Using more sophisticated images with Convolutional Neural Networks

In the previous lesson you saw how to use a CNN to make your recognition of the handwriting digits more efficient. In this lesson you'll take that to the next level, recognizing real images of Cats and Dogs in order to classify an incoming image as one or the other. In particular the handwriting recognition made your life a little easier by having all the images be the same size and shape, and they were all monochrome color. Real-world images aren't like that -- they're in different shapes, aspect ratios etc, and they're usually in color!

So, as part of the task you need to process your data -- not least resizing it to be uniform in shape.

You'll follow these steps:

1. Explore the Example Data of Cats and Dogs
2. Build and Train a Neural Network to recognize the difference between the two
3. Evaluate the Training and Validation accuracy

Explore the Example Data

Let's start by downloading our example data, a .zip of 2,000 JPG pictures of cats and dogs, and extracting it locally in `/tmp`.

NOTE: The 2,000 images used in this exercise are excerpted from the "Dogs vs. Cats" dataset available on Kaggle, which contains 25,000 images. Here, we use a subset of the full dataset to decrease training time for educational purposes.

```
!wget --no-check-certificate \
  https://storage.googleapis.com/mledu-datasets/cats_and_dogs_filtered.zip \
  -O /tmp/cats_and_dogs_filtered.zip
```

```
--2020-09-16 15:56:54--  https://storage.googleapis.com/mledu-datasets/cats_and_dogs_fi
Resolving storage.googleapis.com (storage.googleapis.com)... 64.233.189.128, 108.177.97
Connecting to storage.googleapis.com (storage.googleapis.com)|64.233.189.128|:443... cor
HTTP request sent, awaiting response... 200 OK
Length: 68606236 (65M) [application/zip]
Saving to: '/tmp/cats_and_dogs_filtered.zip'

/tmp/cats_and_dogs_ 100%[===================>]  65.43M   106MB/s    in 0.6s
```

The following python code will use the OS library to use Operating System libraries, giving you access to the file system, and the zipfile library allowing you to unzip the data.

```
import os
import zipfile

local_zip = '/tmp/cats_and_dogs_filtered.zip'

zip_ref = zipfile.ZipFile(local_zip, 'r')

zip_ref.extractall('/tmp')
zip_ref.close()
```

The contents of the .zip are extracted to the base directory `/tmp/cats_and_dogs_filtered`, which contains `train` and `validation` subdirectories for the training and validation datasets (see the Machine Learning Crash Course for a refresher on training, validation, and test sets), which in turn each contain `cats` and `dogs` subdirectories.

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t is used to tell the neural network model that 'this is what a like' etc. The validation data set is images of cats and dogs that the neural network will not see as part of the training, so you can test how well or how badly it does in evaluating if an image contains a cat or a dog.

One thing to pay attention to in this sample: We do not explicitly label the images as cats or dogs. If you remember with the handwriting example earlier, we had labelled 'this is a 1', 'this is a 7' etc. Later you'll see something called an ImageGenerator being used -- and this is coded to read images from subdirectories, and automatically label them from the name of that subdirectory. So, for example, you will have a 'training' directory containing a 'cats' directory and a 'dogs' one. ImageGenerator will label the images appropriately for you, reducing a coding step.

Let's define each of these directories:

```
base_dir = '/tmp/cats_and_dogs_filtered'

train_dir = os.path.join(base_dir, 'train')
validation_dir = os.path.join(base_dir, 'validation')

# Directory with our training cat/dog pictures
```

```
# Directory with our training cat/dog pictures
train_cats_dir = os.path.join(train_dir, 'cats')
train_dogs_dir = os.path.join(train_dir, 'dogs')

# Directory with our validation cat/dog pictures
validation_cats_dir = os.path.join(validation_dir, 'cats')
validation_dogs_dir = os.path.join(validation_dir, 'dogs')
```

