

assignment06-2a_muley_tushar

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Assignment: Assignment 6-2a

Date: January 9, 2022

Assignment 6.2a Using section 5.2 in Deep Learning with Python as a guide, create a ConvNet model that classifies images CIFAR10 small images classification dataset. Do not use dropout or data-augmentation in this part.

```
[1]: # get data
from keras.datasets import cifar10
from keras.utils import to_categorical
```

```
[2]: # library
import pandas as pd
from keras import layers
from keras import models
```

```
[3]: # breakout data
(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 [=====] - 14s 0us/step

```
[4]: # check the training data
x_train.shape, y_train.shape
```

```
[4]: ((50000, 32, 32, 3), (50000, 1))
```

```
[5]: # check the test data
x_test.shape, y_test.shape
```

```
[5]: ((10000, 32, 32, 3), (10000, 1))
```

```
[6]: model = models.Sequential()
model.add(layers.Conv2D(32, (3,3), activation='relu', input_shape=(32,32,3)))
model.add(layers.MaxPooling2D(2,2))
model.add(layers.Conv2D(64, (3,3), activation='relu'))
model.add(layers.MaxPooling2D(2,2))
```

```

model.add(layers.Conv2D(64, (3,3), activation='relu'))
model.add(layers.MaxPooling2D(2,2))
model.add(layers.Flatten())
model.add(layers.Dense(512, activation='relu'))
model.add(layers.Dense(10, activation='sigmoid'))

```

```
[7]: model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 30, 30, 32)	896
max_pooling2d (MaxPooling2D)	(None, 15, 15, 32)	0
conv2d_1 (Conv2D)	(None, 13, 13, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 6, 6, 64)	0
conv2d_2 (Conv2D)	(None, 4, 4, 64)	36928
max_pooling2d_2 (MaxPooling2D)	(None, 2, 2, 64)	0
flatten (Flatten)	(None, 256)	0
dense (Dense)	(None, 512)	131584
dense_1 (Dense)	(None, 10)	5130

Total params: 193,034
 Trainable params: 193,034
 Non-trainable params: 0

```
[8]: model.compile(optimizer='rmsprop',
loss='categorical_crossentropy',
metrics=['accuracy'])
```

```
[9]: # preprocess the data
x_train = x_train.astype("float32") / 255
x_test = x_test.astype("float32") / 255
y_train = to_categorical(y_train)
y_test = to_categorical(y_test)

# reserve 10K for validation
x_val = x_train[-10000:]
y_val = y_train[-10000:]

```

```
x_train = x_train[:-10000]
y_train = y_train[:-10000]
```

```
[10]: # check sample
      x_val.shape, y_val.shape
```

```
[10]: ((10000, 32, 32, 3), (10000, 10))
```

```
[11]: history = model.fit(x_train, y_train, epochs=100, validation_data=(x_val,y_val))
```

```
Epoch 1/100
1250/1250 [=====] - 45s 33ms/step - loss: 1.8359 -
accuracy: 0.3269 - val_loss: 1.4621 - val_accuracy: 0.4850
Epoch 2/100
1250/1250 [=====] - 43s 34ms/step - loss: 1.2246 -
accuracy: 0.5634 - val_loss: 1.0588 - val_accuracy: 0.6308
Epoch 3/100
1250/1250 [=====] - 40s 32ms/step - loss: 1.0348 -
accuracy: 0.6326 - val_loss: 1.0182 - val_accuracy: 0.6515
Epoch 4/100
1250/1250 [=====] - 45s 36ms/step - loss: 0.9155 -
accuracy: 0.6751 - val_loss: 1.0605 - val_accuracy: 0.6403
Epoch 5/100
1250/1250 [=====] - 28s 22ms/step - loss: 0.8219 -
accuracy: 0.7108 - val_loss: 0.9920 - val_accuracy: 0.6637
Epoch 6/100
1250/1250 [=====] - 30s 24ms/step - loss: 0.7485 -
accuracy: 0.7379 - val_loss: 1.1147 - val_accuracy: 0.6302
Epoch 7/100
1250/1250 [=====] - 37s 30ms/step - loss: 0.6865 -
accuracy: 0.7629 - val_loss: 1.2606 - val_accuracy: 0.6178
Epoch 8/100
1250/1250 [=====] - 31s 25ms/step - loss: 0.6568 -
accuracy: 0.7755 - val_loss: 0.9155 - val_accuracy: 0.7007
Epoch 9/100
1250/1250 [=====] - 29s 23ms/step - loss: 0.6263 -
accuracy: 0.7859 - val_loss: 1.0432 - val_accuracy: 0.6926
Epoch 10/100
1250/1250 [=====] - 29s 23ms/step - loss: 0.6255 -
accuracy: 0.7854 - val_loss: 1.0788 - val_accuracy: 0.6995
Epoch 11/100
1250/1250 [=====] - 28s 23ms/step - loss: 0.6033 -
accuracy: 0.7927 - val_loss: 1.0889 - val_accuracy: 0.6526
Epoch 12/100
1250/1250 [=====] - 29s 23ms/step - loss: 0.6105 -
accuracy: 0.7911 - val_loss: 1.1144 - val_accuracy: 0.6942
Epoch 13/100
1250/1250 [=====] - 32s 25ms/step - loss: 0.5880 -
```

