

## assignment 6.2a

October 10, 2022

```
[1]: # Import necessary packages
```

```
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.datasets import mnist
from keras.utils import to_categorical
from keras import layers, models
import numpy as np
import matplotlib.pyplot as plt
from keras import optimizers
from sklearn.metrics import confusion_matrix
import os, shutil

from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = 'all'
```

```
[2]: # load the data
```

```
(x_train, y_train), (x_test, y_test) = keras.datasets.cifar10.load_data()
```

```
[3]: # display the size of data sets
```

```
x_train.shape
x_test.shape
y_train.shape
y_test.shape
```

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

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

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

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

```
[4]: cifar10_classes = ["airplane", "automobile", "bird", "cat", "deer", "dog",  
    ↪ "frog", "horse", "ship", "truck"]
```

```
[5]: # split data into train and validation

# Scale the data
x_train = x_train.astype('float32') / 255.0
x_test = x_test.astype('float32') / 255.0

# Transform target variable into one-hotencoding
y_train = to_categorical(y_train)
y_test = to_categorical(y_test)

x_val = x_train[:10000]
partial_x_train = x_train[10000:]

y_val = y_train[:10000]
partial_y_train = y_train[10000:]
```

```
[6]: x_train.shape
x_test.shape
y_train.shape
y_test.shape
partial_y_train.shape
partial_x_train.shape

y_train[0]
```

```
[6]: (50000, 32, 32, 3)
```

```
[6]: (10000, 32, 32, 3)
```

```
[6]: (50000, 10)
```

```
[6]: (10000, 10)
```

```
[6]: (40000, 10)
```

```
[6]: (40000, 32, 32, 3)
```

```
[6]: array([0., 0., 0., 0., 0., 0., 1., 0., 0., 0.], dtype=float32)
```

```
[7]: # Model
model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu', padding='same',
                        input_shape=(32, 32, 3)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu', padding='same'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(128, (3, 3), activation='relu', padding='same'))
```

```

model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(128, (3, 3), activation='relu', padding='same'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Flatten())
model.add(layers.Dense(512, activation='relu'))
model.add(layers.Dense(10, activation='sigmoid'))

```

[8]: *# display model summary*

```
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
=====		
conv2d (Conv2D)	(None, 32, 32, 32)	896
-----		
max_pooling2d (MaxPooling2D)	(None, 16, 16, 32)	0
-----		
conv2d_1 (Conv2D)	(None, 16, 16, 64)	18496
-----		
max_pooling2d_1 (MaxPooling2D)	(None, 8, 8, 64)	0
-----		
conv2d_2 (Conv2D)	(None, 8, 8, 128)	73856
-----		
max_pooling2d_2 (MaxPooling2D)	(None, 4, 4, 128)	0
-----		
conv2d_3 (Conv2D)	(None, 4, 4, 128)	147584
-----		
max_pooling2d_3 (MaxPooling2D)	(None, 2, 2, 128)	0
-----		
flatten (Flatten)	(None, 512)	0
-----		
dense (Dense)	(None, 512)	262656
-----		
dense_1 (Dense)	(None, 10)	5130
=====		
Total params: 508,618		
Trainable params: 508,618		
Non-trainable params: 0		
-----		

[9]: *# compile the model*

