

Assignment11_ErenAkgunduz

April 20, 2024

1 Assignment 11

1.1 Eren Akgunduz

1.1.1 Deep Learning — 20 April 2024

1.1.2 [Link to notebook](#)

```
[1]: import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import tensorflow as tf
from keras.callbacks import ModelCheckpoint
from keras.datasets import cifar10
from keras.models import Sequential, load_model
from keras.regularizers import l2
from keras.layers import Dense, Conv2D, Flatten, Dropout, Activation, \
    MaxPooling2D
from keras.utils import to_categorical
from sklearn.metrics import accuracy_score, confusion_matrix, recall_score
```

1.1.3 Helper functions

```
[2]: def img_plt(images, labels):
    plt.figure()
    for i in range(1, 11):
        plt.subplot(2, 5, i)
        plt.imshow(images[i-1, :, :])
        plt.title(f"Label: {str(labels[i-1])}")
    plt.show()
```

```
[3]: def feat_plot(features, labels, classes):
    for class_i in classes:
        plt.plot(features[labels[:,0]==classes[class_i],0], features[labels[:,0]==classes[class_i],1], 'o', markersize=15)

    plt.xlabel('x: feature 1')
    plt.ylabel('y: feature 2')
    plt.legend(['Class' + str(classes[class_i]) for class_i in classes])
```

```
plt.show()
```

```
[4]: def acc_fun(labels_actual, labels_pred):  
      acc = np.sum(labels_actual==labels_pred)/len(labels_actual) * 100  
      return acc
```

```
[5]: def plot_curve(accuracy_train, loss_train, accuracy_val, loss_val):  
      epochs = np.arange(loss_train.shape[0])  
      plt.subplot(1,2,1)  
      plt.plot(epochs, accuracy_train, epochs, accuracy_val)  
      plt.xlabel('Epoch #')  
      plt.ylabel('Accuracy')  
      plt.title('Accuracy')  
      plt.legend(['Training', 'Validation'])  
  
      plt.subplot(1,2,2)  
      plt.plot(epochs, loss_train, epochs, loss_val)  
      plt.xlabel('Epoch #')  
      plt.ylabel('Binary crossentropy loss')  
      plt.title('Loss')  
      plt.legend(['Training', 'Validation'])  
      plt.show()
```

1.1.4 Dataset

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

```
[7]: classes = np.arange(10)  
      print(x_train.shape)
```

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

```
[8]: # Selecting 20% of training data as the validation set  
      num_train_img=x_train.shape[0]  
      train_ind=np.arange(0,num_train_img)  
      train_ind_s=np.random.permutation(train_ind)  
      x_train=x_train[train_ind_s,:,:,:]  
      y_train=y_train[train_ind_s]  
      # Selecting 20% of training images for validation  
      x_val=x_train[0:int(0.2*num_train_img),,:,:]  
      y_val=y_train[0:int(0.2*num_train_img)]  
      # The rest of the training set  
      x_train=x_train[int(0.2*num_train_img):,:,:]  
      y_train=y_train[int(0.2*num_train_img):]
```

1.1.5 Preprocessing

```
[9]: # Scaling the images
x_train=x_train.astype('float32')
x_val=x_val.astype('float32')
x_test=x_test.astype('float32')
x_train /= 255
x_val /= 255
x_test /= 255

# convert class vectors to binary class matrices
y_train_c = to_categorical(y_train, len(classes))
y_val_c = to_categorical(y_val, len(classes))
y_test_c = to_categorical(y_test, len(classes))
```

1.1.6 Model

```
[10]: model_a = Sequential()
model_a.add(Conv2D(32, (3, 3), padding='same', input_shape=x_train.shape[1:]))
model_a.add(Activation('relu'))
model_a.add(Conv2D(32, (3, 3), padding='same'))
model_a.add(Activation('relu'))
model_a.add(MaxPooling2D(pool_size=(2, 2)))

model_a.add(Conv2D(64, (3, 3), padding='same'))
model_a.add(Activation('relu'))
model_a.add(Conv2D(64, (3, 3), padding='same'))
model_a.add(Activation('relu'))
model_a.add(MaxPooling2D(pool_size=(2, 2)))

model_a.add(Flatten())
model_a.add(Dense(units=512, activation='relu'))
model_a.add(Dropout(0.5))
model_a.add(Dense(units=len(classes), activation='softmax'))
model_a.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 32, 32, 32)	896
activation (Activation)	(None, 32, 32, 32)	0
conv2d_1 (Conv2D)	(None, 32, 32, 32)	9248
activation_1 (Activation)	(None, 32, 32, 32)	0

max_pooling2d (MaxPooling2D)	(None, 16, 16, 32)	0
conv2d_2 (Conv2D)	(None, 16, 16, 64)	18496
activation_2 (Activation)	(None, 16, 16, 64)	0
conv2d_3 (Conv2D)	(None, 16, 16, 64)	36928
activation_3 (Activation)	(None, 16, 16, 64)	0
max_pooling2d_1 (MaxPooling2D)	(None, 8, 8, 64)	0
flatten (Flatten)	(None, 4096)	0
dense (Dense)	(None, 512)	2097664
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 10)	5130

```

=====
Total params: 2168362 (8.27 MB)
Trainable params: 2168362 (8.27 MB)
Non-trainable params: 0 (0.00 Byte)
=====

```

```

[11]: opt = tf.keras.optimizers.Adam(learning_rate=0.001)
      model_a.compile(optimizer=opt,
                      loss="categorical_crossentropy",
                      metrics=["accuracy"])

```

```

[12]: # Creating a checkpoint to save the best model based on the lowest validation
      ↪ loss.
      save_path='/content/drive/My Drive/model_a_cifar10.h5'
      callbacks_save=ModelCheckpoint(save_path, monitor='val_loss', verbose=0,
      ↪ save_best_only=True, period=1)

      history=model_a.fit(x_train, y_train_c,
                          batch_size=32,
                          epochs=50,
                          verbose=1,
                          validation_data=(x_val, y_val_c),
                          callbacks=[callbacks_save])

```

WARNING:tensorflow: `period` argument is deprecated. Please use `save_freq` to specify the frequency in number of batches seen.

```

Epoch 1/50
1250/1250 [=====] - 23s 10ms/step - loss: 1.4961 -
accuracy: 0.4559 - val_loss: 1.0912 - val_accuracy: 0.6080
Epoch 2/50
 12/1250 [...] - ETA: 6s - loss: 1.1437 - accuracy:
0.6016

/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3103:
UserWarning: You are saving your model as an HDF5 file via `model.save()`. This
file format is considered legacy. We recommend using instead the native Keras
format, e.g. `model.save('my_model.keras')`.
  saving_api.save_model(