Now, let's see what the filenames look like in the `cats` and `dogs` `train` directories (file naming conventions are the same in the `validation` directory):

```
train_cat_fnames = os.listdir( train_cats_dir )
train_dog_fnames = os.listdir( train_dogs_dir )

print(train_cat_fnames[:10])
print(train_dog_fnames[:10])
```

```
['cat.915.jpg', 'cat.749.jpg', 'cat.615.jpg', 'cat.699.jpg', 'cat.654.jpg', 'cat.448.jpg
['dog.203.jpg', 'dog.259.jpg', 'dog.283.jpg', 'dog.477.jpg', 'dog.414.jpg', 'dog.572.jpg
```

Let's find out the total number of cat and dog images in the `train` and `validation` directories:

```
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 ) ))
```

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

For both cats and dogs, we have 1,000 training images and 500 validation images.

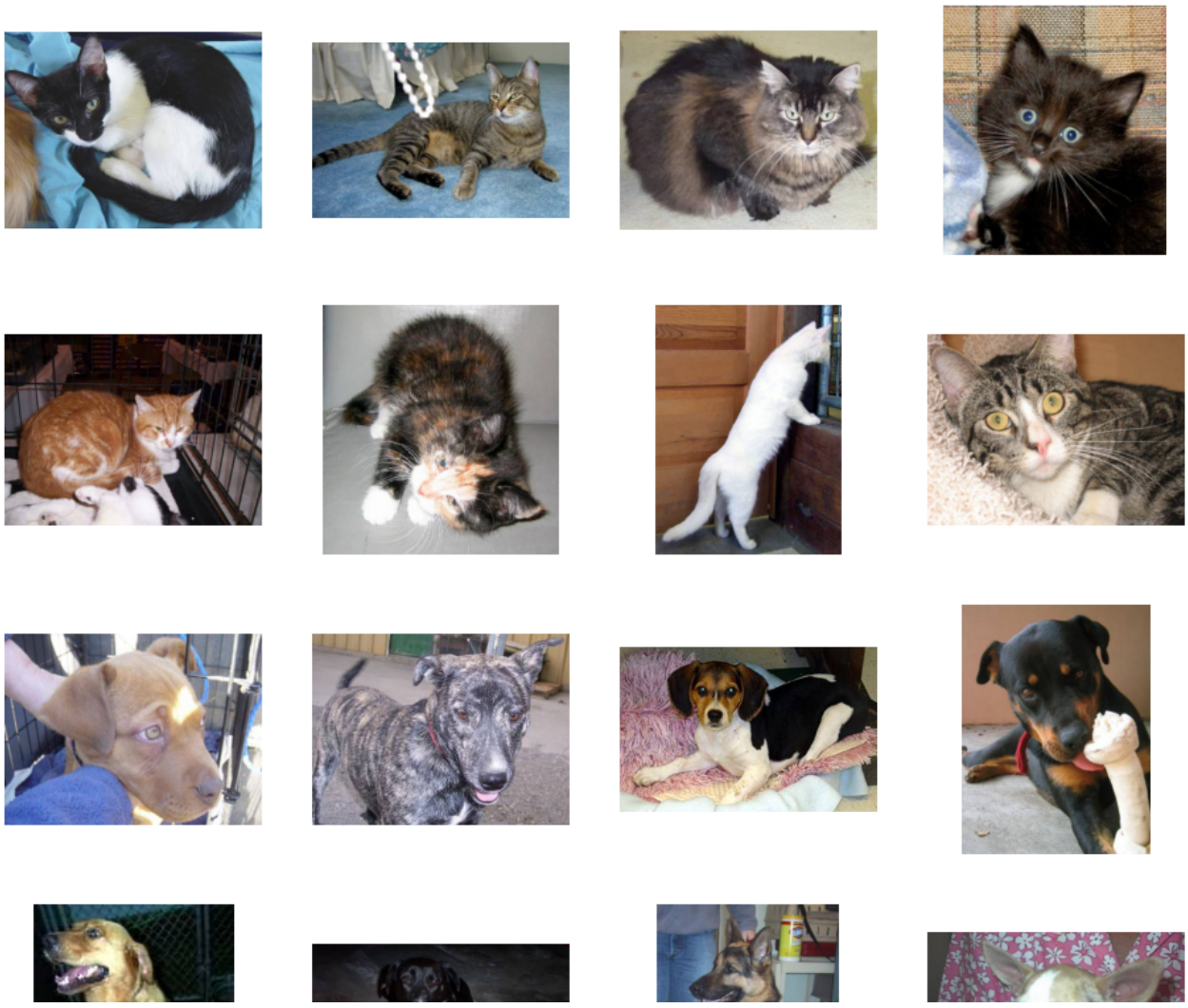
Now let's take a look at a few pictures to get a better sense of what the cat and dog datasets look like. First, configure the matplot parameters:

```
%matplotlib inline

import matplotlib.image as mpimg
import matplotlib.pyplot as plt

# Parameters for our graph; we'll output images in a 4x4 configuration
nrows = 4
ncols = 4
```

```
pic_index = 0 # Index for iterating over images
```