```

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

```

```
[10]: history = model.fit(
    partial_x_train, partial_y_train,
    epochs=30,
    batch_size=64,
    validation_data=(x_val, y_val),
    validation_steps=50)
```

Epoch 1/30

625/625 [=====] - 19s 31ms/step - loss: 0.2984 - acc: 0.2765 - val\_loss: 0.2725 - val\_acc: 0.3491

Epoch 2/30

625/625 [=====] - 18s 28ms/step - loss: 0.2540 - acc: 0.4040 - val\_loss: 0.2387 - val\_acc: 0.4425

Epoch 3/30

625/625 [=====] - 17s 28ms/step - loss: 0.2369 - acc: 0.4499 - val\_loss: 0.2317 - val\_acc: 0.4591

Epoch 4/30

625/625 [=====] - 17s 28ms/step - loss: 0.2245 - acc: 0.4882 - val\_loss: 0.2158 - val\_acc: 0.5113

Epoch 5/30

625/625 [=====] - 18s 29ms/step - loss: 0.2142 - acc: 0.5192 - val\_loss: 0.2143 - val\_acc: 0.5284

Epoch 6/30

625/625 [=====] - 18s 29ms/step - loss: 0.2054 - acc: 0.5441 - val\_loss: 0.2047 - val\_acc: 0.5506

Epoch 7/30

625/625 [=====] - 18s 29ms/step - loss: 0.1979 - acc: 0.5640 - val\_loss: 0.1963 - val\_acc: 0.5694

Epoch 8/30

625/625 [=====] - 18s 29ms/step - loss: 0.1907 - acc: 0.5835 - val\_loss: 0.1863 - val\_acc: 0.5894

Epoch 9/30

625/625 [=====] - 18s 28ms/step - loss: 0.1846 - acc: 0.6000 - val\_loss: 0.1810 - val\_acc: 0.6147

Epoch 10/30

625/625 [=====] - 17s 27ms/step - loss: 0.1787 - acc: 0.6148 - val\_loss: 0.1765 - val\_acc: 0.6212

Epoch 11/30

625/625 [=====] - 15s 24ms/step - loss: 0.1732 - acc: 0.6289 - val\_loss: 0.1749 - val\_acc: 0.6231

Epoch 12/30

625/625 [=====] - 15s 24ms/step - loss: 0.1679 - acc: 0.6444 - val\_loss: 0.1728 - val\_acc: 0.6334

Epoch 13/30

625/625 [=====] - 15s 24ms/step - loss: 0.1628 - acc: 0.6566 - val\_loss: 0.1648 - val\_acc: 0.6572

Epoch 14/30

625/625 [=====] - 15s 24ms/step - loss: 0.1583 - acc: 0.6662 - val\_loss: 0.1629 - val\_acc: 0.6488  
Epoch 15/30  
625/625 [=====] - 15s 23ms/step - loss: 0.1537 - acc: 0.6789 - val\_loss: 0.1643 - val\_acc: 0.6491  
Epoch 16/30  
625/625 [=====] - 15s 24ms/step - loss: 0.1494 - acc: 0.6930 - val\_loss: 0.1612 - val\_acc: 0.6634  
Epoch 17/30  
625/625 [=====] - 15s 24ms/step - loss: 0.1452 - acc: 0.7007 - val\_loss: 0.1554 - val\_acc: 0.6703  
Epoch 18/30  
625/625 [=====] - 15s 23ms/step - loss: 0.1414 - acc: 0.7096 - val\_loss: 0.1514 - val\_acc: 0.6747  
Epoch 19/30  
625/625 [=====] - 15s 23ms/step - loss: 0.1375 - acc: 0.7199 - val\_loss: 0.1509 - val\_acc: 0.6931  
Epoch 20/30  
625/625 [=====] - 15s 23ms/step - loss: 0.1337 - acc: 0.7288 - val\_loss: 0.1492 - val\_acc: 0.6847  
Epoch 21/30  
625/625 [=====] - 14s 23ms/step - loss: 0.1298 - acc: 0.7390 - val\_loss: 0.1512 - val\_acc: 0.6916  
Epoch 22/30  
625/625 [=====] - 15s 23ms/step - loss: 0.1262 - acc: 0.7470 - val\_loss: 0.1448 - val\_acc: 0.6944  
Epoch 23/30  
625/625 [=====] - 15s 23ms/step - loss: 0.1227 - acc: 0.7538 - val\_loss: 0.1494 - val\_acc: 0.6884  
Epoch 24/30  
625/625 [=====] - 15s 24ms/step - loss: 0.1191 - acc: 0.7617 - val\_loss: 0.1454 - val\_acc: 0.6972  
Epoch 25/30  
625/625 [=====] - 15s 24ms/step - loss: 0.1159 - acc: 0.7717 - val\_loss: 0.1487 - val\_acc: 0.6906  
Epoch 26/30  
625/625 [=====] - 15s 23ms/step - loss: 0.1125 - acc: 0.7796 - val\_loss: 0.1396 - val\_acc: 0.7063  
Epoch 27/30  
625/625 [=====] - 15s 23ms/step - loss: 0.1095 - acc: 0.7865 - val\_loss: 0.1483 - val\_acc: 0.6972  
Epoch 28/30  
625/625 [=====] - 15s 23ms/step - loss: 0.1061 - acc: 0.7938 - val\_loss: 0.1520 - val\_acc: 0.6909  
Epoch 29/30  
625/625 [=====] - 15s 23ms/step - loss: 0.1029 - acc: 0.8024 - val\_loss: 0.1377 - val\_acc: 0.7153  
Epoch 30/30

```
625/625 [=====] - 15s 23ms/step - loss: 0.0999 - acc: 0.8094 - val_loss: 0.1390 - val_acc: 0.7225
```