1250/1250 [=====] - 8s 6ms/step - loss: 1.0301 -
accuracy: 0.6339 - val_loss: 0.9334 - val_accuracy: 0.6714
Epoch 3/50
1250/1250 [=====] - 8s 7ms/step - loss: 0.8358 -
accuracy: 0.7078 - val_loss: 0.7672 - val_accuracy: 0.7328
Epoch 4/50
1250/1250 [=====] - 8s 7ms/step - loss: 0.7037 -
accuracy: 0.7551 - val_loss: 0.7373 - val_accuracy: 0.7445
Epoch 5/50
1250/1250 [=====] - 7s 6ms/step - loss: 0.5956 -
accuracy: 0.7916 - val_loss: 0.7653 - val_accuracy: 0.7455
Epoch 6/50
1250/1250 [=====] - 8s 6ms/step - loss: 0.5087 -
accuracy: 0.8220 - val_loss: 0.7413 - val_accuracy: 0.7567
Epoch 7/50
1250/1250 [=====] - 8s 6ms/step - loss: 0.4283 -
accuracy: 0.8495 - val_loss: 0.7453 - val_accuracy: 0.7612
Epoch 8/50
1250/1250 [=====] - 7s 6ms/step - loss: 0.3655 -
accuracy: 0.8727 - val_loss: 0.8016 - val_accuracy: 0.7618
Epoch 9/50
1250/1250 [=====] - 8s 7ms/step - loss: 0.3109 -
accuracy: 0.8909 - val_loss: 0.8478 - val_accuracy: 0.7535
Epoch 10/50
1250/1250 [=====] - 7s 6ms/step - loss: 0.2788 -
accuracy: 0.9024 - val_loss: 0.8613 - val_accuracy: 0.7633
Epoch 11/50
1250/1250 [=====] - 7s 6ms/step - loss: 0.2454 -
accuracy: 0.9153 - val_loss: 0.9225 - val_accuracy: 0.7575
Epoch 12/50
1250/1250 [=====] - 8s 6ms/step - loss: 0.2245 -
accuracy: 0.9222 - val_loss: 1.0720 - val_accuracy: 0.7503
Epoch 13/50
1250/1250 [=====] - 9s 7ms/step - loss: 0.2078 -
accuracy: 0.9277 - val_loss: 1.0330 - val_accuracy: 0.7602
Epoch 14/50

```

1250/1250 [=====] - 8s 7ms/step - loss: 0.1983 - accuracy: 0.9310 - val_loss: 1.0323 - val_accuracy: 0.7487
Epoch 15/50
1250/1250 [=====] - 8s 6ms/step - loss: 0.1888 - accuracy: 0.9342 - val_loss: 1.1015 - val_accuracy: 0.7569
Epoch 16/50
1250/1250 [=====] - 8s 6ms/step - loss: 0.1720 - accuracy: 0.9400 - val_loss: 1.1018 - val_accuracy: 0.7610
Epoch 17/50
1250/1250 [=====] - 8s 7ms/step - loss: 0.1706 - accuracy: 0.9418 - val_loss: 1.1453 - val_accuracy: 0.7534
Epoch 18/50
1250/1250 [=====] - 8s 6ms/step - loss: 0.1677 - accuracy: 0.9424 - val_loss: 1.1574 - val_accuracy: 0.7626
Epoch 19/50
1250/1250 [=====] - 7s 6ms/step - loss: 0.1567 - accuracy: 0.9471 - val_loss: 1.2490 - val_accuracy: 0.7592
Epoch 20/50
1250/1250 [=====] - 8s 7ms/step - loss: 0.1563 - accuracy: 0.9475 - val_loss: 1.1909 - val_accuracy: 0.7612
Epoch 21/50
1250/1250 [=====] - 8s 6ms/step - loss: 0.1461 - accuracy: 0.9502 - val_loss: 1.2493 - val_accuracy: 0.7557
Epoch 22/50
1250/1250 [=====] - 7s 6ms/step - loss: 0.1521 - accuracy: 0.9495 - val_loss: 1.1816 - val_accuracy: 0.7600
Epoch 23/50
1250/1250 [=====] - 8s 7ms/step - loss: 0.1465 - accuracy: 0.9502 - val_loss: 1.3041 - val_accuracy: 0.7613
Epoch 24/50