Now, display a batch of 8 cat and 8 dog pictures. You can rerun the cell to see a fresh batch each time:

```
# Set up matplotlib fig, and size it to fit 4x4 pics
fig = plt.gcf()
fig.set_size_inches(ncols*4, nrows*4)

pic_index+=8

next_cat_pix = [os.path.join(train_cats_dir, fname)
                for fname in train_cat_fnames[ pic_index-8:pic_index]
               ]

next_dog_pix = [os.path.join(train_dogs_dir, fname)
                for fname in train_dog_fnames[ pic_index-8:pic_index]
               ]

for i, img_path in enumerate(next_cat_pix+next_dog_pix):
  # Set up subplot; subplot indices start at 1
  sp = plt.subplot(nrows, ncols, i + 1)
  sp.axis('Off') # Don't show axes (or gridlines)

  img = mpimg.imread(img_path)
  plt.imshow(img)
```



It may not be obvious from looking at the images in this grid, but an important note here, and a lesson is that these images come in all shapes and sizes. When you did the handwriting recognition example, you had 28x28 greyscale images to work with. These are color and in a variety of shapes. Before training a Neural network with them you'll need to tweak the images. You'll see that in the next section.

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Ok, now that you have an idea for what your data looks like, the next step is to define the model that will be trained to recognize cats or dogs from these images

Building a Small Model from Scratch to Get to ~72% Accuracy

In the previous section you saw that the images were in a variety of shapes and sizes. In order to train a neural network to handle them you'll need them to be in a uniform size. We've chosen 150x150 for this, and you'll see the code that preprocesses the images to that shape shortly.

But before we continue, let's start defining the model:

Step 1 will be to import tensorflow.

```
import tensorflow as tf
```

Next we will define a Sequential layer as before, adding some convolutional layers first. Note the input shape parameter this time. In the earlier example it was 28x28x1, because the image was 28x28 in greyscale (8 bits, 1 byte for color depth). This time it is 150x150 for the size and 3 (24 bits, 3 bytes) for the color depth.

We then add a couple of convolutional layers as in the previous example, and flatten the final result to feed into the densely connected layers.

Finally we add the densely connected layers.

Note that because we are facing a two-class classification problem, i.e. a *binary classification problem*, we will end our network with a [*sigmoid* activation](), so that the output of our network will be a single scalar between 0 and 1, encoding the probability that the current image is class 1 (as opposed to class 0).

```
model = tf.keras.models.Sequential([
    # Note the input shape is the desired size of the image 150x150 with 3 bytes color
    tf.keras.layers.Conv2D(16, (3,3), activation='relu', input_shape=(150, 150, 3)),
    tf.keras.layers.MaxPooling2D(2,2),
    tf.keras.layers.Conv2D(32, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2,2),
    tf.keras.layers.Conv2D(64, (3,3), activation='relu'),
    ),
    to a DNN
    # 512 neuron hidden layer
    tf.keras.layers.Dense(512, activation='relu'),
    # Only 1 output neuron. It will contain a value from 0-1 where 0 for 1 class ('cats') and
    tf.keras.layers.Dense(1, activation='sigmoid')
])
```