```
[11]: plt.figure(figsize=(10,7))

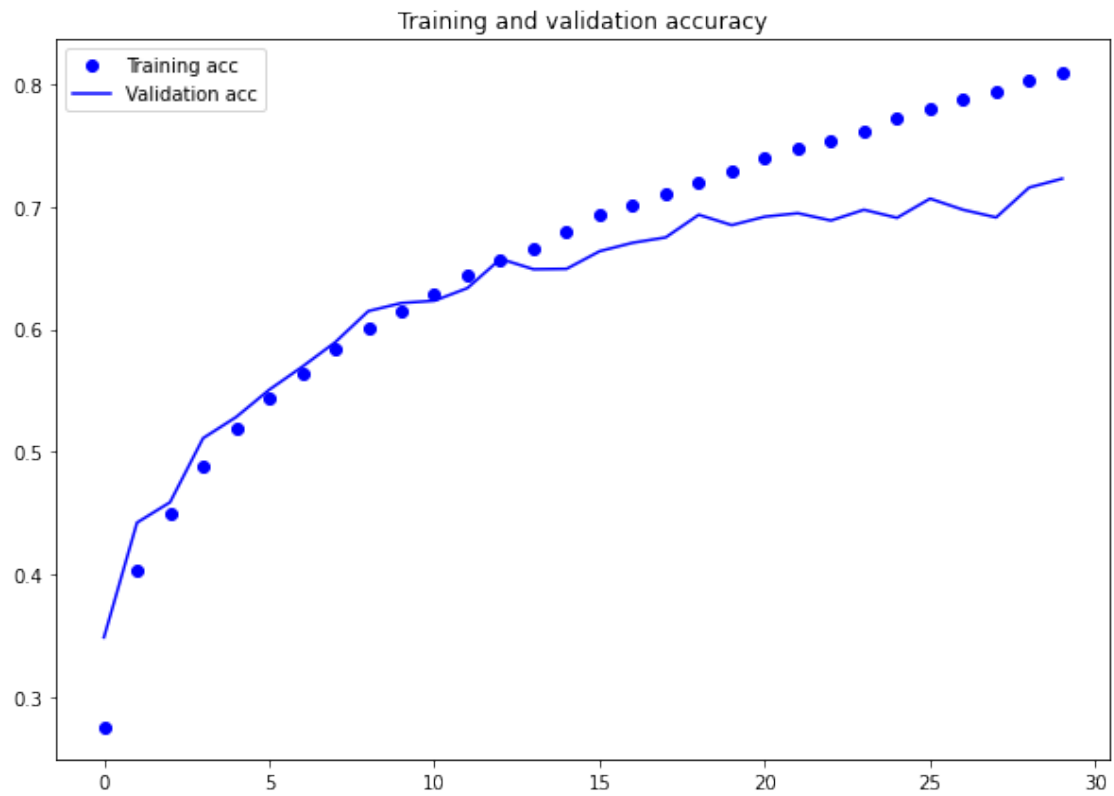
acc = history.history['acc']
val_acc = history.history['val_acc']
loss = history.history['loss']
val_loss = history.history['val_loss']

epochs = range(len(acc))

