An Introduction to Deep Learning With Python

[5.3] Using a pretrained convnet

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Instantiating the VGG16 convolutional base

Using TensorFlow backend.

WARNING:tensorflow:From C:\Users\pablo\AppData\Roaming\Python\Python36\site-packages\tensorflow\python\framework\op_def_library.py:263: colocate_with (from tensorflow.python.framework.ops) is deprecated and will be removed in a future version.

Instructions for updating:

Colocations handled automatically by placer.

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 150, 150, 3)	0
block1_conv1 (Conv2D)	(None, 150, 150, 64)	1792
block1_conv2 (Conv2D)	(None, 150, 150, 64)	36928
block1_pool (MaxPooling2D)	(None, 75, 75, 64)	0
block2_conv1 (Conv2D)	(None, 75, 75, 128)	73856
block2_conv2 (Conv2D)	(None, 75, 75, 128)	147584
block2_pool (MaxPooling2D)	(None, 37, 37, 128)	0
block3_conv1 (Conv2D)	(None, 37, 37, 256)	295168
block3_conv2 (Conv2D)	(None, 37, 37, 256)	590080
block3_conv3 (Conv2D)	(None, 37, 37, 256)	590080
block3_pool (MaxPooling2D)	(None, 18, 18, 256)	0
block4_conv1 (Conv2D)	(None, 18, 18, 512)	1180160
block4_conv2 (Conv2D)	(None, 18, 18, 512)	2359808
block4_conv3 (Conv2D)	(None, 18, 18, 512)	2359808
block4_pool (MaxPooling2D)	(None, 9, 9, 512)	0
block5_conv1 (Conv2D)	(None, 9, 9, 512)	2359808
block5_conv2 (Conv2D)	(None, 9, 9, 512)	2359808
block5_conv3 (Conv2D)	(None, 9, 9, 512)	2359808
block5_pool (MaxPooling2D)	(None, 4, 4, 512)	0

Total params: 14,714,688 Trainable params: 14,714,688 Non-trainable params: 0

Extracting features using the pretrained convolutional base

```
In [2]: import os
        import numpy as np
        from keras.preprocessing.image import ImageDataGenerator
        base_dir = '../CAP_5/cats_and_dogs_small'
        train_dir = os.path.join(base_dir, 'train')
        validation_dir = os.path.join(base_dir, 'validation')
        test_dir = os.path.join(base_dir, 'test')
        datagen = ImageDataGenerator(rescale=1./255)
        batch_size = 20
        def extract_features(directory, sample_count):
            features = np.zeros(shape=(sample_count, 4, 4, 512))
            labels = np.zeros(shape=(sample_count))
            generator = datagen.flow_from_directory(directory,
                                                     target_size=(150, 150),
                                                     batch_size=batch_size,
                                                     class_mode='binary')
            i = 0
            for inputs_batch, labels_batch in generator:
                features batch = conv base.predict(inputs batch)
                features[i * batch_size : (i + 1) * batch_size] = features_batch
                labels[i * batch_size : (i + 1) * batch_size] = labels_batch
                i += 1
                if i * batch_size >= sample_count:
                    break
            return features, labels
In [3]: | train_features, train_labels = extract_features(train_dir, 2000)
        validation_features, validation_labels = extract_features(validation_dir, 1000)
        test_features, test_labels = extract_features(test_dir, 1000)
        Found 2000 images belonging to 2 classes.
        Found 1000 images belonging to 2 classes.
        Found 1000 images belonging to 2 classes.
In [4]: train_features = np.reshape(train_features, (2000, 4 * 4 * 512))
        validation_features = np.reshape(validation_features, (1000, 4 * 4 * 512))
        test_features = np.reshape(test_features, (1000, 4 * 4 * 512))
```

Defining and training the densely connected classifier

```
In [5]: from keras.models import Sequential
    from keras.layers import Dense, Dropout
    from keras.optimizers import RMSprop

model = Sequential()
    model.add(Dense(256, activation='relu', input_dim=4 * 4 * 512))
    model.add(Dropout(0.5))
    model.add(Dense(1, activation='sigmoid'))
    model.summary()
```

WARNING:tensorflow:From C:\Users\pablo\Python\envs\DAVID\lib\site-packages\keras\backend\tensorflow_backend.py:3445: calling dropout (from tensorflow.python.ops.nn_ops) with keep_prob is deprecate d and will be removed in a future version.

Instructions for updating:

Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 - keep_prob`.

Layer (type)	Output Shape	Param #
dense_1 (Dense)	(None, 256)	2097408
dropout_1 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 1)	257

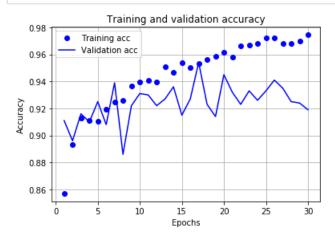
Total params: 2,097,665 Trainable params: 2,097,665 Non-trainable params: 0

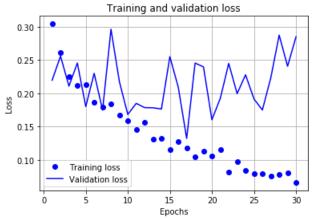
```
WARNING:tensorflow:From C:\Users\pablo\AppData\Roaming\Python\Python36\site-packages\tensorflow\py
thon\ops\math_ops.py:3066: to_int32 (from tensorflow.python.ops.math_ops) is deprecated and will b
e removed in a future version.
Instructions for updating:
Use tf.cast instead.
Train on 2000 samples, validate on 1000 samples
Epoch 1/30
2000/2000 [============ - 3s 2ms/step - loss: 0.6150 - acc: 0.6705 - val loss:
0.4784 - val_acc: 0.7820
Epoch 2/30
2000/2000 [=========== ] - 3s 1ms/step - loss: 0.4401 - acc: 0.8015 - val loss:
0.3699 - val_acc: 0.8600
Epoch 3/30
0.3285 - val_acc: 0.8750
Epoch 4/30
0.3045 - val_acc: 0.8850
Epoch 5/30
0.2866 - val acc: 0.8930
Epoch 6/30
0.2792 - val_acc: 0.8910
Epoch 7/30
0.2681 - val_acc: 0.8920
Epoch 8/30
0.2629 - val_acc: 0.8950
Epoch 9/30
0.2674 - val acc: 0.8900
Epoch 10/30
2000/2000 [============ - 3s 1ms/step - loss: 0.2145 - acc: 0.9125 - val loss:
0.2505 - val acc: 0.8980
Epoch 11/30
0.2485 - val_acc: 0.8990
Epoch 12/30
0.2450 - val_acc: 0.9000
Epoch 13/30
0.2477 - val_acc: 0.8940
Epoch 14/30
2000/2000 [============== ] - 3s 1ms/step - loss: 0.1711 - acc: 0.9415 - val loss:
0.2428 - val_acc: 0.9010
Epoch 15/30
0.2422 - val_acc: 0.8980
Epoch 16/30
0.2433 - val_acc: 0.8990
Epoch 17/30
0.2373 - val_acc: 0.9040
Epoch 18/30
0.2368 - val_acc: 0.9030
Epoch 19/30
0.2350 - val_acc: 0.9060
Epoch 20/30
0.2352 - val_acc: 0.9010
Epoch 21/30
2000/2000 [============== ] - 3s 1ms/step - loss: 0.1306 - acc: 0.9585 - val loss:
0.2356 - val_acc: 0.9020
Epoch 22/30
0.2378 - val_acc: 0.9020
Epoch 23/30
0.2355 - val_acc: 0.9050
Epoch 24/30
```

```
0.2411 - val_acc: 0.9030
Epoch 25/30
0.2399 - val_acc: 0.9000
Epoch 26/30
0.2358 - val_acc: 0.9050
Epoch 27/30
0.2371 - val_acc: 0.9050
Epoch 28/30
0.2408 - val_acc: 0.9050
Epoch 29/30
0.2472 - val_acc: 0.9030
Epoch 30/30
0.2393 - val_acc: 0.9030
```

Plotting the results

```
In [21]: import matplotlib.pyplot as plt
           acc = history.history['acc']
           val_acc = history.history['val_acc']
           loss = history.history['loss']
           val_loss = history.history['val_loss']
           epochs = range(1, len(acc) + 1)
           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.grid()
           plt.legend()
           plt.figure()
           plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
           plt.title('Training and validation loss')
           plt.xlabel('Epochs')
           plt.ylabel('Loss')
           plt.grid()
           plt.legend()
           plt.show()
```





Adding a densely connected classifier on top of the convolutional base

```
In [8]: from keras.layers import Flatten

model = Sequential()
model.add(conv_base)
model.add(Flatten())
model.add(Dense(256, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
model.summary()
```

Layer (type)	Output	Shape	Param #
vgg16 (Model)	(None,	4, 4, 512)	14714688
flatten_1 (Flatten)	(None,	8192)	0
dense_3 (Dense)	(None,	256)	2097408
dense_4 (Dense)	(None,	1)	257
Total params: 16,812,353 Trainable params: 16,812,353			

Total params: 16,812,353
Trainable params: 16,812,353
Non-trainable params: 0

```
In [9]: print('This is the number of trainable weights before freezing the conv base: ', len(model.trainab le_weights))
```

This is the number of trainable weights before freezing the conv base: 30

```
In [10]: conv_base.trainable = False
    print('This is the number of trainable weights before freezing the conv base: ', len(model.trainab le_weights))
```

This is the number of trainable weights before freezing the conv base: 4

Training the model end to end with a frozen convolutional base

```
In [11]: | from keras.preprocessing.image import ImageDataGenerator
          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,
                                             fill_mode='nearest')
          test_datagen = ImageDataGenerator(rescale=1./255)
          train_generator = train_datagen.flow_from_directory(train_dir,
                                                               target_size=(150, 150),
                                                               batch_size=20,
                                                               class_mode='binary')
          validation_generator = test_datagen.flow_from_directory(validation_dir,
                                                                   target_size=(150, 150),
                                                                   batch_size=20,
                                                                   class_mode='binary')
```

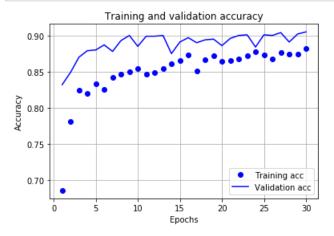
Found 2000 images belonging to 2 classes. Found 1000 images belonging to 2 classes.

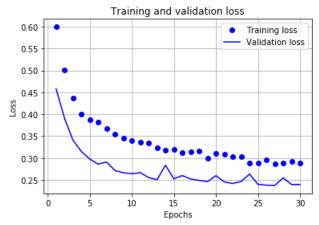
```
Epoch 1/30
0.4581 - val_acc: 0.8320
Epoch 2/30
0.3908 - val_acc: 0.8490
Epoch 3/30
0.3407 - val_acc: 0.8700
Epoch 4/30
0.3150 - val_acc: 0.8790
Epoch 5/30
0.2976 - val_acc: 0.8800
Epoch 6/30
0.2861 - val_acc: 0.8870
Epoch 7/30
0.2909 - val acc: 0.8780
Epoch 8/30
0.2716 - val_acc: 0.8930
Epoch 9/30
0.2664 - val_acc: 0.9000
Epoch 10/30
0.2643 - val_acc: 0.8850
Epoch 11/30
0.2666 - val_acc: 0.8990
Epoch 12/30
0.2554 - val acc: 0.8990
Epoch 13/30
0.2506 - val_acc: 0.9000
Epoch 14/30
0.2836 - val_acc: 0.8750
Epoch 15/30
0.2525 - val_acc: 0.8910
Epoch 16/30
0.2601 - val_acc: 0.8970
Epoch 17/30
0.2521 - val_acc: 0.8900
Epoch 18/30
0.2490 - val_acc: 0.8940
Epoch 19/30
0.2461 - val_acc: 0.8950
Epoch 20/30
100/100 [============] - 307s 3s/step - loss: 0.3107 - acc: 0.8640 - val_loss:
0.2598 - val_acc: 0.8860
Epoch 21/30
0.2455 - val_acc: 0.8960
Epoch 22/30
0.2419 - val_acc: 0.9000
Epoch 23/30
0.2464 - val_acc: 0.9010
Epoch 24/30
0.2634 - val_acc: 0.8840
Epoch 25/30
0.2399 - val_acc: 0.9010
```