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The model.summary() method call prints a summary of the NN

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 148, 148, 16)      448
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 74, 74, 16)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 72, 72, 32)        4640
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 36, 36, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 34, 34, 64)        18496
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 17, 17, 64)        0
_________________________________________________________________
flatten (Flatten)            (None, 18496)             0
_________________________________________________________________
```

The "output shape" column shows how the size of your feature map evolves in each successive layer. The convolution layers reduce the size of the feature maps by a bit due to padding, and each pooling layer halves the dimensions.

Next, we'll configure the specifications for model training. We will train our model with the `binary_crossentropy` loss, because it's a binary classification problem and our final activation is a sigmoid. (For a refresher on loss metrics, see the Machine Learning Crash Course.) We will use the `rmsprop` optimizer with a learning rate of `0.001`. During training, we will want to monitor classification accuracy.

Saved successfully!

optimization algorithm is preferable to stochastic gradient mates learning-rate tuning for us. (Other optimizers, such as Adam and Adagrad, also automatically adapt the learning rate during training, and would work equally well here.)

```
from tensorflow.keras.optimizers import RMSprop

model.compile(optimizer=RMSprop(lr=0.001),
              loss='binary_crossentropy',
              metrics = ['accuracy'])
```

Data Preprocessing

Let's set up data generators that will read pictures in our source folders, convert them to `float32` tensors, and feed them (with their labels) to our network. We'll have one generator for the training images and one for the validation images. Our generators will yield batches of 20 images of size 150x150 and their labels (binary).

As you may already know, data that goes into neural networks should usually be normalized in some way to make it more amenable to processing by the network. (It is uncommon to feed raw pixels into a convnet.) In our case, we will preprocess our images by normalizing the pixel values to be in the `[0, 1]` range (originally all values are in the `[0, 255]` range).

In Keras this can be done via the `keras.preprocessing.image.ImageDataGenerator` class using the `rescale` parameter. This `ImageDataGenerator` class allows you to instantiate generators of augmented image batches (and their labels) via `.flow(data, labels)` or `.flow_from_directory(directory)`. These generators can then be used with the Keras model methods that accept data generators as inputs: `fit`, `evaluate_generator`, and `predict_generator`.

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator

# All images will be rescaled by 1./255.
train_datagen = ImageDataGenerator( rescale = 1.0/255. )
test_datagen  = ImageDataGenerator( rescale = 1.0/255. )

# --------------------
# Flow training images in batches of 20 using train_datagen generator
# --------------------
train_generator = train_datagen.flow_from_directory(train_dir,
                                                    batch_size=20,
                                                    class_mode='binary',
                                                    target_size=(150, 150))
```

Saved successfully!

```
of 20 using test_datagen generator

validation_generator =  test_datagen.flow_from_directory(validation_dir,
                                                         batch_size=20,
                                                         class_mode  = 'binary',
                                                         target_size = (150, 150))
```

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

Training

Let's train on all 2,000 images available, for 15 epochs, and validate on all 1,000 test images. (This may take a few minutes to run.)

Do note the values per epoch.

You'll see 4 values per epoch -- Loss, Accuracy, Validation Loss and Validation Accuracy.

The Loss and Accuracy are a great indication of progress of training. It's making a guess as to the classification of the training data, and then measuring it against the known label, calculating the result. Accuracy is the portion of correct guesses. The Validation accuracy is the measurement with the data that has not been used in training. As expected this would be a bit lower. You'll learn about why this occurs in the section on overfitting later in this course.

```
history = model.fit(train_generator,
                            validation_data=validation_generator,
                            steps_per_epoch=100,
                            epochs=15,
                            validation_steps=50,
                            verbose=2)
```

```
Epoch 1/15
100/100 - 63s - loss: 0.9003 - accuracy: 0.5455 - val_loss: 0.6811 - val_accuracy: 0.549
Epoch 2/15
100/100 - 63s - loss: 0.6446 - accuracy: 0.6420 - val_loss: 0.6065 - val_accuracy: 0.676
Epoch 3/15
100/100 - 63s - loss: 0.5564 - accuracy: 0.7310 - val_loss: 0.6307 - val_accuracy: 0.670
Epoch 4/15
100/100 - 63s - loss: 0.4908 - accuracy: 0.7760 - val_loss: 0.5649 - val_accuracy: 0.724
Epoch 5/15
100/100 - 63s - loss: 0.4082 - accuracy: 0.8155 - val_loss: 0.5887 - val_accuracy: 0.736
Epoch 6/15
100/100 - 61s - loss: 0.3080 - accuracy: 0.8635 - val_loss: 0.7901 - val_accuracy: 0.647
Epoch 7/15
100/100 - 61s - loss: 0.2283 - accuracy: 0.9050 - val_loss: 0.7793 - val_accuracy: 0.702
Epoch 8/15
                                accuracy: 0.9365 - val_loss: 1.1290 - val_accuracy: 0.694
                                accuracy: 0.9610 - val_loss: 0.9801 - val_accuracy: 0.720
Epoch 10/15
100/100 - 61s - loss: 0.0634 - accuracy: 0.9755 - val_loss: 1.2770 - val_accuracy: 0.736
Epoch 11/15
100/100 - 61s - loss: 0.0680 - accuracy: 0.9800 - val_loss: 1.4996 - val_accuracy: 0.677
Epoch 12/15
100/100 - 61s - loss: 0.1309 - accuracy: 0.9830 - val_loss: 2.0388 - val_accuracy: 0.712
Epoch 13/15
100/100 - 61s - loss: 0.0619 - accuracy: 0.9845 - val_loss: 2.2313 - val_accuracy: 0.643
Epoch 14/15
100/100 - 61s - loss: 0.0375 - accuracy: 0.9865 - val_loss: 1.9605 - val_accuracy: 0.718
Epoch 15/15
100/100 - 61s - loss: 0.1024 - accuracy: 0.9810 - val_loss: 1.7230 - val_accuracy: 0.693
```

Saved successfully!

Running the Model

Let's now take a look at actually running a prediction using the model. This code will allow you to choose 1 or more files from your file system, it will then upload them, and run them through the model, giving an indication of whether the object is a dog or a cat.

```
import numpy as np

from google.colab import files
from keras.preprocessing import image

uploaded=files.upload()

for fn in uploaded.keys():

  # predicting images
  path='/content/' + fn
  img=image.load_img(path, target_size=(150, 150))

  x=image.img_to_array(img)
  x=np.expand_dims(x, axis=0)
  images = np.vstack([x])

  classes = model.predict(images, batch_size=10)

  print(classes[0])

  if classes[0]>0:
    print(fn + " is a dog")

  else:
    print(fn + " is a cat")
```

Choose Files 14908356_5...4527_n.jpg

Saved successfully!

1421035942214527_n.jpg(image/jpeg) - 91943 bytes, last modified:

```
Saving 14908356_561425447400198_7521421035942214527_n.jpg to 14908356_561425447400198_75
[1.]
14908356_561425447400198_7521421035942214527_n.jpg is a dog
```

Visualizing Intermediate Representations

To get a feel for what kind of features our convnet has learned, one fun thing to do is to visualize how an input gets transformed as it goes through the convnet.

Let's pick a random cat or dog image from the training set, and then generate a figure where each row is the output of a layer, and each image in the row is a specific filter in that output feature map. Rerun this cell to generate intermediate representations for a variety of training images.

