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1. (1%) 請說明你實作的 CNN model，其模型架構、訓練過程和準確率為何？

模型架構

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 48, 48, 64)	640
activation_1 (Activation)	(None, 48, 48, 64)	0
max_pooling2d_1 (MaxPooling2	(None, 24, 24, 64)	0
dropout_1 (Dropout)	(None, 24, 24, 64)	0
conv2d_2 (Conv2D)	(None, 24, 24, 128)	73856
activation_2 (Activation)	(None, 24, 24, 128)	0
conv2d_3 (Conv2D)	(None, 24, 24, 128)	147584
activation_3 (Activation)	(None, 24, 24, 128)	0
max_pooling2d_2 (MaxPooling2	(None, 12, 12, 128)	0
dropout_2 (Dropout)	(None, 12, 12, 128)	0
conv2d_4 (Conv2D)	(None, 12, 12, 256)	295168
activation_4 (Activation)	(None, 12, 12, 256)	0
conv2d_5 (Conv2D)	(None, 12, 12, 256)	590080
activation_5 (Activation)	(None, 12, 12, 256)	0
max_pooling2d_3 (MaxPooling2	(None, 6, 6, 256)	0
dropout_3 (Dropout)	(None, 6, 6, 256)	0
flatten_1 (Flatten)	(None, 9216)	0
dense_1 (Dense)	(None, 1024)	9438208
dropout_4 (Dropout)	(None, 1024)	0
dense_2 (Dense)	(None, 1024)	1049600
dropout_5 (Dropout)	(None, 1024)	0
dense_3 (Dense)	(None, 7)	7175
activation_6 (Activation)	(None, 7)	0

Total params: 11,602,311.0

訓練過程

剛開始我依照cnn一般的架構:

1. filter 少-->多 (剛開始只看比較簡單的filter)
2. Use relu as activation function for cnn(to avoid gradient vanishing)
3. add fully feed network after cnn layers

但一直train得很慘，accuracy在training data上面就上不去。 後來發現optimizer從adam換成adadelta或sgd就好很多了，但很明顯train久一點就會overfitting（training data的accuracy一直提高但validation data的accuracy就會停止上升甚至減少）。To avoid overfitting， I added more dropout layer. 之後我 tune了一下filter的數量與調整了dropout layer的數量（太多dropout layer也會train不起來)，最後決定使用大一點的network，雖然要train比較久但結果比較好。基本上包含三層convolution layer(在一層convolution layer使用兩層filter的layer才會接著max pooling與dropout layer)與兩層fully feedforward network，每層基本上接著一個dropout layer，activation 除了output使用softmax其他都使用relu.

我參考這個論文中的作法，做image cropping與翻轉，把data變成12倍在拿去train.
https://arxiv.org/pdf/1611.04251.pdf
至於對於image的preprocessing，我把所有pixel的值都線性的移到[0,1]之間（直接除255)