accuracy: 0.8033 - val_loss: 1.1963 - val_accuracy: 0.6676
 Epoch 14/100
 1250/1250 [=====] - 30s 24ms/step - loss: 0.6048 -
 accuracy: 0.7946 - val_loss: 1.1257 - val_accuracy: 0.6785
 Epoch 15/100
 1250/1250 [=====] - 31s 25ms/step - loss: 0.5957 -
 accuracy: 0.8022 - val_loss: 1.1461 - val_accuracy: 0.6815
 Epoch 16/100
 1250/1250 [=====] - 36s 28ms/step - loss: 0.5900 -
 accuracy: 0.8020 - val_loss: 1.2578 - val_accuracy: 0.6584
 Epoch 17/100
 1250/1250 [=====] - 35s 28ms/step - loss: 0.5980 -
 accuracy: 0.7992 - val_loss: 1.2337 - val_accuracy: 0.6879
 Epoch 18/100
 1250/1250 [=====] - 36s 29ms/step - loss: 0.5820 -
 accuracy: 0.8052 - val_loss: 1.2124 - val_accuracy: 0.6905
 Epoch 19/100
 1250/1250 [=====] - 29s 23ms/step - loss: 0.5783 -
 accuracy: 0.8104 - val_loss: 1.2467 - val_accuracy: 0.6834
 Epoch 20/100
 1250/1250 [=====] - 35s 28ms/step - loss: 0.5973 -
 accuracy: 0.8028 - val_loss: 1.3658 - val_accuracy: 0.6705
 Epoch 21/100
 1250/1250 [=====] - 29s 23ms/step - loss: 0.5939 -
 accuracy: 0.8062 - val_loss: 1.2275 - val_accuracy: 0.6880
 Epoch 22/100
 1250/1250 [=====] - 32s 26ms/step - loss: 0.6042 -
 accuracy: 0.8045 - val_loss: 1.3989 - val_accuracy: 0.6955
 Epoch 23/100
 1250/1250 [=====] - 35s 28ms/step - loss: 0.6111 -
 accuracy: 0.8016 - val_loss: 1.3010 - val_accuracy: 0.7018
 Epoch 24/100
 1250/1250 [=====] - 35s 28ms/step - loss: 0.6028 -
 accuracy: 0.8052 - val_loss: 1.1473 - val_accuracy: 0.6558
 Epoch 25/100
 1250/1250 [=====] - 36s 28ms/step - loss: 0.6097 -
 accuracy: 0.8038 - val_loss: 1.6226 - val_accuracy: 0.6797
 Epoch 26/100
 1250/1250 [=====] - 35s 28ms/step - loss: 0.6076 -
 accuracy: 0.8048 - val_loss: 1.3226 - val_accuracy: 0.6620
 Epoch 27/100
 1250/1250 [=====] - 35s 28ms/step - loss: 0.5925 -
 accuracy: 0.8108 - val_loss: 1.4596 - val_accuracy: 0.6563
 Epoch 28/100
 1250/1250 [=====] - 35s 28ms/step - loss: 0.6117 -
 accuracy: 0.8090 - val_loss: 1.5850 - val_accuracy: 0.6884
 Epoch 29/100
 1250/1250 [=====] - 35s 28ms/step - loss: 0.6254 -