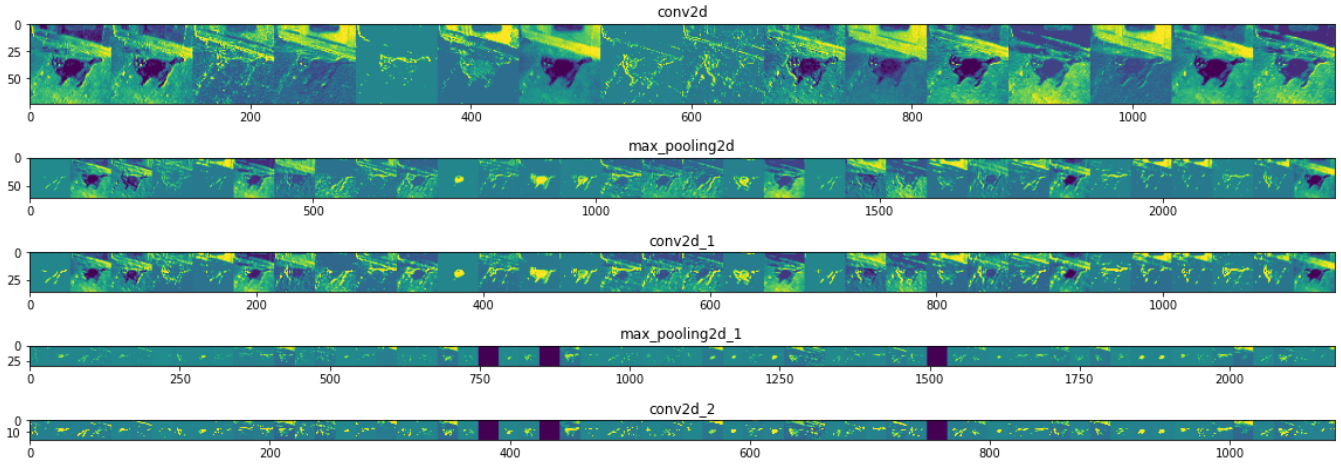
```
import numpy as np
import random
from   tensorflow.keras.preprocessing.image import img_to_array, load_img

# Let's define a new Model that will take an image as input, and will output
# intermediate representations for all layers in the previous model after
```

```
# intermediate representations for all layers in the previous model after
# the first.
successive_outputs = [layer.output for layer in model.layers[1:]]

#visualization_model = Model(img_input, successive_outputs)
visualization_model = tf.keras.models.Model(inputs = model.input, outputs = successive_output

# Let's prepare a random input image of a cat or dog from the training set.
cat_img_files = [os.path.join(train_cats_dir, f) for f in train_cat_fnames]
dog_img_files = [os.path.join(train_dogs_dir, f) for f in train_dog_fnames]

img_path = random.choice(cat_img_files + dog_img_files)
img = load_img(img_path, target_size=(150, 150))  # this is a PIL image

x   = img_to_array(img)                           # Numpy array with shape (150, 150, 3)
x   = x.reshape((1,) + x.shape)                   # Numpy array with shape (1, 150, 150, 3)

# Rescale by 1/255
x /= 255.0

# Let's run our image through our network, thus obtaining all
# intermediate representations for this image.
successive_feature_maps = visualization_model.predict(x)

# These are the names of the layers, so can have them as part of our plot
layer_names = [layer.name for layer in model.layers]

# -----------------------------------------------------------------------
# Now let's display our representations
# -----------------------------------------------------------------------
                                    ayer_names, successive_feature_maps):
  if len(feature_map.shape) == 4:

    #----------------------------------------
    # Just do this for the conv / maxpool layers, not the fully-connected layers
    #----------------------------------------
    n_features = feature_map.shape[-1]  # number of features in the feature map
    size       = feature_map.shape[ 1]  # feature map shape (1, size, size, n_features)

    # We will tile our images in this matrix
    display_grid = np.zeros((size, size * n_features))

    #------------------------------------------------
    # Postprocess the feature to be visually palatable
    #------------------------------------------------
    for i in range(n_features):
      x  = feature_map[0, :, :, i]
      x -= x.mean()
      x /= x.std ()
      x *=  64
      x += 128
```