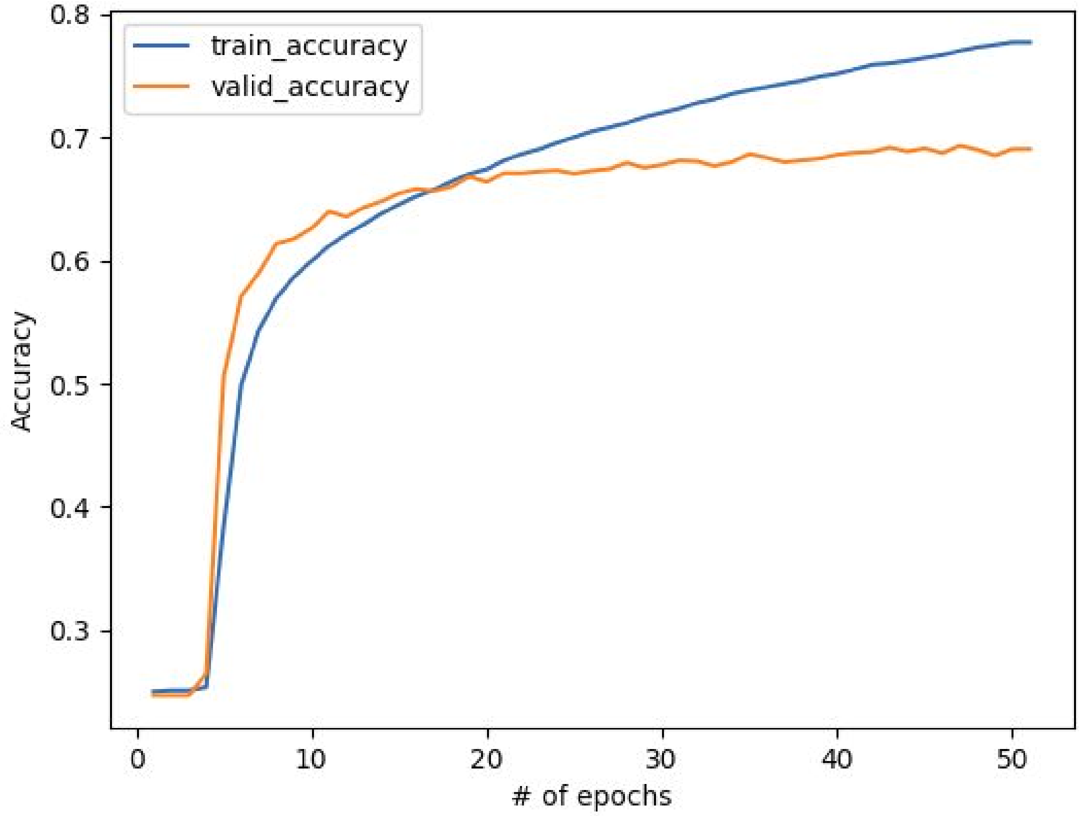
SGD(lr=0.005, decay=0.00001, momentum=0.9)

loss=’categorical_crossentropy’, batch_size=50

Tuned parameters:

- learning rate of SGD
- filter 的數量
- dropout layer的dropout rate(0.5)

Tune 的方法基本上都是先查查看一般別人用的參數是怎麼樣，然後再做一些trial and error



準確率 Best accuracy on public data: 0.69072

2. (1%) 承上題，請用與上述 CNN 接近的參數量，實做簡單的 DNN model。其模型架構、訓練過程和準確率為何？試與上題結果做比較，並說明你觀察到了什麼？

