

## assignment 6.2b

October 10, 2022

```
[1]: 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 keras.preprocessing.image import ImageDataGenerator

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

```
[4]: # 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, 10)
    y_test = to_categorical(y_test, 10)

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

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

[5]: *# build the 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.Dropout(0.5))
model.add(layers.Dense(512, activation='relu'))
model.add(layers.Dense(10, activation='softmax'))

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

[6]:

```
batch_size = 32
data_generator = ImageDataGenerator(width_shift_range=0.1, height_shift_range=0.
    ↪1, horizontal_flip=True)
train_generator = data_generator.flow(partial_x_train, partial_y_train,
    ↪batch_size)
```

[7]: *# train the model using data augmentation and dropout:*

```
history = model.fit(
    train_generator,
    steps_per_epoch=100,
    epochs=30,
    validation_data=(x_test, y_test))
```

Epoch 1/30

100/100 [=====] - 5s 53ms/step - loss: 2.2870 - acc: 0.1231 - val\_loss: 2.2463 - val\_acc: 0.1169

Epoch 2/30

100/100 [=====] - 6s 57ms/step - loss: 2.1822 - acc: 0.1966 - val\_loss: 2.0775 - val\_acc: 0.2596

Epoch 3/30

100/100 [=====] - 6s 63ms/step - loss: 2.0680 - acc: 0.2325 - val\_loss: 1.9812 - val\_acc: 0.2553

Epoch 4/30

100/100 [=====] - 6s 60ms/step - loss: 2.0063 - acc: 0.2597 - val\_loss: 1.9498 - val\_acc: 0.2763

Epoch 5/30  
100/100 [=====] - 6s 60ms/step - loss: 1.9524 - acc:  
0.2753 - val\_loss: 1.8585 - val\_acc: 0.3144  
Epoch 6/30  
100/100 [=====] - 6s 61ms/step - loss: 1.9011 - acc:  
0.3006 - val\_loss: 1.8118 - val\_acc: 0.3371  
Epoch 7/30  
100/100 [=====] - 6s 59ms/step - loss: 1.8757 - acc:  
0.3209 - val\_loss: 1.7986 - val\_acc: 0.3492  
Epoch 8/30  
100/100 [=====] - 6s 60ms/step - loss: 1.8526 - acc:  
0.3169 - val\_loss: 1.7551 - val\_acc: 0.3671  
Epoch 9/30  
100/100 [=====] - 6s 61ms/step - loss: 1.8376 - acc:  
0.3300 - val\_loss: 1.7826 - val\_acc: 0.3672  
Epoch 10/30  
100/100 [=====] - 6s 60ms/step - loss: 1.8206 - acc:  
0.3378 - val\_loss: 1.7034 - val\_acc: 0.3831  
Epoch 11/30  
100/100 [=====] - 6s 58ms/step - loss: 1.7966 - acc:  
0.3506 - val\_loss: 1.6729 - val\_acc: 0.3917  
Epoch 12/30  
100/100 [=====] - 6s 58ms/step - loss: 1.7809 - acc:  
0.3381 - val\_loss: 1.6869 - val\_acc: 0.3805  
Epoch 13/30  
100/100 [=====] - 6s 59ms/step - loss: 1.7527 - acc:  
0.3425 - val\_loss: 1.6465 - val\_acc: 0.4065  
Epoch 14/30  
100/100 [=====] - 6s 58ms/step - loss: 1.7475 - acc:  
0.3613 - val\_loss: 1.6465 - val\_acc: 0.3953  
Epoch 15/30  
100/100 [=====] - 6s 60ms/step - loss: 1.7085 - acc:  
0.3694 - val\_loss: 1.6632 - val\_acc: 0.3987  
Epoch 16/30  
100/100 [=====] - 6s 58ms/step - loss: 1.6907 - acc:  
0.3688 - val\_loss: 1.7006 - val\_acc: 0.3912  
Epoch 17/30  
100/100 [=====] - 6s 58ms/step - loss: 1.7084 - acc:  
0.3797 - val\_loss: 1.6326 - val\_acc: 0.3988  
Epoch 18/30  
100/100 [=====] - 6s 61ms/step - loss: 1.6734 - acc:  
0.3825 - val\_loss: 1.5709 - val\_acc: 0.4184  
Epoch 19/30  
100/100 [=====] - 6s 59ms/step - loss: 1.6711 - acc:  
0.3853 - val\_loss: 1.5765 - val\_acc: 0.4243  
Epoch 20/30  
100/100 [=====] - 6s 58ms/step - loss: 1.6757 - acc:  
0.3841 - val\_loss: 1.5849 - val\_acc: 0.4321

```

Epoch 21/30
100/100 [=====] - 6s 61ms/step - loss: 1.6299 - acc:
0.4025 - val_loss: 1.5651 - val_acc: 0.4207
Epoch 22/30
100/100 [=====] - 6s 59ms/step - loss: 1.6095 - acc:
0.4112 - val_loss: 1.5442 - val_acc: 0.4292
Epoch 23/30
100/100 [=====] - 6s 60ms/step - loss: 1.6232 - acc:
0.4159 - val_loss: 1.5608 - val_acc: 0.4299
Epoch 24/30
100/100 [=====] - 6s 60ms/step - loss: 1.6126 - acc:
0.3975 - val_loss: 1.5182 - val_acc: 0.4424
Epoch 25/30
100/100 [=====] - 6s 60ms/step - loss: 1.5772 - acc:
0.4278 - val_loss: 1.5242 - val_acc: 0.4388
Epoch 26/30
100/100 [=====] - 6s 58ms/step - loss: 1.5832 - acc:
0.4263 - val_loss: 1.4584 - val_acc: 0.4663
Epoch 27/30
100/100 [=====] - 6s 61ms/step - loss: 1.5793 - acc:
0.4250 - val_loss: 1.4574 - val_acc: 0.4625
Epoch 28/30
100/100 [=====] - 6s 61ms/step - loss: 1.5612 - acc:
0.4328 - val_loss: 1.4485 - val_acc: 0.4730
Epoch 29/30
100/100 [=====] - 6s 58ms/step - loss: 1.5554 - acc:
0.4334 - val_loss: 1.6001 - val_acc: 0.4308
Epoch 30/30
100/100 [=====] - 6s 60ms/step - loss: 1.5592 - acc:
0.4284 - val_loss: 1.4751 - val_acc: 0.4560

```

```
[8]: # save the model
```

```
model.save('cnn_classifier_2.h5')
```

```
[9]: # Plot the training vs validation - accuracy and loss
```

```

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')

```

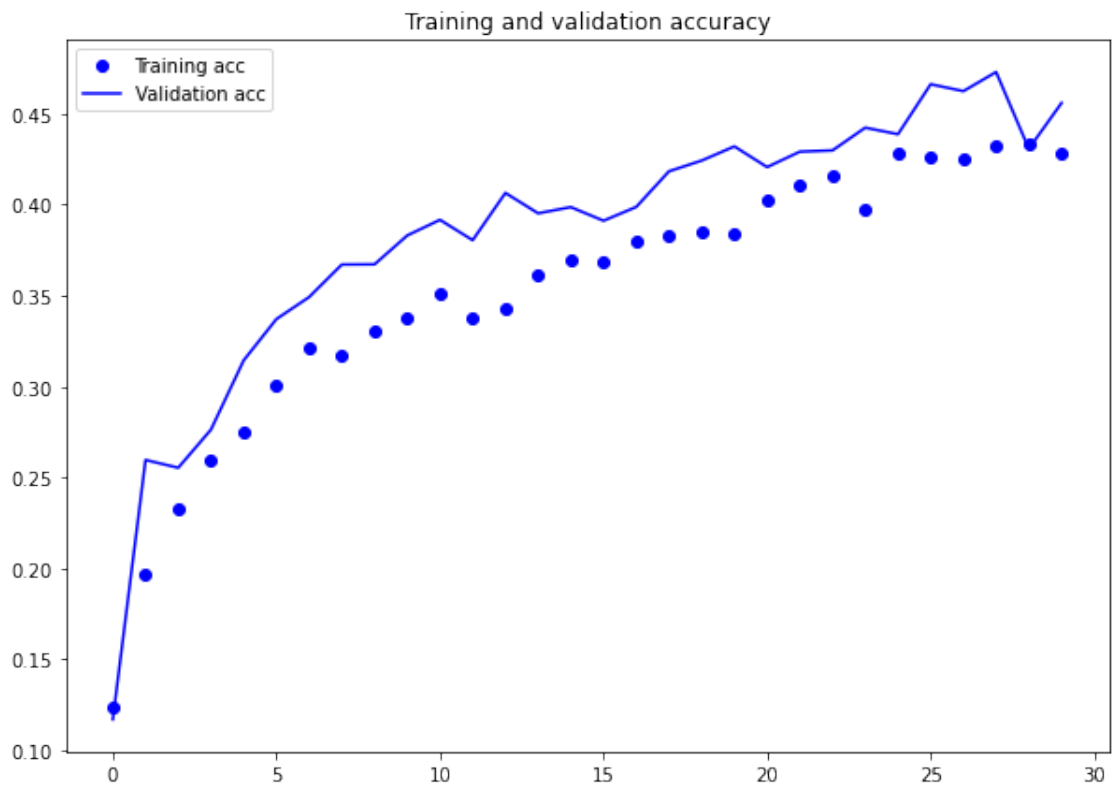
```

plt.title('Training and validation accuracy')
plt.legend()

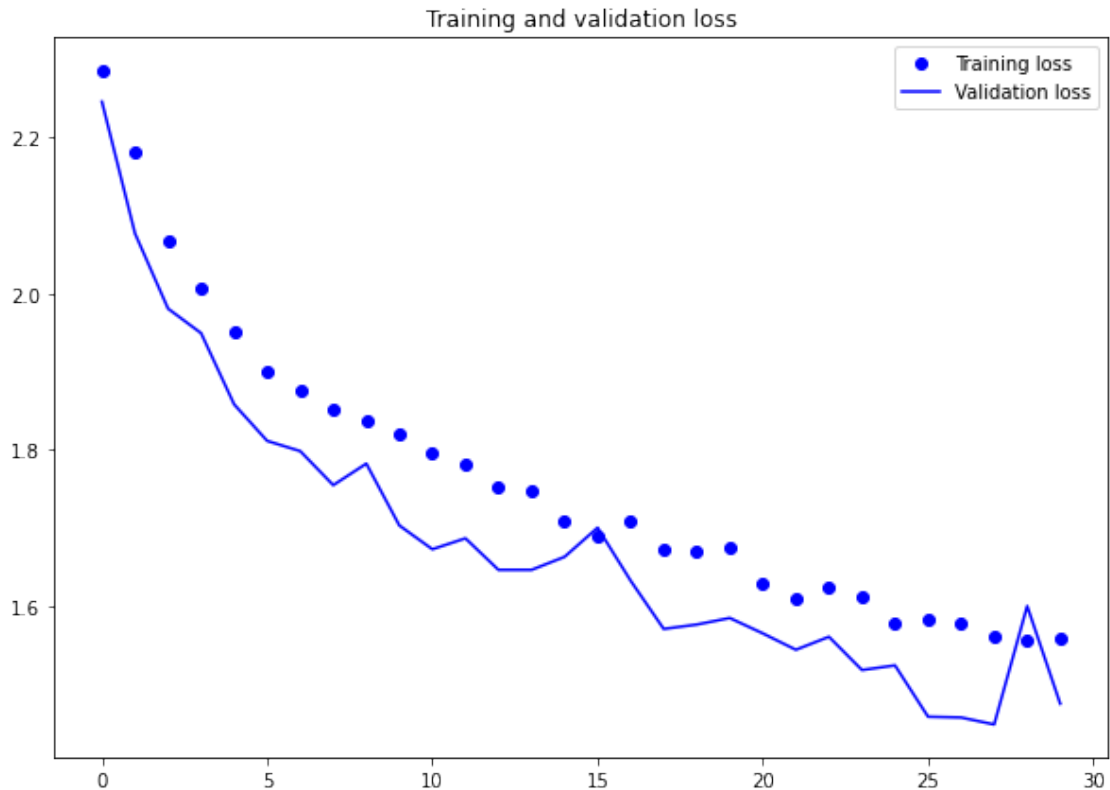
plt.figure()
plt.figure(figsize=(10,7))
plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()

plt.show();

```



<Figure size 432x288 with 0 Axes>



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

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

```
313/313 [=====] - 3s 8ms/step - loss: 1.4751 - acc:
0.4560
The accuracy of the model is 46.0%
```

```
[11]: # 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)
```

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

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

```
[13]: # 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();

```



[ ]: