```
import keras
keras.__version__
```

```
'2.4.3'
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
import os, shutil
```

```
base_dir = '/content/drive/MyDrive/cats_and_dogs_small'
!ls '/content/drive/MyDrive/cats_and_dogs_small'
```

```
test  train  validation
```

```
# Directories for our training,
# validation and test splits
train_dir = os.path.join(base_dir,'train')
validation_dir = os.path.join(base_dir,'validation')
test_dir = os.path.join(base_dir,'test')

# Directory with our training cat pictures
train_cats_dir = os.path.join(train_dir,'cats')

# Directory with our training dog pictures
train_dogs_dir = os.path.join(train_dir,'dogs')

# Directory with our validation cat pictures
validation_cats_dir = os.path.join(validation_dir,'cats')

# Directory with our validation dog pictures
validation_dogs_dir = os.path.join(validation_dir,'dogs')

# Directory with our validation cat pictures
test_cats_dir = os.path.join(test_dir,'cats')

# Directory with our validation dog pictures
test_dogs_dir = os.path.join(test_dir,'dogs')
```

```
print('total training cat images:', len(os.listdir(train_cats_dir)))
print('total training dog images:', len(os.listdir(train_dogs_dir)))
print('total validation cat images:', len(os.listdir(validation_cats_dir)))
print('total validation dog images:', len(os.listdir(validation_dogs_dir)))
print('total test cat images:', len(os.listdir(test_cats_dir)))
print('total test dog images:', len(os.listdir(test_dogs_dir)))
```

```
     total training dog images: 1000
     total validation cat images:
     500 total validation dog
total training cat images: 1000
     images: 500 total test cat images:
     499 total test dog images: 500
```

```
from keras import layers from keras import models  model = models.Sequential() model.add(layers.Conv2D(32, (3, 3),
activation='relu',                         input_shape=(150, 150, 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(128, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2))) model.add(layers.Conv2D(128, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2))) model.add(layers.Flatten()) model.add(layers.Dense(512, activation='relu'))
model.add(layers.Dense(1, activation='sigmoid'))
```

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
================================================================= conv2d (Conv2D)              (None, 148, 148, 32)
896       _________________________________________________________________ max_pooling2d (MaxPooling2D) (None, 74, 74,
32)       0         _________________________________________________________________ conv2d_1 (Conv2D)
(None, 72, 72, 64)        18496     _________________________________________________________________ max_pooling2d_1
(MaxPooling2 (None, 36, 36, 64)        0         _________________________________________________________________
conv2d_2 (Conv2D)            (None, 34, 34, 128)       73856
_________________________________________________________________ max_pooling2d_2 (MaxPooling2 (None, 17, 17, 128)
0         _________________________________________________________________ conv2d_3 (Conv2D)            (None, 15, 15,
128)      147584    _________________________________________________________________ max_pooling2d_3 (MaxPooling2
(None, 7, 7, 128)         0         _________________________________________________________________ flatten (Flatten)
(None, 6272)              0         _________________________________________________________________ dense (Dense)
```

```
(None, 512)              3211776    _________________________________________________________________ dense_1 (Dense)
(None, 1)                513
=================================================================
Total params: 3,453,121
Trainable params: 3,453,121
Non-trainable params: 0
_________________________________________________________________
```

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

```
from keras.preprocessing.image import ImageDataGenerator
 # All images will be rescaled by 1./255 train_datagen = ImageDataGenerator(rescale=1./255) test_datagen =
ImageDataGenerator(rescale=1./255)
  train_generator = train_datagen.flow_from_directory(
        # This is the target directory         train_dir,         # All images will be resized to 150x150
target_size=(150, 150),         batch_size=20,
        # Since we use binary_crossentropy loss, we need binary labels         class_mode='binary')
 validation_generator = test_datagen.flow_from_directory(         validation_dir,         target_size=(150, 150),
batch_size=20,         class_mode='binary')
```

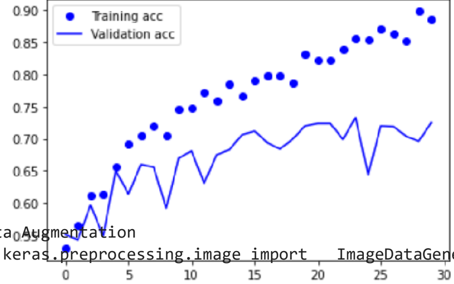
```
Found 2000 images belonging to 2 classes.
Found 1000 images belonging to 2 classes.
```

```
for data_batch, labels_batch in train_generator:     print('data batch shape:', data_batch.shape)     print('labels batch
shape:', labels_batch.shape)     break
```

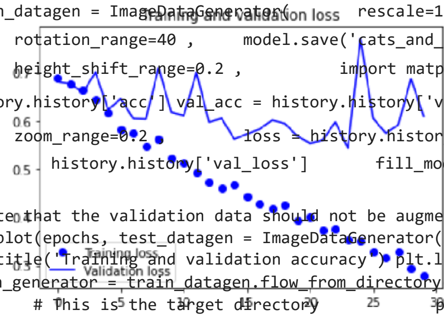
```
data batch shape: (20, 150, 150, 3)
labels batch shape: (20,)
```

```
history = model.fit_generator(       train_generator,       steps_per_epoch=50,       epochs=30,
validation_data=validation_generator,       validation_steps=50)
```

```
50/50 [==============================] - 233s 5s/step - loss: 0.6821 - acc: 0.5631 - val_loss: 0.6769 - val_acc: 0.5430
Epoch 3/30
50/50 [==============================] - 109s 2s/step - loss: 0.6567 - acc: 0.6068 - val_loss: 0.6583 - val_acc: 0.5970
Epoch 4/30
50/50 [==============================] - 69s 1s/step - loss: 0.6426 - acc: 0.6104 - val_loss: 0.7008 - val_acc: 0.5490
Epoch 5/30
50/50 [==============================] - 62s 1s/step - loss: 0.6345 - acc: 0.6371 - val_loss: 0.6234 - val_acc: 0.6510
Epoch 6/30
50/50 [==============================] - 58s 1s/step - loss: 0.5992 - acc: 0.6813 - val_loss: 0.6455 - val_acc: 0.6140
Epoch 7/30
50/50 [==============================] - 57s 1s/step - loss: 0.5706 - acc: 0.7020 - val_loss: 0.6046 - val_acc: 0.6600
Epoch 8/30
50/50 [==============================] - 63s 1s/step - loss: 0.5407 - acc: 0.7370 - val_loss: 0.6036 - val_acc: 0.6560
Epoch 9/30
50/50 [==============================] - 56s 1s/step - loss: 0.5765 - acc: 0.6942 - val_loss: 0.7102 - val_acc: 0.5920
Epoch 10/30
50/50 [==============================] - 57s 1s/step - loss: 0.5207 - acc: 0.7393 - val_loss: 0.6179 - val_acc: 0.6700
Epoch 11/30
50/50 [                              ] 56 1 / t      l     0 5084       0 7547     l l    0 6112     l      0 6810
50/50 [==============================] - 56s 1s/step - loss: 0.5084 - acc: 0.7547 - val_loss: 0.6112 - val_acc: 0.6810
Epoch 12/30
50/50 [==============================] - 56s 1s/step - loss: 0.5020 - acc: 0.7706 - val_loss: 0.7002 - val_acc: 0.6310
Epoch 13/30
50/50 [==============================] - 56s 1s/step - loss: 0.4664 - acc: 0.7715 - val_loss: 0.5973 - val_acc: 0.6750
Epoch 14/30
50/50 [==============================] - 56s 1s/step - loss: 0.4631 - acc: 0.7958 - val_loss: 0.6052 - val_acc: 0.6830
Epoch 15/30
50/50 [==============================] - 56s 1s/step - loss: 0.4501 - acc: 0.7713 - val_loss: 0.5620 - val_acc: 0.7060
Epoch 16/30
50/50 [==============================] - 56s 1s/step - loss: 0.4181 - acc: 0.8057 - val_loss: 0.5727 - val_acc: 0.7120
Epoch 17/30
50/50 [==============================] - 56s 1s/step - loss: 0.4469 - acc: 0.7777 - val_loss: 0.5828 - val_acc: 0.6940
Epoch 18/30
50/50 [==============================] - 56s 1s/step - loss: 0.4103 - acc: 0.8068 - val_loss: 0.6017 - val_acc: 0.6840
Epoch 19/30
50/50 [==============================] - 56s 1s/step - loss: 0.4197 - acc: 0.7891 - val_loss: 0.5943 - val_acc: 0.6990
Epoch 20/30
50/50 [==============================] - 56s 1s/step - loss: 0.3893 - acc: 0.8356 - val_loss: 0.5682 - val_acc: 0.7200
Epoch 21/30
50/50 [==============================] - 56s 1s/step - loss: 0.3990 - acc: 0.8226 - val_loss: 0.5534 - val_acc: 0.7240
Epoch 22/30
50/50 [==============================] - 56s 1s/step - loss: 0.3587 - acc: 0.8419 - val_loss: 0.5600 - val_acc: 0.7240
Epoch 23/30
50/50 [==============================] - 56s 1s/step - loss: 0.3768 - acc: 0.8289 - val_loss: 0.5976 - val_acc: 0.6990
Epoch 24/30
50/50 [==============================] - 57s 1s/step - loss: 0.3454 - acc: 0.8585 - val_loss: 0.5433 - val_acc: 0.7330
Epoch 25/30
50/50 [==============================] - 56s 1s/step - loss: 0.3380 -
acc: 0.8583 - val_loss: 0.7705 - val_acc: 0.6440 Epoch 26/30
50/50 [==============================] - 56s 1s/step - loss: 0.3208 -
acc: 0.8751 - val_loss: 0.6051 - val_acc: 0.7200 Epoch 27/30
```




```
50/50 [==============================] - 57s 1s/step - loss: 0.3045 -
acc: 0.8604 - val_loss: 0.5744 - val_acc: 0.7190 Epoch 28/30
50/50 [==============================] - 57s 1s/step - loss: 0.3256 -
acc: 0.8625 - val_loss: 0.5919 - val_acc: 0.7040 Epoch 29/30
50/50 [==============================] - 56s 1s/step - loss: 0.2986 -
acc: 0.8956 - val_loss: 0.6872 - val_acc: 0.6960 Epoch 30/30
50/50 [==============================] - 56s 1s/step - loss: 0.2789
- acc: 0.8851 - val_loss: 0.6095 - val_acc: 0.7250
```

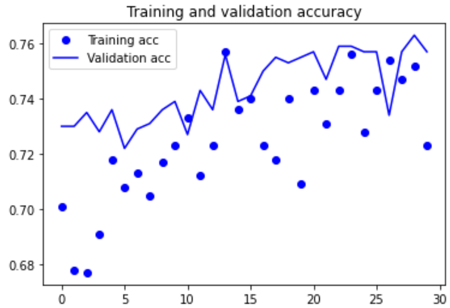


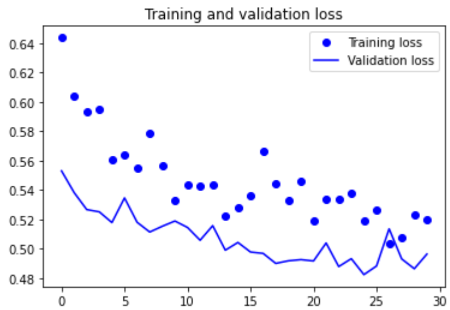

```
# Data Augmentation
from keras.preprocessing.image import   ImageDataGenerator

train_datagen = ImageDataGenerator(      rescale=1 ./ 255 ,
      rotation_range=40 ,     model.save('cats_and_dogs_small_1.h5')       width_shift_range=0.2 ,
      height_shift_range=0.2 ,          import matplotlib.pyplot as plt       shear_range=0.2 ,      acc =
history.history['acc'] val_acc = history.history['val_acc']
      zoom_range=0.2          loss = history.history['loss'] val_loss =       horizontal_flip=True ,
      history.history['val_loss']       fill_mode='nearest'        )          epochs = range(len(acc))

# Note that the validation data should not be augmented!     plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, test_datagen = ImageDataGenerator(rescale=1./  255 )           val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy') plt.legend()
train_generator = train_datagen.flow_from_directory(     plt.figure()
        # This is the target directory      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()


        train_dir,         # All images will be resized to 150x150         target_size=(150, 150),         batch_size=20,
        # Since we use binary_crossentropy loss, we need binary labels         class_mode='binary')
  validation_generator = test_datagen.flow_from_directory(         validation_dir,         target_size=(150, 150),
batch_size=20,         class_mode='binary')
 model.compile(loss='binary_crossentropy',               optimizer=optimizers.RMSprop(lr=2e-5),
metrics=['acc'])
  history = model.fit_generator(       train_generator,       steps_per_epoch=50,       epochs=30,
validation_data=validation_generator,       validation_steps=50,       verbose=2)
```

```
50/50 - 60s - loss: 0.6041 - acc: 0.6780 - val_loss: 0.5383 - val_acc: 0.7300 Epoch 3/30
50/50 - 60s - loss: 0.5933 - acc: 0.6770 - val_loss: 0.5267 - val_acc: 0.7350 Epoch 4/30
50/50 - 60s - loss: 0.5949 - acc: 0.6910 - val_loss: 0.5252 - val_acc: 0.7280 Epoch 5/30
50/50 - 61s - loss: 0.5609 - acc: 0.7180 - val_loss: 0.5179 - val_acc: 0.7360 Epoch 6/30
50/50 - 60s - loss: 0.5640 - acc: 0.7080 - val_loss: 0.5346 - val_acc: 0.7220 Epoch 7/30
50/50 - 60s - loss: 0.5547 - acc: 0.7130 - val_loss: 0.5181 - val_acc: 0.7290 Epoch 8/30
50/50 - 60s - loss: 0.5787 - acc: 0.7050 - val_loss: 0.5114 - val_acc: 0.7310 Epoch 9/30
50/50 - 60s - loss: 0.5562 - acc: 0.7170 - val_loss: 0.5154 - val_acc: 0.7360 Epoch 10/30
50/50 - 60s - loss: 0.5327 - acc: 0.7230 - val_loss: 0.5189 - val_acc: 0.7390 Epoch
11/30
50/50 - 60s - loss: 0.5436 - acc: 0.7330 - val_loss: 0.5145 - val_acc: 0.7270 Epoch
12/30
50/50 - 60s - loss: 0.5424 - acc: 0.7120 - val_loss: 0.5058 - val_acc: 0.7430 Epoch
13/30
50/50 - 60s - loss: 0.5432 - acc: 0.7230 - val_loss: 0.5158 - val_acc: 0.7360 Epoch
14/30
50/50 - 60s - loss: 0.5227 - acc: 0.7570 - val_loss: 0.4991 - val_acc: 0.7560 Epoch
15/30
50/50 - 60s - loss: 0.5280 - acc: 0.7360 - val_loss: 0.5043 - val_acc: 0.7390 Epoch
16/30
50/50 - 60s - loss: 0.5359 - acc: 0.7400 - val_loss: 0.4978 - val_acc: 0.7410

Epoch 17/30
50/50 - 60s - loss: 0.5667 - acc: 0.7230 - val_loss: 0.4969 - val_acc: 0.7500 Epoch
18/30
50/50 - 60s - loss: 0.5446 - acc: 0.7180 - val_loss: 0.4901 - val_acc: 0.7550 Epoch
19/30
50/50 - 60s - loss: 0.5326 - acc: 0.7400 - val_loss: 0.4918 - val_acc: 0.7530  Epoch
20/30
50/50 - 60s - loss: 0.5463 - acc: 0.7090 - val loss: 0.4927 - val acc: 0.7550
50/50  60s  loss: 0.5463  acc: 0.7090  val_loss: 0.4927  val_acc: 0.7550  Epoch
21/30
50/50 - 60s - loss: 0.5194 - acc: 0.7430 - val_loss: 0.4917 - val_acc: 0.7570 Epoch
22/30
50/50 - 60s - loss: 0.5338 - acc: 0.7310 - val_loss: 0.5040 - val_acc: 0.7470
Epoch 23/30
50/50 - 60s - loss: 0.5337 - acc: 0.7430 - val_loss: 0.4879 - val_acc: 0.7590 Epoch
24/30
50/50 - 60s - loss: 0.5382 - acc: 0.7560 - val_loss: 0.4933 - val_acc: 0.7590 Epoch
25/30
50/50 - 60s - loss: 0.5191 - acc: 0.7280 - val_loss: 0.4825 - val_acc: 0.7570 Epoch
26/30
50/50 - 60s - loss: 0.5265 - acc: 0.7430 - val_loss: 0.4883 - val_acc: 0.7570 Epoch
27/30
50/50 - 60s - loss: 0.5037 - acc: 0.7540 - val_loss: 0.5136 - val_acc: 0.7340 Epoch
28/30
50/50 - 60s - loss: 0.5073 - acc: 0.7470 - val_loss: 0.4931 - val_acc: 0.7570 Epoch
29/30
50/50 - 60s - loss: 0.5234 - acc: 0.7520 - val_loss: 0.4865 - val_acc: 0.7630 Epoch
30/30
50/50 - 60s - loss: 0.5201 - acc: 0.7230 - val_loss: 0.4964 - val_acc: 0.7570
```

```
model.save('cats_and_dogs_small_2.h5')
```

```
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(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.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()
```






```
from keras import layers from keras import models  model = models.Sequential() model.add(layers.Conv2D(32, (3, 3),
activation='relu',                          input_shape=(150,
150, 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(128, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(128, (3, 3), activation='relu')) model.add(layers.MaxPooling2D((2, 2))) model.add(layers.Flatten())
model.add(layers.Dense(512, activation='relu')) model.add(layers.Dense(1, activation='sigmoid'))
```

```
from keras import optimizers
 model.compile(loss='binary_crossentropy',              optimizer=optimizers.RMSprop(lr=1e-4),
metrics=['acc'])
from keras.preprocessing.image import ImageDataGenerator
 # All images will be rescaled by 1./255 train_datagen = ImageDataGenerator(rescale=1./255) test_datagen =
ImageDataGenerator(rescale=1./255)
  train_generator = train_datagen.flow_from_directory(
        # This is the target directory         train_dir,         # All images will be resized to 150x150
target_size=(150, 150),         batch_size=20,
        # Since we use binary_crossentropy loss, we need binary labels         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.
```

```
for data_batch, labels_batch in train_generator:     print('data batch shape:', data_batch.shape)     print('labels batch
shape:', labels_batch.shape)     break
```

```
    data batch shape: (20, 150, 150, 3)
    labels batch shape: (20,)
```

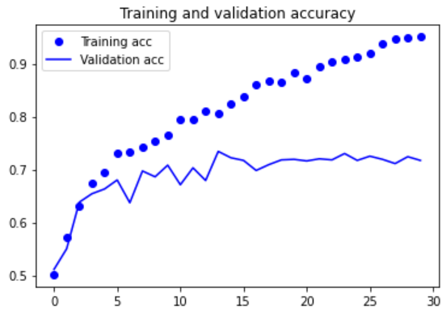
```
history = model.fit_generator(       train_generator,       steps_per_epoch=75,       epochs=30,
validation_data=validation_generator,       validation_steps=50)
```

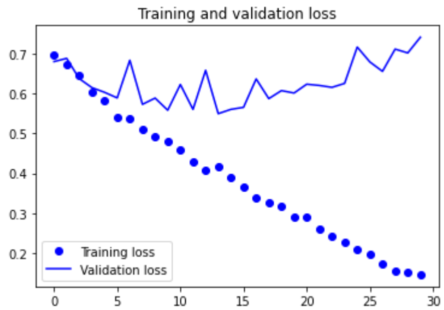
```
    75/75 [==============================] - 77s 1s/step - loss: 0.6801 - acc: 0.5488 - val_loss: 0.6877 - val_acc: 0.5500
    Epoch 3/30
    75/75 [==============================] - 77s 1s/step - loss: 0.6569 - acc: 0.6134 - val_loss: 0.6370 - val_acc: 0.6380
    Epoch 4/30
    75/75 [==============================] - 77s 1s/step - loss: 0.6104 - acc: 0.6725 - val_loss: 0.6145 - val_acc: 0.6540
    Epoch 5/30
    75/75 [==============================] - 77s 1s/step - loss: 0.5741 - acc: 0.7102 - val_loss: 0.6028 - val_acc: 0.6630
    Epoch 6/30
    75/75 [==============================] - 77s 1s/step - loss: 0.5375 - acc: 0.7285 - val_loss: 0.5888 - val_acc: 0.6800
    Epoch 7/30
    75/75 [==============================] - 77s 1s/step - loss: 0.5454 - acc: 0.7328 - val_loss: 0.6830 - val_acc: 0.6370
    Epoch 8/30
```

```
75/75 [==============================] - 77s 1s/step - loss: 0.5286 - acc: 0.7300 - val_loss: 0.5727 - val_acc: 0.6970
Epoch 9/30
75/75 [==============================] - 77s 1s/step - loss: 0.5050 - acc: 0.7565 - val_loss: 0.5884 - val_acc: 0.6860
Epoch 10/30
75/75 [==============================] - 77s 1s/step - loss: 0.4848 - acc: 0.7619 - val_loss: 0.5580 - val_acc: 0.7080
Epoch 11/30
75/75 [==============================] - 77s 1s/step - loss: 0.4728 - acc: 0.7840 - val_loss: 0.6224 - val_acc: 0.6710
Epoch 12/30
75/75 [==============================] - 81s 1s/step - loss: 0.4294 - acc: 0.7934 - val_loss: 0.5601 - val_acc: 0.7030
Epoch 13/30
75/75 [==============================] - 78s 1s/step - loss: 0.4264 - acc: 0.8023 - val_loss: 0.6578 - val_acc: 0.6790
Epoch 14/30
75/75 [==============================] - 78s 1s/step - loss: 0.4109 - acc: 0.8088 - val_loss: 0.5494 - val_acc: 0.7340
Epoch 15/30
75/75 [==============================] - 78s 1s/step - loss: 0.3823 - acc: 0.8308 - val_loss: 0.5601 - val_acc: 0.7220
Epoch 16/30
75/75 [==============================] - 78s 1s/step - loss: 0.3764 - acc: 0.8383 - val_loss: 0.5652 - val_acc: 0.7170

Epoch 17/30
75/75 [==============================] - 78s 1s/step - loss: 0.3322 - acc: 0.8599 - val_loss: 0.6363 - val_acc: 0.6980
Epoch 18/30
75/75 [==============================] - 78s 1s/step - loss: 0.3294 - acc: 0.8677 - val_loss: 0.5870 - val_acc: 0.7090
Epoch 19/30
75/75 [==============================] - 78s 1s/step - loss: 0.2942 - acc: 0.8846 - val loss: 0.6071 - val acc: 0.7180

75/75 [                              ]  78s 1s/step  loss: 0.2942  acc: 0.8846  val_loss: 0.6071  val_acc: 0.7180
Epoch 20/30
75/75 [==============================] - 78s 1s/step - loss: 0.2935 - acc: 0.8730 - val_loss: 0.6010 - val_acc: 0.7190
Epoch 21/30
75/75 [==============================] - 78s 1s/step - loss: 0.2742 - acc: 0.8765 - val_loss: 0.6231 - val_acc: 0.7160
Epoch 22/30
75/75 [==============================] - 78s 1s/step - loss: 0.2626 - acc: 0.8937 - val_loss: 0.6200 - val_acc: 0.7200
Epoch 23/30
75/75 [==============================] - 78s 1s/step - loss: 0.2343 - acc: 0.9096 - val_loss: 0.6152 - val_acc: 0.7180
Epoch 24/30
75/75 [==============================] - 77s 1s/step - loss: 0.2224 - acc: 0.9087 - val_loss: 0.6251 - val_acc: 0.7300
Epoch 25/30
75/75 [==============================] - 78s 1s/step - loss: 0.2100 - acc: 0.9050 - val_loss: 0.7161 - val_acc: 0.7170
Epoch 26/30
75/75 [==============================] - 78s 1s/step - loss: 0.1896 - acc: 0.9312 - val_loss: 0.6788 - val_acc: 0.7250
Epoch 27/30
75/75 [==============================] - 78s 1s/step - loss: 0.1561 - acc: 0.9545 - val_loss: 0.6553 - val_acc: 0.7190
Epoch 28/30
75/75 [==============================] - 78s 1s/step - loss: 0.1497 - acc: 0.9529 - val_loss: 0.7110 - val_acc: 0.7110
Epoch 29/30
75/75 [==============================] - 78s 1s/step - loss: 0.1374 - acc: 0.9560 - val_loss: 0.7013 - val_acc: 0.7240
Epoch 30/30
75/75 [==============================] - 78s 1s/step - loss: 0.1311 - acc: 0.9540 - val_loss: 0.7407 - val_acc: 0.7170
```

```
model.save('cats_and_dogs_small_3.h5')
```

```
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(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.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()
```





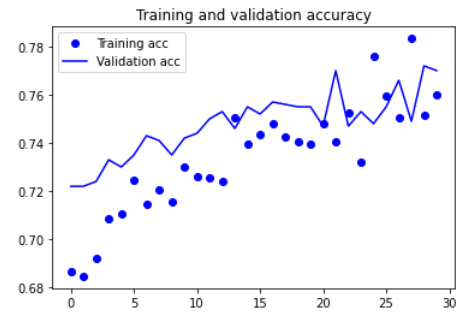