1250/1250 [=====] - 7s 6ms/step - loss: 0.1374 - accuracy: 0.9538 - val_loss: 1.3896 - val_accuracy: 0.7550
Epoch 25/50
1250/1250 [=====] - 8s 6ms/step - loss: 0.1478 - accuracy: 0.9516 - val_loss: 1.2869 - val_accuracy: 0.7548
Epoch 26/50
1250/1250 [=====] - 8s 7ms/step - loss: 0.1373 - accuracy: 0.9557 - val_loss: 1.3708 - val_accuracy: 0.7506
Epoch 27/50
1250/1250 [=====] - 7s 6ms/step - loss: 0.1336 - accuracy: 0.9558 - val_loss: 1.3789 - val_accuracy: 0.7621
Epoch 28/50
1250/1250 [=====] - 8s 7ms/step - loss: 0.1275 - accuracy: 0.9582 - val_loss: 1.3954 - val_accuracy: 0.7589
Epoch 29/50
1250/1250 [=====] - 11s 9ms/step - loss: 0.1340 - accuracy: 0.9550 - val_loss: 1.3548 - val_accuracy: 0.7594
Epoch 30/50

1250/1250 [=====] - 11s 9ms/step - loss: 0.1369 - accuracy: 0.9560 - val_loss: 1.3786 - val_accuracy: 0.7606
Epoch 31/50
1250/1250 [=====] - 7s 6ms/step - loss: 0.1193 - accuracy: 0.9608 - val_loss: 1.4086 - val_accuracy: 0.7645
Epoch 32/50
1250/1250 [=====] - 10s 8ms/step - loss: 0.1301 - accuracy: 0.9578 - val_loss: 1.4394 - val_accuracy: 0.7604
Epoch 33/50
1250/1250 [=====] - 8s 7ms/step - loss: 0.1264 - accuracy: 0.9585 - val_loss: 1.3499 - val_accuracy: 0.7666
Epoch 34/50
1250/1250 [=====] - 8s 6ms/step - loss: 0.1244 - accuracy: 0.9596 - val_loss: 1.3703 - val_accuracy: 0.7485
Epoch 35/50
1250/1250 [=====] - 8s 6ms/step - loss: 0.1189 - accuracy: 0.9610 - val_loss: 1.3678 - val_accuracy: 0.7580
Epoch 36/50
1250/1250 [=====] - 8s 6ms/step - loss: 0.1270 - accuracy: 0.9595 - val_loss: 1.5382 - val_accuracy: 0.7517
Epoch 37/50
1250/1250 [=====] - 7s 6ms/step - loss: 0.1149 - accuracy: 0.9624 - val_loss: 1.4389 - val_accuracy: 0.7625
Epoch 38/50
1250/1250 [=====] - 9s 7ms/step - loss: 0.1123 - accuracy: 0.9645 - val_loss: 1.6158 - val_accuracy: 0.7596
Epoch 39/50
1250/1250 [=====] - 8s 6ms/step - loss: 0.1284 - accuracy: 0.9598 - val_loss: 1.5106 - val_accuracy: 0.7581
Epoch 40/50
1250/1250 [=====] - 8s 6ms/step - loss: 0.1100 - accuracy: 0.9652 - val_loss: 1.5956 - val_accuracy: 0.7618
Epoch 41/50
1250/1250 [=====] - 8s 6ms/step - loss: 0.1228 - accuracy: 0.9613 - val_loss: 1.5210 - val_accuracy: 0.7578
Epoch 42/50
1250/1250 [=====] - 7s 6ms/step - loss: 0.1119 - accuracy: 0.9646 - val_loss: 1.5974 - val_accuracy: 0.7566
Epoch 43/50
1250/1250 [=====] - 9s 7ms/step - loss: 0.1197 - accuracy: 0.9632 - val_loss: 1.4392 - val_accuracy: 0.7633
Epoch 44/50
1250/1250 [=====] - 8s 6ms/step - loss: 0.1086 - accuracy: 0.9665 - val_loss: 1.5151 - val_accuracy: 0.7567
Epoch 45/50
1250/1250 [=====] - 7s 6ms/step - loss: 0.1093 - accuracy: 0.9656 - val_loss: 1.5396 - val_accuracy: 0.7533
Epoch 46/50