accuracy: 0.8032 - val_loss: 1.6789 - val_accuracy: 0.6827
 Epoch 30/100
 1250/1250 [=====] - 35s 28ms/step - loss: 0.6130 -
 accuracy: 0.8051 - val_loss: 1.2540 - val_accuracy: 0.6500
 Epoch 31/100
 1250/1250 [=====] - 37s 30ms/step - loss: 0.6196 -
 accuracy: 0.8011 - val_loss: 1.6076 - val_accuracy: 0.6927
 Epoch 32/100
 1250/1250 [=====] - 35s 28ms/step - loss: 0.6343 -
 accuracy: 0.8020 - val_loss: 1.2851 - val_accuracy: 0.6581
 Epoch 33/100
 1250/1250 [=====] - 37s 30ms/step - loss: 0.6173 -
 accuracy: 0.8018 - val_loss: 1.4253 - val_accuracy: 0.6842
 Epoch 34/100
 1250/1250 [=====] - 37s 30ms/step - loss: 0.6591 -
 accuracy: 0.7905 - val_loss: 1.2248 - val_accuracy: 0.6288
 Epoch 35/100
 1250/1250 [=====] - 37s 30ms/step - loss: 0.6345 -
 accuracy: 0.8044 - val_loss: 1.4401 - val_accuracy: 0.6584
 Epoch 36/100
 1250/1250 [=====] - 35s 28ms/step - loss: 0.6484 -
 accuracy: 0.7996 - val_loss: 1.4441 - val_accuracy: 0.6581
 Epoch 37/100
 1250/1250 [=====] - 34s 27ms/step - loss: 0.6506 -
 accuracy: 0.8023 - val_loss: 1.6454 - val_accuracy: 0.6527
 Epoch 38/100
 1250/1250 [=====] - 38s 30ms/step - loss: 0.6489 -
 accuracy: 0.7993 - val_loss: 1.5955 - val_accuracy: 0.5976
 Epoch 39/100
 1250/1250 [=====] - 35s 28ms/step - loss: 0.6675 -
 accuracy: 0.7947 - val_loss: 2.0528 - val_accuracy: 0.6854
 Epoch 40/100
 1250/1250 [=====] - 35s 28ms/step - loss: 0.6773 -
 accuracy: 0.7924 - val_loss: 1.7016 - val_accuracy: 0.6676
 Epoch 41/100
 1250/1250 [=====] - 35s 28ms/step - loss: 0.6704 -
 accuracy: 0.7948 - val_loss: 1.4472 - val_accuracy: 0.6163
 Epoch 42/100
 1250/1250 [=====] - 35s 28ms/step - loss: 0.6953 -
 accuracy: 0.7855 - val_loss: 2.3117 - val_accuracy: 0.6828
 Epoch 43/100
 1250/1250 [=====] - 33s 27ms/step - loss: 0.6832 -
 accuracy: 0.7930 - val_loss: 1.3057 - val_accuracy: 0.6521
 Epoch 44/100
 1250/1250 [=====] - 32s 26ms/step - loss: 0.6691 -
 accuracy: 0.7942 - val_loss: 1.8548 - val_accuracy: 0.6347
 Epoch 45/100
 1250/1250 [=====] - 32s 25ms/step - loss: 0.6860 -

accuracy: 0.7892 - val_loss: 1.7781 - val_accuracy: 0.6739
 Epoch 46/100
 1250/1250 [=====] - 32s 26ms/step - loss: 0.6897 -
 accuracy: 0.7904 - val_loss: 1.5058 - val_accuracy: 0.6674
 Epoch 47/100
 1250/1250 [=====] - 32s 26ms/step - loss: 0.7068 -
 accuracy: 0.7849 - val_loss: 1.7811 - val_accuracy: 0.6577
 Epoch 48/100
 1250/1250 [=====] - 33s 26ms/step - loss: 0.7003 -
 accuracy: 0.7878 - val_loss: 1.4099 - val_accuracy: 0.6699
 Epoch 49/100
 1250/1250 [=====] - 30s 24ms/step - loss: 0.7012 -
 accuracy: 0.7868 - val_loss: 1.6122 - val_accuracy: 0.6636
 Epoch 50/100
 1250/1250 [=====] - 30s 24ms/step - loss: 0.7121 -
 accuracy: 0.7827 - val_loss: 1.2997 - val_accuracy: 0.6009
 Epoch 51/100
 1250/1250 [=====] - 27s 22ms/step - loss: 0.7033 -
 accuracy: 0.7796 - val_loss: 1.5868 - val_accuracy: 0.6712
 Epoch 52/100
 1250/1250 [=====] - 25s 20ms/step - loss: 0.7234 -
 accuracy: 0.7801 - val_loss: 2.0812 - val_accuracy: 0.6593
 Epoch 53/100
 1250/1250 [=====] - 26s 21ms/step - loss: 0.7357 -
 accuracy: 0.7782 - val_loss: 1.3825 - val_accuracy: 0.6335
 Epoch 54/100
 1250/1250 [=====] - 25s 20ms/step - loss: 0.7190 -
 accuracy: 0.7765 - val_loss: 1.7406 - val_accuracy: 0.6805
 Epoch 55/100
 1250/1250 [=====] - 26s 21ms/step - loss: 0.7115 -
 accuracy: 0.7814 - val_loss: 1.5623 - val_accuracy: 0.6572
 Epoch 56/100
 1250/1250 [=====] - 25s 20ms/step - loss: 0.7293 -
 accuracy: 0.7786 - val_loss: 1.4875 - val_accuracy: 0.6389
 Epoch 57/100
 1250/1250 [=====] - 25s 20ms/step - loss: 0.7283 -
 accuracy: 0.7759 - val_loss: 1.8414 - val_accuracy: 0.6602
 Epoch 58/100
 1250/1250 [=====] - 25s 20ms/step - loss: 0.7229 -
 accuracy: 0.7781 - val_loss: 1.3578 - val_accuracy: 0.6666
 Epoch 59/100
 1250/1250 [=====] - 25s 20ms/step - loss: 0.7084 -
 accuracy: 0.7866 - val_loss: 1.7043 - val_accuracy: 0.6717
 Epoch 60/100
 1250/1250 [=====] - 25s 20ms/step - loss: 0.7240 -
 accuracy: 0.7799 - val_loss: 1.8645 - val_accuracy: 0.6750
 Epoch 61/100
 1250/1250 [=====] - 25s 20ms/step - loss: 0.7294 -

accuracy: 0.7777 - val_loss: 1.4217 - val_accuracy: 0.6399
 Epoch 62/100
 1250/1250 [=====] - 26s 21ms/step - loss: 0.7086 -
 accuracy: 0.7818 - val_loss: 1.7239 - val_accuracy: 0.6453
 Epoch 63/100
 1250/1250 [=====] - 29s 23ms/step - loss: 0.7189 -
 accuracy: 0.7781 - val_loss: 1.2878 - val_accuracy: 0.6216
 Epoch 64/100
 1250/1250 [=====] - 30s 24ms/step - loss: 0.7400 -
 accuracy: 0.7767 - val_loss: 1.3993 - val_accuracy: 0.6432
 Epoch 65/100
 1250/1250 [=====] - 25s 20ms/step - loss: 0.7198 -
 accuracy: 0.7855 - val_loss: 1.2909 - val_accuracy: 0.6489
 Epoch 66/100
 1250/1250 [=====] - 25s 20ms/step - loss: 0.7096 -
 accuracy: 0.7765 - val_loss: 1.2580 - val_accuracy: 0.6741
 Epoch 67/100
 1250/1250 [=====] - 25s 20ms/step - loss: 0.7202 -
 accuracy: 0.7767 - val_loss: 1.3813 - val_accuracy: 0.6738
 Epoch 68/100
 1250/1250 [=====] - 25s 20ms/step - loss: 0.7086 -
 accuracy: 0.7787 - val_loss: 1.4085 - val_accuracy: 0.6528
 Epoch 69/100
 1250/1250 [=====] - 25s 20ms/step - loss: 0.6995 -
 accuracy: 0.7807 - val_loss: 1.5318 - val_accuracy: 0.6491
 Epoch 70/100
 1250/1250 [=====] - 25s 20ms/step - loss: 0.7013 -
 accuracy: 0.7826 - val_loss: 2.0221 - val_accuracy: 0.6489
 Epoch 71/100
 1250/1250 [=====] - 28s 22ms/step - loss: 0.7239 -
 accuracy: 0.7776 - val_loss: 1.3145 - val_accuracy: 0.6558
 Epoch 72/100
 1250/1250 [=====] - 25s 20ms/step - loss: 0.6977 -
 accuracy: 0.7835 - val_loss: 1.5881 - val_accuracy: 0.6540
 Epoch 73/100
 1250/1250 [=====] - 25s 20ms/step - loss: 0.6955 -
 accuracy: 0.7827 - val_loss: 1.5039 - val_accuracy: 0.6407
 Epoch 74/100
 1250/1250 [=====] - 26s 21ms/step - loss: 0.6956 -
 accuracy: 0.7821 - val_loss: 1.3095 - val_accuracy: 0.6561
 Epoch 75/100
 1250/1250 [=====] - 25s 20ms/step - loss: 0.6929 -
 accuracy: 0.7818 - val_loss: 1.6257 - val_accuracy: 0.5840
 Epoch 76/100
 1250/1250 [=====] - 25s 20ms/step - loss: 0.6991 -
 accuracy: 0.7810 - val_loss: 1.2542 - val_accuracy: 0.6420
 Epoch 77/100
 1250/1250 [=====] - 24s 20ms/step - loss: 0.6962 -