```
# Data Augmentation from keras.preprocessing.image import ImageDataGenerator  train_datagen = ImageDataGenerator(
rescale=1./255,
      rescale 1./255,       rotation_range=40,       width_shift_range=0.2,       height_shift_range=0.2,
shear_range=0.2,       zoom_range=0.2,       horizontal_flip=True,       fill_mode='nearest')

# Note that the validation data should not be augmented!
test_datagen = ImageDataGenerator(rescale=1./255)
  train_generator = train_datagen.flow_from_directory(         # This is the target directory         train_dir,         #
All
images will be resized to 150x150         target_size=(150, 150),         batch_size=20,
        # Since we use binary_crossentropy loss, we need binary labels         class_mode='binary')
 validation_generator = test_datagen.flow_from_directory(         validation_dir,         target_size=(150, 150),
batch_size=20,         class_mode='binary')

model.compile(loss='binary_crossentropy',               optimizer=optimizers.RMSprop(lr=2e-5),               metrics=['acc'])
history = model.fit_generator(       train_generator,       steps_per_epoch=75,       epochs=30,
validation_data=validation_generator,       validation_steps=50,       verbose=2)
```

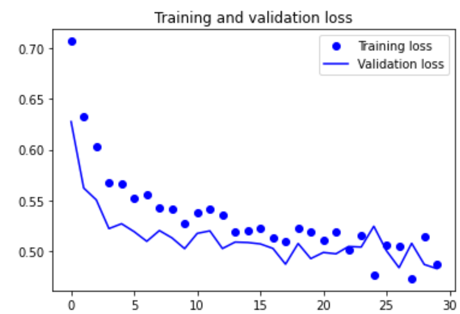
```
75/75 - 85s - loss: 0.6331 - acc: 0.6847 - val_loss: 0.5622 - val_acc: 0.7220 Epoch 3/30
75/75 - 84s - loss: 0.6025 - acc: 0.6920 - val_loss: 0.5505 - val_acc: 0.7240 Epoch 4/30
75/75 - 84s - loss: 0.5676 - acc: 0.7087 - val_loss: 0.5222 - val_acc: 0.7330 Epoch 5/30
75/75 - 84s - loss: 0.5669 - acc: 0.7107 - val_loss: 0.5270 - val_acc: 0.7300 Epoch 6/30
75/75 - 84s - loss: 0.5517 - acc: 0.7247 - val_loss: 0.5192 - val_acc: 0.7350 Epoch 7/30
75/75 - 84s - loss: 0.5557 - acc: 0.7147 - val_loss: 0.5097 - val_acc: 0.7430 Epoch 8/30
75/75 - 84s - loss: 0.5424 - acc: 0.7207 - val_loss: 0.5203 - val_acc: 0.7410 Epoch 9/30
75/75 - 84s - loss: 0.5411 - acc: 0.7153 - val_loss: 0.5131 - val_acc: 0.7350 Epoch 10/30
75/75 - 84s - loss: 0.5270 - acc: 0.7300 - val_loss: 0.5025 - val_acc: 0.7420 Epoch 11/30
75/75 - 84s - loss: 0.5385 - acc: 0.7260 - val_loss: 0.5175 - val_acc: 0.7440 Epoch 12/30
75/75 - 84s - loss: 0.5417 - acc: 0.7253 - val_loss: 0.5200 - val_acc: 0.7500 Epoch 13/30
75/75 - 84s - loss: 0.5361 - acc: 0.7240 - val_loss: 0.5026 - val_acc: 0.7530 Epoch 14/30
75/75 - 84s - loss: 0.5187 - acc: 0.7507 - val_loss: 0.5090 - val_acc: 0.7460 Epoch 15/30
75/75 - 84s - loss: 0.5203 - acc: 0.7393 - val_loss: 0.5085 - val_acc: 0.7550 Epoch
16/30
75/75 - 84s - loss: 0.5220 - acc: 0.7433 - val_loss: 0.5072 - val_acc: 0.7520 Epoch
17/30
75/75 - 84s - loss: 0.5126 - acc: 0.7480 - val_loss: 0.5027 - val_acc: 0.7570 Epoch
18/30
75/75 - 84s - loss: 0.5093 - acc: 0.7427 - val_loss: 0.4872 - val_acc: 0.7560 Epoch
19/30
75/75 - 84s - loss: 0.5229 - acc: 0.7407 - val_loss: 0.5075 - val_acc: 0.7550 Epoch
20/30
75/75 - 84s - loss: 0.5187 - acc: 0.7393 - val_loss: 0.4927 - val_acc: 0.7550 Epoch
21/30
75/75 - 84s - loss: 0.5106 - acc: 0.7480 - val_loss: 0.4987 - val_acc: 0.7470 Epoch
22/30
75/75 - 83s - loss: 0.5191 - acc: 0.7407 - val_loss: 0.4974 - val_acc: 0.7700 Epoch
23/30
75/75 - 83s - loss: 0.5008 - acc: 0.7527 - val_loss: 0.5046 - val_acc: 0.7470 Epoch
24/30
75/75 - 83s - loss: 0.5154 - acc: 0.7320 - val_loss: 0.5040 - val_acc: 0.7530 Epoch
25/30
75/75 - 83s - loss: 0.4762 - acc: 0.7760 - val_loss: 0.5245 - val_acc: 0.7480 Epoch
26/30
75/75 - 83s - loss: 0.5062 - acc: 0.7593 - val_loss: 0.5005 - val_acc: 0.7550 Epoch
27/30
75/75 - 83s - loss: 0.5047 - acc: 0.7507 - val_loss: 0.4837 - val_acc: 0.7660 Epoch
28/30
```

```
75/75 - 83s - loss: 0.4730 - acc: 0.7833 - val_loss: 0.5078 - val_acc: 0.7490  Epoch
29/30
Epoch 29/30
75/75 - 83s - loss: 0.5142 - acc: 0.7513 - val_loss: 0.4869 - val_acc: 0.7720 Epoch
30/30
75/75 - 83s - loss: 0.4868 - acc: 0.7600 - val_loss: 0.4828 - val_acc: 0.7700
```

```
model.save('cats_and_dogs_small_4.h5')
```

```
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(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.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()
```






```
from keras import layers from keras import models  model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu',                         input_shape=(150, 150, 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(128, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2))) model.add(layers.Conv2D(128, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2))) model.add(layers.Flatten()) model.add(layers.Dense(512, activation='relu'))
model.add(layers.Dense(1, activation='sigmoid'))
```

```
from keras import optimizers  model.compile(loss='binary_crossentropy',               optimizer=optimizers.RMSprop(lr=1e-4),
metrics=['acc'])
from keras.preprocessing.image import ImageDataGenerator
 # All images will be rescaled by 1./255 train_datagen = ImageDataGenerator(rescale=1./255) test_datagen =
ImageDataGenerator(rescale=1./255)  train_generator = train_datagen.flow_from_directory(
        # This is the target directory         train_dir,         # All images will be resized to 150x150
target_size=(150, 150),         batch_size=20,
        # Since we use binary_crossentropy loss, we need binary labels         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.
```

```
for data_batch, labels_batch in train_generator:     print('data batch shape:', data_batch.shape)     print('labels batch
shape:', labels_batch.shape)     break
```

```
data batch shape: (20, 150, 150, 3)
labels batch shape: (20,)
```

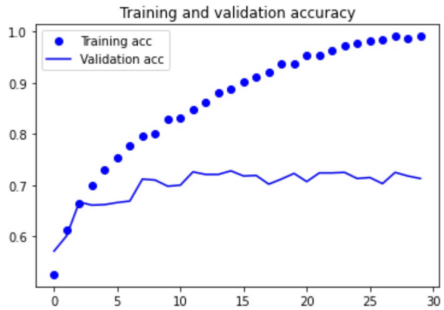
```
history = model.fit_generator(       train_generator,       steps_per_epoch=100,       epochs=30,
validation_data=validation_generator,       validation_steps=50)
```

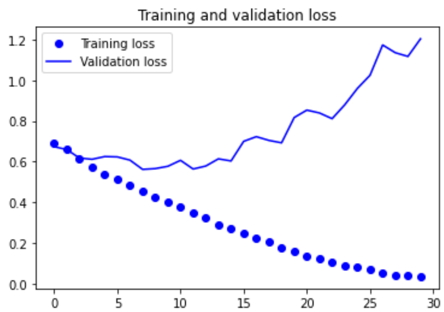
```
100/100 [==============================] - 99s 994ms/step - loss: 0.6687 - acc: 0.6151 - val_loss: 0.6593 - val_acc:
0.6010 Epoch 3/30
100/100 [==============================] - 100s 997ms/step - loss: 0.6230 - acc: 0.6575 - val_loss: 0.6180 - val_acc:
0.6670
Epoch 4/30
100/100 [==============================] - 100s 998ms/step - loss: 0.5829 - acc: 0.7049 - val_loss: 0.6117 - val_acc:
0.6610 Epoch 5/30
```

```
100/100 [==============================] - 100s 1s/step - loss: 0.5388 - acc: 0.7293 - val_loss: 0.6251 - val_acc: 0.6620
Epoch 6/30
100/100 [==============================] - 100s 1s/step - loss: 0.5179 - acc: 0.7433 - val_loss: 0.6235 - val_acc: 0.6660
Epoch 7/30
100/100 [==============================] - 100s 1s/step - loss: 0.4838 - acc: 0.7792 - val_loss: 0.6076 - val_acc:
0.6690 Epoch 8/30
100/100 [==============================] - 100s 999ms/step - loss: 0.4497 - acc: 0.7916 - val_loss: 0.5622 - val_acc:
0.7120
Epoch 9/30
100/100 [==============================] - 100s 999ms/step - loss: 0.4293 - acc: 0.7958 - val_loss: 0.5659 - val_acc:
0.7100
Epoch 10/30
100/100 [==============================] - 100s 998ms/step - loss: 0.3960 - acc: 0.8378 - val_loss: 0.5773 - val_acc:
0.6980
Epoch 11/30
100/100 [==============================] - 100s 997ms/step - loss: 0.3805 - acc: 0.8239 - val_loss: 0.6066 - val_acc:
0.7000
Epoch 12/30
100/100 [==============================] - 100s 996ms/step - loss: 0.3462 - acc: 0.8456 - val_loss: 0.5639 - val_acc:
0.7260 Epoch 13/30
100/100 [==============================] - 99s 994ms/step - loss: 0.3186 - acc: 0.8705 - val_loss: 0.5786 - val_acc:
0.7210
Epoch 14/30
100/100 [==============================] - 99s 993ms/step - loss: 0.2872 - acc: 0.8781 - val_loss: 0.6139 - val_acc:
0.7210 Epoch 15/30
100/100 [==============================] - 100s 999ms/step - loss: 0.2718 - acc: 0.8965 - val_loss: 0.6034 - val_acc:
0.7280 Epoch 16/30
100/100 [==============================] - 99s 994ms/step - loss: 0.2594 - acc: 0.8915 - val_loss: 0.6998 - val_acc:
0.7180
Epoch 17/30
100/100 [==============================] - 99s 994ms/step - loss: 0.2265 - acc: 0.9134 - val_loss: 0.7229 - val_acc:
0.7190 Epoch 18/30
100/100 [==============================] - 100s 999ms/step - loss: 0.2011 - acc: 0.9297 - val_loss: 0.7045 - val_acc:
0.7020 Epoch 19/30
100/100 [==============================] - 100s 1s/step - loss: 0.1739 - acc: 0.9369 - val_loss: 0.6925 - val_acc:
0.7120 Epoch 20/30
100/100 [==============================] - 100s 999ms/step - loss: 0.1458 - acc: 0.9508 - val_loss: 0.8168 - val_acc:
0.7230 Epoch 21/30
100/100 [==============================] - 102s 1s/step - loss: 0.1430 - acc: 0.9559 - val_loss: 0.8532 - val_acc:
0.7070
Epoch 22/30
100/100 [==============================] - 100s 1s/step - loss: 0.1106 - acc: 0.9629 - val_loss: 0.8392 - val_acc:
0.7240
Epoch 23/30
100/100 [==============================] - 100s 1s/step - loss: 0.0992 - acc: 0.9677 - val_loss: 0.8111 - val_acc: 0.7240
Epoch 24/30
100/100 [==============================] - 101s 1s/step - loss: 0.0896 - acc: 0.9716 - val_loss: 0.8794 - val_acc:
0.7250
Epoch 25/30
100/100 [==============================] - 101s 1s/step - loss: 0.1070 - acc: 0.9717 - val_loss: 0.9596 - val_acc:
0.7130
Epoch 26/30
100/100 [==============================] - 101s 1s/step - loss: 0.0739 - acc: 0.9774 - val_loss: 1.0243 - val_acc:
0.7150
Epoch 27/30
100/100 [==============================] - 101s 1s/step - loss: 0.0521 - acc: 0.9860 - val_loss: 1.1731 - val_acc: 0.7030
Epoch 28/30
Epoch 28/30
100/100 [==============================] - 101s 1s/step - loss: 0.0398 - acc: 0.9917 - val_loss: 1.1352 - val_acc:
0.7250
Epoch 29/30
100/100 [==============================] - 101s 1s/step - loss: 0.0461 - acc: 0.9863 - val_loss: 1.1168 - val_acc:
0.7180
Epoch 30/30
100/100 [==============================] - 101s 1s/step - loss: 0.0326 - acc: 0.9919 - val_loss: 1.2036 - val_acc: 0.7130
```

```
model.save('cats_and_dogs_small_5.h5')
```

```
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(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.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()
```



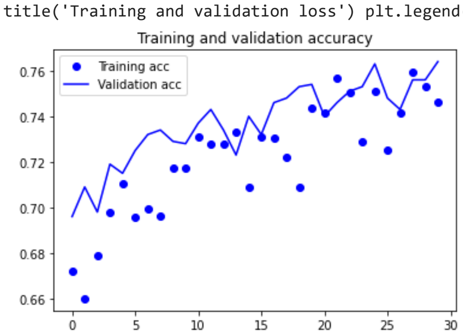


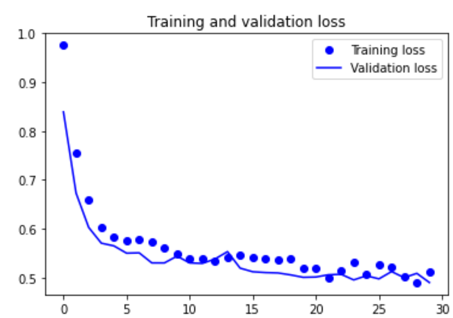

```
# Data Augmentation
from keras.preprocessing.image import ImageDataGenerator
  train_datagen = ImageDataGenerator(       rescale=1./255,       rotation_range=40,       width_shift_range=0.2,
height_shift_range=0.2,       shear_range=0.2,       zoom_range=0.2,       horizontal_flip=True,       fill_mode='nearest')

# Note that the validation data should not be augmented! test_datagen = ImageDataGenerator(rescale=1./255)  train_generator =
train_datagen.flow_from_directory(
        # This is the target directory         train_dir,
        # All images will be resized to 150x150
        # All images will be resized to 150x150         target_size=(150, 150),         batch_size=20,
        # Since we use binary_crossentropy loss, we need binary labels         class_mode='binary')
  validation_generator = test_datagen.flow_from_directory(         validation_dir,         target_size=(150, 150),
batch_size=20,         class_mode='binary')
 model.compile(loss='binary_crossentropy',               optimizer=optimizers.RMSprop(lr=2e-5),
metrics=['acc'])
 history = model.fit_generator(       train_generator,       steps_per_epoch=100,       epochs=30,
validation_data=validation_generator,
validation_steps=50,       verbose=2) poc /30
     100/100 - 108s - loss: 0.7553 - acc: 0.6600 - val_loss: 0.6731 - val_acc: 0.7090 Epoch 3/30
     100/100 - 107s - loss: 0.6592 - acc: 0.6790 - val_loss: 0.6028 - val_acc: 0.6980 Epoch 4/30
     100/100 - 107s - loss: 0.6027 - acc: 0.6980 - val_loss: 0.5706 - val_acc: 0.7190 Epoch 5/30
     100/100 - 108s - loss: 0.5843 - acc: 0.7105 - val_loss: 0.5650 - val_acc: 0.7150 Epoch 6/30
     100/100 - 107s - loss: 0.5748 - acc: 0.6955 - val_loss: 0.5501 - val_acc: 0.7250 Epoch 7/30
     100/100 - 107s - loss: 0.5784 - acc: 0.6995 - val_loss: 0.5508 - val_acc: 0.7320 Epoch 8/30
     100/100 - 107s - loss: 0.5724 - acc: 0.6960 - val_loss: 0.5302 - val_acc: 0.7340 Epoch 9/30
     100/100 - 109s - loss: 0.5621 - acc: 0.7175 - val_loss: 0.5302 - val_acc: 0.7290 Epoch 10/30
     100/100 - 107s - loss: 0.5479 - acc: 0.7175 - val_loss: 0.5441 - val_acc: 0.7280 Epoch
     11/30
     100/100 - 107s - loss: 0.5389 - acc: 0.7310 - val_loss: 0.5301 - val_acc: 0.7370 Epoch
     12/30
     100/100 - 107s - loss: 0.5396 - acc: 0.7280 - val_loss: 0.5291 - val_acc: 0.7430 Epoch
     13/30
     100/100 - 107s - loss: 0.5346 - acc: 0.7280 - val_loss: 0.5380 - val_acc: 0.7340 Epoch
     14/30
     100/100 - 108s - loss: 0.5402 - acc: 0.7330 - val_loss: 0.5533 - val_acc: 0.7230 Epoch
     15/30
     100/100 - 107s - loss: 0.5460 - acc: 0.7090 - val_loss: 0.5195 - val_acc: 0.7400 Epoch
     16/30
     100/100 - 107s - loss: 0.5408 - acc: 0.7310 - val_loss: 0.5120 - val_acc: 0.7320 Epoch
     17/30
     100/100 - 109s - loss: 0.5378 - acc: 0.7305 - val_loss: 0.5104 - val_acc: 0.7460 Epoch
     18/30
     100/100 - 109s - loss: 0.5369 - acc: 0.7220 - val_loss: 0.5096 - val_acc: 0.7480 Epoch
     19/30
     100/100 - 108s - loss: 0.5387 - acc: 0.7090 - val_loss: 0.5056 - val_acc: 0.7530 Epoch
     20/30
```

```
100/100 - 109s - loss: 0.5190 - acc: 0.7435 - val_loss: 0.5007 - val_acc: 0.7540 Epoch
21/30
100/100 - 108s - loss: 0.5193 - acc: 0.7415 - val_loss: 0.5013 - val_acc: 0.7400 Epoch
22/30
100/100 - 108s - loss: 0.5001 - acc: 0.7570 - val_loss: 0.5059 - val_acc: 0.7460 Epoch
23/30
100/100 - 108s - loss: 0.5143 - acc: 0.7505 - val_loss: 0.5070 - val_acc: 0.7510 Epoch
24/30
100/100 - 108s - loss: 0.5321 - acc: 0.7290 - val_loss: 0.4954 - val_acc: 0.7530 Epoch
25/30
100/100 - 108s - loss: 0.5071 - acc: 0.7510 - val_loss: 0.5039 - val_acc: 0.7630 Epoch
26/30
100/100 - 109s - loss: 0.5270 - acc: 0.7250 - val_loss: 0.4975 - val_acc: 0.7480 Epoch
27/30
100/100 - 109s - loss: 0.5229 - acc: 0.7415 - val_loss: 0.5124 - val_acc: 0.7430 Epoch
28/30
100/100 - 108s - loss: 0.5018 - acc: 0.7595 - val_loss: 0.5000 - val_acc: 0.7560 Epoch
29/30
100/100 - 108s - loss: 0.4899 - acc: 0.7530 - val_loss: 0.5088 - val_acc: 0.7560 Epoch
30/30
100/100 - 107s - loss: 0.5109 - acc: 0.7465 - val_loss: 0.4900 - val_acc: 0.7640
```

```
model.save('cats_and_dogs_small_5.h5')
```

```
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'] 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.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()
```






```
from keras.applications import VGG16  conv_base = VGG16(weights='imagenet',                   include_top=False,
input_shape=(150, 150, 3))
```

Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16_weights_tf_dim_ordering_tf_kernels_notop.h5 58892288/58889256 [==============================] - 1s 0us/step

```
conv_base.summary()
```

```
Model: "vgg16"
_________________________________________________________________
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
_________________________________________________________________
```

```
from keras import models from keras import layers  model = models.Sequential() model.add(conv_base)
model.add(layers.Flatten()) model.add(layers.Dense(256, activation='relu'))
model.add(layers.Dense(1, activation='sigmoid'))
```

```
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
================================================================= vgg16
(Functional)           (None, 4, 4, 512)        14714688
_________________________________________________________________
flatten (Flatten)            (None, 8192)              0
_________________________________________________________________ dense
(Dense)                (None, 256)              2097408
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 257
=================================================================
Total params: 16,812,353
Trainable params: 16,812,353
Non-trainable params: 0
_________________________________________________________________
```

```
print('This is the number of trainable weights '
      'before freezing the conv base:', len(model.trainable_weights))
```

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

```
conv_base.trainable = False
```

```
print('This is the number of trainable weights '
      'after freezing the conv base:', len(model.trainable_weights))
```

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

```
from keras.preprocessing.image import ImageDataGenerator from keras import models from keras import layers from keras import
optimizers 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')

# Note that the validation data should not be augmented! test_datagen = ImageDataGenerator(rescale=1./255)
 train_generator = train_datagen.flow_from_directory(        # This is the target directory        train_dir,        # All
images will be resized to 150x150        target_size=(150, 150),        batch_size=20,
        # Since we use binary_crossentropy loss, we need binary labels        class_mode='binary')
  validation_generator = test_datagen.flow_from_directory(        validation_dir, target size=(150 150)
        target_size=(150, 150),        batch_size=20,        class_mode='binary')
  model.compile(loss='binary_crossentropy',              optimizer=optimizers.RMSprop(lr=2e-5),
metrics=['acc'])  history = model.fit_generator(      train_generator,      steps_per_epoch=50,      epochs=6,
validation_data=validation_generator,      validation_steps=50,      verbose=2)
```

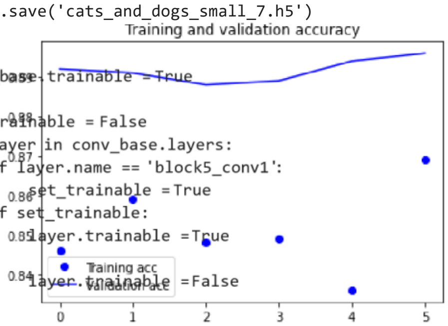
```
Found 2000 images belonging to 2 classes.
Found 1000 images belonging to 2 classes.
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/training.py:1844: UserWarning: `Model.fit_generator` is deprecated
and will be rem   warnings.warn('`Model.fit_generator` is deprecated and '
Epoch 1/6
50/50 - 434s - loss: 0.3503 - acc: 0.8460 - val_loss: 0.2703 - val_acc: 0.8920 Epoch 2/6
50/50 - 433s - loss: 0.3392 - acc: 0.8590 - val_loss: 0.2733 - val_acc: 0.8910 Epoch 3/6
50/50 - 433s - loss: 0.3473 - acc: 0.8480 - val_loss: 0.2726 - val_acc: 0.8880 Epoch 4/6
50/50 - 433s - loss: 0.3528 - acc: 0.8490 - val_loss: 0.2673 - val_acc: 0.8890 Epoch 5/6
```

```
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(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')
```

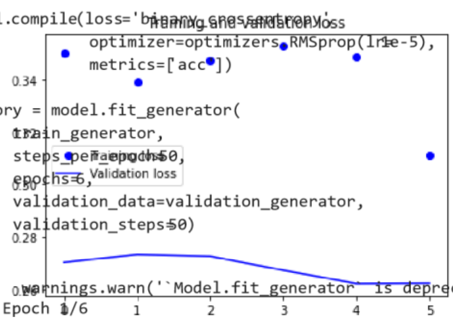
```
50/50 - 433s - loss: 0.3490 - acc: 0.8360 - val_loss: 0.2622 - val_acc: 0.8940 Epoch
6/6
50/50 - 433s - loss: 0.3113 - acc: 0.8690 - val_loss: 0.2624 - val_acc: 0.8960
```

```
model.save('cats_and_dogs_small_7.h5')
```

```
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.legend()  plt.show()
```



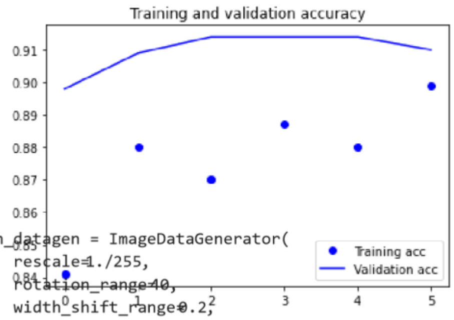