Model Structure

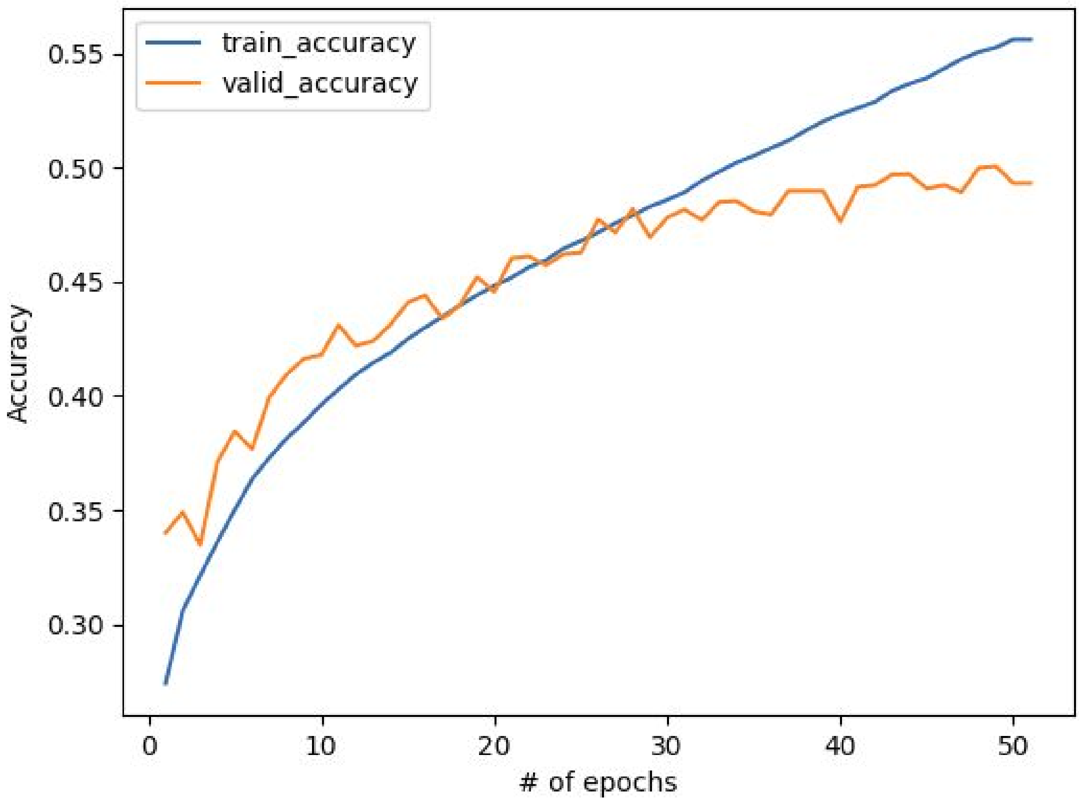
Layer (type)	Output Shape	Param #
flatten_1 (Flatten)	(None, 2304)	0
dense_1 (Dense)	(None, 1024)	2360320
dropout_1 (Dropout)	(None, 1024)	0
activation_1 (Activation)	(None, 1024)	0
dense_2 (Dense)	(None, 1024)	1049600
dropout_2 (Dropout)	(None, 1024)	0
activation_2 (Activation)	(None, 1024)	0
dense_3 (Dense)	(None, 1024)	1049600
dropout_3 (Dropout)	(None, 1024)	0
activation_3 (Activation)	(None, 1024)	0
dense_4 (Dense)	(None, 1024)	1049600
dropout_4 (Dropout)	(None, 1024)	0
activation_4 (Activation)	(None, 1024)	0
dense_5 (Dense)	(None, 1024)	1049600
dropout_5 (Dropout)	(None, 1024)	0
activation_5 (Activation)	(None, 1024)	0
dense_6 (Dense)	(None, 1024)	1049600
dropout_6 (Dropout)	(None, 1024)	0
activation_6 (Activation)	(None, 1024)	0

```
dense_8 (Dense)              (None, 1024)              1049600
_________________________________________________________________
dropout_8 (Dropout)          (None, 1024)              0
_________________________________________________________________
activation_8 (Activation)    (None, 1024)              0
_________________________________________________________________
dense_9 (Dense)              (None, 1024)              1049600
_________________________________________________________________
dropout_9 (Dropout)          (None, 1024)              0
_________________________________________________________________
activation_9 (Activation)    (None, 1024)              0
_________________________________________________________________
dense_10 (Dense)             (None, 1024)              1049600
_________________________________________________________________
dropout_10 (Dropout)         (None, 1024)              0
_________________________________________________________________
activation_10 (Activation)   (None, 1024)              0
_________________________________________________________________
dense_11 (Dense)             (None, 1024)              1049600
_________________________________________________________________
dropout_11 (Dropout)         (None, 1024)              0
_________________________________________________________________
activation_11 (Activation)   (None, 1024)              0
_________________________________________________________________
dense_12 (Dense)             (None, 7)                 7175
_________________________________________________________________
activation_12 (Activation)   (None, 7)                 0
=================================================================
Total params: 12,863,495.0
Trainable params: 12,863,495.0
Non-trainable params: 0.0
```

