assignment06_BasitAbdul

October 7, 2022

1 Assignment 6.1

1.0.1 Using section 5.1 in Deep Learning with Python as a guide (listing 5.3 in particular), create a ConvNet model that classifies images in the MNIST digit dataset. Save the model, predictions, metrics, and validation plots in the dsc650/assignments/assignment06/results directory. If you are using JupyterHub, you can include those plots in your Jupyter notebook.

[1]:
```python
from keras import layers
from keras import models
```

[2]:
```python
# instantiate a model
model = models.Sequential()
model.add(layers.Conv2D(32, (3,3), activation='relu', input_shape=(28, 28, 1)))
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'))

# add a classifier on top of Convnet
model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(10, activation = 'softmax'))

# view summary
model.summary()
```

```
Model: "sequential"

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 26, 26, 32)        320

_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 13, 13, 32)        0

_________________________________________________________________
conv2d_1 (Conv2D)            (None, 11, 11, 64)        18496

_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 5, 5, 64)          0
```

```
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 3, 3, 64)          36928
_________________________________________________________________
flatten (Flatten)            (None, 576)               0
_________________________________________________________________
dense (Dense)                (None, 64)                36928
_________________________________________________________________
dense_1 (Dense)              (None, 10)                650
=================================================================
Total params: 93,322
Trainable params: 93,322
Non-trainable params: 0
_________________________________________________________________
```

[3]:
```python
from keras.datasets import mnist
from keras.utils import to_categorical
import numpy as np
```

[4]:
```python
(train_images, train_labels), (test_images, test_labels) = mnist.load_data()

train_images = train_images.reshape((60000, 28, 28, 1))
train_images = train_images.astype('float32') / 255

test_images = test_images.reshape((10000, 28, 28, 1))
test_images = test_images.astype('float32') / 255

train_labels = to_categorical(train_labels)
test_labels = to_categorical(test_labels)
```

[5]:
```python
# shuffle training set
for _ in range(5):
    indexes = np.random.permutation(len(train_images))

train_images = train_images[indexes]
train_labels = train_labels[indexes]

# put 10,000 aside for validation
val_images = train_images[:10000,:]
val_labels = train_labels[:10000,:]

# keep the rest in training set
train_images2 = train_images[10000:,:]
train_labels2 = train_labels[10000:,:]

# view their shape
train_images2.shape, val_images.shape
```

[5]: ((50000, 28, 28, 1), (10000, 28, 28, 1))

[6]:
```
model.compile(optimizer='rmsprop',
              loss='categorical_crossentropy',
              metrics=['accuracy'])

history = model.fit(train_images2, train_labels2, epochs=5, batch_size=64,
                    validation_data = (val_images, val_labels))
```

```
Epoch 1/5
782/782 [==============================] - 12s 16ms/step - loss: 0.1913 -
accuracy: 0.9408 - val_loss: 0.0492 - val_accuracy: 0.9839
Epoch 2/5
782/782 [==============================] - 12s 15ms/step - loss: 0.0518 -
accuracy: 0.9844 - val_loss: 0.0485 - val_accuracy: 0.9854
Epoch 3/5
782/782 [==============================] - 11s 15ms/step - loss: 0.0370 -
accuracy: 0.9887 - val_loss: 0.0306 - val_accuracy: 0.9898
Epoch 4/5
782/782 [==============================] - 11s 15ms/step - loss: 0.0255 -
accuracy: 0.9917 - val_loss: 0.0429 - val_accuracy: 0.9873
Epoch 5/5
782/782 [==============================] - 11s 15ms/step - loss: 0.0209 -
accuracy: 0.9938 - val_loss: 0.0279 - val_accuracy: 0.9916
```

[7]:
```
history.history.keys()
```

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

[8]:
```
import matplotlib.pyplot as plt
```

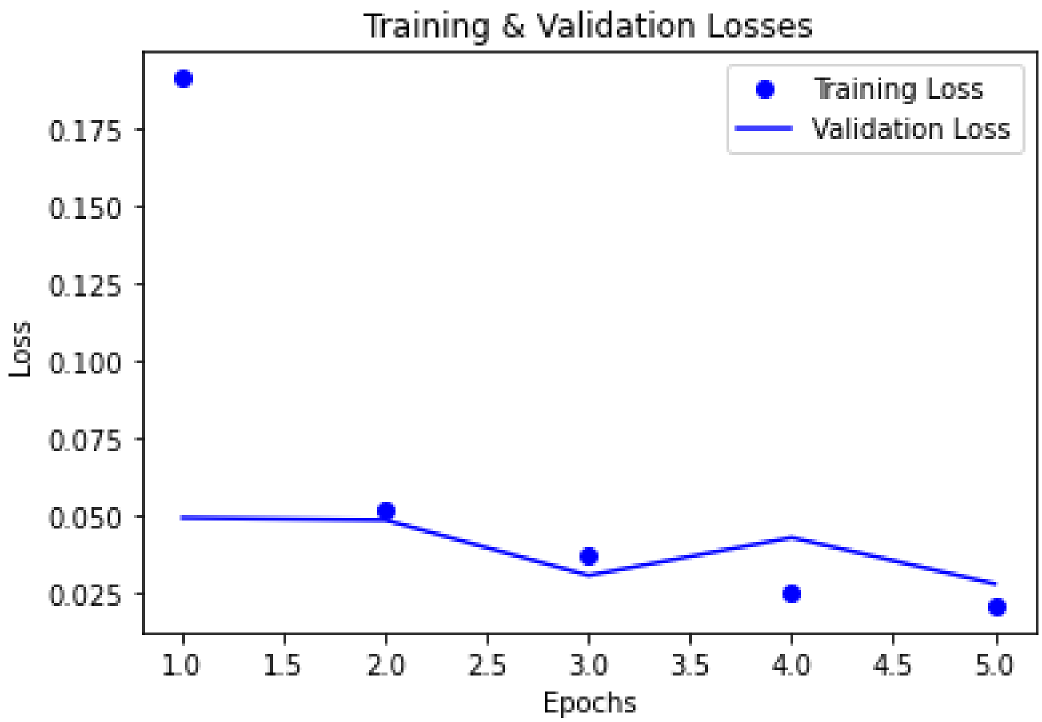
[13]:
```
import os
```

[14]:
```
os.getcwd()
```

[14]: '/home/jovyan/dsc650/dsc650'