```
conv_base.trainable = True

set_trainable = False
for layer in conv_base.layers:
    if layer.name == 'block5_conv1':
        set_trainable = True
    if set_trainable:
        layer.trainable = True
    else:
        layer.trainable = False

model.compile(loss='binary_crossentropy',
              optimizer=optimizers.RMSprop(lr=1e-5),
              metrics=['acc'])

history = model.fit_generator(
      train_generator,
      steps_per_epoch=50,
      epochs=6,
      validation_data=validation_generator,
      validation_steps=50)
```

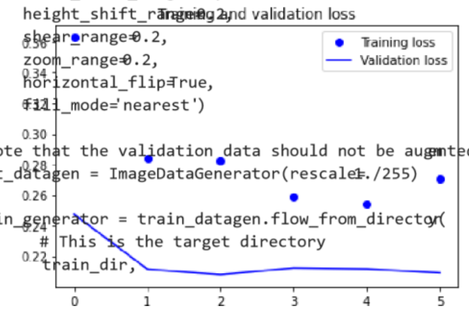



```
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/training.py:1844:
UserWarning: `Model.fit_generator` is deprecated and will be rem
  warnings.warn('`Model.fit_generator` is deprecated and '
Epoch 1/6
50/50 [==============================] - 481s 10s/step - loss: 0.3742 - acc: 0.8324 - val_loss: 0.2474 - val_acc: 0.8980
Epoch 2/6
50/50 [==============================] - 478s 10s/step - loss: 0.2838 - acc: 0.8849 - val_loss: 0.2116 - val_acc: 0.9090
Epoch 3/6
50/50 [==============================] - 477s 10s/step - loss: 0.2770 - acc: 0.8686 - val_loss: 0.2080 - val_acc: 0.9140
Epoch 4/6
50/50 [==============================] - 477s 10s/step - loss: 0.2708 - acc: 0.8856 - val_loss: 0.2124 - val_acc: 0.9140
Epoch 5/6
50/50 [==============================] - 477s 10s/step - loss: 0.2572 - acc: 0.8686 - val_loss: 0.2117 - val_acc: 0.9140
Epoch 6/6
50/50 [==============================] - 482s 10s/step - loss: 0.2990 - acc: 0.8944 - val_loss: 0.2092 - val_acc: 0.9100
```

```
model.save('cats_and_dogs_small_8.h5')
```

```
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(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.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()
```

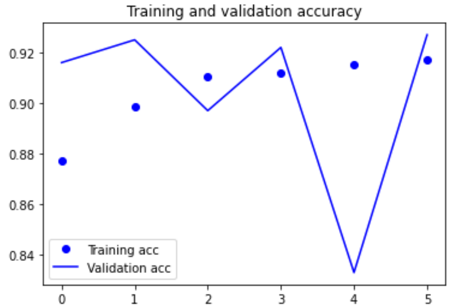


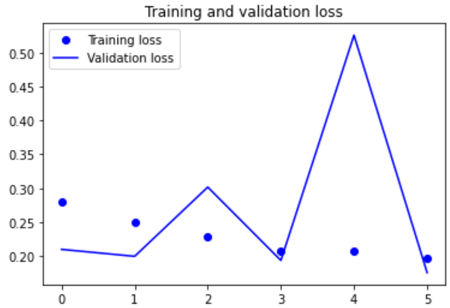



```
train_datagen = ImageDataGenerator(
      rescale=1./255,
      rotation_range=40,
      width_shift_range=0.2,
      height_shift_range=0.2,
      shear_range=0.2,
      zoom_range=0.2,
      horizontal_flip=True,
      fill_mode='nearest')

# Note that the validation data should not be augmented!
test_datagen = ImageDataGenerator(rescale=1./255)

train_generator = train_datagen.flow_from_directory(
        # This is the target directory
        train_dir,
        # All images will be resized to 150x150        target_size=(150 ,  150 ) ,
                                                           batch_size=20,
        # Since we use binary_crossentropy loss, we need
binary labels         class_mode='binary')
 validation_generator        =        test_datagen.flow_from_directory(
validation_dir,          target_size=(150, 150),          batch_size=20,
class_mode='binary')

model.compile(loss='binary_crossentropy',
optimizer=optimizers.RMSprop(lr=2e-5),
metrics=['acc'])
 history = model.fit_generator(       train_generator,
steps_per_epoch=75,       epochs=6,
validation_data=validation_generator,
validation_steps=50,
verbose=2)
```

```
Found 2000 images belonging to 2 classes.
Found 1000 images belonging to 2 classes.
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/training.py:1844: UserWarning: `Model.fit_generator` is deprecated
and will be rem   warnings.warn('`Model.fit_generator` is deprecated and '
Epoch 1/6
75/75 - 621s - loss: 0.2795 - acc: 0.8773 - val_loss: 0.2099 - val_acc: 0.9160 Epoch 2/6
75/75 - 628s - loss: 0.2492 - acc: 0.8987 - val_loss: 0.1996 - val_acc: 0.9250 Epoch 3/6
75/75 - 620s - loss: 0.2291 - acc: 0.9107 - val_loss: 0.3017 - val_acc: 0.8970 Epoch 4/6
75/75 - 621s - loss: 0.2080 - acc: 0.9120 - val_loss: 0.1936 - val_acc: 0.9220 Epoch 5/6
75/75 - 623s - loss: 0.2073 - acc: 0.9153 - val_loss: 0.5256 - val_acc: 0.8330 Epoch
6/6
75/75 - 620s - loss: 0.1963 - acc: 0.9173 - val_loss: 0.1757 - val_acc: 0.9270
```

```
model.save('cats_and_dogs_small_9.h5')

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(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.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()
```

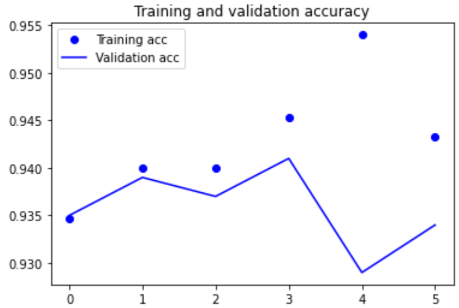


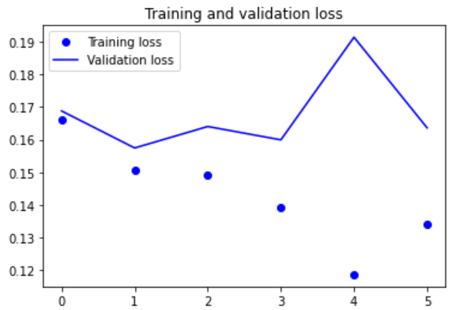



```
conv_base.trainable = True  set_trainable = False for layer in conv_base.layers:     if layer.name == 'block5_conv1':
set_trainable = True     if set_trainable:         layer.trainable = True     else:         layer.trainable = False


model.compile(loss='binary_crossentropy',               optimizer=optimizers.RMSprop(lr=1e-5),               metrics=['acc'])
history = model.fit_generator(       train_generator,       steps_per_epoch=75,       epochs=6,
validation_data=validation_generator,       validation_steps=50)
```

```
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/training.py:1844: UserWarning: `Model.fit_generator` is
deprecated and will be rem   warnings.warn('`Model.fit_generator` is deprecated and '
Epoch 1/6
75/75 [==============================] - 618s 8s/step - loss: 0.1855 - acc: 0.9283 - val_loss: 0.1688 - val_acc: 0.9350
Epoch 2/6
75/75 [==============================] - 617s 8s/step - loss: 0.1608 - acc: 0.9387 - val_loss: 0.1574 - val_acc: 0.9390
Epoch 3/6
75/75 [==============================] - 617s 8s/step - loss: 0.1449 - acc: 0.9450 - val_loss: 0.1640 - val_acc: 0.9370
Epoch 4/6
75/75 [==============================] - 617s 8s/step - loss: 0.1353 - acc: 0.9407 - val_loss: 0.1599 - val_acc: 0.9410
Epoch 5/6
75/75 [==============================] - 617s 8s/step - loss: 0.1123 - acc: 0.9590 - val_loss: 0.1915 - val_acc: 0.9290
Epoch 6/6
75/75 [==============================] - 617s 8s/step - loss: 0.1520 - acc: 0.9298 - val_loss: 0.1636 - val_acc: 0.9340
```

```
model.save('cats_and_dogs_small_10.h5')

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']


    h          (l ( ))
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.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()
```