Number of trainable params: 12, 836, 495

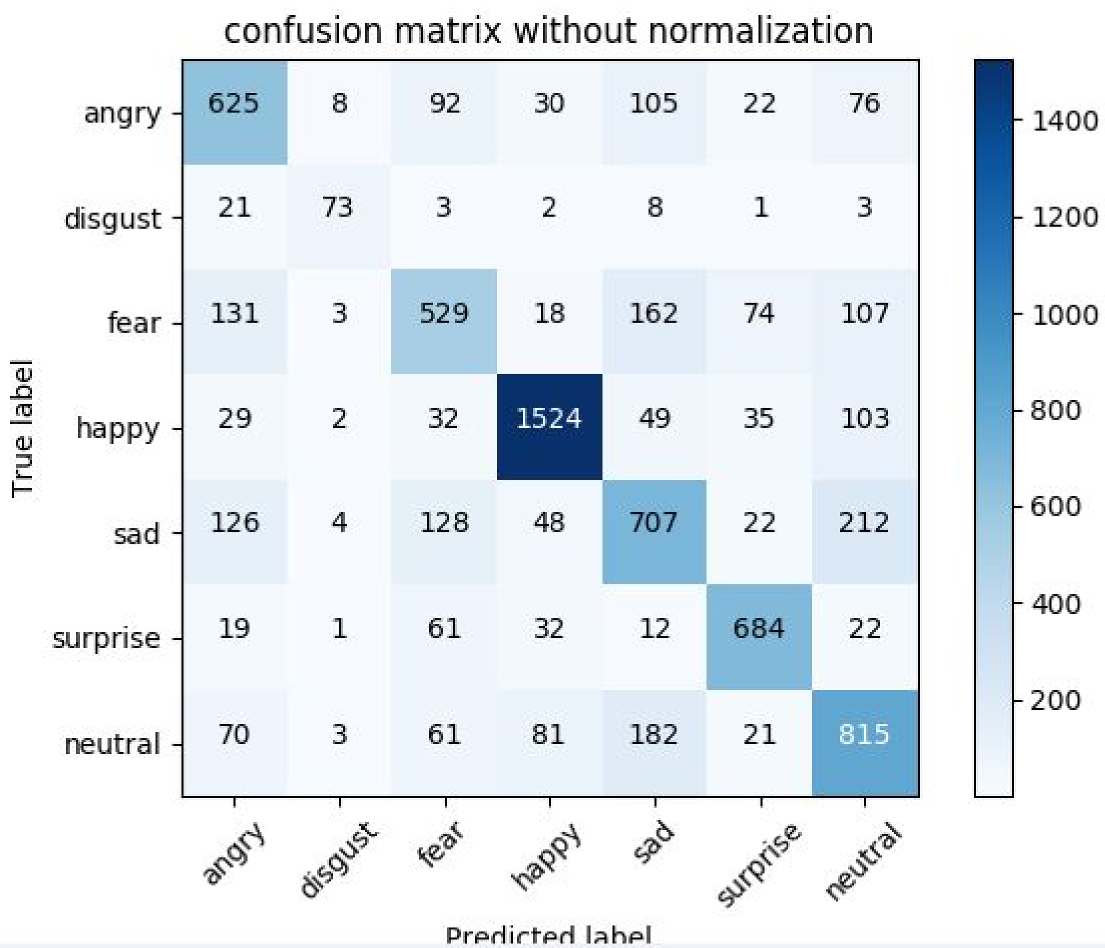
Training Procedure

我疊了10層的hidden layer, 每曾為regular densely-connected NN layer with units=1024(I leaned that people nowadays tend to give every hidden layer the same unit. If the number of units are more than needed, the network will learn that too.)，參數量與上述的CNN差不多（皆為一千萬左右)，除了network的架構以外與epoch次數不同以外（I did early stopping on dnn to avoid overfitting)，其餘的方法完全一樣(activation 除了output使用softmax其他都使用relu to avoid gradient vanishing problem)。
可以發現再相同參數的情況上，cnn再這個task上的performance明顯比較好。 而且dnn也train得比較慢（cnn在10個epoch以內就到達0.6以上的accuracy, 30個epoch就接近best performance), dnn上升的很慢，50個epoch左右才能到達model最好的performance。



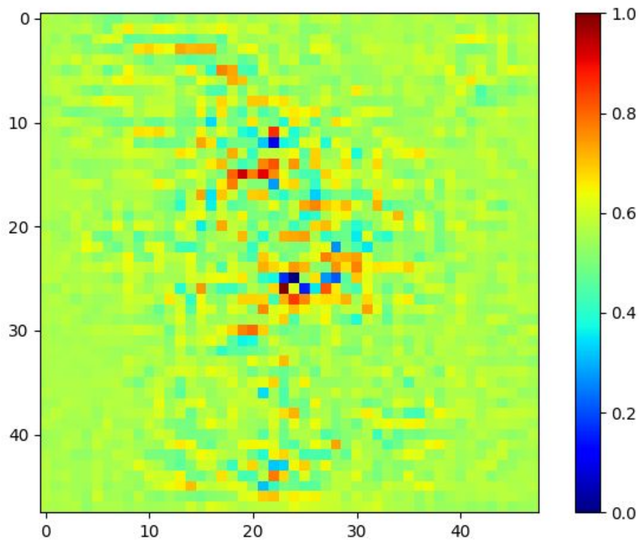
準確率 Best accuracy on public data: 0.52299

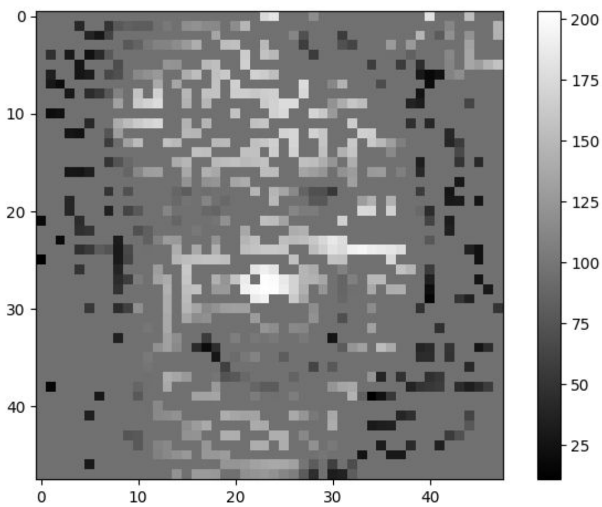
3. (1%) 觀察答錯的圖片中，哪些 class 彼此間容易用混？[繪出 confusion matrix 分析]



- pictures labeled disgust are likely to be classified as angry
- pictures labeled fear are likely to be classified as angry and sad
- pictures labeled sad are likely to be classified as neutral
- pictures labeled neutral are likely to be classified as sad

4. (1%) 從(1)(2)可以發現，使用 CNN 的確有些好處，試繪出其 saliency maps，觀察模型在做 classification 時，是 focus 在圖片的哪些部份？