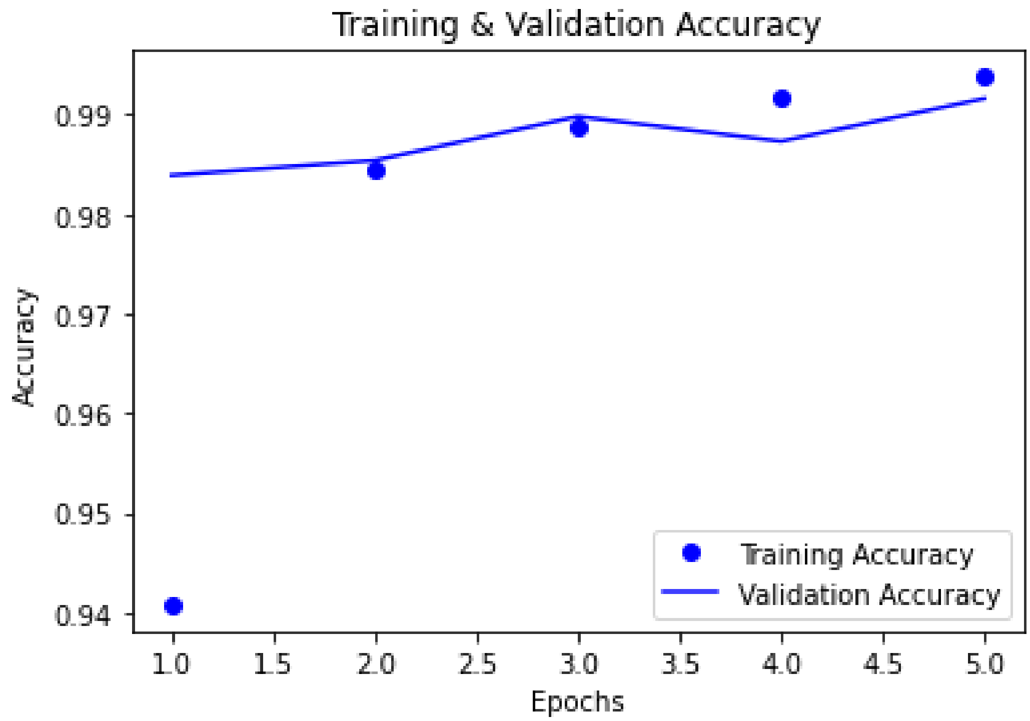
[15]:
```
train_loss = history.history['loss']
val_loss = history.history['val_loss']

epochs = range(1, len(history.history['loss']) + 1)

plt.plot(epochs, train_loss, 'bo', label = 'Training Loss')
plt.plot(epochs, val_loss, 'b', label = 'Validation Loss')
plt.title('Training & Validation Losses')
plt.xlabel('Epochs')
plt.ylabel('Loss')
```

```
plt.legend()
plt.show()
plt.savefig('/home/jovyan/dsc650/dsc650/assignments/assignment06/results/
 ↪6_1_Loss.png')
```



<Figure size 432x288 with 0 Axes>

[16]:
```
train_acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

epcohs = range(1, len(history.history['accuracy']) + 1)

plt.plot(epochs, train_acc, 'bo', label = 'Training Accuracy')
plt.plot(epochs, val_acc, 'b', label = 'Validation Accuracy')
plt.title('Training & Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
plt.savefig('/home/jovyan/dsc650/dsc650/assignments/assignment06/results/
 ↪6_1_Accuracy')
```




```
<Figure size 432x288 with 0 Axes>
```

[17]:

```
# retrain model & evaluate for 3 epochs
model.compile(optimizer='rmsprop',
              loss='categorical_crossentropy',
              metrics=['accuracy'])

history = model.fit(train_images, train_labels, epochs = 3, batch_size = 64)
results = model.evaluate(test_images, test_labels)
```

```
Epoch 1/3
938/938 [==============================] - 12s 13ms/step - loss: 0.0207 -
accuracy: 0.9936
Epoch 2/3
938/938 [==============================] - 12s 13ms/step - loss: 0.0157 -
accuracy: 0.9953
Epoch 3/3
938/938 [==============================] - 12s 13ms/step - loss: 0.0135 -
accuracy: 0.9959
313/313 [==============================] - 1s 4ms/step - loss: 0.0342 -
accuracy: 0.9912
```

[18]:

```
results
```

[18]: [0.03418023884296417, 0.9911999702453613]

[19]:
```
history.history
```

[19]: {'loss': [0.020670166239142418, 0.015682034194469452, 0.013516470789909363],
 'accuracy': [0.9936166405677795, 0.9952666759490967, 0.9959499835968018]}

[20]:
```
model.save('/home/jovyan/dsc650/dsc650/assignments/assignment06/results/
↪6_1_model.h5')
```