```
from keras import models from keras import layers
  model = models.Sequential() model.add(conv_base) model.add(layers.Flatten()) model.add(layers.Dense(256,
activation='relu'))
model.add(layers.Dense(1, activation='sigmoid'))
```

```
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
================================================================= vgg16
(Functional)           (None, 4, 4, 512)         14714688
_________________________________________________________________
flatten_1 (Flatten)          (None, 8192)              0
_________________________________________________________________
dense_2 (Dense)              (None, 256)               2097408
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 257
=================================================================
Total params: 16,812,353
Trainable params: 9,177,089
Non-trainable params: 7,635,264
_________________________________________________________________
```

```
print('This is the number of trainable weights '
      'before freezing the conv base:', len(model.trainable_weights))
```

```
This is the number of trainable weights before freezing the conv base: 10
```

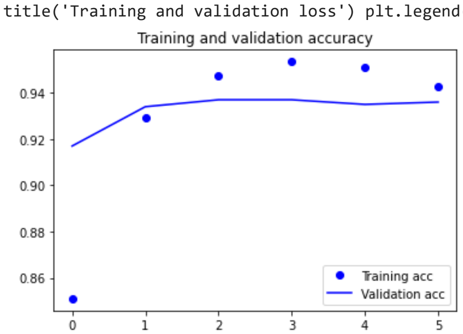
```
conv_base.trainable = False
```

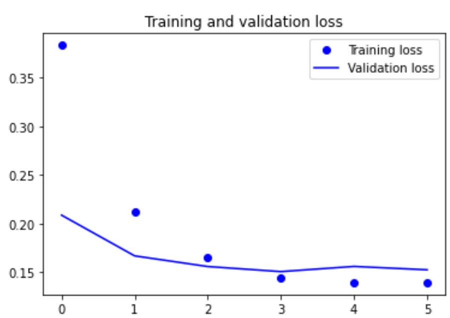
```
print('This is the number of trainable weights '
      'after freezing the conv base:', len(model.trainable_weights)) This is the number of trainable weights after freezing

the conv base: 4
```

```
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')

# Note that the validation data should not be augmented! test_datagen = ImageDataGenerator(rescale=1./255)  train_generator =
train_datagen.flow_from_directory(
        # This is the target directory         train_dir,         # All images will be resized to 150x150
target_size=(150, 150),         batch_size=20,
        # Since we use binary_crossentropy loss, we need binary labels         class_mode='binary')
 validation_generator = test_datagen.flow_from_directory(         validation_dir,         target_size=(150, 150),
batch_size=20,         class_mode='binary')
  model.compile(loss='binary_crossentropy',               optimizer=optimizers.RMSprop(lr=2e-5),
metrics=['acc'])  history = model.fit_generator(       train_generator,       steps_per_epoch=100,       epochs=6,
validation_data=validation_generator,       validation_steps=50,       verbose=2)
```

```
Found 2000 images belonging to 2 classes.
Found 1000 images belonging to 2 classes.
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/training.py:1844: UserWarning: `Model.fit_generator` is
deprecated and will be rem   warnings.warn('`Model.fit_generator` is deprecated and '
Epoch 1/6
100/100 - 659s - loss: 0.3833 - acc: 0.8510 - val_loss: 0.2088 - val_acc: 0.9170 Epoch 2/6
100/100 - 658s - loss: 0.2121 - acc: 0.9290 - val_loss: 0.1670 - val_acc: 0.9340 Epoch 3/6
100/100 - 658s - loss: 0.1649 - acc: 0.9475 - val_loss: 0.1560 - val_acc: 0.9370 Epoch 4/6
100/100 - 660s - loss: 0.1449 - acc: 0.9535 - val_loss: 0.1508 - val_acc: 0.9370 Epoch 5/6
100/100 - 656s - loss: 0.1396 - acc: 0.9510 - val_loss: 0.1561 - val_acc: 0.9350 Epoch 6/6
100/100 - 655s - loss: 0.1398 - acc: 0.9425 - val_loss: 0.1527 - val_acc: 0.9360
```

```
model.save('cats_and_dogs_small_11.h5')

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(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.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()
```



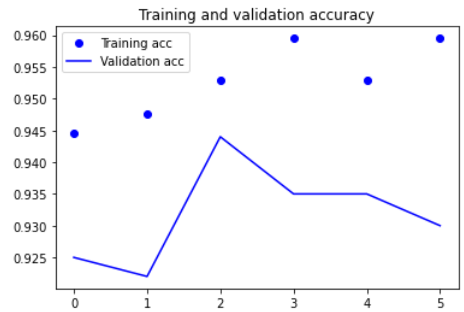


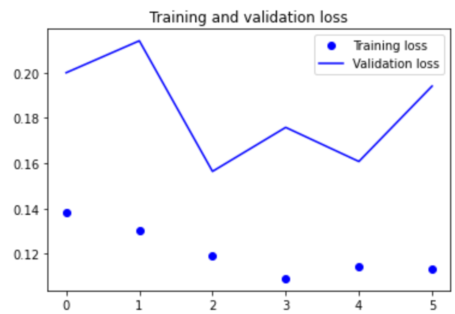

```
conv_base.trainable = True
  set_trainable = False for layer in conv_base.layers:     if layer.name == 'block5_conv1':         set_trainable = True
if set_trainable:         layer.trainable = True     else:         layer.trainable = False


model.compile(loss='binary_crossentropy',               optimizer=optimizers.RMSprop(lr=1e-5),               metrics=['acc'])
history = model.fit_generator(       train_generator,       steps_per_epoch=100,       epochs=6,
validation_data=validation_generator,       validation_steps=50)
```

```
/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/engine/training.py:1844: UserWarning: `Model.fit_generator` is
deprecated and will be rem   warnings.warn('`Model.fit_generator` is deprecated and '
Epoch 1/6
100/100 [==============================] - 748s 7s/step - loss: 0.1362 - acc: 0.9445 - val_loss: 0.1999 - val_acc: 0.9250
Epoch 2/6
100/100 [==============================] - 745s 7s/step - loss: 0.1357 - acc: 0.9457 - val_loss: 0.2141 - val_acc: 0.9220
Epoch 3/6
100/100 [==============================] - 745s 7s/step - loss: 0.1179 - acc: 0.9512 - val_loss: 0.1564 - val_acc: 0.9440
Epoch 4/6
```

```
100/100 [==============================] - 746s 7s/step - loss: 0.1261 - acc: 0.9514 - val_loss: 0.1758 - val_acc: 0.9350
Epoch 5/6
100/100 [==============================] - 746s 7s/step - loss: 0.1226 - acc: 0.9508 - val_loss: 0.1608 - val_acc: 0.9350
Epoch 6/6
100/100 [==============================] - 747s 7s/step - loss: 0.1081 - acc: 0.9598 - val_loss: 0.1940 - val_acc: 0.9300
```

```
model.save('cats_and_dogs_small_12.h5')

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(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.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()
```





The classification model's accuracy and validation loss were assessed using various techniques at different stages of training. When the dataset size increased from 1000 to 1500, the validation accuracy remained unchanged. However, after applying data augmentation and regularization, there was a noticeable 4% increase in accuracy. The use of a pretrained network led to a significant improvement in validation accuracy (25%), which further increased to 28% with data augmentation and regularization. The same trend was observed when the dataset size was increased to 2000, where data augmentation and regularization proved to be more effective than simply expanding the dataset. The most effective method for classification models was found to be using pretrained networks, resulting in a significant increase in validation accuracy (29%). Moreover, this improvement further increased to 31% with the use of data augmentation and regularization. Additionally, the validation loss decreased with each applied technique. Overall, the results suggest that data augmentation and regularization are more effective for training a network, but pretrained networks are most effective for classification models.

The classification model's accuracy and validation loss were assessed using various techniques at different stages of training. When the dataset size increased from 1000 to 1500, the validation accuracy remained unchanged. However, after applying data augmentation and regularization, there was a noticeable 4% increase in accuracy. The use of a pretrained network led to a significant improvement in validation accuracy (25%), which further increased to 28% with data augmentation and regularization. The same trend was observed when the dataset size was increased to 2000, where data augmentation and regularization proved to be more effective than simply expanding the dataset. The most effective method for classification models was found to be using pretrained networks, resulting in a significant increase in validation accuracy (29%). Moreover, this improvement further increased to 31% with the use of data augmentation and regularization. Additionally, the validation loss decreased with each applied technique. Overall, the results suggest that data augmentation and regularization are more effective for training a network, but pretrained networks are most effective for classification models.

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16s completed at 9:30 AM