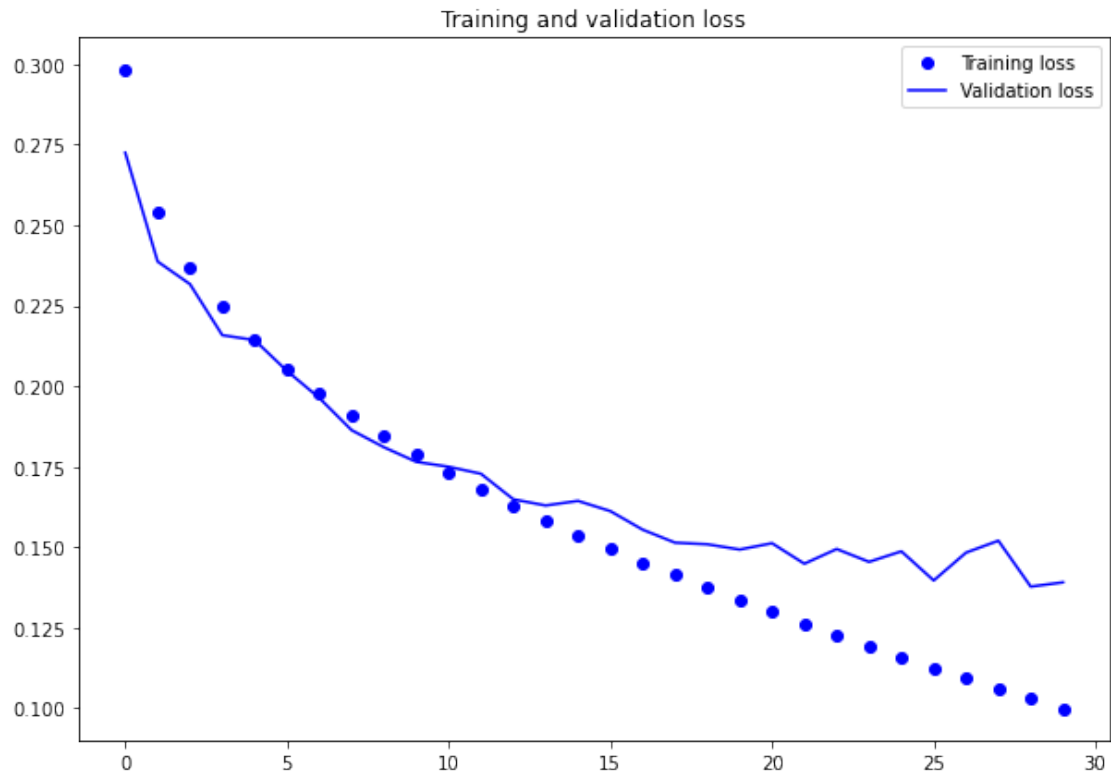
plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
plt.legend()

plt.figure()
plt.figure(figsize=(10,7))
plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()

plt.show();
```



<Figure size 432x288 with 0 Axes>



```
[12]: results = model.evaluate(x_test, y_test)
```

```
313/313 [=====] - 2s 7ms/step - loss: 0.1424 - acc: 0.7167
```

```
[13]: print(f"The accuracy of the model is {round(results[1],2)*100}%")
```

```
The accuracy of the model is 72.0%
```

```
[14]: # Predicting test data
```

```
y_pred_test = model.predict(x_test)
y_pred_test_classes = np.argmax(y_pred_test, axis=1)
y_pred_test_max_probas = np.max(y_pred_test, axis=1)
```

```
[15]: # reverse y_test from categorical
```

```
y_test = np.argmax(y_test,axis=1)
```

```
[16]: # display the predictions
```

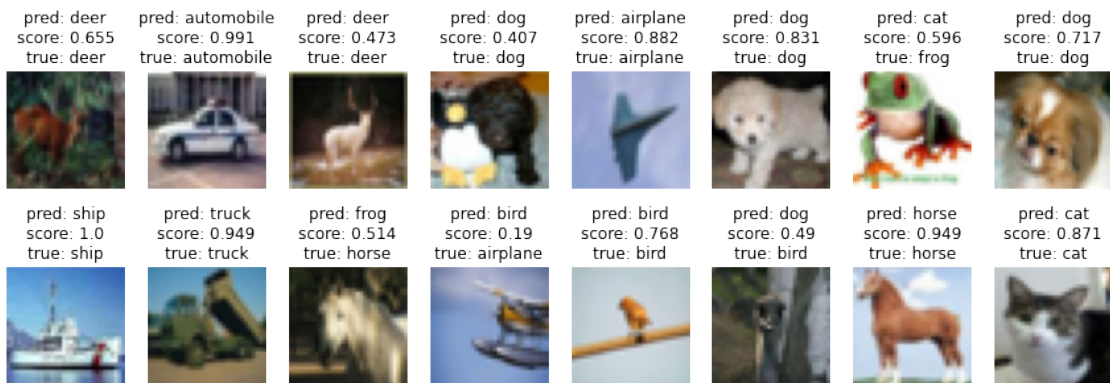
```
cols = 8
```



```

rows = 2
fig = plt.figure(figsize=(2 * cols - 1, 3 * rows - 1))
for i in range(cols):
    for j in range(rows):
        random_index = np.random.randint(0, len(y_test))
        ax = fig.add_subplot(rows, cols, i * rows + j + 1)
        ax.grid('off')
        ax.axis('off')
        ax.imshow(x_test[random_index, :])
        pred_label = cifar10_classes[y_pred_test_classes[random_index]]
        pred_proba = y_pred_test_max_probas[random_index]
        true_label = cifar10_classes[y_test[random_index]]
        ax.set_title("pred: {}\nscore: {:.3}\ntrue: {}".format(pred_label,
↪pred_proba, true_label))
plt.show();

```



[ ]: