

CNN-Copy1

2018 年 8 月 3 日



1 再論 CNN

1.1 介紹

上一章節我們已經試過了超簡化版的 VGG-16，我們再來加上一些深度，看看加上深度到底對我們整個模型的影響為何

```
In [1]: from keras.datasets import cifar10
        # MAC 一定要加入此行，才不會把對方伺服器的 SSL 證書視為無效
        import ssl
        ssl._create_default_https_context = ssl._create_unverified_context
        import matplotlib.pyplot as plt
        %matplotlib inline

        (x_train, y_train), (x_test, y_test) = cifar10.load_data()
```

Using TensorFlow backend.

一樣看看 shape

```
In [2]: print(x_train.shape)
        print(x_test.shape)
```

```
(50000, 32, 32, 3)
```

```
(10000, 32, 32, 3)
```

```
In [3]: label = {0:"飛機", 1:"車", 2:"鳥", 3:"貓", 4:"鹿",  
                5:"狗", 6:"青蛙", 7:"馬", 8:"船", 9:"卡車"}
```

可視化你想看的圖片

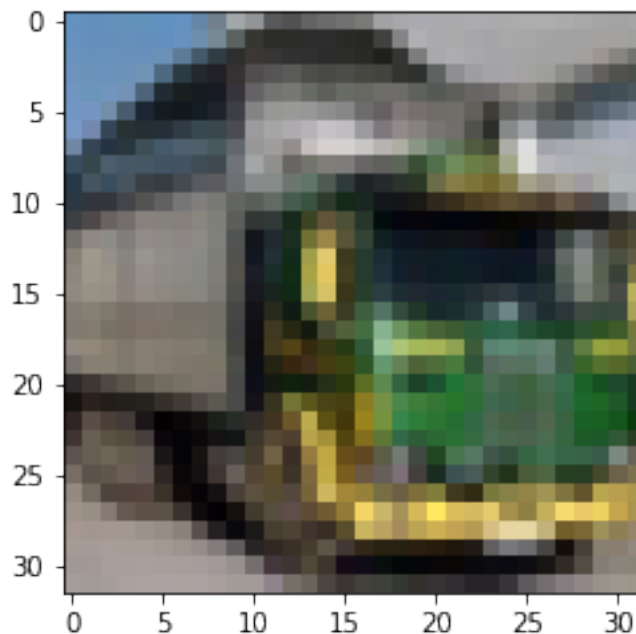
```
In [4]: a = int(input("請輸入你想可視化的圖片 [0-49999]:"))  
        print("你想可視化的圖片號碼是", a)  
        print("圖片答案是", label[y_train[a][0]])  
        plt.imshow(x_train[a])
```

請輸入你想可視化的圖片 [0-49999]:14

你想可視化的圖片號碼是 14

圖片答案是 卡車

```
Out[4]: <matplotlib.image.AxesImage at 0x12490d6d8>
```



一樣對特徵做出標準化，並且對目標做出 One-hot 編碼

```
In [5]: from keras.utils import np_utils
        x_train_shaped = x_train.astype("float32") / 255
        x_test_shaped = x_test.astype("float32") / 255
        y_train_cat = np_utils.to_categorical(y_train)
        y_test_cat = np_utils.to_categorical(y_test)
```

這次我們真的遵照 VGG-16 的結構來構建卷積層，我們總共做了 6 次的卷積 (特徵萃取)，三次的池化 (減少計算量)，最後在接上全連接層做出分類

```
In [6]: from keras.models import Sequential
        from keras.layers import Dense, Dropout, Activation, Flatten
        from keras.layers import Conv2D, MaxPooling2D, ZeroPadding2D

        model = Sequential()

        model.add(Conv2D(filters=64,
                          kernel_size=(3, 3),
                          input_shape=(32, 32, 3),
                          activation='relu',
                          padding='same'))
        model.add(Conv2D(filters=64,
                          kernel_size=(3, 3),
                          activation='relu',
                          padding='same'))
        model.add(MaxPooling2D(pool_size=(2, 2)))

        model.add(Dropout(0.25))
        model.add(Conv2D(filters=128,
                          kernel_size=(3, 3),
                          activation='relu',
                          padding='same'))
        model.add(Conv2D(filters=128,
                          kernel_size=(3, 3),
                          activation='relu',
                          padding='same'))
        model.add(MaxPooling2D(pool_size=(2, 2)))
```

```

model.add(Dropout(0.25))
model.add(Conv2D(filters=256,
                  kernel_size=(3, 3),
                  activation='relu',
                  padding='same'))
model.add(Conv2D(filters=256,
                  kernel_size=(3, 3),
                  activation='relu',
                  padding='same'))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Flatten())
model.add(Dropout(rate=0.25))

model.add(Dense(1024, activation='relu'))
model.add(Dropout(rate=0.25))

model.add(Dense(10, activation='softmax'))
model.summary()

```

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 32, 32, 64)	1792
conv2d_2 (Conv2D)	(None, 32, 32, 64)	36928
max_pooling2d_1 (MaxPooling2D)	(None, 16, 16, 64)	0
dropout_1 (Dropout)	(None, 16, 16, 64)	0
conv2d_3 (Conv2D)	(None, 16, 16, 128)	73856
conv2d_4 (Conv2D)	(None, 16, 16, 128)	147584
max_pooling2d_2 (MaxPooling2D)	(None, 8, 8, 128)	0

dropout_2 (Dropout)	(None, 8, 8, 128)	0

conv2d_5 (Conv2D)	(None, 8, 8, 256)	295168

conv2d_6 (Conv2D)	(None, 8, 8, 256)	590080

max_pooling2d_3 (MaxPooling2D)	(None, 4, 4, 256)	0

flatten_1 (Flatten)	(None, 4096)	0

dropout_3 (Dropout)	(None, 4096)	0

dense_1 (Dense)	(None, 1024)	4195328

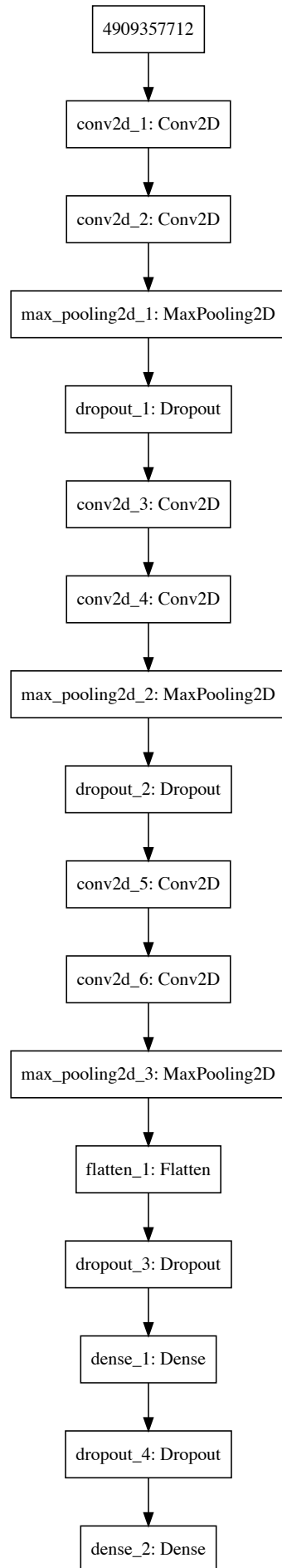
dropout_4 (Dropout)	(None, 1024)	0

dense_2 (Dense)	(None, 10)	10250
=====		
Total params: 5,350,986		
Trainable params: 5,350,986		
Non-trainable params: 0		

```
In [ ]: from IPython.display import SVG
        from keras.utils.vis_utils import model_to_dot

        SVG(model_to_dot(model).create(prog='dot', format='svg'))

Out[None]:
```



```
In [ ]: model.compile(loss="categorical_crossentropy",
                      optimizer = "adam",
                      metrics = ['accuracy'])
train_history = model.fit(x = x_train_shaped, y = y_train_cat,
                          validation_split = 0.1,
                          epochs = 25,
                          batch_size = 200,
                          verbose = 2)
```

Train on 45000 samples, validate on 5000 samples

Epoch 1/25

- 506s - loss: 1.7535 - acc: 0.3524 - val_loss: 1.3401 - val_acc: 0.5048

Epoch 2/25

- 1332s - loss: 1.2987 - acc: 0.5338 - val_loss: 1.1006 - val_acc: 0.6030

Epoch 3/25

- 530s - loss: 1.0836 - acc: 0.6148 - val_loss: 0.9409 - val_acc: 0.6720

Epoch 4/25

- 524s - loss: 0.9304 - acc: 0.6695 - val_loss: 0.8318 - val_acc: 0.7104

Epoch 5/25

- 548s - loss: 0.8294 - acc: 0.7091 - val_loss: 0.7503 - val_acc: 0.7418

Epoch 6/25

- 572s - loss: 0.7383 - acc: 0.7391 - val_loss: 0.6894 - val_acc: 0.7628

Epoch 7/25

- 577s - loss: 0.6673 - acc: 0.7651 - val_loss: 0.6526 - val_acc: 0.7760

Epoch 8/25

- 562s - loss: 0.6147 - acc: 0.7840 - val_loss: 0.6549 - val_acc: 0.7792

Epoch 9/25

- 560s - loss: 0.5583 - acc: 0.8043 - val_loss: 0.6476 - val_acc: 0.7808

Epoch 10/25

- 549s - loss: 0.5181 - acc: 0.8192 - val_loss: 0.5955 - val_acc: 0.8032

Epoch 11/25

```
In [ ]: plt.plot(train_history.history["loss"])
        plt.plot(train_history.history["val_loss"])
```

```
plt.title("Loss Graph")  
plt.legend(['loss', 'val_loss'], loc="upper left")
```

```
In [ ]: model.evaluate(x_test_shaped, y_test_cat)
```