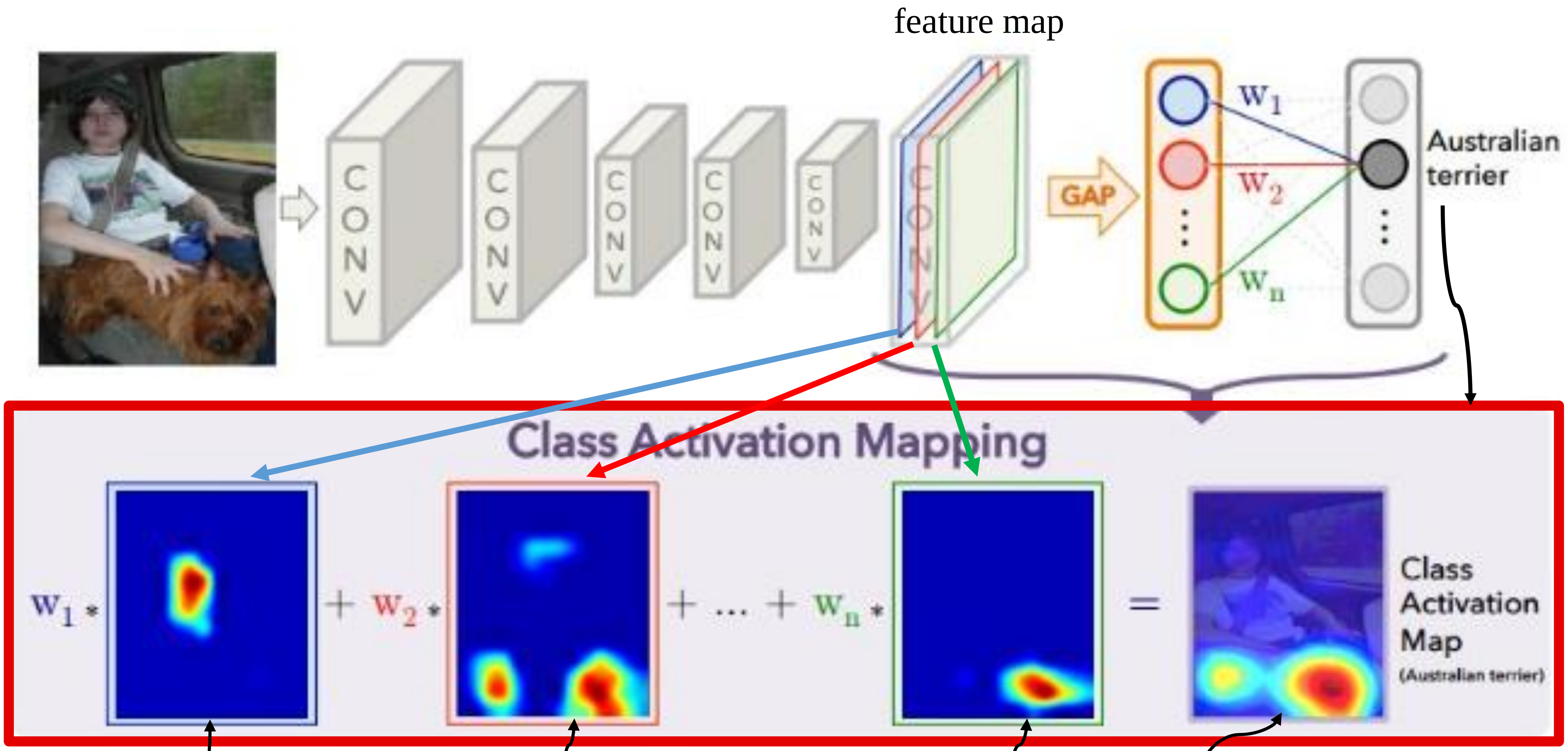
Low-Level Feature → Middle-Level Feature → High-Level Feature

https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2

CNN取什麼特徵?


CNN
特徵萃取
Conv 3*3
(BN +ReLu)
Ch=64, stride = 1
Conv 3*3
(BN +ReLu)
Ch=128, stride = 1
Conv 3*3
(BN +ReLu)
Ch=128, stride = 1
GAP
FC
分類
4
5

觀察模型針對這張圖在**特定類別**看得區塊



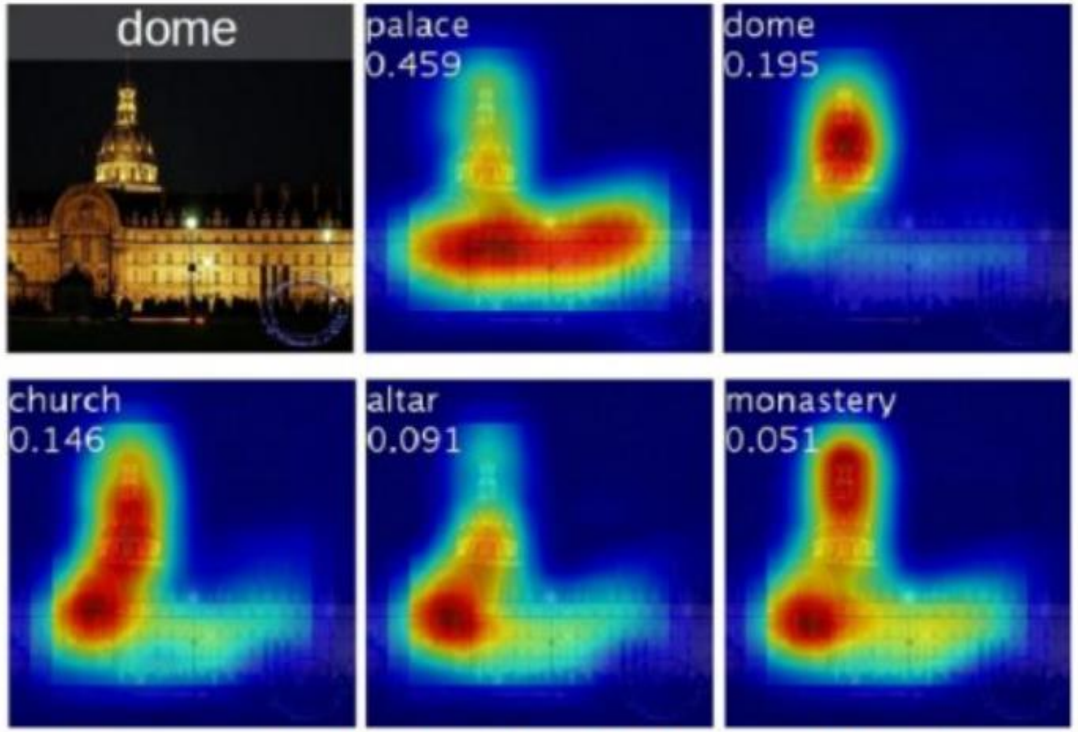
這個channel 看的是人的feature

這個channel 看的是人的狗的feature

這個channel 看的是人的狗頭的feature

合成出來代表Australian terrier的feature map

觀察模型針對這張圖在**特定類別**看得區塊



Class activation maps of top 5 predictions

Class activation maps for one object class