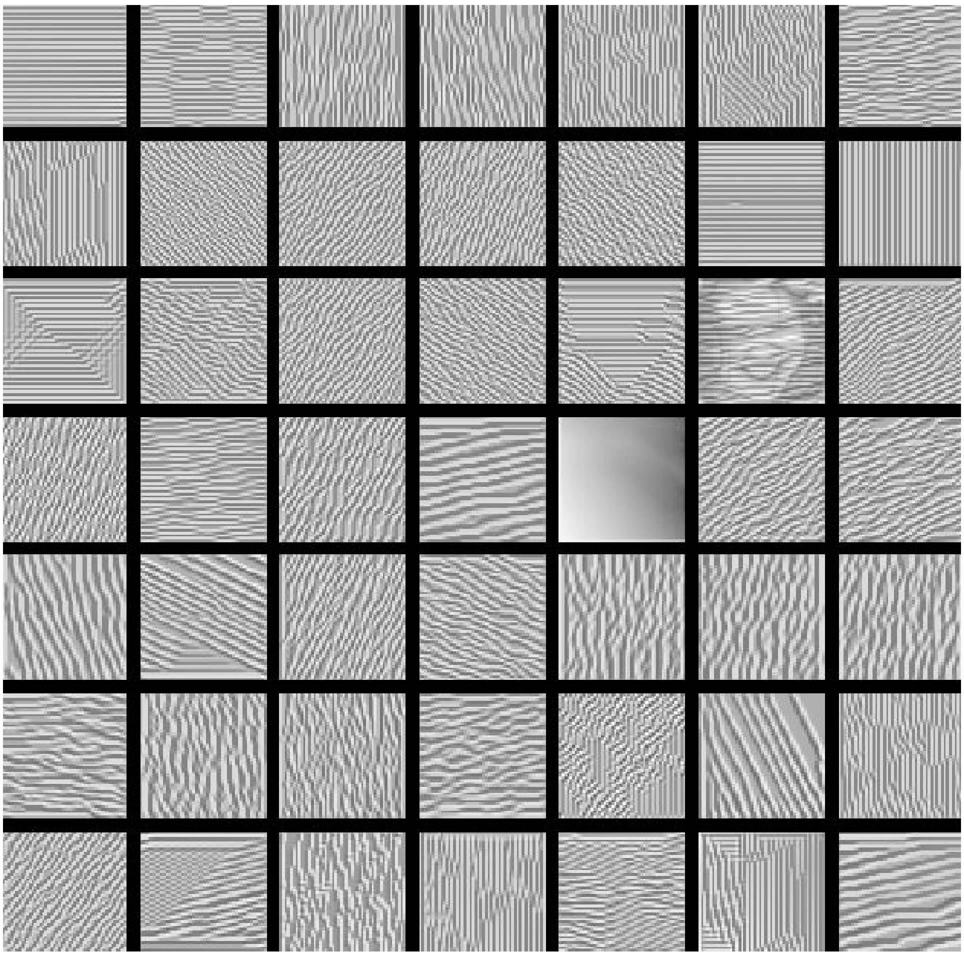


大致上在這張圖上，眼睛跟鼻子是圖片的重點區域。在下面那張圖中可以看到雖然牙齒都不太高，但唇型大致上並沒有被mask掉，所以估計唇型也是一個high level feature(但是很不明顯的因為從heatmap中看不出唇型，不太清楚是什麼原因)。

5. (1%) 承(1)(2)，利用上課所提到的 gradient ascent 方法，觀察特定層的filter最容易被哪種圖片 activate。

Filters of layer activation_1 (# Ascent steps: 100)