Epoch 26/30

Plotting the results

In [13]: import matplotlib.pyplot as plt acc = history.history['acc'] val_acc = history.history['val_acc'] loss = history.history['loss'] val_loss = history.history['val_loss'] epochs = range(1, len(acc) + 1) 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.grid() plt.legend() plt.figure() plt.plot(epochs, loss, 'bo', label='Training loss') plt.plot(epochs, val_loss, 'b', label='Validation loss') plt.title('Training and validation loss') plt.xlabel('Epochs') plt.ylabel('Loss') plt.grid() plt.legend() plt.show()





Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 150, 150, 3)	0
block1_conv1 (Conv2D)	(None, 150, 150, 64)	1792
block1_conv2 (Conv2D)	(None, 150, 150, 64)	36928
block1_pool (MaxPooling2D)	(None, 75, 75, 64)	0
block2_conv1 (Conv2D)	(None, 75, 75, 128)	73856
block2_conv2 (Conv2D)	(None, 75, 75, 128)	147584
block2_pool (MaxPooling2D)	(None, 37, 37, 128)	0
block3_conv1 (Conv2D)	(None, 37, 37, 256)	295168
block3_conv2 (Conv2D)	(None, 37, 37, 256)	590080
block3_conv3 (Conv2D)	(None, 37, 37, 256)	590080
block3_pool (MaxPooling2D)	(None, 18, 18, 256)	0
block4_conv1 (Conv2D)	(None, 18, 18, 512)	1180160
block4_conv2 (Conv2D)	(None, 18, 18, 512)	2359808
block4_conv3 (Conv2D)	(None, 18, 18, 512)	2359808
block4_pool (MaxPooling2D)	(None, 9, 9, 512)	0
block5_conv1 (Conv2D)	(None, 9, 9, 512)	2359808
block5_conv2 (Conv2D)	(None, 9, 9, 512)	2359808
block5_conv3 (Conv2D)	(None, 9, 9, 512)	2359808
block5_pool (MaxPooling2D)	(None, 4, 4, 512)	0
Total params: 14,714,688 Trainable params: 0		

Non-trainable params: 14,714,688

Freezing all layers up to a specific one

```
In [15]: conv_base.trainable = True
         set_trainable = False
         for layer in conv_base.layers:
             if layer.name == 'block5_conv1':
                 set_trainable = True
             if set_trainable:
                 layer.trainable = True
                 layer.trainable = False
```

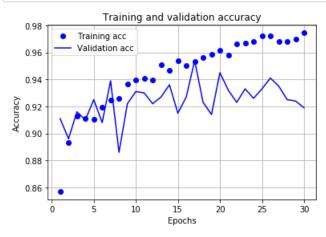
Fine-tuning the model

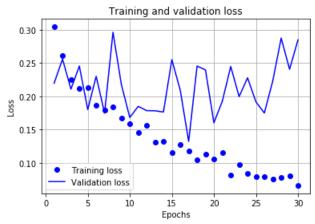
```
Epoch 1/30
0.2197 - val_acc: 0.9110
Epoch 2/30
0.2561 - val_acc: 0.8960
Epoch 3/30
0.2110 - val_acc: 0.9160
Epoch 4/30
0.2456 - val_acc: 0.9100
Epoch 5/30
0.1803 - val_acc: 0.9250
Epoch 6/30
0.2302 - val_acc: 0.9080
Epoch 7/30
0.1749 - val acc: 0.9390
Epoch 8/30
0.2963 - val_acc: 0.8860
Epoch 9/30
0.2177 - val_acc: 0.9220
Epoch 10/30
0.1684 - val_acc: 0.9310
Epoch 11/30
0.1851 - val_acc: 0.9300
Epoch 12/30
0.1787 - val acc: 0.9220
Epoch 13/30
0.1785 - val_acc: 0.9270
Epoch 14/30
0.1766 - val_acc: 0.9360
Epoch 15/30
0.2552 - val_acc: 0.9150
Epoch 16/30
0.2094 - val_acc: 0.9270
Epoch 17/30
0.1324 - val_acc: 0.9540
Epoch 18/30
0.2456 - val_acc: 0.9230
Epoch 19/30
0.2398 - val_acc: 0.9140
Epoch 20/30
100/100 [============] - 356s 4s/step - loss: 0.1057 - acc: 0.9615 - val_loss:
0.1605 - val_acc: 0.9450
Epoch 21/30
0.1927 - val_acc: 0.9320
Epoch 22/30
0.2450 - val_acc: 0.9230
Epoch 23/30
0.1997 - val_acc: 0.9330
Epoch 24/30
0.2280 - val_acc: 0.9260
Epoch 25/30
0.1918 - val_acc: 0.9330
```

Epoch 26/30

Plotting the results

```
In [17]: import matplotlib.pyplot as plt
           acc = history.history['acc']
           val_acc = history.history['val_acc']
           loss = history.history['loss']
           val_loss = history.history['val_loss']
           epochs = range(1, len(acc) + 1)
           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.grid()
           plt.legend()
           plt.figure()
           plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
           plt.title('Training and validation loss')
           plt.xlabel('Epochs')
           plt.ylabel('Loss')
           plt.grid()
           plt.legend()
           plt.show()
```





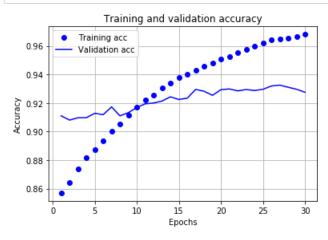
Smoothing the plots

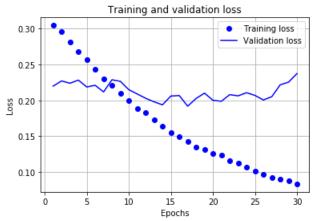
```
In [18]: def smooth_curve(points, factor=0.8):
    smoothed_points = []
    for point in points:
        if smoothed_points:
            previous = smoothed_points[-1]
            smoothed_points.append(previous * factor + point * (1 - factor))
        else:
            smoothed_points.append(point)
    return smoothed_points
```

```
In [19]:
    plt.plot(epochs, smooth_curve(acc), 'bo', label='Training acc')
    plt.plot(epochs, smooth_curve(val_acc), 'b', label='Validation acc')
    plt.title('Training and validation accuracy')
    plt.ylabel('Epochs')
    plt.ylabel('Accuracy')
    plt.grid()
    plt.legend()

plt.figure()

plt.plot(epochs, smooth_curve(loss), 'bo', label='Training loss')
    plt.plot(epochs, smooth_curve(val_loss), 'b', label='Validation loss')
    plt.title('Training and validation loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.grid()
    plt.legend()
    plt.legend()
    plt.show()
```





Found 1000 images belonging to 2 classes. Test acc: 0.9249999916553497

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