

# DIP\_HW10

December 20, 2019

## 1 Digital Image Processing - HW10 - 98722278 - Mohammad Doosti Lakhani

In this notebook, I have solved the assignment's problems which are as follows: 1. Answer following questions: 1. Why Convolutional Neural Networks have been used for image processing instead of fully connected neural networks? 2. What are the benefits of using Pooling layer? 3. What is the role of non-linear activation functions such as sigmoid and tanh? Is it possible to use linear activation functions? 4. What is the main reason that number of parameters in *GoogleNet* with 22 layers are much less than *AlexNet* with 8 layers?

### 2. Summarize [Xception](#) model

1. LeNet
2. AlexNet
3. VGG
4. ResNet
5. Inception (GoogleNet)
6. Xception

### 3. Train a [Keras](#) model on CIFAR10 dataset and report accuracy and Confusion Matrix

1. Libraries
2. Preparing Data
  1. Loading
  2. Normalizing
  3. Onehot Vector For Labels
3. Setting Hyperparameters
4. Learning Rate Decay Callbacks
5. Defining ResNet110V2
6. Compile Model
7. Save Model Callbacks
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9. ImageDataGenerator
10. Train Model
11. Evaluate Model
  1. Last Model
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  3. Confusion Matrix of Best Model
12. 10 Worst Predictions

## 1.1 1 Answer following questions:

1. Why Convolutional Neural Networks have been used for image processing instead of fully connected neural networks?
2. What are the benefits of using Pooling layer?
3. What is the role of non-linear activation functions such as sigmoid and tanh? Is it possible to use linear activation functions?
4. What is the main reason that number of parameters in *GoogleNet* with 22 layers are much less than *AlexNet* with 8 layers?

Image credits mainly from the corresponding papers and [this](#)

### 1.1.1 1.A CNN vs FCN

The major reason of introducing CNNs is that FCNs combine all features by connecting all neurons in each layer to the all neurons of next layer while CNNs incorporate spatial features regarding of position of filters w.r.t. to input layers. Also CNNs preserve receptive fields regarding different sizes of filters which cannot be obtained in any form of fully connected neural networks. In other words, each neuron in CNN only is connected to a small chunk of input image.

Other major reason is the processing manners. CNNs can learn much more features with less number of parameters as FCNs cannot properly learn spatial features. Also because CNNs are smaller in term of features, they are fast too.

### 1.1.2 1.B Why Pooling layer

In summary, images are huge in size and number of features before passing them to any network. So when we start to train a network, after learning some features using convolutional layers, still we have huge matrix in term of spatial size so the best way to reduce considering local connectivity (each neuron only is connected to small chunk of input image) is to taking pooling such as max or average.

The reason that this approach works is that in high spatial size matrices, a neuron can represent its locality as it is the feature of images where pixels are partially relative, so pooling just retain the most dominant information and exclude all duplicate info which can be ignored.

### 1.1.3 1.C Why non-linear Activation Functions?

In term of computing convolution of FCN, logic is same, we have  $w \times x$  for a single layer. Now let's have 3 layers. Here is the forward operation considering weights are optimal:  $w_3 \times w_2 \times w_1 \times x$ .

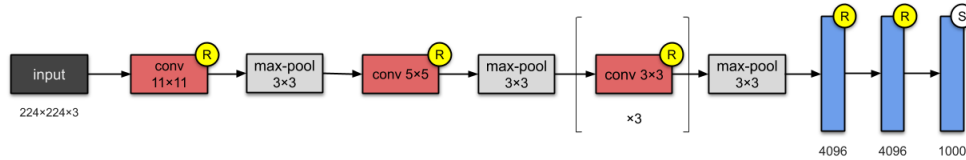
As we can see all the operations are linear between layers so we can reduce  $w_3 \times w_2 \times w_1$  to  $w$  as convolution of multiple matrices are still linear. So the main idea of neural networks that can learn non-linearity of data has been gone!

To prevent this problem from happening, we had a non-linear function such as sigmoid or tanh to help eliminating linearity between each layer. Note that if we use linear functions, still convolving different matrices will be linear.

### 1.1.4 1.D 7M Parameters InceptionV1 model vs. 56M parameters AlexNet

It is better to have an intuition of network before explaining the difference.

AlexNet:



alex net arch

convpool_5 (MaxPooling2D)	(None, 256, 6, 6)	0	conv_5[0][0]
flatten (Flatten)	(None, 9216)	0	convpool_5[0][0]
dense_1 (Dense)	(None, 4096)	37752832	flatten[0][0]
dropout_1 (Dropout)	(None, 4096)	0	dense_1[0][0]
dense_2 (Dense)	(None, 4096)	16781312	dropout_1[0][0]
dropout_2 (Dropout)	(None, 4096)	0	dense_2[0][0]
dense_3_new (Dense)	(None, 2)	8194	dropout_2[0][0]
softmax (Activation)	(None, 2)	0	dense_3_new[0][0]

alex net last fc

Convolution layers in both networks almost have same amount of parameters and because *Inception V1* a.k.a. *GoogLeNet* has more conv layers, it has more parameters excluding fully connected parts.

In term of convolution parameters: 1. Inception: 3.2M 2. AlexNet: 2.5M

But what makes this huge difference is the connection between conv layers and fully connected layers and also the connection between fully connected layers itself.

In *AlexNet*, the connection between last pooling layer and first fully connected layer has about 37M parameters and on top of it, the connection between this layer and next fully connected layer has 16M parameters too so only these 2 layers of 8-layer AlexNet have more than 54M parameters while the entire *Inception* model has 7M parameters which has been explained later. Here is an image of last pooling layer and 2 fully connected layers of *AlexNet*:

What about *Inception*? Inception V1:

About *Inception* we need to focus on two procedure: 1. 1x1 Convs: As we know in Inception module, different convs have been taken and then concatenated but before doing this, they first take 1v1 conv for sake of dimensionality reduction.

2. Using GlobalAveragePooling in the last layer after Inception layers helped to reduce the last convolational layer to only 1024, then a fully connected with 1000 neurons are connected at the last layer.

Note that there are 2 other auxiliary losses with same logic (after Inception4a and Inception 4d) so approximately all three paths have about 3M parameters + 3.2M parameters of inception modules and other conv layers, we reach 7M parameters.

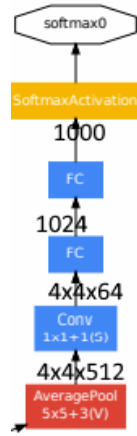
Image above shows the dimensionality of different layers at the connection of conv layers to fully connected for auxiliary loss 1. This is same for aux loss 2 except tensor after avg pooling is 4x4x528 instead of 4x4x512x.

Below image also show the main path (main loss) of GoogleNet:

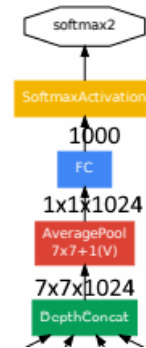
type	patch size/ stride	output size	depth	#1×1	#3×3 reduce	#3×3	#5×5 reduce	#5×5	pool proj	params	ops
convolution	7×7/2	112×112×64	1							2.7K	34M
max pool	3×3/2	56×56×64	0								
convolution	3×3/1	56×56×192	2		64	192				112K	360M
max pool	3×3/2	28×28×192	0								
inception (3a)		28×28×256	2	64	96	128	16	32	32	159K	128M
inception (3b)		28×28×480	2	128	128	192	32	96	64	380K	304M
max pool	3×3/2	14×14×480	0								
inception (4a)		14×14×512	2	192	96	208	16	48	64	364K	73M
inception (4b)		14×14×512	2	160	112	224	24	64	64	437K	88M
inception (4c)		14×14×512	2	128	128	256	24	64	64	463K	100M
inception (4d)		14×14×528	2	112	144	288	32	64	64	580K	119M
inception (4e)		14×14×832	2	256	160	320	32	128	128	840K	170M
max pool	3×3/2	7×7×832	0								
inception (5a)		7×7×832	2	256	160	320	32	128	128	1072K	54M
inception (5b)		7×7×1024	2	384	192	384	48	128	128	1388K	71M
avg pool	7×7/1	1×1×1024	0								
dropout (40%)		1×1×1024	0								
linear		1×1×1000	1							1000K	1M
softmax		1×1×1000	0								

Table 1: GoogLeNet incarnation of the Inception architecture

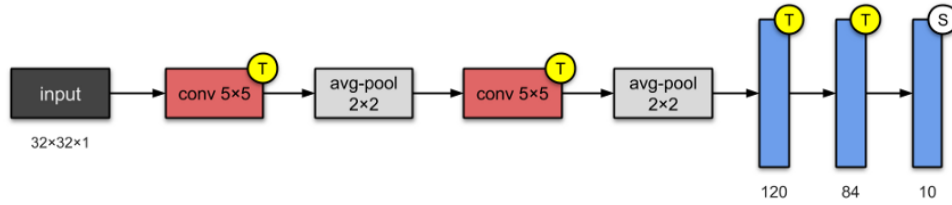
inception v1



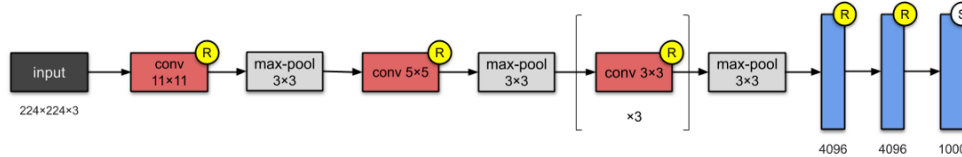
aux loss



main path



lenet



alex net

## 1.2 2 Summarize Xception model

1. LeNet
2. AlexNet
3. VGG
4. ResNet
5. Inception (GoogleNet)
6. Xception

Note: In all modules, circles with  $T=Tanh$ ,  $S=Sigmoid$  and  $R=ReLU$

### 1.2.1 2.A LeNet

LeNet is simplest neural network here, just 2 conv layer and 3 FCs. This model has only 0.6M parameters.

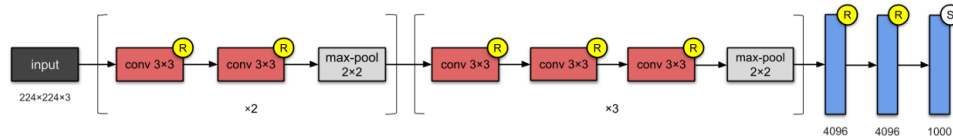
### 1.2.2 2.B AlexNet

AlexNet has 8 layers. What is interesting about this network is that the idea of stacking multiple convolutions then reducing the spatial size of filters has been introduced which is commonly used in almost all networks. The other important note is that they introduced ReLU activation in this paper.

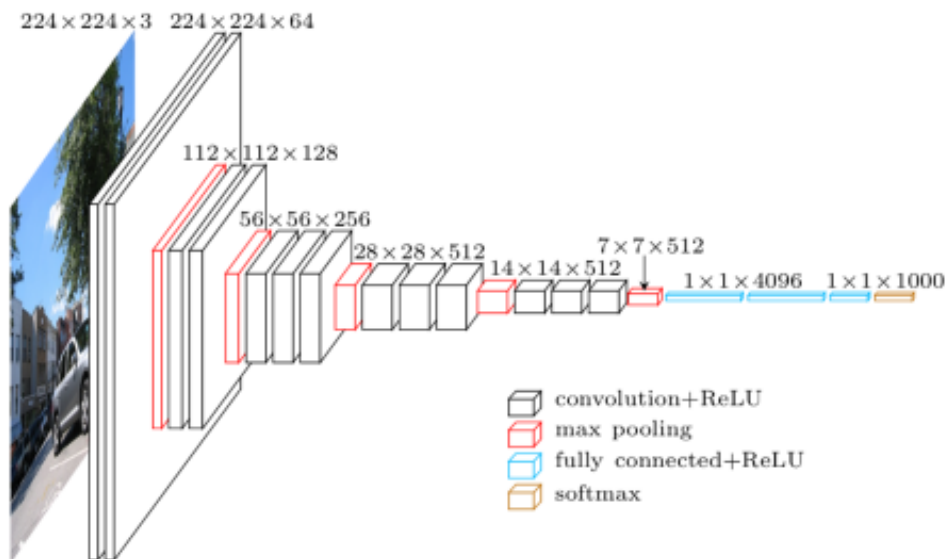
This model has huge capacity with 60M parameters and at the time of publishing, implementing this using available GPUs was challenge so they used parallel implementation of different operation that led them win challenges.

### 1.2.3 2.C VGG

VGG has two main difference from AlexNet 1. VGG uses smaller filter sizes like 2x2 or 3x3 instead of using big ones like 11x11 at first then reduing the filter sizes and reducing volume sizes has been taken care of by maxpooling layers. 2. VGG is much deeper and the reason is that in the



VGG



VGG 2

corresponding paper (or many books) it has been shown that deeper and bigger neural networks has more capacity to learn, so why not deeper?!

They stacked much more layers of smaller filter sizes so as we can guess number of parameters increased to 138M. VGG has different models that a number follows the name VGG which demonstrates number of layers of model. Most reknown ones are VGG-16 and VGG-19.

Something is good to know is that in many different tasks, people use intermediate layers of VGG trained on ImageNet as latent vector of feature extractor or directly transferring knowledge from VGG model for their particular tasks.

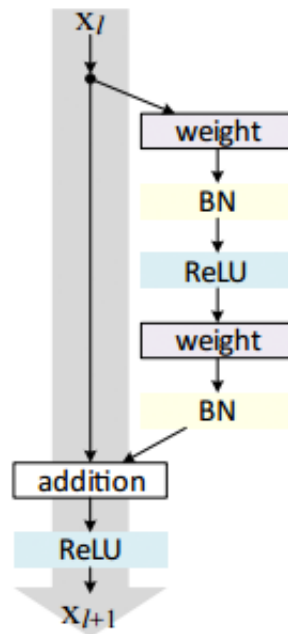
This one may show much better:

### 1.2.4 2.D ResNet

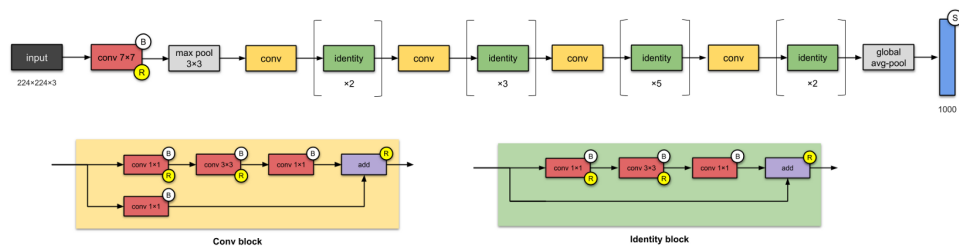
The resnet's idea is really simple in intuitive way, "go deeper and deeper but you might forget what you have learned before, so every time you go deeper, try to learn new thing, if you cannot, retain what ever you have had so far (by identity function!)".

Actually I made up the sentence above but it is absolutely true about ResNet. Here is an image that helps:

The other parts are similar to any other networks, stacking up multiple layers but this time, we stack everytime a single one of aforementioned layers called ResNet block(bottleneck). The straight lines works as identity function in simplified terms called skipping connections.



resnet bottleneck



resnet arch

This architecture helps scientists to build much deeper networks from 20 layers to nowadays 1000 layers with increase in accuracy by increasing layers thanks to those micro-architectures(resnet blocks).

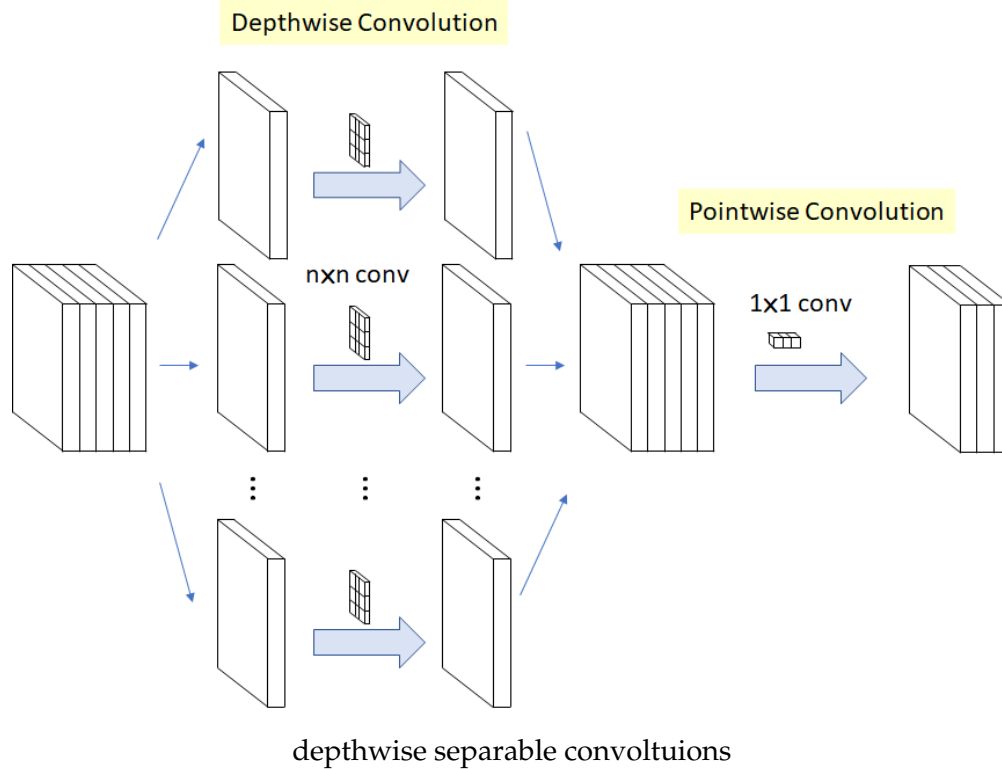
Because ResNet also uses global average pooling(we can see similar effect in Inception module) the number of parameters is much less than AlexNet. For instance, ResNet-50 with 50 layers has only 26M parameters.

### 1.2.5 2.E Inception-V1

please see section 1.D

### 1.2.6 2.F Xception

The first point I would like to focus on is that *Xception* only not introduces new architecture, it also depicts a new approach of taking convolutions called *Depthwise separable convolutions* which



is enormously faster than normal convolution we knew from other models such as *ResNet*, *VGG*.

What is *depthwise convolution*? Multiplication is a expensive operation for computer and in a normal convolution for a image with size of  $H \times H \times M$  and  $N$  filters with size of  $K \times K \times M$ , the number of multiplication will be  $N \times (H-K)^2 \times K^2 \times M$ .

*Depthwise separable convolution* has two steps: 1. Depthwise convolution: Only applies convolution to a channel at a time rather than all channels so we need  $M$  filter with size of  $K \times K \times 1$  too. The output size of this step will be in size of  $(H-K)^M$  which needs  $M \times K^2 \times (H-K)^2$  multiplications. 2. Pointwise convolution: Linear combination of these layers with a filter with size of  $1 \times 1 \times M$ . Assume as normal convolution we need  $N$  filters so we can exapnd the idea here too. The output of this step will be in size of  $N \times (H-K)^2$  which needs  $N \times (H-K)^2 \times M$  multiplications.

Finally, the speedup is equal to  $(1/N) + (1/K^2)$ .

In summary, we have same ratio for number of parameters too which is big deal. This image may help to understand the operation:

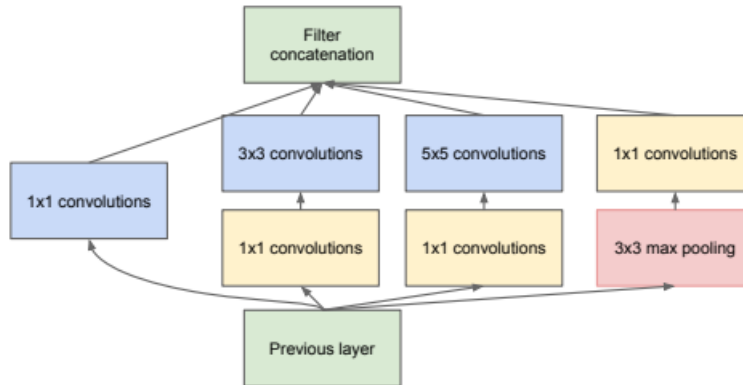
Now we focus on *Xception* module. In *Xception* the order of operations in depthwise separable convolutions has been reversed which means first  $1 \times 1$  convolutions have been used like below image:

*Xception* is the extended version of *Inception-V3* (in term of number of stacked layers) but the main difference as has been explained is using *depthwise separable convolutions* eXtremely which is exactly as the way I have explained in mathematically. The other parts are very similar to *Inception* and convetional CNNs.

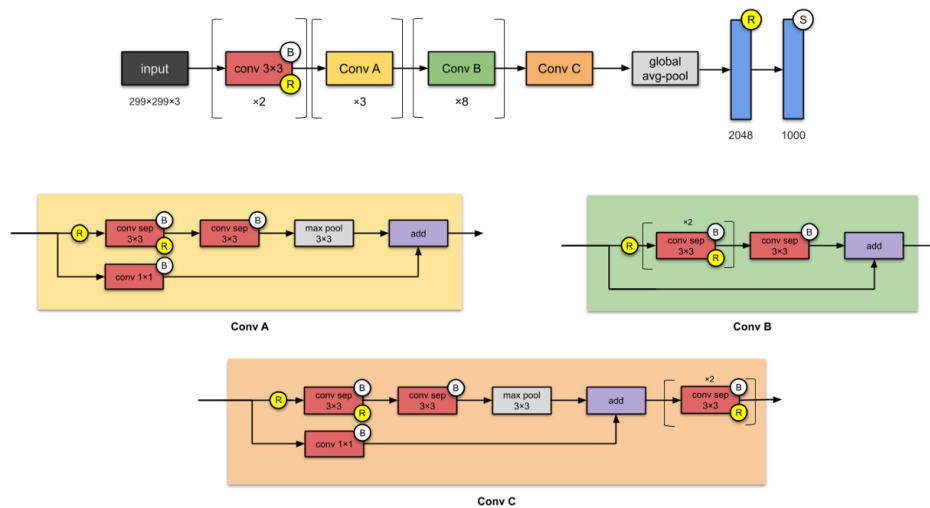
This model has about 23M parameters.

Here is the final model:





simplified inception module



Xception

## 1.3 3 Train a Keras model on CIFAR10

1. Libraries
2. Preparing Data
  1. Loading
  2. Normalizing
  3. Onehot Vector For Labels
3. Setting Hyperparameters
4. Learning Rate Decay Callbacks
5. Defining ResNet110V2
6. Compile Model
7. Save Model Callbacks
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  3. Confusion Matrix of Best Model
12. 10 Worst Predictions

### 1.3.1 3.A Libraries

```
In [ ]: %tensorflow_version 1.x
```

```
from __future__ import print_function
import seaborn as sns
import matplotlib.pyplot as plt
import PIL
import pandas as pd
import numpy as np
from keras import backend as K
from keras.preprocessing.image import ImageDataGenerator
from keras.optimizers import Adam
from keras.callbacks import EarlyStopping, ReduceLROnPlateau, ModelCheckpoint, LearningRateScheduler
from keras.layers import Dense, Conv2D, BatchNormalization, Activation
from keras.layers import AveragePooling2D, Input, Flatten
from keras.regularizers import l2
from keras.models import Model
from keras.utils import to_categorical
import keras

from keras.datasets import cifar10
```

### 1.3.2 3.B Preparing Data

1. loading

2. normalizing
3. converting labels to onehot vectors

### 3.B.a Loading

```
In [5]: (x_train, y_train), (x_test, y_test) = cifar10.load_data()
```

Downloading data from <https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz>  
 170500096/170498071 [=====] - 4s 0us/step

### 3.B.b Normalizing

```
In [6]: x_train = x_train.astype('float32') / 255
        x_test = x_test.astype('float32') / 255
        x_train_mean = np.mean(x_train, axis=0)
        x_train -= x_train_mean
        x_test -= x_train_mean

        print('x_train shape:', x_train.shape)
        print('train samples', x_train.shape[0])
        print('test samples', x_test.shape[0])
        print('y_train shape:', y_train.shape)
```

```
x_train shape: (50000, 32, 32, 3)
train samples 50000
test samples 10000
y_train shape: (50000, 1)
```

### 3.B.c Convert Y to onehot vectors

```
In [8]: num_classes = 10
        y_train = to_categorical(y_train, num_classes)
        y_test = to_categorical(y_test, num_classes)
        print(y_train.shape)
```

```
(50000, 10)
```

## 1.3.3 3.C Setting Hyperparameters

```
In [ ]: batch_size = 32
        epochs = 200

        data_augmentation = True
        subtract_pixel_mean = True

        # resnet 110 v2
```

```

depth = 110
version = 2
model_type = 'ResNet110v2'

```

```
In [ ]: input_shape = x_train.shape[1:]
```

### 1.3.4 3.D Learning Rate Decay Callbacks

```
In [ ]: def lr_schedule(epoch):
```

```
    """
```

```
    Learning Rate Schedule
```

```
    Learning rate is scheduled to be reduced after 80, 120, 160, 180 epochs.  

    Called automatically every epoch as part of callbacks during training.
```

```
    :param epoch: The number of epochs
```

```
    :Returns: lr (float32) learning rate  
    """
```

```

    lr = 1e-3
    if epoch > 180:
        lr *= 0.5e-3
    elif epoch > 160:
        lr *= 1e-3
    elif epoch > 120:
        lr *= 1e-2
    elif epoch > 80:
        lr *= 1e-1
    print('Learning rate: ', lr)
    return lr

```

```
lr_scheduler = LearningRateScheduler(lr_schedule)
```

```
lr_reducer = ReduceLROnPlateau(factor=np.sqrt(0.1), cooldown=0, patience=5, min_lr=0.5e-5)
```

### 1.3.5 3.E Defining ResNet110V2

```
In [ ]: def resnet_layer(inputs, num_filters=16, kernel_size=3, strides=1, activation='relu',
```

```
    """2D Convolution-Batch Normalization-Activation block
```

```
    :param inputs (tensor): input tensor from input image or previous layer
```

```
    :param num_filters (int): Conv2D number of filters
```

```
    :param kernel_size (int): Conv2D kernel dimensions
```

```
    :param strides (int): Conv2D stride dimensions
```

```
    :param activation (string): activation name
```

```
    :param batch_normalization (bool): whether to include batch normalization
```

```
    :param conv_first (bool): conv-bn-activation (True) or bn-activation-conv (False)
```

```

        :return: x (tensor) tensor as input to the next layer
        """
conv = Conv2D(num_filters, kernel_size=kernel_size, strides=strides, padding='same')

x = inputs
if conv_first:
    x = conv(x)
    if batch_normalization:
        x = BatchNormalization()(x)
    if activation is not None:
        x = Activation(activation)(x)
else:
    if batch_normalization:
        x = BatchNormalization()(x)
    if activation is not None:
        x = Activation(activation)(x)
    x = conv(x)
return x

def resnet110v2(input_shape, num_classes=10):
    """
    ResNet Version 2 Model

    Stacks of (1 x 1)-(3 x 3)-(1 x 1) BN-ReLU-Conv2D
    First shortcut connection per layer is 1 x 1 Conv2D.
    Second and onwards shortcut connection is identity.
    At the beginning of each stage, the feature map size is halved (downsampled)
    by a convolutional layer with strides=2, while the number of filter maps is
    doubled. Within each stage, the layers have the same number filters and the
    same filter map sizes.
    Features maps sizes:
    conv1 : 32x32, 16
    stage 0: 32x32, 64
    stage 1: 16x16, 128
    stage 2: 8x8, 256

    :param input_shape (tensor): shape of input tensor
    :param num_classes (int): number of classes

    :return: Keras model instance
    """

    # Start model definition.
    num_filters_in = 16

```

```

num_res_blocks = 12

inputs = Input(shape=input_shape)

x = resnet_layer(inputs=inputs, num_filters=num_filters_in, conv_first=True)

# Instantiate the resnet blocks
for stage in range(3):
    for res_block in range(num_res_blocks):
        activation = 'relu'
        batch_normalization = True
        strides = 1
        if stage == 0:
            num_filters_out = num_filters_in * 4
            if res_block == 0: # first layer and first stage
                activation = None
                batch_normalization = False
        else:
            num_filters_out = num_filters_in * 2
            if res_block == 0: # first layer but not first stage
                strides = 2

        # resnet blocks
        y = resnet_layer(inputs=x, num_filters=num_filters_in, kernel_size=1, strides=
                           batch_normalization=batch_normalization, conv_first=False)
        y = resnet_layer(inputs=y, num_filters=num_filters_in, conv_first=False)
        y = resnet_layer(inputs=y, num_filters=num_filters_out, kernel_size=1, conv
        if res_block == 0:
            # linear projection residual shortcut connection to match
            x = resnet_layer(inputs=x, num_filters=num_filters_out, kernel_size=1, conv
            x = keras.layers.add([x, y])

    num_filters_in = num_filters_out

# add classifier
x = BatchNormalization()(x)
x = Activation('relu')(x)
x = AveragePooling2D(pool_size=8)(x)
y = Flatten()(x)
outputs = Dense(num_classes, activation='softmax', kernel_initializer='he_normal')

# instantiate model
model = Model(inputs=inputs, outputs=outputs)
return model

```

### 1.3.6 3.F Compile Model

```
In [ ]: model = resnet110v2(input_shape=input_shape)
        model.compile(loss='categorical_crossentropy', optimizer=Adam(lr=lr_schedule(0)), metrics=['accuracy'])
        model.summary()
        print(model_type)
```

Learning rate: 0.001

Model: "model\_5"

Layer (type)	Output Shape	Param #	Connected to
input_6 (InputLayer)	(None, 32, 32, 3)	0	
conv2d_454 (Conv2D)	(None, 32, 32, 16)	448	input_6[0][0]
batch_normalization_440 (Batch Normalization)	(None, 32, 32, 16)	64	conv2d_454[0][0]
activation_440 (Activation)	(None, 32, 32, 16)	0	batch_normalization_440[0][0]
conv2d_455 (Conv2D)	(None, 32, 32, 16)	272	activation_440[0][0]
batch_normalization_441 (Batch Normalization)	(None, 32, 32, 16)	64	conv2d_455[0][0]
activation_441 (Activation)	(None, 32, 32, 16)	0	batch_normalization_441[0][0]
conv2d_456 (Conv2D)	(None, 32, 32, 16)	2320	activation_441[0][0]
batch_normalization_442 (Batch Normalization)	(None, 32, 32, 16)	64	conv2d_456[0][0]
activation_442 (Activation)	(None, 32, 32, 16)	0	batch_normalization_442[0][0]
conv2d_458 (Conv2D)	(None, 32, 32, 64)	1088	activation_440[0][0]
conv2d_457 (Conv2D)	(None, 32, 32, 64)	1088	activation_442[0][0]
add_145 (Add)	(None, 32, 32, 64)	0	conv2d_458[0][0] conv2d_457[0][0]
batch_normalization_443 (Batch Normalization)	(None, 32, 32, 64)	256	add_145[0][0]
activation_443 (Activation)	(None, 32, 32, 64)	0	batch_normalization_443[0][0]
conv2d_459 (Conv2D)	(None, 32, 32, 16)	1040	activation_443[0][0]
batch_normalization_444 (Batch Normalization)	(None, 32, 32, 16)	64	conv2d_459[0][0]
activation_444 (Activation)	(None, 32, 32, 16)	0	batch_normalization_444[0][0]

conv2d_460 (Conv2D)	(None, 32, 32, 16)	2320	activation_444[0][0]
batch_normalization_445 (BatchN	(None, 32, 32, 16)	64	conv2d_460[0][0]
activation_445 (Activation)	(None, 32, 32, 16)	0	batch_normalization_445[0][0]
conv2d_461 (Conv2D)	(None, 32, 32, 64)	1088	activation_445[0][0]
add_146 (Add)	(None, 32, 32, 64)	0	add_145[0][0] conv2d_461[0][0]
batch_normalization_446 (BatchN	(None, 32, 32, 64)	256	add_146[0][0]
activation_446 (Activation)	(None, 32, 32, 64)	0	batch_normalization_446[0][0]
conv2d_462 (Conv2D)	(None, 32, 32, 16)	1040	activation_446[0][0]
batch_normalization_447 (BatchN	(None, 32, 32, 16)	64	conv2d_462[0][0]
activation_447 (Activation)	(None, 32, 32, 16)	0	batch_normalization_447[0][0]
conv2d_463 (Conv2D)	(None, 32, 32, 16)	2320	activation_447[0][0]
batch_normalization_448 (BatchN	(None, 32, 32, 16)	64	conv2d_463[0][0]
activation_448 (Activation)	(None, 32, 32, 16)	0	batch_normalization_448[0][0]
conv2d_464 (Conv2D)	(None, 32, 32, 64)	1088	activation_448[0][0]
add_147 (Add)	(None, 32, 32, 64)	0	add_146[0][0] conv2d_464[0][0]
batch_normalization_449 (BatchN	(None, 32, 32, 64)	256	add_147[0][0]
activation_449 (Activation)	(None, 32, 32, 64)	0	batch_normalization_449[0][0]
conv2d_465 (Conv2D)	(None, 32, 32, 16)	1040	activation_449[0][0]
batch_normalization_450 (BatchN	(None, 32, 32, 16)	64	conv2d_465[0][0]
activation_450 (Activation)	(None, 32, 32, 16)	0	batch_normalization_450[0][0]
conv2d_466 (Conv2D)	(None, 32, 32, 16)	2320	activation_450[0][0]
batch_normalization_451 (BatchN	(None, 32, 32, 16)	64	conv2d_466[0][0]
activation_451 (Activation)	(None, 32, 32, 16)	0	batch_normalization_451[0][0]



conv2d_467 (Conv2D)	(None, 32, 32, 64)	1088	activation_451[0][0]
add_148 (Add)	(None, 32, 32, 64)	0	add_147[0][0] conv2d_467[0][0]
batch_normalization_452 (BatchN	(None, 32, 32, 64)	256	add_148[0][0]
activation_452 (Activation)	(None, 32, 32, 64)	0	batch_normalization_452[0][0]
conv2d_468 (Conv2D)	(None, 32, 32, 16)	1040	activation_452[0][0]
batch_normalization_453 (BatchN	(None, 32, 32, 16)	64	conv2d_468[0][0]
activation_453 (Activation)	(None, 32, 32, 16)	0	batch_normalization_453[0][0]
conv2d_469 (Conv2D)	(None, 32, 32, 16)	2320	activation_453[0][0]
batch_normalization_454 (BatchN	(None, 32, 32, 16)	64	conv2d_469[0][0]
activation_454 (Activation)	(None, 32, 32, 16)	0	batch_normalization_454[0][0]
conv2d_470 (Conv2D)	(None, 32, 32, 64)	1088	activation_454[0][0]
add_149 (Add)	(None, 32, 32, 64)	0	add_148[0][0] conv2d_470[0][0]
batch_normalization_455 (BatchN	(None, 32, 32, 64)	256	add_149[0][0]
activation_455 (Activation)	(None, 32, 32, 64)	0	batch_normalization_455[0][0]
conv2d_471 (Conv2D)	(None, 32, 32, 16)	1040	activation_455[0][0]
batch_normalization_456 (BatchN	(None, 32, 32, 16)	64	conv2d_471[0][0]
activation_456 (Activation)	(None, 32, 32, 16)	0	batch_normalization_456[0][0]
conv2d_472 (Conv2D)	(None, 32, 32, 16)	2320	activation_456[0][0]
batch_normalization_457 (BatchN	(None, 32, 32, 16)	64	conv2d_472[0][0]
activation_457 (Activation)	(None, 32, 32, 16)	0	batch_normalization_457[0][0]
conv2d_473 (Conv2D)	(None, 32, 32, 64)	1088	activation_457[0][0]
add_150 (Add)	(None, 32, 32, 64)	0	add_149[0][0] conv2d_473[0][0]
batch_normalization_458 (BatchN	(None, 32, 32, 64)	256	add_150[0][0]

activation_458 (Activation)	(None, 32, 32, 64)	0	batch_normalization_458[0][0]
conv2d_474 (Conv2D)	(None, 32, 32, 16)	1040	activation_458[0][0]
batch_normalization_459 (BatchN	(None, 32, 32, 16)	64	conv2d_474[0][0]
activation_459 (Activation)	(None, 32, 32, 16)	0	batch_normalization_459[0][0]
conv2d_475 (Conv2D)	(None, 32, 32, 16)	2320	activation_459[0][0]
batch_normalization_460 (BatchN	(None, 32, 32, 16)	64	conv2d_475[0][0]
activation_460 (Activation)	(None, 32, 32, 16)	0	batch_normalization_460[0][0]
conv2d_476 (Conv2D)	(None, 32, 32, 64)	1088	activation_460[0][0]
add_151 (Add)	(None, 32, 32, 64)	0	add_150[0][0] conv2d_476[0][0]
batch_normalization_461 (BatchN	(None, 32, 32, 64)	256	add_151[0][0]
activation_461 (Activation)	(None, 32, 32, 64)	0	batch_normalization_461[0][0]
conv2d_477 (Conv2D)	(None, 32, 32, 16)	1040	activation_461[0][0]
batch_normalization_462 (BatchN	(None, 32, 32, 16)	64	conv2d_477[0][0]
activation_462 (Activation)	(None, 32, 32, 16)	0	batch_normalization_462[0][0]
conv2d_478 (Conv2D)	(None, 32, 32, 16)	2320	activation_462[0][0]
batch_normalization_463 (BatchN	(None, 32, 32, 16)	64	conv2d_478[0][0]
activation_463 (Activation)	(None, 32, 32, 16)	0	batch_normalization_463[0][0]
conv2d_479 (Conv2D)	(None, 32, 32, 64)	1088	activation_463[0][0]
add_152 (Add)	(None, 32, 32, 64)	0	add_151[0][0] conv2d_479[0][0]
batch_normalization_464 (BatchN	(None, 32, 32, 64)	256	add_152[0][0]
activation_464 (Activation)	(None, 32, 32, 64)	0	batch_normalization_464[0][0]
conv2d_480 (Conv2D)	(None, 32, 32, 16)	1040	activation_464[0][0]
batch_normalization_465 (BatchN	(None, 32, 32, 16)	64	conv2d_480[0][0]

activation_465 (Activation)	(None, 32, 32, 16)	0	batch_normalization_465[0][0]
conv2d_481 (Conv2D)	(None, 32, 32, 16)	2320	activation_465[0][0]
batch_normalization_466 (BatchN	(None, 32, 32, 16)	64	conv2d_481[0][0]
activation_466 (Activation)	(None, 32, 32, 16)	0	batch_normalization_466[0][0]
conv2d_482 (Conv2D)	(None, 32, 32, 64)	1088	activation_466[0][0]
add_153 (Add)	(None, 32, 32, 64)	0	add_152[0][0] conv2d_482[0][0]
batch_normalization_467 (BatchN	(None, 32, 32, 64)	256	add_153[0][0]
activation_467 (Activation)	(None, 32, 32, 64)	0	batch_normalization_467[0][0]
conv2d_483 (Conv2D)	(None, 32, 32, 16)	1040	activation_467[0][0]
batch_normalization_468 (BatchN	(None, 32, 32, 16)	64	conv2d_483[0][0]
activation_468 (Activation)	(None, 32, 32, 16)	0	batch_normalization_468[0][0]
conv2d_484 (Conv2D)	(None, 32, 32, 16)	2320	activation_468[0][0]
batch_normalization_469 (BatchN	(None, 32, 32, 16)	64	conv2d_484[0][0]
activation_469 (Activation)	(None, 32, 32, 16)	0	batch_normalization_469[0][0]
conv2d_485 (Conv2D)	(None, 32, 32, 64)	1088	activation_469[0][0]
add_154 (Add)	(None, 32, 32, 64)	0	add_153[0][0] conv2d_485[0][0]
batch_normalization_470 (BatchN	(None, 32, 32, 64)	256	add_154[0][0]
activation_470 (Activation)	(None, 32, 32, 64)	0	batch_normalization_470[0][0]
conv2d_486 (Conv2D)	(None, 32, 32, 16)	1040	activation_470[0][0]
batch_normalization_471 (BatchN	(None, 32, 32, 16)	64	conv2d_486[0][0]
activation_471 (Activation)	(None, 32, 32, 16)	0	batch_normalization_471[0][0]
conv2d_487 (Conv2D)	(None, 32, 32, 16)	2320	activation_471[0][0]
batch_normalization_472 (BatchN	(None, 32, 32, 16)	64	conv2d_487[0][0]

activation_472 (Activation)	(None, 32, 32, 16)	0	batch_normalization_472[0][0]
conv2d_488 (Conv2D)	(None, 32, 32, 64)	1088	activation_472[0][0]
add_155 (Add)	(None, 32, 32, 64)	0	add_154[0][0] conv2d_488[0][0]
batch_normalization_473 (BatchN	(None, 32, 32, 64)	256	add_155[0][0]
activation_473 (Activation)	(None, 32, 32, 64)	0	batch_normalization_473[0][0]
conv2d_489 (Conv2D)	(None, 32, 32, 16)	1040	activation_473[0][0]
batch_normalization_474 (BatchN	(None, 32, 32, 16)	64	conv2d_489[0][0]
activation_474 (Activation)	(None, 32, 32, 16)	0	batch_normalization_474[0][0]
conv2d_490 (Conv2D)	(None, 32, 32, 16)	2320	activation_474[0][0]
batch_normalization_475 (BatchN	(None, 32, 32, 16)	64	conv2d_490[0][0]
activation_475 (Activation)	(None, 32, 32, 16)	0	batch_normalization_475[0][0]
conv2d_491 (Conv2D)	(None, 32, 32, 64)	1088	activation_475[0][0]
add_156 (Add)	(None, 32, 32, 64)	0	add_155[0][0] conv2d_491[0][0]
batch_normalization_476 (BatchN	(None, 32, 32, 64)	256	add_156[0][0]
activation_476 (Activation)	(None, 32, 32, 64)	0	batch_normalization_476[0][0]
conv2d_492 (Conv2D)	(None, 16, 16, 64)	4160	activation_476[0][0]
batch_normalization_477 (BatchN	(None, 16, 16, 64)	256	conv2d_492[0][0]
activation_477 (Activation)	(None, 16, 16, 64)	0	batch_normalization_477[0][0]
conv2d_493 (Conv2D)	(None, 16, 16, 64)	36928	activation_477[0][0]
batch_normalization_478 (BatchN	(None, 16, 16, 64)	256	conv2d_493[0][0]
activation_478 (Activation)	(None, 16, 16, 64)	0	batch_normalization_478[0][0]
conv2d_495 (Conv2D)	(None, 16, 16, 128)	8320	add_156[0][0]
conv2d_494 (Conv2D)	(None, 16, 16, 128)	8320	activation_478[0][0]

add_157 (Add)	(None, 16, 16, 128)	0	conv2d_495[0][0] conv2d_494[0][0]
batch_normalization_479 (BatchN	(None, 16, 16, 128)	512	add_157[0][0]
activation_479 (Activation)	(None, 16, 16, 128)	0	batch_normalization_479[0][0]
conv2d_496 (Conv2D)	(None, 16, 16, 64)	8256	activation_479[0][0]
batch_normalization_480 (BatchN	(None, 16, 16, 64)	256	conv2d_496[0][0]
activation_480 (Activation)	(None, 16, 16, 64)	0	batch_normalization_480[0][0]
conv2d_497 (Conv2D)	(None, 16, 16, 64)	36928	activation_480[0][0]
batch_normalization_481 (BatchN	(None, 16, 16, 64)	256	conv2d_497[0][0]
activation_481 (Activation)	(None, 16, 16, 64)	0	batch_normalization_481[0][0]
conv2d_498 (Conv2D)	(None, 16, 16, 128)	8320	activation_481[0][0]
add_158 (Add)	(None, 16, 16, 128)	0	add_157[0][0] conv2d_498[0][0]
batch_normalization_482 (BatchN	(None, 16, 16, 128)	512	add_158[0][0]
activation_482 (Activation)	(None, 16, 16, 128)	0	batch_normalization_482[0][0]
conv2d_499 (Conv2D)	(None, 16, 16, 64)	8256	activation_482[0][0]
batch_normalization_483 (BatchN	(None, 16, 16, 64)	256	conv2d_499[0][0]
activation_483 (Activation)	(None, 16, 16, 64)	0	batch_normalization_483[0][0]
conv2d_500 (Conv2D)	(None, 16, 16, 64)	36928	activation_483[0][0]
batch_normalization_484 (BatchN	(None, 16, 16, 64)	256	conv2d_500[0][0]
activation_484 (Activation)	(None, 16, 16, 64)	0	batch_normalization_484[0][0]
conv2d_501 (Conv2D)	(None, 16, 16, 128)	8320	activation_484[0][0]
add_159 (Add)	(None, 16, 16, 128)	0	add_158[0][0] conv2d_501[0][0]
batch_normalization_485 (BatchN	(None, 16, 16, 128)	512	add_159[0][0]

activation_485 (Activation)	(None, 16, 16, 128)	0	batch_normalization_485[0][0]
conv2d_502 (Conv2D)	(None, 16, 16, 64)	8256	activation_485[0][0]
batch_normalization_486 (BatchN	(None, 16, 16, 64)	256	conv2d_502[0][0]
activation_486 (Activation)	(None, 16, 16, 64)	0	batch_normalization_486[0][0]
conv2d_503 (Conv2D)	(None, 16, 16, 64)	36928	activation_486[0][0]
batch_normalization_487 (BatchN	(None, 16, 16, 64)	256	conv2d_503[0][0]
activation_487 (Activation)	(None, 16, 16, 64)	0	batch_normalization_487[0][0]
conv2d_504 (Conv2D)	(None, 16, 16, 128)	8320	activation_487[0][0]
add_160 (Add)	(None, 16, 16, 128)	0	add_159[0][0] conv2d_504[0][0]
batch_normalization_488 (BatchN	(None, 16, 16, 128)	512	add_160[0][0]
activation_488 (Activation)	(None, 16, 16, 128)	0	batch_normalization_488[0][0]
conv2d_505 (Conv2D)	(None, 16, 16, 64)	8256	activation_488[0][0]
batch_normalization_489 (BatchN	(None, 16, 16, 64)	256	conv2d_505[0][0]
activation_489 (Activation)	(None, 16, 16, 64)	0	batch_normalization_489[0][0]
conv2d_506 (Conv2D)	(None, 16, 16, 64)	36928	activation_489[0][0]
batch_normalization_490 (BatchN	(None, 16, 16, 64)	256	conv2d_506[0][0]
activation_490 (Activation)	(None, 16, 16, 64)	0	batch_normalization_490[0][0]
conv2d_507 (Conv2D)	(None, 16, 16, 128)	8320	activation_490[0][0]
add_161 (Add)	(None, 16, 16, 128)	0	add_160[0][0] conv2d_507[0][0]
batch_normalization_491 (BatchN	(None, 16, 16, 128)	512	add_161[0][0]
activation_491 (Activation)	(None, 16, 16, 128)	0	batch_normalization_491[0][0]
conv2d_508 (Conv2D)	(None, 16, 16, 64)	8256	activation_491[0][0]
batch_normalization_492 (BatchN	(None, 16, 16, 64)	256	conv2d_508[0][0]

activation_492 (Activation)	(None, 16, 16, 64)	0	batch_normalization_492[0][0]
conv2d_509 (Conv2D)	(None, 16, 16, 64)	36928	activation_492[0][0]
batch_normalization_493 (BatchN	(None, 16, 16, 64)	256	conv2d_509[0][0]
activation_493 (Activation)	(None, 16, 16, 64)	0	batch_normalization_493[0][0]
conv2d_510 (Conv2D)	(None, 16, 16, 128)	8320	activation_493[0][0]
add_162 (Add)	(None, 16, 16, 128)	0	add_161[0][0] conv2d_510[0][0]
batch_normalization_494 (BatchN	(None, 16, 16, 128)	512	add_162[0][0]
activation_494 (Activation)	(None, 16, 16, 128)	0	batch_normalization_494[0][0]
conv2d_511 (Conv2D)	(None, 16, 16, 64)	8256	activation_494[0][0]
batch_normalization_495 (BatchN	(None, 16, 16, 64)	256	conv2d_511[0][0]
activation_495 (Activation)	(None, 16, 16, 64)	0	batch_normalization_495[0][0]
conv2d_512 (Conv2D)	(None, 16, 16, 64)	36928	activation_495[0][0]
batch_normalization_496 (BatchN	(None, 16, 16, 64)	256	conv2d_512[0][0]
activation_496 (Activation)	(None, 16, 16, 64)	0	batch_normalization_496[0][0]
conv2d_513 (Conv2D)	(None, 16, 16, 128)	8320	activation_496[0][0]
add_163 (Add)	(None, 16, 16, 128)	0	add_162[0][0] conv2d_513[0][0]
batch_normalization_497 (BatchN	(None, 16, 16, 128)	512	add_163[0][0]
activation_497 (Activation)	(None, 16, 16, 128)	0	batch_normalization_497[0][0]
conv2d_514 (Conv2D)	(None, 16, 16, 64)	8256	activation_497[0][0]
batch_normalization_498 (BatchN	(None, 16, 16, 64)	256	conv2d_514[0][0]
activation_498 (Activation)	(None, 16, 16, 64)	0	batch_normalization_498[0][0]
conv2d_515 (Conv2D)	(None, 16, 16, 64)	36928	activation_498[0][0]
batch_normalization_499 (BatchN	(None, 16, 16, 64)	256	conv2d_515[0][0]

activation_499 (Activation)	(None, 16, 16, 64)	0	batch_normalization_499[0][0]
conv2d_516 (Conv2D)	(None, 16, 16, 128)	8320	activation_499[0][0]
add_164 (Add)	(None, 16, 16, 128)	0	add_163[0][0] conv2d_516[0][0]
batch_normalization_500 (BatchN	(None, 16, 16, 128)	512	add_164[0][0]
activation_500 (Activation)	(None, 16, 16, 128)	0	batch_normalization_500[0][0]
conv2d_517 (Conv2D)	(None, 16, 16, 64)	8256	activation_500[0][0]
batch_normalization_501 (BatchN	(None, 16, 16, 64)	256	conv2d_517[0][0]
activation_501 (Activation)	(None, 16, 16, 64)	0	batch_normalization_501[0][0]
conv2d_518 (Conv2D)	(None, 16, 16, 64)	36928	activation_501[0][0]
batch_normalization_502 (BatchN	(None, 16, 16, 64)	256	conv2d_518[0][0]
activation_502 (Activation)	(None, 16, 16, 64)	0	batch_normalization_502[0][0]
conv2d_519 (Conv2D)	(None, 16, 16, 128)	8320	activation_502[0][0]
add_165 (Add)	(None, 16, 16, 128)	0	add_164[0][0] conv2d_519[0][0]
batch_normalization_503 (BatchN	(None, 16, 16, 128)	512	add_165[0][0]
activation_503 (Activation)	(None, 16, 16, 128)	0	batch_normalization_503[0][0]
conv2d_520 (Conv2D)	(None, 16, 16, 64)	8256	activation_503[0][0]
batch_normalization_504 (BatchN	(None, 16, 16, 64)	256	conv2d_520[0][0]
activation_504 (Activation)	(None, 16, 16, 64)	0	batch_normalization_504[0][0]
conv2d_521 (Conv2D)	(None, 16, 16, 64)	36928	activation_504[0][0]
batch_normalization_505 (BatchN	(None, 16, 16, 64)	256	conv2d_521[0][0]
activation_505 (Activation)	(None, 16, 16, 64)	0	batch_normalization_505[0][0]
conv2d_522 (Conv2D)	(None, 16, 16, 128)	8320	activation_505[0][0]
add_166 (Add)	(None, 16, 16, 128)	0	add_165[0][0] conv2d_522[0][0]



batch_normalization_506 (BatchN	(None, 16, 16, 128)	512	add_166[0][0]
activation_506 (Activation)	(None, 16, 16, 128)	0	batch_normalization_506[0][0]
conv2d_523 (Conv2D)	(None, 16, 16, 64)	8256	activation_506[0][0]
batch_normalization_507 (BatchN	(None, 16, 16, 64)	256	conv2d_523[0][0]
activation_507 (Activation)	(None, 16, 16, 64)	0	batch_normalization_507[0][0]
conv2d_524 (Conv2D)	(None, 16, 16, 64)	36928	activation_507[0][0]
batch_normalization_508 (BatchN	(None, 16, 16, 64)	256	conv2d_524[0][0]
activation_508 (Activation)	(None, 16, 16, 64)	0	batch_normalization_508[0][0]
conv2d_525 (Conv2D)	(None, 16, 16, 128)	8320	activation_508[0][0]
add_167 (Add)	(None, 16, 16, 128)	0	add_166[0][0] conv2d_525[0][0]
batch_normalization_509 (BatchN	(None, 16, 16, 128)	512	add_167[0][0]
activation_509 (Activation)	(None, 16, 16, 128)	0	batch_normalization_509[0][0]
conv2d_526 (Conv2D)	(None, 16, 16, 64)	8256	activation_509[0][0]
batch_normalization_510 (BatchN	(None, 16, 16, 64)	256	conv2d_526[0][0]
activation_510 (Activation)	(None, 16, 16, 64)	0	batch_normalization_510[0][0]
conv2d_527 (Conv2D)	(None, 16, 16, 64)	36928	activation_510[0][0]
batch_normalization_511 (BatchN	(None, 16, 16, 64)	256	conv2d_527[0][0]
activation_511 (Activation)	(None, 16, 16, 64)	0	batch_normalization_511[0][0]
conv2d_528 (Conv2D)	(None, 16, 16, 128)	8320	activation_511[0][0]
add_168 (Add)	(None, 16, 16, 128)	0	add_167[0][0] conv2d_528[0][0]
batch_normalization_512 (BatchN	(None, 16, 16, 128)	512	add_168[0][0]
activation_512 (Activation)	(None, 16, 16, 128)	0	batch_normalization_512[0][0]
conv2d_529 (Conv2D)	(None, 8, 8, 128)	16512	activation_512[0][0]