```

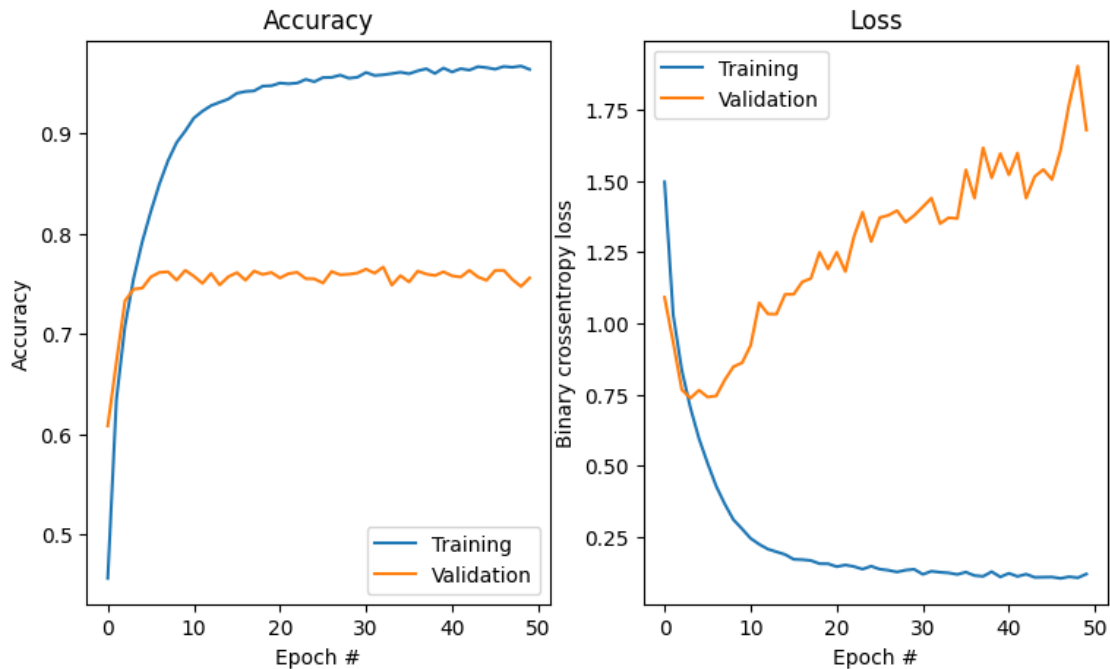
1250/1250 [=====] - 8s 6ms/step - loss: 0.1097 -
accuracy: 0.9641 - val_loss: 1.5046 - val_accuracy: 0.7632
Epoch 47/50
1250/1250 [=====] - 8s 7ms/step - loss: 0.1050 -
accuracy: 0.9667 - val_loss: 1.6076 - val_accuracy: 0.7633
Epoch 48/50
1250/1250 [=====] - 7s 6ms/step - loss: 0.1109 -
accuracy: 0.9660 - val_loss: 1.7698 - val_accuracy: 0.7542
Epoch 49/50
1250/1250 [=====] - 8s 7ms/step - loss: 0.1072 -
accuracy: 0.9672 - val_loss: 1.9027 - val_accuracy: 0.7472
Epoch 50/50
1250/1250 [=====] - 8s 6ms/step - loss: 0.1202 -
accuracy: 0.9639 - val_loss: 1.6780 - val_accuracy: 0.7557

```

```

[13]: plt.figure(figsize=[9, 5])
acc_curve_train = np.array(history.history['accuracy'])
loss_curve_train = np.array(history.history['loss'])
acc_curve_val = np.array(history.history['val_accuracy'])
loss_curve_val = np.array(history.history['val_loss'])
plot_curve(acc_curve_train, loss_curve_train, acc_curve_val, loss_curve_val)

```



1.1.7 Scores

```
[14]: # Loading the best model - saved based on the lowest validation loss
model_a = load_model(save_path)
```

```
[15]: # Evaluating the model on the training samples
score = model_a.evaluate(x_train, y_train_c)
print(f"Total loss on training set: {score[0]}")
print(f"Accuracy of training set: {score[1]}")
```

```
1250/1250 [=====] - 4s 3ms/step - loss: 0.5000 -
accuracy: 0.8353
Total loss on training set: 0.5000460147857666
Accuracy of training set: 0.8352749943733215
```

```
[16]: # Evaluating the model on the validation samples
score = model_a.evaluate(x_val, y_val_c)
print(f"Total loss on validation set: {score[0]}")
print(f"Accuracy of validation set: {score[1]}")
```

```
313/313 [=====] - 1s 3ms/step - loss: 0.7373 -
accuracy: 0.7445
Total loss on validation set: 0.737325131893158
Accuracy of validation set: 0.7444999814033508
```

```
[17]: # Evaluating the model on the held out samples
score = model_a.evaluate(x_test, y_test_c)
print(f"Total loss on testing set: {score[0]}")
print(f"Accuracy of testing set: {score[1]}")
```

```
313/313 [=====] - 1s 4ms/step - loss: 0.7370 -
accuracy: 0.7456
Total loss on testing set: 0.7370343208312988
Accuracy of testing set: 0.7455999851226807
```