[21]:
```
prediction_results = model.predict(test_images)
```

[22]:
```
prediction_results
```

[22]:
```
array([[4.7456681e-14, 2.6592741e-09, 8.4304147e-10, …, 9.9999988e-01,
        7.0049376e-11, 1.5840668e-07],
       [4.5349310e-08, 1.5938194e-07, 9.9999988e-01, …, 5.3458093e-12,
        8.0618217e-14, 4.3560163e-14],
       [8.9553337e-11, 9.9999797e-01, 1.6947376e-09, …, 2.6520308e-07,
        7.3690137e-11, 2.4983045e-09],
       …,
       [7.4172744e-21, 5.1019219e-12, 1.4456140e-15, …, 1.7306298e-10,
        2.2197717e-13, 7.2898625e-11],
       [3.3632121e-11, 1.0755156e-14, 5.3416809e-16, …, 4.8402844e-14,
        5.4988840e-09, 4.9146000e-12],
       [6.2092755e-11, 2.8341900e-14, 7.9025883e-11, …, 2.1255905e-18,
        2.5833360e-11, 2.3249757e-12]], dtype=float32)
```

[24]:
```
with open('/home/jovyan/dsc650/dsc650/assignments/assignment06/results/
↪6_1_metrics.txt', 'w') as f:
    f.write('Training Loss: {}'.format(str(history.history['loss'])))
    f.write('\nTraining Accuracy: {}'.format(str(history.history['accuracy'])))
    f.write('\nTest Loss: {}'.format(results[0]))
    f.write('\nTest Accuracy: {}'.format(results[1]))
```

[25]:
```
import pandas as pd
```

[26]:
```
preds = pd.DataFrame(prediction_results,
                     columns = ['0','1','2','3','4','5','6','7','8','9'])

preds.to_csv('/home/jovyan/dsc650/dsc650/assignments/assignment06/results/
↪6_1_predicitons.csv', index = False)
```

2 Assignment 6.2a

2.0.1 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. Save the model, predictions, metrics, and validation plots in the dsc650/assignments/assignment06/results directory. If you are using JupyterHub, you can include those plots in your Jupyter notebook.

[27]:
```
from keras.datasets import cifar10
from keras.utils import to_categorical
import pandas as pd
```

[28]:
```
(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 [==============================] - 43s 0us/step
```

[29]:
```
x_train.shape, y_train.shape
```

[29]:
```
((50000, 32, 32, 3), (50000, 1))
```

[30]:
```
x_test.shape, y_test.shape
```

[30]:
```
((10000, 32, 32, 3), (10000, 1))
```

[31]:
```
# preprocess 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)

# put 10,000 aside for validation
x_val = x_train[-10000:]
y_val = y_train[-10000:]
x_train = x_train[:-10000]
y_train = y_train[:-10000]
```

[32]:
```
x_val.shape, y_val.shape
```

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

[33]:
```
from keras import models
from keras import layers
```

[34]:
```
# instantiate the model
model = models.Sequential()
model.add(layers.Conv2D(32, (3,3), activation='relu', input_shape=(32, 32, 3)))
```

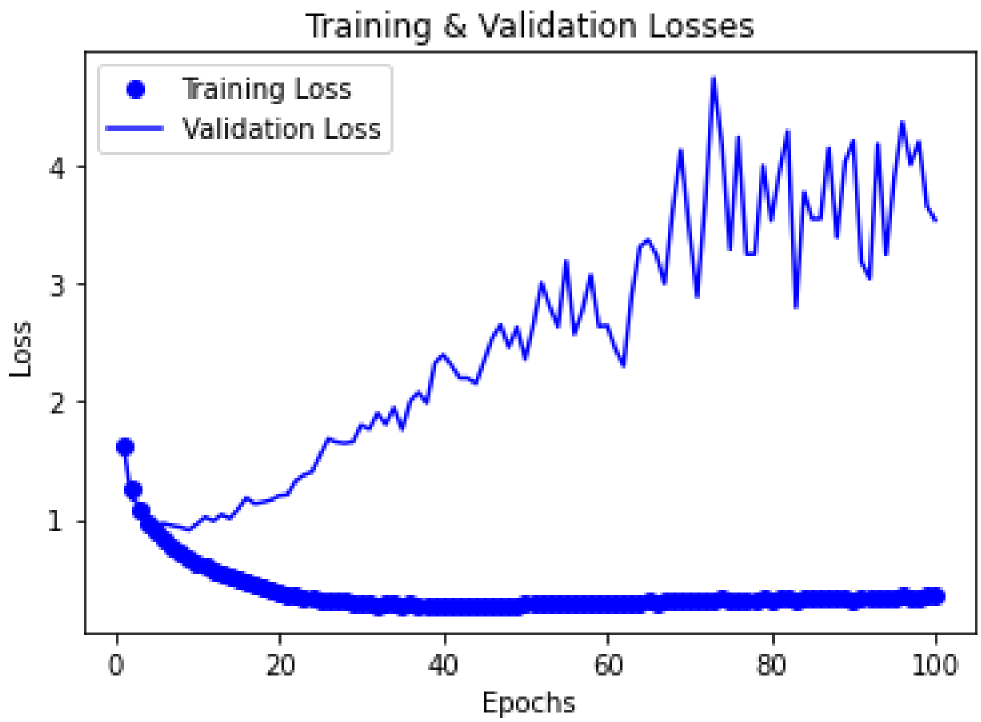
```python
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3,3), activation='relu'))
model.add(layers.MaxPooling2D((2,2)))
model.add(layers.Conv2D(64, (3,3), activation='relu'))
model.add(layers.MaxPooling2D((2,2)))
model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(10, activation = 'softmax'))

# view summary
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_3 (Conv2D)            (None, 30, 30, 32)        896
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 15, 15, 32)        0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 13, 13, 64)        18496
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 6, 6, 64)          0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 4, 4, 64)          36928
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 2, 2, 64)          0
_________________________________________________________________
flatten_1 (Flatten)          (None, 256)               0
_________________________________________________________________
dense_2 (Dense)              (None, 64)                16448
_________________________________________________________________
dense_3 (Dense)              (None, 10)                650
=================================================================
Total params: 73,418
Trainable params: 73,418
Non-trainable params: 0
_________________________________________________________________
```