accuracy: 0.7809 - val_loss: 1.2289 - val_accuracy: 0.6609
Epoch 78/100
1250/1250 [=====] - 25s 20ms/step - loss: 0.7004 -
accuracy: 0.7830 - val_loss: 1.3193 - val_accuracy: 0.6469
Epoch 79/100
1250/1250 [=====] - 25s 20ms/step - loss: 0.6674 -
accuracy: 0.7896 - val_loss: 1.2697 - val_accuracy: 0.6825
Epoch 80/100
1250/1250 [=====] - 25s 20ms/step - loss: 0.6884 -
accuracy: 0.7826 - val_loss: 1.4066 - val_accuracy: 0.6833
Epoch 81/100
1250/1250 [=====] - 25s 20ms/step - loss: 0.6760 -
accuracy: 0.7857 - val_loss: 1.2521 - val_accuracy: 0.6512
Epoch 82/100
1250/1250 [=====] - 25s 20ms/step - loss: 0.6919 -
accuracy: 0.7790 - val_loss: 1.4214 - val_accuracy: 0.6362
Epoch 83/100
1250/1250 [=====] - 25s 20ms/step - loss: 0.6849 -
accuracy: 0.7825 - val_loss: 1.2615 - val_accuracy: 0.6520
Epoch 84/100
1250/1250 [=====] - 25s 20ms/step - loss: 0.6905 -
accuracy: 0.7844 - val_loss: 1.5496 - val_accuracy: 0.6694
Epoch 85/100
1250/1250 [=====] - 25s 20ms/step - loss: 0.6801 -
accuracy: 0.7848 - val_loss: 1.3567 - val_accuracy: 0.6598
Epoch 86/100
1250/1250 [=====] - 27s 22ms/step - loss: 0.6757 -
accuracy: 0.7864 - val_loss: 2.4631 - val_accuracy: 0.6636
Epoch 87/100
1250/1250 [=====] - 29s 23ms/step - loss: 0.7057 -
accuracy: 0.7804 - val_loss: 2.5179 - val_accuracy: 0.6797
Epoch 88/100
1250/1250 [=====] - 25s 20ms/step - loss: 0.6747 -
accuracy: 0.7866 - val_loss: 1.4089 - val_accuracy: 0.6470
Epoch 89/100
1250/1250 [=====] - 24s 19ms/step - loss: 0.6834 -
accuracy: 0.7843 - val_loss: 1.3715 - val_accuracy: 0.6728
Epoch 90/100
1250/1250 [=====] - 25s 20ms/step - loss: 0.6661 -
accuracy: 0.7875 - val_loss: 1.4632 - val_accuracy: 0.6247
Epoch 91/100
1250/1250 [=====] - 24s 20ms/step - loss: 0.6779 -
accuracy: 0.7893 - val_loss: 2.0835 - val_accuracy: 0.6677
Epoch 92/100
1250/1250 [=====] - 25s 20ms/step - loss: 0.6625 -
accuracy: 0.7908 - val_loss: 1.5524 - val_accuracy: 0.6594
Epoch 93/100
1250/1250 [=====] - 25s 20ms/step - loss: 0.6661 -


```

accuracy: 0.7937 - val_loss: 1.3946 - val_accuracy: 0.6622
Epoch 94/100
1250/1250 [=====] - 25s 20ms/step - loss: 0.6510 -
accuracy: 0.7958 - val_loss: 1.3060 - val_accuracy: 0.6333
Epoch 95/100
1250/1250 [=====] - 24s 20ms/step - loss: 0.6662 -
accuracy: 0.7895 - val_loss: 1.7688 - val_accuracy: 0.6423
Epoch 96/100
1250/1250 [=====] - 25s 20ms/step - loss: 0.6523 -
accuracy: 0.7934 - val_loss: 1.4366 - val_accuracy: 0.6609
Epoch 97/100
1250/1250 [=====] - 25s 20ms/step - loss: 0.6445 -
accuracy: 0.7922 - val_loss: 1.5374 - val_accuracy: 0.6284
Epoch 98/100
1250/1250 [=====] - 24s 20ms/step - loss: 0.6415 -
accuracy: 0.7932 - val_loss: 2.0326 - val_accuracy: 0.6223
Epoch 99/100
1250/1250 [=====] - 25s 20ms/step - loss: 0.6436 -
accuracy: 0.7908 - val_loss: 1.3589 - val_accuracy: 0.6638
Epoch 100/100
1250/1250 [=====] - 24s 20ms/step - loss: 0.6616 -
accuracy: 0.7964 - val_loss: 1.2924 - val_accuracy: 0.6511

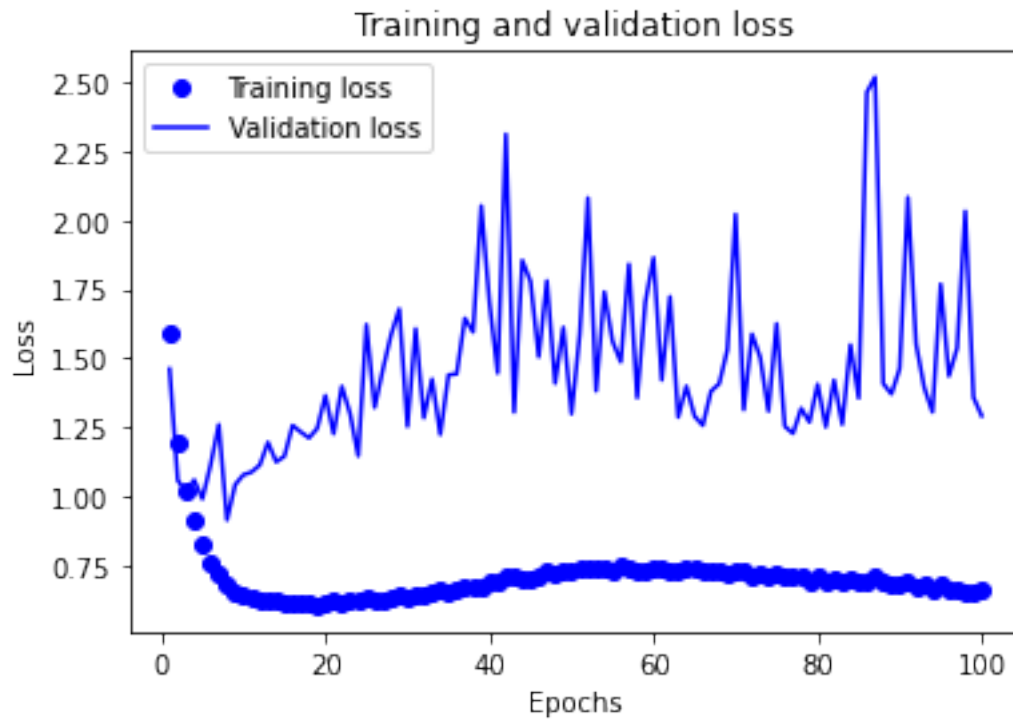
```

```
[12]: history_dict = history.history
      history_dict.keys()
```