Saved successfully!

```
    x  = np.clip(x, 0, 255).astype('uint8')
    display_grid[:, i * size : (i + 1) * size] = x # Tile each filter into a horizontal gri

#-----------------
# Display the grid
#-----------------

scale = 20. / n_features
plt.figure( figsize=(scale * n_features, scale) )
plt.title ( layer_name )
plt.grid  ( False )
plt.imshow( display_grid, aspect='auto', cmap='viridis' )
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:55: RuntimeWarning: invalid
```



Saved successfully!

As you can see we go from the raw pixels of the images to increasingly abstract and compact representations. The representations downstream start highlighting what the network pays attention to, and they show fewer and fewer features being "activated"; most are set to zero. This is called "sparsity." Representation sparsity is a key feature of deep learning.

These representations carry increasingly less information about the original pixels of the image, but increasingly refined information about the class of the image. You can think of a convnet (or a deep network in general) as an information distillation pipeline.

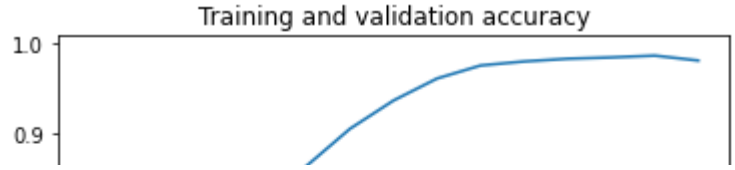
Evaluating Accuracy and Loss for the Model

Let's plot the training/validation accuracy and loss as collected during training:

```
#-----------------------------------------------------------
# Retrieve a list of list results on training and test data
# sets for each training epoch
#-----------------------------------------------------------
acc      = history.history[     'accuracy' ]
val_acc  = history.history[ 'val_accuracy' ]
loss     = history.history[    'loss' ]
val_loss = history.history['val_loss' ]

epochs   = range(len(acc)) # Get number of epochs

#------------------------------------------------
# Plot training and validation accuracy per epoch
#------------------------------------------------
plt.plot  ( epochs,     acc )
plt.plot  ( epochs, val_acc )
plt.title ('Training and validation accuracy')
plt.figure()

#------------------------------------------------
# Plot training and validation loss per epoch
#------------------------------------------------
plt.plot  ( epochs,     loss )
plt.plot  ( epochs, val_loss )
plt.title ('Training and validation loss'   )
```


Saved successfully!

```
Text(0.5, 1.0, 'Training and validation loss')
```



As you can see, we are **overfitting** like it's getting out of fashion. Our training accuracy (in blue) gets close to 100% (!) while our validation accuracy (in green) stalls as 70%. Our validation loss reaches its minimum after only five epochs.

Since we have a relatively small number of training examples (2000), overfitting should be our number one concern. Overfitting happens when a model exposed to too few examples learns patterns that do not generalize to new data, i.e. when the model starts using irrelevant features for making predictions. For instance, if you, as a human, only see three images of people who are lumberjacks, and three images of people who are sailors, and among them the only person wearing a cap is a lumberjack, you might start thinking that wearing a cap is a sign of being a lumberjack as opposed to a sailor. You would then make a pretty lousy lumberjack/sailor classifier.

Overfitting is the central problem in machine learning: given that we are fitting the parameters of our model to a given dataset, how can we make sure that the representations learned by the model will be applicable to data never seen before? How do we avoid learning things that are specific to the training data?

In the next exercise, we'll look at ways to prevent overfitting in the cat vs. dog classification model.

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Before running the next exercise, run the following cell to terminate the kernel and free memory resources:

```
import os, signal

os.kill(     os.getpid() ,
         signal.SIGKILL
       )
```

Saved successfully!