batch_normalization_513 (BatchN	(None, 8, 8, 128)	512	conv2d_529[0][0]
activation_513 (Activation)	(None, 8, 8, 128)	0	batch_normalization_513[0][0]
conv2d_530 (Conv2D)	(None, 8, 8, 128)	147584	activation_513[0][0]
batch_normalization_514 (BatchN	(None, 8, 8, 128)	512	conv2d_530[0][0]
activation_514 (Activation)	(None, 8, 8, 128)	0	batch_normalization_514[0][0]
conv2d_532 (Conv2D)	(None, 8, 8, 256)	33024	add_168[0][0]
conv2d_531 (Conv2D)	(None, 8, 8, 256)	33024	activation_514[0][0]
add_169 (Add)	(None, 8, 8, 256)	0	conv2d_532[0][0] conv2d_531[0][0]
batch_normalization_515 (BatchN	(None, 8, 8, 256)	1024	add_169[0][0]
activation_515 (Activation)	(None, 8, 8, 256)	0	batch_normalization_515[0][0]
conv2d_533 (Conv2D)	(None, 8, 8, 128)	32896	activation_515[0][0]
batch_normalization_516 (BatchN	(None, 8, 8, 128)	512	conv2d_533[0][0]
activation_516 (Activation)	(None, 8, 8, 128)	0	batch_normalization_516[0][0]
conv2d_534 (Conv2D)	(None, 8, 8, 128)	147584	activation_516[0][0]
batch_normalization_517 (BatchN	(None, 8, 8, 128)	512	conv2d_534[0][0]
activation_517 (Activation)	(None, 8, 8, 128)	0	batch_normalization_517[0][0]
conv2d_535 (Conv2D)	(None, 8, 8, 256)	33024	activation_517[0][0]
add_170 (Add)	(None, 8, 8, 256)	0	add_169[0][0] conv2d_535[0][0]
batch_normalization_518 (BatchN	(None, 8, 8, 256)	1024	add_170[0][0]
activation_518 (Activation)	(None, 8, 8, 256)	0	batch_normalization_518[0][0]
conv2d_536 (Conv2D)	(None, 8, 8, 128)	32896	activation_518[0][0]
batch_normalization_519 (BatchN	(None, 8, 8, 128)	512	conv2d_536[0][0]
activation_519 (Activation)	(None, 8, 8, 128)	0	batch_normalization_519[0][0]

conv2d_537 (Conv2D)	(None, 8, 8, 128)	147584	activation_519[0][0]
batch_normalization_520 (BatchN	(None, 8, 8, 128)	512	conv2d_537[0][0]
activation_520 (Activation)	(None, 8, 8, 128)	0	batch_normalization_520[0][0]
conv2d_538 (Conv2D)	(None, 8, 8, 256)	33024	activation_520[0][0]
add_171 (Add)	(None, 8, 8, 256)	0	add_170[0][0] conv2d_538[0][0]
batch_normalization_521 (BatchN	(None, 8, 8, 256)	1024	add_171[0][0]
activation_521 (Activation)	(None, 8, 8, 256)	0	batch_normalization_521[0][0]
conv2d_539 (Conv2D)	(None, 8, 8, 128)	32896	activation_521[0][0]
batch_normalization_522 (BatchN	(None, 8, 8, 128)	512	conv2d_539[0][0]
activation_522 (Activation)	(None, 8, 8, 128)	0	batch_normalization_522[0][0]
conv2d_540 (Conv2D)	(None, 8, 8, 128)	147584	activation_522[0][0]
batch_normalization_523 (BatchN	(None, 8, 8, 128)	512	conv2d_540[0][0]
activation_523 (Activation)	(None, 8, 8, 128)	0	batch_normalization_523[0][0]
conv2d_541 (Conv2D)	(None, 8, 8, 256)	33024	activation_523[0][0]
add_172 (Add)	(None, 8, 8, 256)	0	add_171[0][0] conv2d_541[0][0]
batch_normalization_524 (BatchN	(None, 8, 8, 256)	1024	add_172[0][0]
activation_524 (Activation)	(None, 8, 8, 256)	0	batch_normalization_524[0][0]
conv2d_542 (Conv2D)	(None, 8, 8, 128)	32896	activation_524[0][0]
batch_normalization_525 (BatchN	(None, 8, 8, 128)	512	conv2d_542[0][0]
activation_525 (Activation)	(None, 8, 8, 128)	0	batch_normalization_525[0][0]
conv2d_543 (Conv2D)	(None, 8, 8, 128)	147584	activation_525[0][0]
batch_normalization_526 (BatchN	(None, 8, 8, 128)	512	conv2d_543[0][0]
activation_526 (Activation)	(None, 8, 8, 128)	0	batch_normalization_526[0][0]

conv2d_544 (Conv2D)	(None, 8, 8, 256)	33024	activation_526[0][0]
add_173 (Add)	(None, 8, 8, 256)	0	add_172[0][0] conv2d_544[0][0]
batch_normalization_527 (BatchN	(None, 8, 8, 256)	1024	add_173[0][0]
activation_527 (Activation)	(None, 8, 8, 256)	0	batch_normalization_527[0][0]
conv2d_545 (Conv2D)	(None, 8, 8, 128)	32896	activation_527[0][0]
batch_normalization_528 (BatchN	(None, 8, 8, 128)	512	conv2d_545[0][0]
activation_528 (Activation)	(None, 8, 8, 128)	0	batch_normalization_528[0][0]
conv2d_546 (Conv2D)	(None, 8, 8, 128)	147584	activation_528[0][0]
batch_normalization_529 (BatchN	(None, 8, 8, 128)	512	conv2d_546[0][0]
activation_529 (Activation)	(None, 8, 8, 128)	0	batch_normalization_529[0][0]
conv2d_547 (Conv2D)	(None, 8, 8, 256)	33024	activation_529[0][0]
add_174 (Add)	(None, 8, 8, 256)	0	add_173[0][0] conv2d_547[0][0]
batch_normalization_530 (BatchN	(None, 8, 8, 256)	1024	add_174[0][0]
activation_530 (Activation)	(None, 8, 8, 256)	0	batch_normalization_530[0][0]
conv2d_548 (Conv2D)	(None, 8, 8, 128)	32896	activation_530[0][0]
batch_normalization_531 (BatchN	(None, 8, 8, 128)	512	conv2d_548[0][0]
activation_531 (Activation)	(None, 8, 8, 128)	0	batch_normalization_531[0][0]
conv2d_549 (Conv2D)	(None, 8, 8, 128)	147584	activation_531[0][0]
batch_normalization_532 (BatchN	(None, 8, 8, 128)	512	conv2d_549[0][0]
activation_532 (Activation)	(None, 8, 8, 128)	0	batch_normalization_532[0][0]
conv2d_550 (Conv2D)	(None, 8, 8, 256)	33024	activation_532[0][0]
add_175 (Add)	(None, 8, 8, 256)	0	add_174[0][0] conv2d_550[0][0]

batch_normalization_533 (BatchN	(None, 8, 8, 256)	1024	add_175[0] [0]
activation_533 (Activation)	(None, 8, 8, 256)	0	batch_normalization_533[0] [0]
conv2d_551 (Conv2D)	(None, 8, 8, 128)	32896	activation_533[0] [0]
batch_normalization_534 (BatchN	(None, 8, 8, 128)	512	conv2d_551[0] [0]
activation_534 (Activation)	(None, 8, 8, 128)	0	batch_normalization_534[0] [0]
conv2d_552 (Conv2D)	(None, 8, 8, 128)	147584	activation_534[0] [0]
batch_normalization_535 (BatchN	(None, 8, 8, 128)	512	conv2d_552[0] [0]
activation_535 (Activation)	(None, 8, 8, 128)	0	batch_normalization_535[0] [0]
conv2d_553 (Conv2D)	(None, 8, 8, 256)	33024	activation_535[0] [0]
add_176 (Add)	(None, 8, 8, 256)	0	add_175[0] [0] conv2d_553[0] [0]
batch_normalization_536 (BatchN	(None, 8, 8, 256)	1024	add_176[0] [0]
activation_536 (Activation)	(None, 8, 8, 256)	0	batch_normalization_536[0] [0]
conv2d_554 (Conv2D)	(None, 8, 8, 128)	32896	activation_536[0] [0]
batch_normalization_537 (BatchN	(None, 8, 8, 128)	512	conv2d_554[0] [0]
activation_537 (Activation)	(None, 8, 8, 128)	0	batch_normalization_537[0] [0]
conv2d_555 (Conv2D)	(None, 8, 8, 128)	147584	activation_537[0] [0]
batch_normalization_538 (BatchN	(None, 8, 8, 128)	512	conv2d_555[0] [0]
activation_538 (Activation)	(None, 8, 8, 128)	0	batch_normalization_538[0] [0]
conv2d_556 (Conv2D)	(None, 8, 8, 256)	33024	activation_538[0] [0]
add_177 (Add)	(None, 8, 8, 256)	0	add_176[0] [0] conv2d_556[0] [0]
batch_normalization_539 (BatchN	(None, 8, 8, 256)	1024	add_177[0] [0]
activation_539 (Activation)	(None, 8, 8, 256)	0	batch_normalization_539[0] [0]
conv2d_557 (Conv2D)	(None, 8, 8, 128)	32896	activation_539[0] [0]

batch_normalization_540 (BatchN	(None, 8, 8, 128)	512	conv2d_557[0][0]
activation_540 (Activation)	(None, 8, 8, 128)	0	batch_normalization_540[0][0]
conv2d_558 (Conv2D)	(None, 8, 8, 128)	147584	activation_540[0][0]
batch_normalization_541 (BatchN	(None, 8, 8, 128)	512	conv2d_558[0][0]
activation_541 (Activation)	(None, 8, 8, 128)	0	batch_normalization_541[0][0]
conv2d_559 (Conv2D)	(None, 8, 8, 256)	33024	activation_541[0][0]
add_178 (Add)	(None, 8, 8, 256)	0	add_177[0][0] conv2d_559[0][0]
batch_normalization_542 (BatchN	(None, 8, 8, 256)	1024	add_178[0][0]
activation_542 (Activation)	(None, 8, 8, 256)	0	batch_normalization_542[0][0]
conv2d_560 (Conv2D)	(None, 8, 8, 128)	32896	activation_542[0][0]
batch_normalization_543 (BatchN	(None, 8, 8, 128)	512	conv2d_560[0][0]
activation_543 (Activation)	(None, 8, 8, 128)	0	batch_normalization_543[0][0]
conv2d_561 (Conv2D)	(None, 8, 8, 128)	147584	activation_543[0][0]
batch_normalization_544 (BatchN	(None, 8, 8, 128)	512	conv2d_561[0][0]
activation_544 (Activation)	(None, 8, 8, 128)	0	batch_normalization_544[0][0]
conv2d_562 (Conv2D)	(None, 8, 8, 256)	33024	activation_544[0][0]
add_179 (Add)	(None, 8, 8, 256)	0	add_178[0][0] conv2d_562[0][0]
batch_normalization_545 (BatchN	(None, 8, 8, 256)	1024	add_179[0][0]
activation_545 (Activation)	(None, 8, 8, 256)	0	batch_normalization_545[0][0]
conv2d_563 (Conv2D)	(None, 8, 8, 128)	32896	activation_545[0][0]
batch_normalization_546 (BatchN	(None, 8, 8, 128)	512	conv2d_563[0][0]
activation_546 (Activation)	(None, 8, 8, 128)	0	batch_normalization_546[0][0]
conv2d_564 (Conv2D)	(None, 8, 8, 128)	147584	activation_546[0][0]

batch_normalization_547 (BatchN	(None, 8, 8, 128)	512	conv2d_564[0][0]
activation_547 (Activation)	(None, 8, 8, 128)	0	batch_normalization_547[0][0]
conv2d_565 (Conv2D)	(None, 8, 8, 256)	33024	activation_547[0][0]
add_180 (Add)	(None, 8, 8, 256)	0	add_179[0][0] conv2d_565[0][0]
batch_normalization_548 (BatchN	(None, 8, 8, 256)	1024	add_180[0][0]
activation_548 (Activation)	(None, 8, 8, 256)	0	batch_normalization_548[0][0]
average_pooling2d_5 (AveragePoo	(None, 1, 1, 256)	0	activation_548[0][0]
flatten_5 (Flatten)	(None, 256)	0	average_pooling2d_5[0][0]
dense_5 (Dense)	(None, 10)	2570	flatten_5[0][0]

=====  
 Total params: 3,323,210  
 Trainable params: 3,302,442  
 Non-trainable params: 20,768  
 =====  
 ResNet110v2

### 1.3.7 3.G Save Model Callbacks

```

In [ ]: import os
        def prepare_directory(model_type):
            save_dir = os.path.join(os.getcwd(), 'saved_model')
            model_name = 'cifar10_%s_model.{epoch:03d}.h5' % model_type
            if not os.path.isdir(save_dir):
                os.makedirs(save_dir)
            filepath = os.path.join(save_dir, model_name)
            return filepath

        filepath = prepare_directory(model_type)

        checkpoint = ModelCheckpoint(filepath=filepath, monitor='val_acc', verbose=1, save_best_only=True)

        # gather all callbacks
        callbacks = [checkpoint, lr_reducer, lr_scheduler]

        # set ImageDataGenerator to use data augmentation
  
```

### 1.3.8 3.H Cutout Regularization

```
In [ ]: import numpy as np
def get_random_eraser(p=0.5, s_l=0.02, s_h=0.4, r_1=0.3, r_2=1/0.3, v_l=0, v_h=255, pi):
    def eraser(input_img):
        img_h, img_w, img_c = input_img.shape
        p_1 = np.random.rand()
        if p_1 > p:
            return input_img
        while True:
            s = np.random.uniform(s_l, s_h) * img_h * img_w
            r = np.random.uniform(r_1, r_2)
            w = int(np.sqrt(s / r))
            h = int(np.sqrt(s * r))
            left = np.random.randint(0, img_w)
            top = np.random.randint(0, img_h)

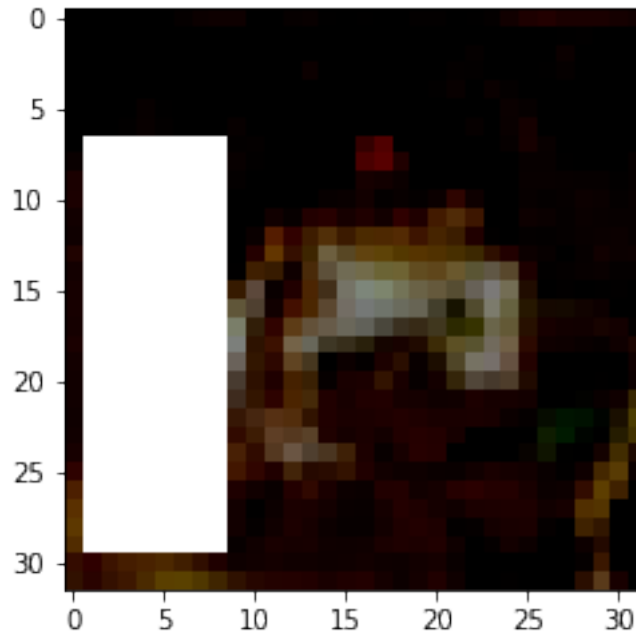
            if left + w <= img_w and top + h <= img_h:
                break
        if pixel_level:
            c = np.random.uniform(v_l, v_h, (h, w, img_c))
        else:
            c = np.random.uniform(v_l, v_h)
            input_img[top:top + h, left:left + w, :] = c
        return input_img
    return eraser

In [ ]: from copy import deepcopy
z = deepcopy(x_train[0])
plt.imshow(get_random_eraser()(z))
```

Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255]

```
Out[ ]: <matplotlib.image.AxesImage at 0x7f0898ed5cf8>
```





### 1.3.9 3.I ImageDataGenerator

```
In [ ]: datagen = ImageDataGenerator(
        rotation_range=20,
        width_shift_range=0.1,
        height_shift_range=0.1,
        fill_mode='nearest',
        cval=0.,
        zoom_range=0.1,
        horizontal_flip=True,
        rescale=None,
        preprocessing_function=get_random_eraser(v_l=0, v_h=1, pixel_level=False))

        datagen.fit(x_train)
```

### 1.3.10 3.J Train Model

```
In [89]: model.fit_generator(datagen.flow(x_train, y_train, batch_size=batch_size),
                             validation_data=(x_test, y_test), epochs=epochs, verbose=1, workers=1)
```

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow\_core/python/ops/math\_ops.py:3066: tf.nn.conv2d is deprecated and will be removed in a future version.

Instructions for updating:

Use tf.nn.conv2d in 2.0, which has the same broadcast rule as np.where

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:396: tf.nn.conv2d is deprecated and will be removed in a future version.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:396: tf.nn.conv2d is deprecated and will be removed in a future version.

Epoch 1/200  
Learning rate: 0.001  
1563/1563 [=====] - 736s 471ms/step - loss: 2.5089 - acc: 0.4288 - val\_loss: 2.5089  
Epoch 00001: val\_acc improved from -inf to 0.46530, saving model to /content/saved\_model/cifar100/epoch\_00001  
Epoch 2/200  
Learning rate: 0.001  
1563/1563 [=====] - 668s 428ms/step - loss: 1.6728 - acc: 0.5514 - val\_loss: 1.6728  
Epoch 00002: val\_acc improved from 0.46530 to 0.50460, saving model to /content/saved\_model/cifar100/epoch\_00002  
Epoch 3/200  
Learning rate: 0.001  
1563/1563 [=====] - 661s 423ms/step - loss: 1.4663 - acc: 0.6035 - val\_loss: 1.4663  
Epoch 00003: val\_acc improved from 0.50460 to 0.54330, saving model to /content/saved\_model/cifar100/epoch\_00003  
Epoch 4/200  
Learning rate: 0.001  
1563/1563 [=====] - 663s 424ms/step - loss: 1.3443 - acc: 0.6397 - val\_loss: 1.3443  
Epoch 00004: val\_acc improved from 0.54330 to 0.57700, saving model to /content/saved\_model/cifar100/epoch\_00004  
Epoch 5/200  
Learning rate: 0.001  
1563/1563 [=====] - 664s 425ms/step - loss: 1.2577 - acc: 0.6681 - val\_loss: 1.2577  
Epoch 00005: val\_acc improved from 0.57700 to 0.64620, saving model to /content/saved\_model/cifar100/epoch\_00005  
Epoch 6/200  
Learning rate: 0.001  
1563/1563 [=====] - 665s 426ms/step - loss: 1.1900 - acc: 0.6888 - val\_loss: 1.1900  
Epoch 00006: val\_acc improved from 0.64620 to 0.64650, saving model to /content/saved\_model/cifar100/epoch\_00006  
Epoch 7/200  
Learning rate: 0.001  
1563/1563 [=====] - 664s 425ms/step - loss: 1.1353 - acc: 0.7021 - val\_loss: 1.1353  
Epoch 00007: val\_acc improved from 0.64650 to 0.67940, saving model to /content/saved\_model/cifar100/epoch\_00007  
Epoch 8/200  
Learning rate: 0.001  
1563/1563 [=====] - 661s 423ms/step - loss: 1.0915 - acc: 0.7131 - val\_loss: 1.0915  
Epoch 00008: val\_acc improved from 0.67940 to 0.72560, saving model to /content/saved\_model/cifar100/epoch\_00008  
Epoch 9/200  
Learning rate: 0.001  
1563/1563 [=====] - 662s 423ms/step - loss: 1.0495 - acc: 0.7275 - val\_loss: 1.0495  
Epoch 00009: val\_acc did not improve from 0.72560  
Epoch 10/200  
Learning rate: 0.001

1563/1563 [=====] - 667s 427ms/step - loss: 1.0190 - acc: 0.7342 - val\_acc: 0.72560

Epoch 00010: val\_acc did not improve from 0.72560

Epoch 11/200

Learning rate: 0.001

1563/1563 [=====] - 663s 424ms/step - loss: 0.9953 - acc: 0.7428 - val\_acc: 0.72560

Epoch 00011: val\_acc did not improve from 0.72560

Epoch 12/200

Learning rate: 0.001

1563/1563 [=====] - 665s 425ms/step - loss: 0.9653 - acc: 0.7523 - val\_acc: 0.72560

Epoch 00012: val\_acc improved from 0.72560 to 0.73550, saving model to /content/saved\_model/cifar100\_00012.h5

Epoch 13/200

Learning rate: 0.001

1563/1563 [=====] - 663s 424ms/step - loss: 0.9463 - acc: 0.7571 - val\_acc: 0.73550

Epoch 00013: val\_acc improved from 0.73550 to 0.77580, saving model to /content/saved\_model/cifar100\_00013.h5

Epoch 14/200

Learning rate: 0.001

1563/1563 [=====] - 663s 424ms/step - loss: 0.9306 - acc: 0.7644 - val\_acc: 0.77580

Epoch 00014: val\_acc did not improve from 0.77580

Epoch 15/200

Learning rate: 0.001

1563/1563 [=====] - 665s 425ms/step - loss: 0.9081 - acc: 0.7692 - val\_acc: 0.77580

Epoch 00015: val\_acc improved from 0.77580 to 0.79450, saving model to /content/saved\_model/cifar100\_00015.h5

Epoch 16/200

Learning rate: 0.001

1563/1563 [=====] - 662s 423ms/step - loss: 0.8867 - acc: 0.7762 - val\_acc: 0.79450

Epoch 00016: val\_acc did not improve from 0.79450

Epoch 17/200

Learning rate: 0.001

1563/1563 [=====] - 665s 425ms/step - loss: 0.8761 - acc: 0.7804 - val\_acc: 0.79450

Epoch 00017: val\_acc did not improve from 0.79450

Epoch 18/200

Learning rate: 0.001

1563/1563 [=====] - 663s 424ms/step - loss: 0.8550 - acc: 0.7835 - val\_acc: 0.79450

Epoch 00018: val\_acc improved from 0.79450 to 0.80160, saving model to /content/saved\_model/cifar100\_00018.h5

Epoch 19/200

Learning rate: 0.001

1563/1563 [=====] - 662s 424ms/step - loss: 0.8470 - acc: 0.7880 - val\_acc: 0.80160

Epoch 00019: val\_acc did not improve from 0.80160

Epoch 20/200  
Learning rate: 0.001  
1563/1563 [=====] - 663s 424ms/step - loss: 0.8328 - acc: 0.7918 - val\_

Epoch 00020: val\_acc did not improve from 0.80160  
Epoch 21/200  
Learning rate: 0.001  
1563/1563 [=====] - 662s 424ms/step - loss: 0.8248 - acc: 0.7935 - val\_

Epoch 00021: val\_acc improved from 0.80160 to 0.80270, saving model to /content/saved\_model/ci  
Epoch 22/200  
Learning rate: 0.001  
1563/1563 [=====] - 662s 424ms/step - loss: 0.8126 - acc: 0.7986 - val\_

Epoch 00022: val\_acc improved from 0.80270 to 0.81100, saving model to /content/saved\_model/ci  
Epoch 23/200  
Learning rate: 0.001  
1563/1563 [=====] - 663s 424ms/step - loss: 0.8095 - acc: 0.7982 - val\_

Epoch 00023: val\_acc did not improve from 0.81100  
Epoch 24/200  
Learning rate: 0.001  
1563/1563 [=====] - 663s 424ms/step - loss: 0.7983 - acc: 0.8012 - val\_

Epoch 00024: val\_acc did not improve from 0.81100  
Epoch 25/200  
Learning rate: 0.001  
1563/1563 [=====] - 661s 423ms/step - loss: 0.7898 - acc: 0.8066 - val\_

Epoch 00025: val\_acc did not improve from 0.81100  
Epoch 26/200  
Learning rate: 0.001  
1563/1563 [=====] - 664s 425ms/step - loss: 0.7797 - acc: 0.8088 - val\_

Epoch 00026: val\_acc did not improve from 0.81100  
Epoch 27/200  
Learning rate: 0.001  
1563/1563 [=====] - 667s 427ms/step - loss: 0.7751 - acc: 0.8099 - val\_

Epoch 00027: val\_acc improved from 0.81100 to 0.84430, saving model to /content/saved\_model/ci  
Epoch 28/200  
Learning rate: 0.001  
1563/1563 [=====] - 668s 427ms/step - loss: 0.7702 - acc: 0.8101 - val\_

Epoch 00028: val\_acc did not improve from 0.84430  
Epoch 29/200  
Learning rate: 0.001  
1563/1563 [=====] - 662s 424ms/step - loss: 0.7594 - acc: 0.8139 - val\_

Epoch 00029: val\_acc did not improve from 0.84430

Epoch 30/200

Learning rate: 0.001

1563/1563 [=====] - 664s 425ms/step - loss: 0.7575 - acc: 0.8137 - va

Epoch 00030: val\_acc did not improve from 0.84430

Epoch 31/200

Learning rate: 0.001

1563/1563 [=====] - 668s 427ms/step - loss: 0.7533 - acc: 0.8178 - va

Epoch 00031: val\_acc did not improve from 0.84430

Epoch 32/200

Learning rate: 0.001

1563/1563 [=====] - 665s 425ms/step - loss: 0.7410 - acc: 0.8198 - va

Epoch 00032: val\_acc did not improve from 0.84430

Epoch 33/200

Learning rate: 0.001

1563/1563 [=====] - 663s 424ms/step - loss: 0.7369 - acc: 0.8247 - va

Epoch 00033: val\_acc did not improve from 0.84430

Epoch 34/200

Learning rate: 0.001

1563/1563 [=====] - 665s 425ms/step - loss: 0.7355 - acc: 0.8219 - va

Epoch 00034: val\_acc did not improve from 0.84430

Epoch 35/200

Learning rate: 0.001

1563/1563 [=====] - 668s 427ms/step - loss: 0.7338 - acc: 0.8223 - va

Epoch 00035: val\_acc did not improve from 0.84430

Epoch 36/200

Learning rate: 0.001

1563/1563 [=====] - 663s 424ms/step - loss: 0.7272 - acc: 0.8244 - va

Epoch 00036: val\_acc did not improve from 0.84430

Epoch 37/200

Learning rate: 0.001

1563/1563 [=====] - 663s 424ms/step - loss: 0.7205 - acc: 0.8290 - va

Epoch 00037: val\_acc did not improve from 0.84430

Epoch 38/200

Learning rate: 0.001

1095/1563 [=====>...] - ETA: 3:12 - loss: 0.7156 - acc: 0.8279Buffered data was

### 1.3.11 3.K Evaluate Model

1. Last Model
2. Best Model
3. Confusion Matrix of Best

#### 3.K.a Last Model

```
In [90]: scores = model.evaluate(x_test, y_test, verbose=1)
         print('Test loss:', scores[0])
         print('Test accuracy:', scores[1])
```

```
10000/10000 [=====] - 25s 2ms/step
Test loss: 0.8169160022735595
Test accuracy: 0.8198
```

#### 3.K.b Best Model

```
In [11]: from keras.models import load_model
         best_model = load_model('drive/My Drive/IUST-DIP/cifar10_ResNet110v2_model.039.h5')
         scores = best_model.evaluate(x_test, y_test, verbose=1)
         print('Test loss:', scores[0])
         print('Test accuracy:', scores[1])
```

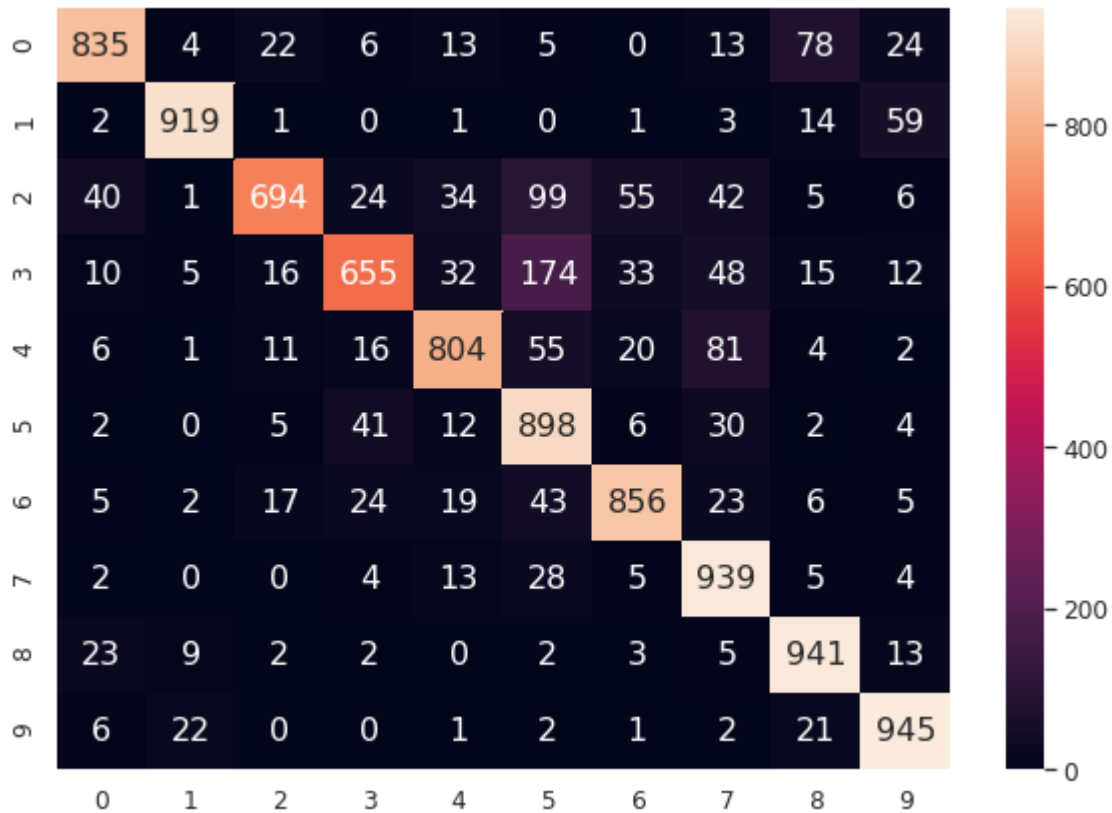
```
10000/10000 [=====] - 13s 1ms/step
Test loss: 0.6827598980903625
Test accuracy: 0.8486
```

#### 3.K.c Confusion Matrix of Best Model

```
In [28]: from sklearn.metrics import confusion_matrix
         pred = best_model.predict(x_test, verbose=1)
         cm = confusion_matrix(np.argmax(y_test, axis=-1), np.argmax(pred, axis=-1))

         df_cm = pd.DataFrame(cm, range(10), range(10))
         plt.figure(figsize = (10,7))
         sns.set(font_scale=1.1)
         sns.heatmap(df_cm, annot=True, annot_kws={"size": 16}, fmt='g')

         plt.show()
```



### 1.3.12 3.L 10 Worst Predictions

```
In [ ]: wrongs = np.argmax(best_model.predict(x_test), axis=-1) != np.argmax(y_test, axis=-1)
        wrongs_idx = (wrongs*1).nonzero()[0]
        wrongs_probs = best_model.predict(x_test[wrongs_idx])
        wrongs_true_prob = np.diag(wrongs_probs[:, np.argmax(y_test, axis=-1)])
        worst_preds_idx = np.argpartition(wrongs_true_prob, 10)[:10]
        worst_preds_idx = wrongs_idx[worst_preds_idx]
```

```
In [94]: fig = plt.figure(figsize=(50, 50)) # width, height in inches
```

```
for i, idx in enumerate(worst_preds_idx):
    sub = fig.add_subplot(len(worst_preds_idx), 1, i + 1)
    sub.imshow(x_test[idx,:,:], interpolation='nearest')
    print('Predicted:', np.argmax(pred[idx], axis=-1), '----- True class', np.argmax
```

Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers)

Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers)

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Predicted: 0 ----- True class 9  
Predicted: 9 ----- True class 1  
Predicted: 9 ----- True class 1  
Predicted: 9 ----- True class 1  
Predicted: 7 ----- True class 4  
Predicted: 5 ----- True class 4  
Predicted: 1 ----- True class 9  
Predicted: 9 ----- True class 0  
Predicted: 5 ----- True class 3  
Predicted: 9 ----- True class 1