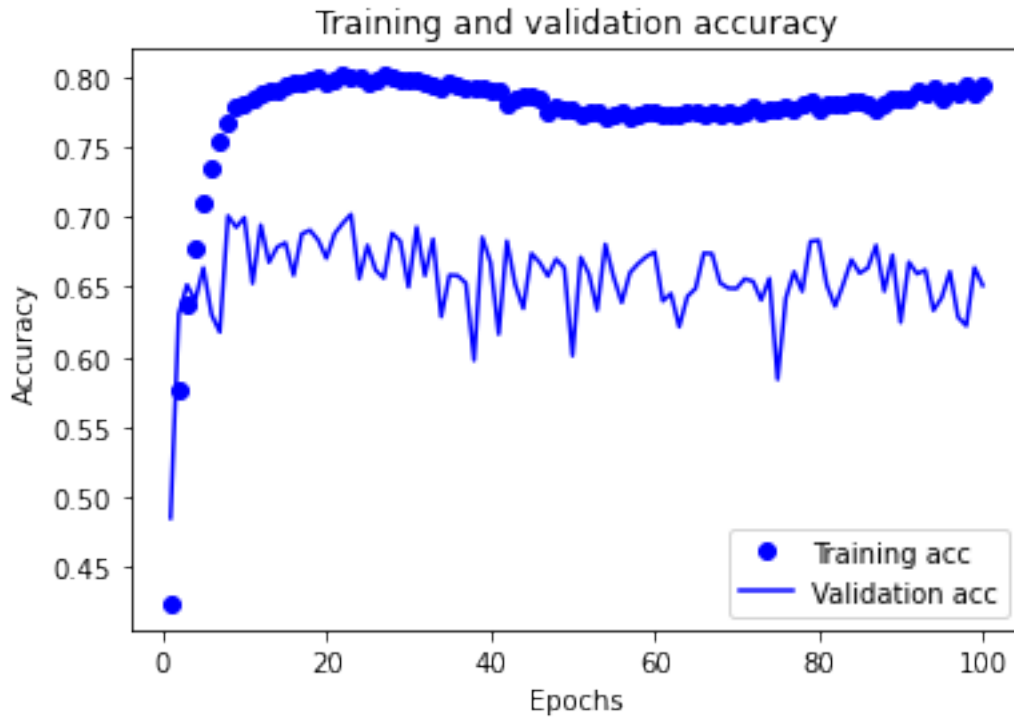
```
[12]: dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