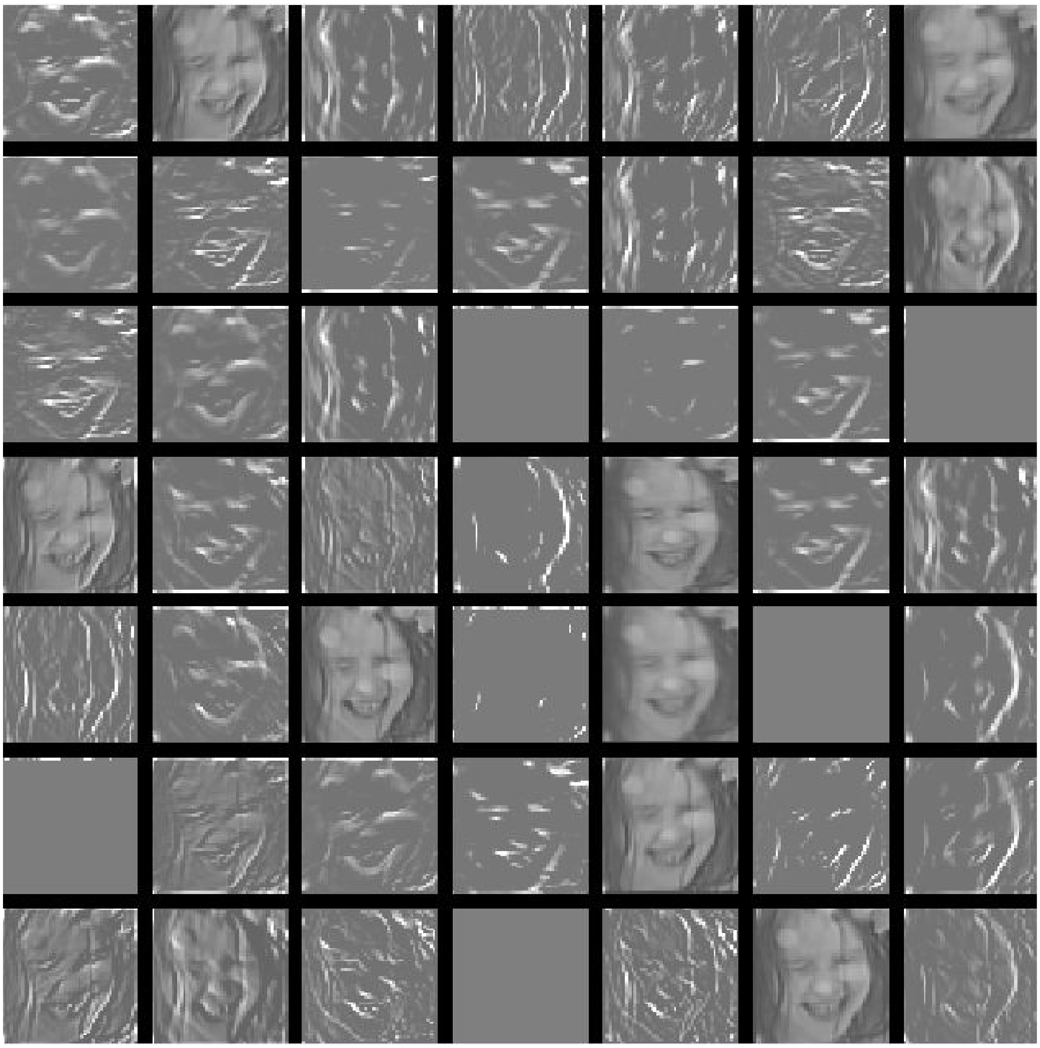
利用梯度遞增法，找出最能激活特定filter的圖片(從白噪音開始)



```
for i in range(20):

        loss_value, grads_value = iterate([input_img_data])

        input_img_data += grads_value * step

  return input_img_data
```

Output of layer activation_1

給定輸入圖片，取出特定層的輸出



基本上可以從第1張圖中觀察到，第1層的filter主要是偵測簡單的feature像是點，線，不同粗細與不同角度。能在第一層看出臉形的大概只有一個（圖中的49個是從64個裡面選出gradient ascent 之後loss比較高的)。同一層的output則很多還能看出原圖的樣子，但也有很多圖幾乎式灰色一片看不出任何東西了，我猜應該是因為我第1層用了64個filter，但實際上也沒需要那麼多，所以可能model在自己learn完之後，學出不少filter是多餘的（這張圖裡49個是從64個裡面random取的)。

[Bonus] (1%) 從 training data 中移除部份 label，實做 semi-supervised learning

My full code at ML2017/hw3/semi_supervised/main.py

Remove some label in training data as **unlabeled data**

```
unlabeled_size = 10000
global unlabeled_x
unlabeled_x = x_test[:unlabeled_size]

x_test = x_test[unlabeled_size:]
y_test = y_test[unlabeled_size:]
```

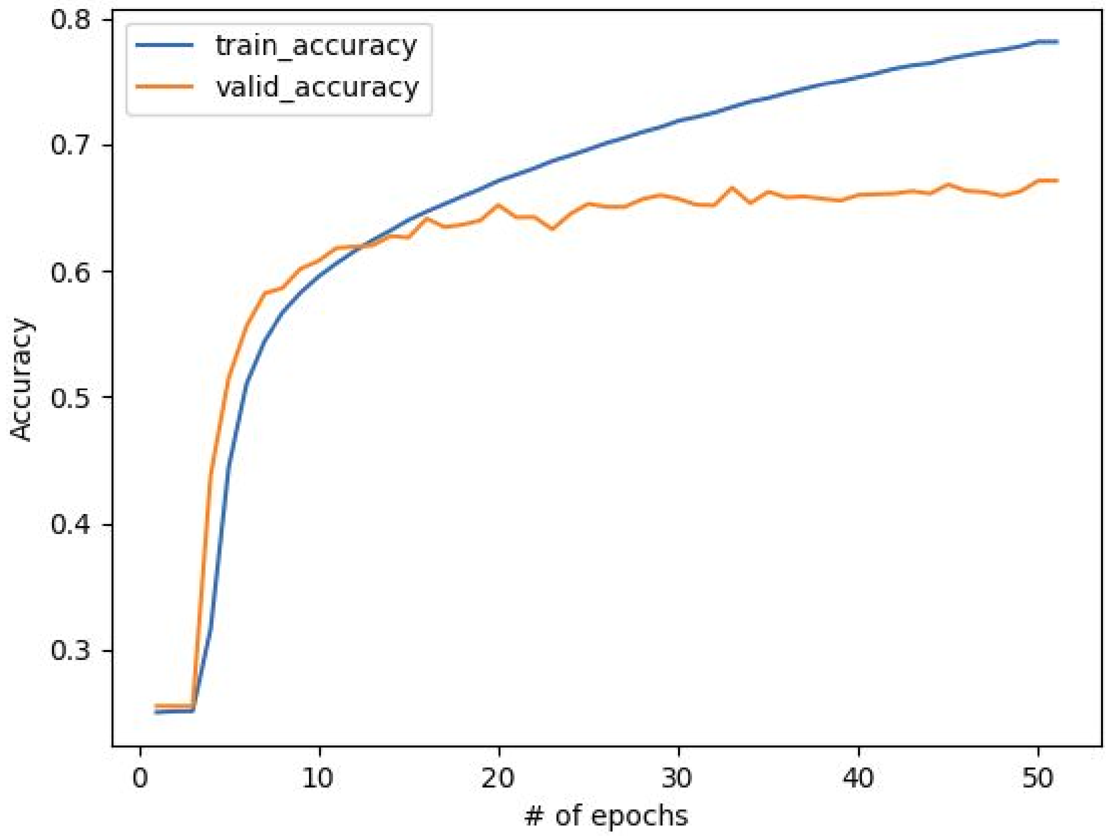
Implement semi-supervised learning algorithm(semi supervised by entropy-based minimization, or regularization)

```
def semi_loss( y_test, y_pred ):
    labeled_loss = K.categorical_crossentropy(y_test, y_pred)
    unlabeled_pred = model.predict( unlabeled_x ).flatten()
    unlabeled_loss = sum(np.log( unlabeled_pred ) * unlabeled_pred)
    return labeled_loss + lamda*unlabeled_loss
```

compile my model with semi_loss

```
#sgd = SGD(lr=0.005, decay=0.00001, momentum=0.9)
sgd = SGD(lr=0.005, decay=0.00001, momentum=0.9)
model.compile(loss=semi_loss, optimizer=sgd, metrics=['accuracy'])
```

Result



準確率 Best accuracy on public data: **0.67456**

[Bonus] (1%) 在Problem 5 中，提供了3個 hint，可以嘗試實作及觀察 (但也可以不限於 hint 所提到的方向，也可以自己去研究更多關於 CNN 細節的資料)，並說明你做了些什麼？ [完成1個: +0.4%, 完成2個: +0.7%, 完成3個: +1%]