[35]:
```python
model.compile(optimizer='rmsprop',
              loss='categorical_crossentropy',
              metrics=['accuracy'])

history = model.fit(x_train, y_train, epochs=100,
                    validation_data = (x_val, y_val), verbose=0)
```

[36]:
```python
import matplotlib.pyplot as plt
```

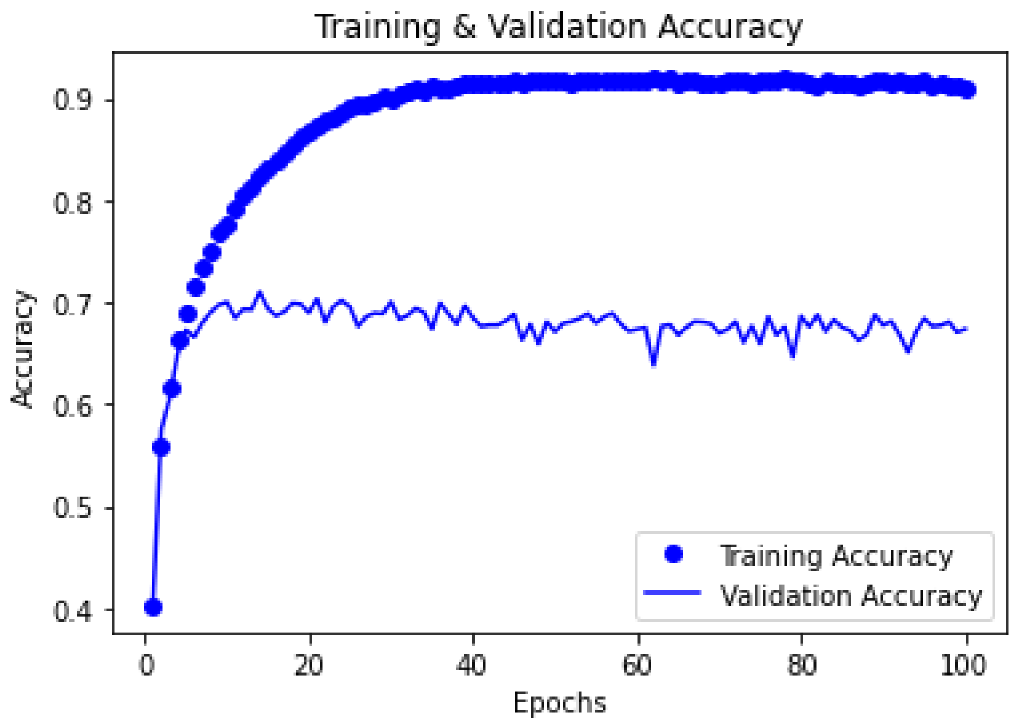
[37]:
```
train_loss = history.history['loss']
val_loss = history.history['val_loss']

epochs = range(1, len(history.history['loss']) + 1)

plt.plot(epochs, train_loss, 'bo', label = 'Training Loss')
plt.plot(epochs, val_loss, 'b', label = 'Validation Loss')
plt.title('Training & Validation Losses')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
plt.savefig('/home/jovyan/dsc650/dsc650/assignments/assignment06/results/
↪6_2A_Loss.png')
```




```
<Figure size 432x288 with 0 Axes>
```

[38]:
```
train_acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
epcohs = range(1, len(history.history['accuracy']) + 1)
plt.plot(epochs, train_acc, 'bo', label = 'Training Accuracy')
plt.plot(epochs, val_acc, 'b', label = 'Validation Accuracy')
plt.title('Training & Validation Accuracy')
```

```
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
plt.savefig('/home/jovyan/dsc650/dsc650/assignments/assignment06/results/
↪6_2A_Accuracy')
```




```
<Figure size 432x288 with 0 Axes>
```

[39]:

```
# retrain model & evaluate
(x_train, y_train), (x_test, y_test) = cifar10.load_data()

# preprocess 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 [==============================] - 17s 11ms/step - loss: 0.9244 -
accuracy: 0.7719
Epoch 2/10
1563/1563 [==============================] - 17s 11ms/step - loss: 0.8006 -
accuracy: 0.7762
Epoch 3/10
1563/1563 [==============================] - 17s 11ms/step - loss: 0.7414 -
accuracy: 0.7833
Epoch 4/10
1563/1563 [==============================] - 17s 11ms/step - loss: 0.7111 -
accuracy: 0.7844
Epoch 5/10
1563/1563 [==============================] - 17s 11ms/step - loss: 0.6919 -
accuracy: 0.7906
Epoch 6/10
1563/1563 [==============================] - 17s 11ms/step - loss: 0.6718 -
accuracy: 0.7904
Epoch 7/10
1563/1563 [==============================] - 17s 11ms/step - loss: 0.6699 -
accuracy: 0.7903
Epoch 8/10
1563/1563 [==============================] - 17s 11ms/step - loss: 0.6611 -
accuracy: 0.7914
Epoch 9/10
1563/1563 [==============================] - 16s 11ms/step - loss: 0.6350 -
accuracy: 0.7985
Epoch 10/10
1563/1563 [==============================] - 16s 10ms/step - loss: 0.6107 -
accuracy: 0.8008
313/313 [==============================] - 1s 4ms/step - loss: 1.8254 -
accuracy: 0.6618
```

[40]:
```
model.save('/home/jovyan/dsc650/dsc650/assignments/assignment06/results/
↪6_2A_model.h5')
```

[41]:
```
prediction_results = model.predict(x_test)
```

[42]:
```
prediction_results
```

[42]:
```
array([[1.3920501e-01, 5.8909663e-08, 1.1701636e-02, …, 4.1717396e-04,
         1.1220261e-02, 1.6795846e-05],
        [1.0745206e-16, 9.9999857e-01, 4.0205821e-26, …, 1.7141741e-30,
         1.4746651e-06, 4.9971474e-13],
        [1.8164767e-01, 5.2700706e-02, 4.6945876e-03, …, 5.8623154e-05,
```

```
 7.4497205e-01, 1.2249864e-02],
…,
[2.8897497e-07, 1.7487033e-05, 1.4496895e-02, …, 2.0005475e-01,
 1.8892171e-08, 2.0966316e-05],
[1.6626522e-05, 4.6448240e-06, 4.1795922e-03, …, 1.5234439e-05,
 4.6754668e-08, 3.6247652e-08],
[0.0000000e+00, 0.0000000e+00, 1.9029255e-34, …, 1.0000000e+00,
 0.0000000e+00, 0.0000000e+00]], dtype=float32)
```

[43]:
```
with open('/home/jovyan/dsc650/dsc650/assignments/assignment06/results/
↪6_2A_metrics.txt', 'w') as f:
    f.write('Training Loss: {}'.format(str(history.history['loss'])))
    f.write('\nTraining Accuracy: {}'.format(str(history.history['accuracy'])))
    f.write('\nTest Loss: {}'.format(results[0]))
    f.write('\nTest Accuracy: {}'.format(results[1]))
```

[44]:
```
preds = pd.DataFrame(prediction_results,
                     columns = ['0','1','2','3','4','5','6','7','8','9'])

preds.to_csv('/home/jovyan/dsc650/dsc650/assignments/assignment06/results/
↪6_2A_predicitons.csv', index = False)
```

[ ]:
```

```

3 Assignment 6.2b

3.0.1 Using section 5.2 in Deep Learning with Python as a guide, create a ConvNet model that classifies images CIFAR10 small images classification dataset. This time includes dropout and data-augmentation. Save the model, predictions, metrics, and validation plots in the dsc650/assignments/assignment06/results directory. If you are using JupyterHub, you can include those plots in your Jupyter notebook.

[45]:
```
from keras.datasets import cifar10
from keras.utils import to_categorical
from keras.preprocessing.image import ImageDataGenerator
import pandas as pd
import matplotlib.pyplot as plt
```

[46]:
```
(x_train, y_train), (x_test, y_test) = cifar10.load_data()
```

[47]:
```
x_train.shape, y_train.shape
```

[47]:
```
((50000, 32, 32, 3), (50000, 1))
```

[48]:
```
x_test.shape, y_test.shape
```

[48]: ((10000, 32, 32, 3), (10000, 1))

[49]:
```
# preprocess data
x_train = x_train.astype('float32')
x_test = x_test.astype('float32')
y_train = to_categorical(y_train)
y_test = to_categorical(y_test)

# put 10,000 aside for validation
x_val = x_train[-10000:]
y_val = y_train[-10000:]
x_train2 = x_train[:-10000]
y_train2 = y_train[:-10000]
```

[50]:
```
train_datagen = ImageDataGenerator(rescale=1./255,
                                   rotation_range=40,
                                   width_shift_range=0.2,
                                   height_shift_range=0.2,
                                   shear_range=0.2,
                                   zoom_range=0.2,
                                   horizontal_flip=True)

test_datagen = ImageDataGenerator(rescale=1./255)

train_generator = train_datagen.flow(x_train2, y_train2, batch_size=32)

validation_generator = train_datagen.flow(x_val, y_val, batch_size=32)
```

[51]:
```
from keras import models
from keras import layers
```

[52]:
```
# instantiate the model
# add dropout layer
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.Dropout(0.5))
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(10, activation = 'softmax'))

# view summary
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_6 (Conv2D)            (None, 30, 30, 32)        896
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 15, 15, 32)        0
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 13, 13, 64)        18496
_________________________________________________________________
max_pooling2d_6 (MaxPooling2 (None, 6, 6, 64)          0
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 4, 4, 64)          36928
_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (None, 2, 2, 64)          0
_________________________________________________________________
flatten_2 (Flatten)          (None, 256)               0
_________________________________________________________________
dropout (Dropout)            (None, 256)               0
_________________________________________________________________
dense_4 (Dense)              (None, 64)                16448
_________________________________________________________________
dense_5 (Dense)              (None, 10)                650
=================================================================
Total params: 73,418
Trainable params: 73,418
Non-trainable params: 0
_________________________________________________________________
```

[53]:
```
from keras import optimizers
```

[54]:
```
model.compile(optimizer=optimizers.RMSprop(lr=1e-4),
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

[55]:
```
history = model.fit_generator(train_generator,
                              steps_per_epoch=len(x_train2) / 32,
                              epochs = 30,
                              validation_data=validation_generator,
                              validation_steps=len(x_val) / 32)
```