```
[14]: # plot the training and validation loss
import matplotlib.pyplot as plt
history_dict = history.history
loss_values = history_dict["loss"]
val_loss_values = history_dict["val_loss"]
epochs = range(1, len(loss_values) + 1)
plt.plot(epochs, loss_values, "bo", label="Training loss")
plt.plot(epochs, val_loss_values, "b", label="Validation loss")
plt.title("Training and validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()

```



```
[15]: # plot the training and validation accuracy
plt.clf()
acc = history_dict["accuracy"]
val_acc = history_dict["val_accuracy"]
plt.plot(epochs, acc, "bo", label="Training acc")
plt.plot(epochs, val_acc, "b", label="Validation acc")
plt.title("Training and validation accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```



```
[16]: # retrain the model
(x_train, y_train), (x_test, y_test) = cifar10.load_data()

# preprocess the data
x_train = x_train.astype("float32") / 255
x_test = x_test.astype("float32") / 255
y_train = to_categorical(y_train)
y_test = to_categorical(y_test)
model.compile(optimizer='rmsprop',
loss='categorical_crossentropy',
metrics=['accuracy'])
history = model.fit(x_train, y_train, epochs=10)
results = model.evaluate(x_test, y_test)
```

```
Epoch 1/10
1563/1563 [=====] - 30s 18ms/step - loss: 0.8621 -
accuracy: 0.7425
Epoch 2/10
1563/1563 [=====] - 33s 21ms/step - loss: 0.7850 -
accuracy: 0.75360s - loss: 0.7849 - accura
Epoch 3/10
1563/1563 [=====] - 36s 23ms/step - loss: 0.7789 -
accuracy: 0.7581
Epoch 4/10
```

```

1563/1563 [=====] - 33s 21ms/step - loss: 0.7755 -
accuracy: 0.7540
Epoch 5/10
1563/1563 [=====] - 30s 19ms/step - loss: 0.7620 -
accuracy: 0.7608
Epoch 6/10
1563/1563 [=====] - 31s 20ms/step - loss: 0.7477 -
accuracy: 0.7637
Epoch 7/10
1563/1563 [=====] - 30s 19ms/step - loss: 0.7574 -
accuracy: 0.7581
Epoch 8/10
1563/1563 [=====] - 31s 20ms/step - loss: 0.7640 -
accuracy: 0.7569
Epoch 9/10
1563/1563 [=====] - 32s 21ms/step - loss: 0.7653 -
accuracy: 0.7579
Epoch 10/10
1563/1563 [=====] - 30s 19ms/step - loss: 0.7346 -
accuracy: 0.7614
313/313 [=====] - 3s 8ms/step - loss: 1.4350 -
accuracy: 0.6515

```

```

[17]: # print the results
results

```

```

[17]: [1.4349656105041504, 0.6514999866485596]

```

```

[18]: # using a trained model to generate predictions on new data
model.predict(x_test)

```

```

[18]: array([[0.0000000e+00, 0.0000000e+00, 0.0000000e+00, ..., 0.0000000e+00,
0.0000000e+00, 0.0000000e+00],
[3.0394677e-31, 1.7475647e-31, 4.7103405e-35, ..., 6.9648780e-37,
2.3962413e-30, 8.8907534e-32],
[4.8058961e-22, 5.4047130e-22, 2.2406346e-22, ..., 2.4171372e-22,
6.1508722e-21, 6.1663518e-22],
...,
[0.0000000e+00, 0.0000000e+00, 0.0000000e+00, ..., 0.0000000e+00,
0.0000000e+00, 0.0000000e+00],
[5.2398946e-34, 2.3454804e-36, 5.3544291e-32, ..., 5.3570209e-33,
9.0837745e-37, 1.8028205e-36],
[0.0000000e+00, 0.0000000e+00, 0.0000000e+00, ..., 0.0000000e+00,
0.0000000e+00, 0.0000000e+00]], dtype=float32)

```