```
WARNING:tensorflow:From <ipython-input-55-fb3623de6afc>:1: Model.fit_generator
(from tensorflow.python.keras.engine.training) is deprecated and will be removed
in a future version.
Instructions for updating:
Please use Model.fit, which supports generators.
Epoch 1/30
1250/1250 [==============================] - 55s 44ms/step - loss: 2.1326 -
```

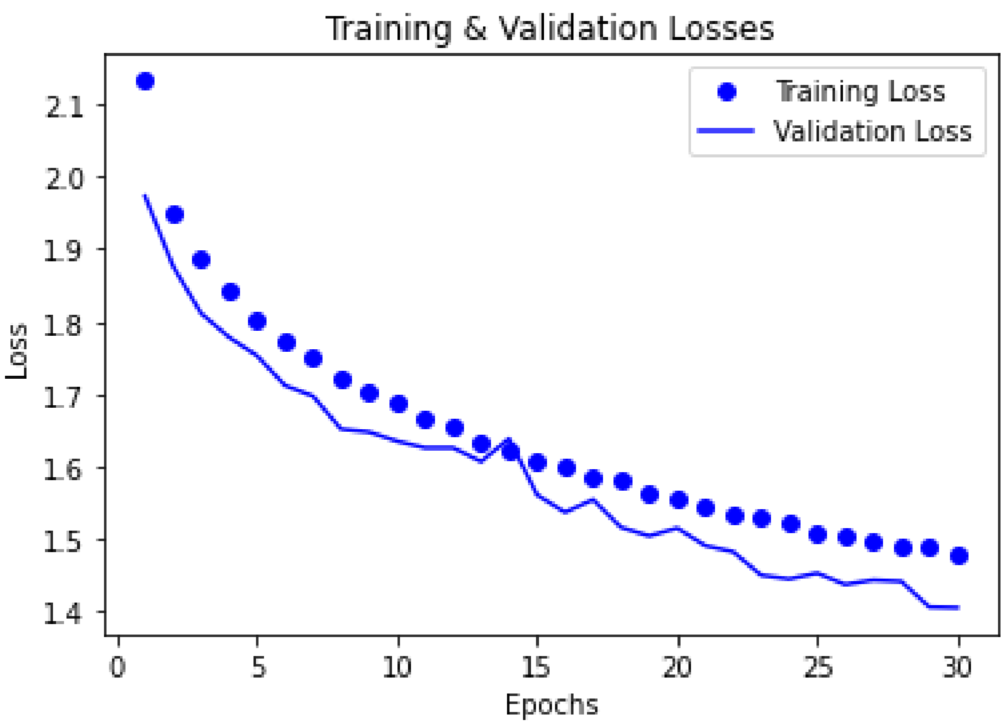
```
accuracy: 0.2008 - val_loss: 1.9729 - val_accuracy: 0.2817
Epoch 2/30
1250/1250 [==============================] - 55s 44ms/step - loss: 1.9495 -
accuracy: 0.2679 - val_loss: 1.8764 - val_accuracy: 0.3108
Epoch 3/30
1250/1250 [==============================] - 55s 44ms/step - loss: 1.8876 -
accuracy: 0.2911 - val_loss: 1.8117 - val_accuracy: 0.3378
Epoch 4/30
1250/1250 [==============================] - 55s 44ms/step - loss: 1.8428 -
accuracy: 0.3110 - val_loss: 1.7786 - val_accuracy: 0.3480
Epoch 5/30
1250/1250 [==============================] - 44s 35ms/step - loss: 1.8038 -
accuracy: 0.3295 - val_loss: 1.7531 - val_accuracy: 0.3587
Epoch 6/30
1250/1250 [==============================] - 41s 33ms/step - loss: 1.7748 -
accuracy: 0.3468 - val_loss: 1.7120 - val_accuracy: 0.3743
Epoch 7/30
1250/1250 [==============================] - 42s 34ms/step - loss: 1.7528 -
accuracy: 0.3517 - val_loss: 1.6974 - val_accuracy: 0.3812
Epoch 8/30
1250/1250 [==============================] - 42s 33ms/step - loss: 1.7226 -
accuracy: 0.3655 - val_loss: 1.6519 - val_accuracy: 0.4028
Epoch 9/30
1250/1250 [==============================] - 42s 34ms/step - loss: 1.7018 -
accuracy: 0.3754 - val_loss: 1.6478 - val_accuracy: 0.4042
Epoch 10/30
1250/1250 [==============================] - 50s 40ms/step - loss: 1.6889 -
accuracy: 0.3810 - val_loss: 1.6352 - val_accuracy: 0.4084
Epoch 11/30
1250/1250 [==============================] - 55s 44ms/step - loss: 1.6658 -
accuracy: 0.3938 - val_loss: 1.6261 - val_accuracy: 0.4041
Epoch 12/30
1250/1250 [==============================] - 55s 44ms/step - loss: 1.6539 -
accuracy: 0.3982 - val_loss: 1.6261 - val_accuracy: 0.4183
Epoch 13/30
1250/1250 [==============================] - 55s 44ms/step - loss: 1.6341 -
accuracy: 0.4044 - val_loss: 1.6071 - val_accuracy: 0.4148
Epoch 14/30
1250/1250 [==============================] - 55s 44ms/step - loss: 1.6232 -
accuracy: 0.4125 - val_loss: 1.6387 - val_accuracy: 0.4095
Epoch 15/30
1250/1250 [==============================] - 55s 44ms/step - loss: 1.6071 -
accuracy: 0.4177 - val_loss: 1.5613 - val_accuracy: 0.4407
Epoch 16/30
1250/1250 [==============================] - 56s 45ms/step - loss: 1.5999 -
accuracy: 0.4218 - val_loss: 1.5372 - val_accuracy: 0.4468
Epoch 17/30
1250/1250 [==============================] - 55s 44ms/step - loss: 1.5860 -
```

```
accuracy: 0.4254 - val_loss: 1.5548 - val_accuracy: 0.4429
Epoch 18/30
1250/1250 [==============================] - 46s 36ms/step - loss: 1.5804 -
accuracy: 0.4291 - val_loss: 1.5164 - val_accuracy: 0.4548
Epoch 19/30
1250/1250 [==============================] - 42s 34ms/step - loss: 1.5647 -
accuracy: 0.4354 - val_loss: 1.5046 - val_accuracy: 0.4596
Epoch 20/30
1250/1250 [==============================] - 42s 34ms/step - loss: 1.5559 -
accuracy: 0.4390 - val_loss: 1.5155 - val_accuracy: 0.4459
Epoch 21/30
1250/1250 [==============================] - 42s 33ms/step - loss: 1.5463 -
accuracy: 0.4436 - val_loss: 1.4912 - val_accuracy: 0.4651
Epoch 22/30
1250/1250 [==============================] - 41s 33ms/step - loss: 1.5341 -
accuracy: 0.4483 - val_loss: 1.4829 - val_accuracy: 0.4740
Epoch 23/30
1250/1250 [==============================] - 42s 33ms/step - loss: 1.5311 -
accuracy: 0.4477 - val_loss: 1.4504 - val_accuracy: 0.4856
Epoch 24/30
1250/1250 [==============================] - 42s 34ms/step - loss: 1.5230 -
accuracy: 0.4545 - val_loss: 1.4452 - val_accuracy: 0.4824
Epoch 25/30
1250/1250 [==============================] - 41s 33ms/step - loss: 1.5096 -
accuracy: 0.4574 - val_loss: 1.4533 - val_accuracy: 0.4828
Epoch 26/30
1250/1250 [==============================] - 42s 34ms/step - loss: 1.5041 -
accuracy: 0.4601 - val_loss: 1.4376 - val_accuracy: 0.4906
Epoch 27/30
1250/1250 [==============================] - 42s 33ms/step - loss: 1.4963 -
accuracy: 0.4651 - val_loss: 1.4438 - val_accuracy: 0.4882
Epoch 28/30
1250/1250 [==============================] - 42s 33ms/step - loss: 1.4901 -
accuracy: 0.4674 - val_loss: 1.4420 - val_accuracy: 0.4833
Epoch 29/30
1250/1250 [==============================] - 42s 33ms/step - loss: 1.4898 -
accuracy: 0.4644 - val_loss: 1.4066 - val_accuracy: 0.4982
Epoch 30/30
1250/1250 [==============================] - 41s 33ms/step - loss: 1.4797 -
accuracy: 0.4715 - val_loss: 1.4056 - val_accuracy: 0.4983
```

[56]:

```python
train_loss = history.history['loss']
val_loss = history.history['val_loss']

epochs = range(1, len(history.history['loss']) + 1)

plt.plot(epochs, train_loss, 'bo', label = 'Training Loss')
```

```
plt.plot(epochs, val_loss, 'b', label = 'Validation Loss')
plt.title('Training & Validation Losses')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
plt.savefig('/home/jovyan/dsc650/dsc650/assignments/assignment06/results/
↪6_2B_Loss.png')
```

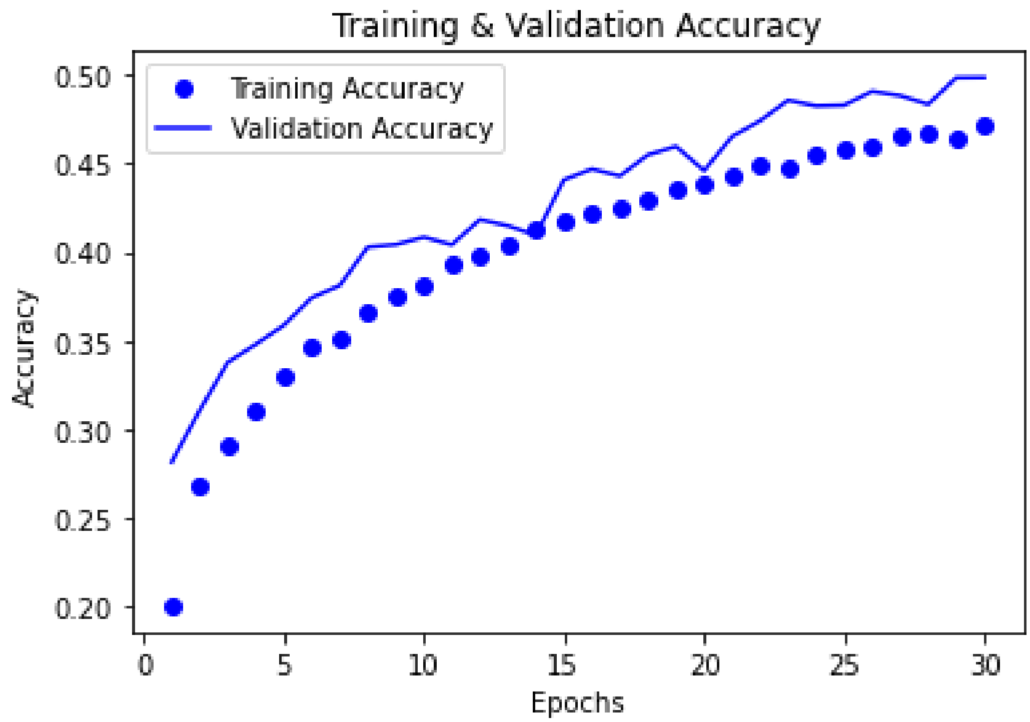



```
<Figure size 432x288 with 0 Axes>
```

[57]:

```
train_acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

epcohs = range(1, len(history.history['accuracy']) + 1)

plt.plot(epochs, train_acc, 'bo', label = 'Training Accuracy')
plt.plot(epochs, val_acc, 'b', label = 'Validation Accuracy')
plt.title('Training & Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

```
plt.savefig('/home/jovyan/dsc650/dsc650/assignments/assignment06/results/
↪6_2B_Accuracy')
```



<Figure size 432x288 with 0 Axes>

[58]:
```
# retrain model & evaluate
train_generator = train_datagen.flow(x_train, y_train, batch_size=32)

model.compile(optimizer=optimizers.RMSprop(lr=1e-4),
              loss='categorical_crossentropy',
              metrics=['accuracy'])

history = model.fit_generator(train_generator,
                              steps_per_epoch=len(x_train) / 32,
                              epochs = 16)

results = model.evaluate(x_test, y_test)
```

```
Epoch 1/16
1563/1562 [==============================] - 43s 28ms/step - loss: 1.4701 -
accuracy: 0.4726
Epoch 2/16
1563/1562 [==============================] - 43s 27ms/step - loss: 1.4612 -
```

```
accuracy: 0.4755
Epoch 3/16
1563/1562 [==============================] - 43s 27ms/step - loss: 1.4560 -
accuracy: 0.4782
Epoch 4/16
1563/1562 [==============================] - 43s 28ms/step - loss: 1.4530 -
accuracy: 0.4812
Epoch 5/16
1563/1562 [==============================] - 43s 27ms/step - loss: 1.4449 -
accuracy: 0.4824
Epoch 6/16
1563/1562 [==============================] - 43s 27ms/step - loss: 1.4340 -
accuracy: 0.4865
Epoch 7/16
1563/1562 [==============================] - 43s 27ms/step - loss: 1.4267 -
accuracy: 0.4859
Epoch 8/16
1563/1562 [==============================] - 43s 27ms/step - loss: 1.4250 -
accuracy: 0.4919
Epoch 9/16
1563/1562 [==============================] - 43s 27ms/step - loss: 1.4182 -
accuracy: 0.4939
Epoch 10/16
1563/1562 [==============================] - 43s 27ms/step - loss: 1.4086 -
accuracy: 0.4984
Epoch 11/16
1563/1562 [==============================] - 43s 27ms/step - loss: 1.4072 -
accuracy: 0.4984
Epoch 12/16
1563/1562 [==============================] - 43s 27ms/step - loss: 1.4001 -
accuracy: 0.5005
Epoch 13/16
1563/1562 [==============================] - 43s 27ms/step - loss: 1.3929 -
accuracy: 0.5068
Epoch 14/16
1563/1562 [==============================] - 43s 27ms/step - loss: 1.3890 -
accuracy: 0.5030
Epoch 15/16
1563/1562 [==============================] - 42s 27ms/step - loss: 1.3851 -
accuracy: 0.5058
Epoch 16/16
1563/1562 [==============================] - 43s 27ms/step - loss: 1.3803 -
accuracy: 0.5094
313/313 [==============================] - 1s 4ms/step - loss: 259.6964 -
accuracy: 0.3569
```

[59]:
```python
model.save('/home/jovyan/dsc650/dsc650/assignments/assignment06/results/
↪6_2B_model.h5')
```

[60]:
```python
prediction_results = model.predict(x_test)
```

[61]:
```python
prediction_results
```

[61]:
```
array([[0.0000000e+00, 0.0000000e+00, 0.0000000e+00, …, 0.0000000e+00,
        1.0000000e+00, 0.0000000e+00],
       [0.0000000e+00, 1.0000000e+00, 0.0000000e+00, …, 0.0000000e+00,
        0.0000000e+00, 0.0000000e+00],
       [0.0000000e+00, 1.0000000e+00, 0.0000000e+00, …, 0.0000000e+00,
        0.0000000e+00, 0.0000000e+00],
       …,
       [0.0000000e+00, 0.0000000e+00, 0.0000000e+00, …, 2.1403628e-29,
        0.0000000e+00, 0.0000000e+00],
       [0.0000000e+00, 1.0000000e+00, 0.0000000e+00, …, 0.0000000e+00,
        0.0000000e+00, 0.0000000e+00],
       [0.0000000e+00, 0.0000000e+00, 0.0000000e+00, …, 1.0000000e+00,
        0.0000000e+00, 0.0000000e+00]], dtype=float32)
```

[62]:
```python
with open('/home/jovyan/dsc650/dsc650/assignments/assignment06/results/
↪6_2B_metrics.txt', 'w') as f:
    f.write('Training Loss: {}'.format(str(history.history['loss'])))
    f.write('\nTraining Accuracy: {}'.format(str(history.history['accuracy'])))
    f.write('\nTest Loss: {}'.format(results[0]))
    f.write('\nTest Accuracy: {}'.format(results[1]))
```

[63]:
```python
preds = pd.DataFrame(prediction_results,
                     columns = ['0','1','2','3','4','5','6','7','8','9'])

preds.to_csv('/home/jovyan/dsc650/dsc650/assignments/assignment06/results/
↪6_2B_predicitons.csv', index = False)
```

[ ]:
```python

```