

The background image shows a vast mountain range under a sky transitioning from deep blue to vibrant orange and pink at the horizon. In the foreground, a bright orange tent is set up on a rocky, grassy slope, its light reflecting softly. A small body of water is visible in the middle ground.

DEELEARNING

TENSORFLOW

<https://www.tensorflow.org>

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TENSORFLOW

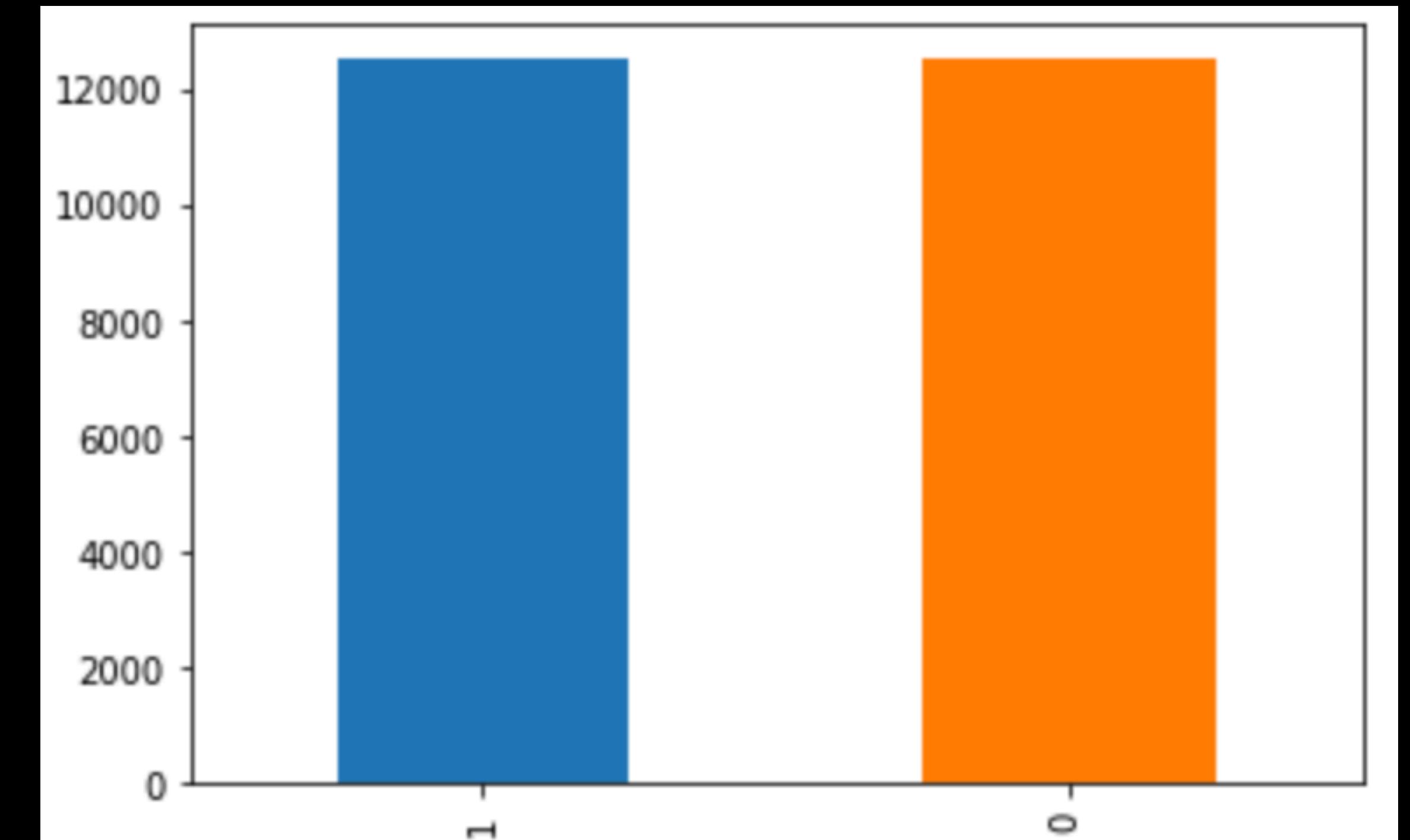
USANDO UMA BASE DE
DADOS GRANDE

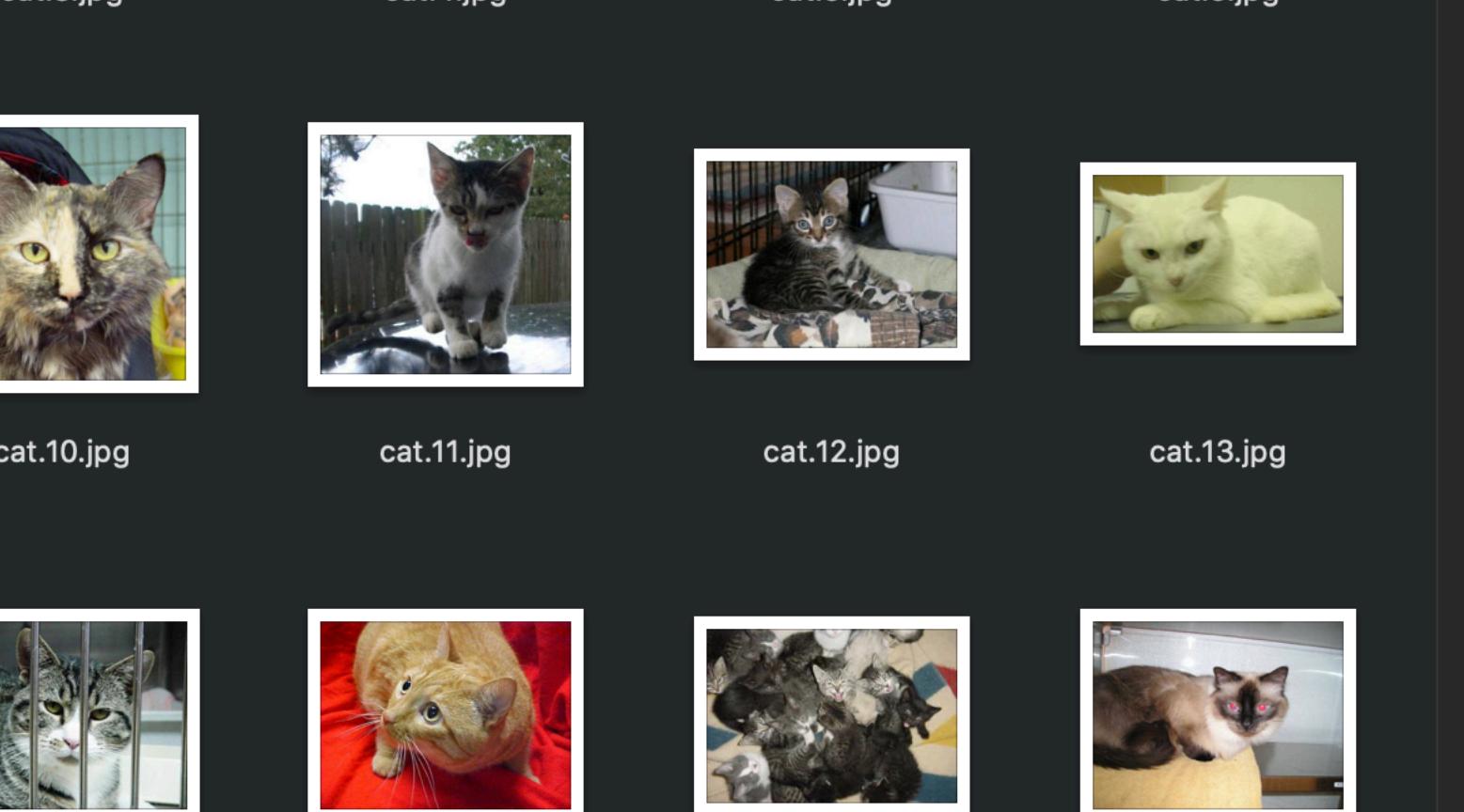
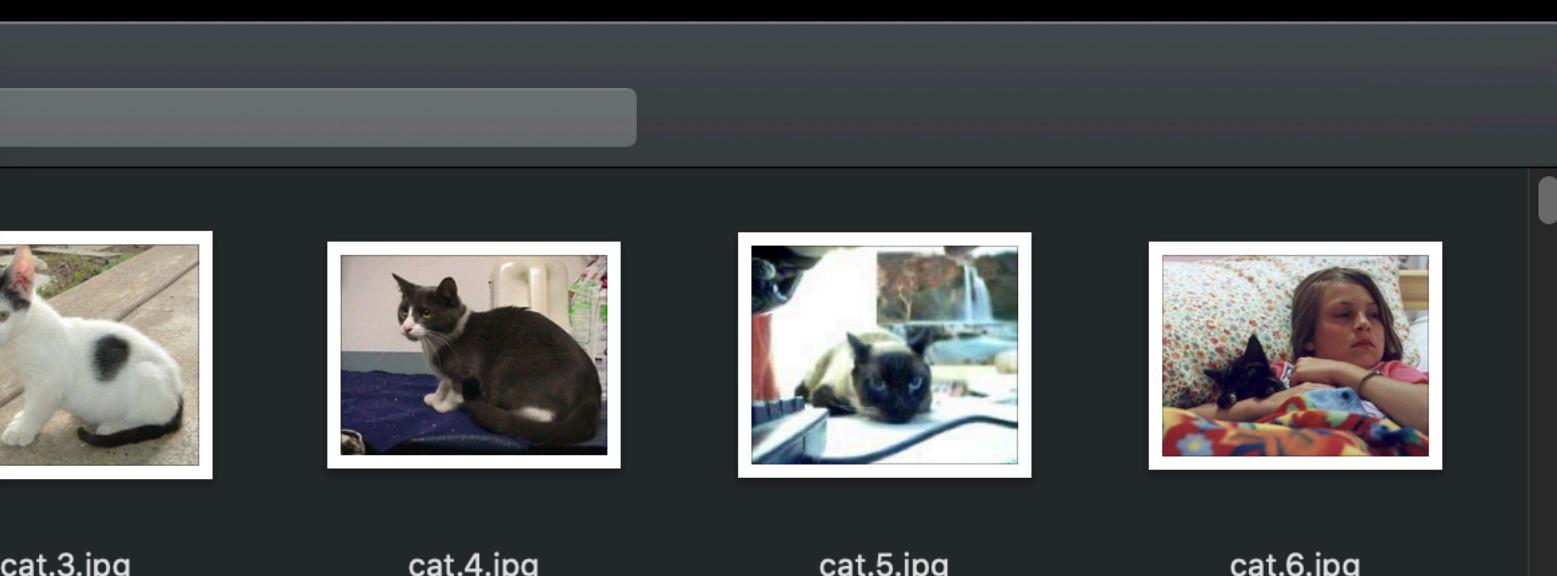
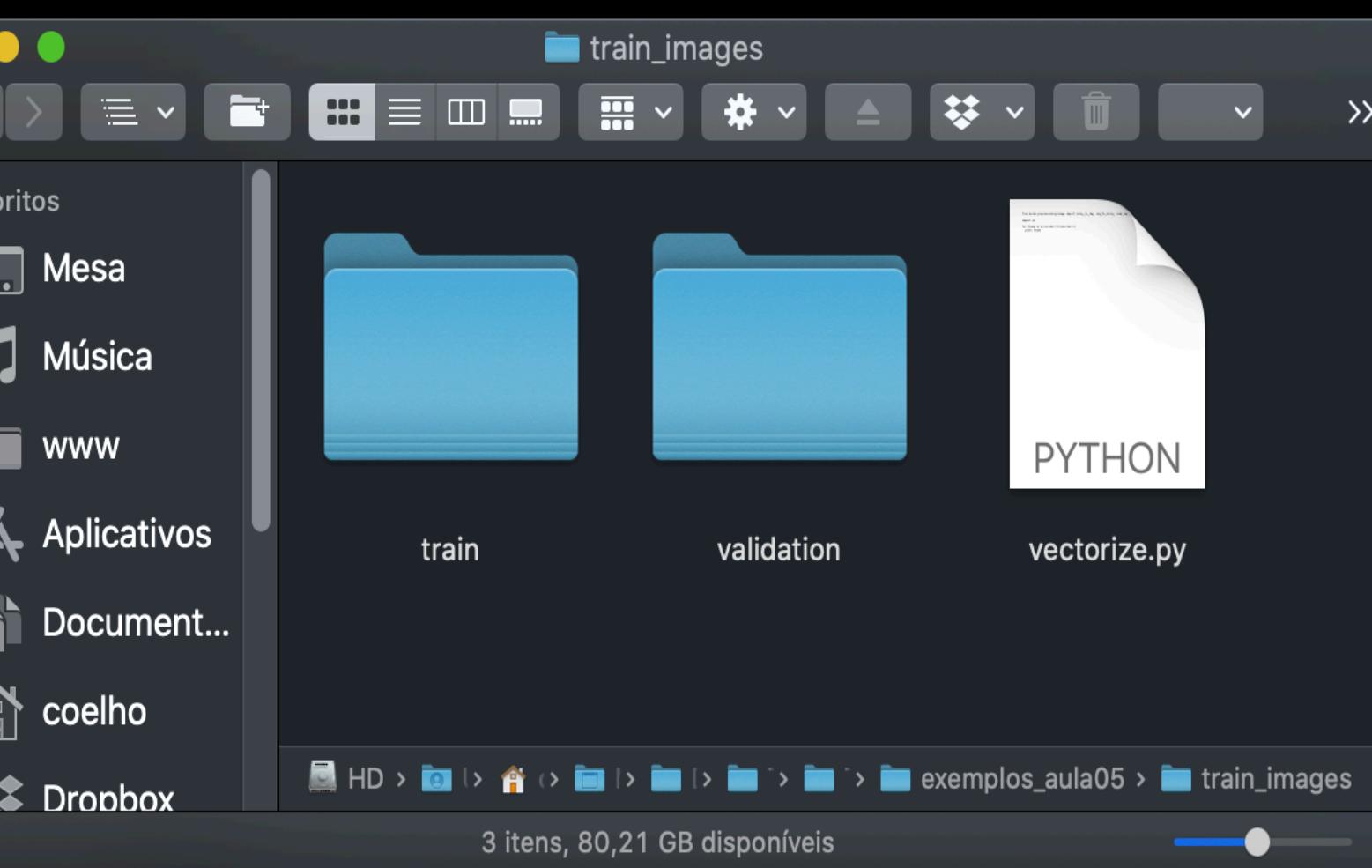
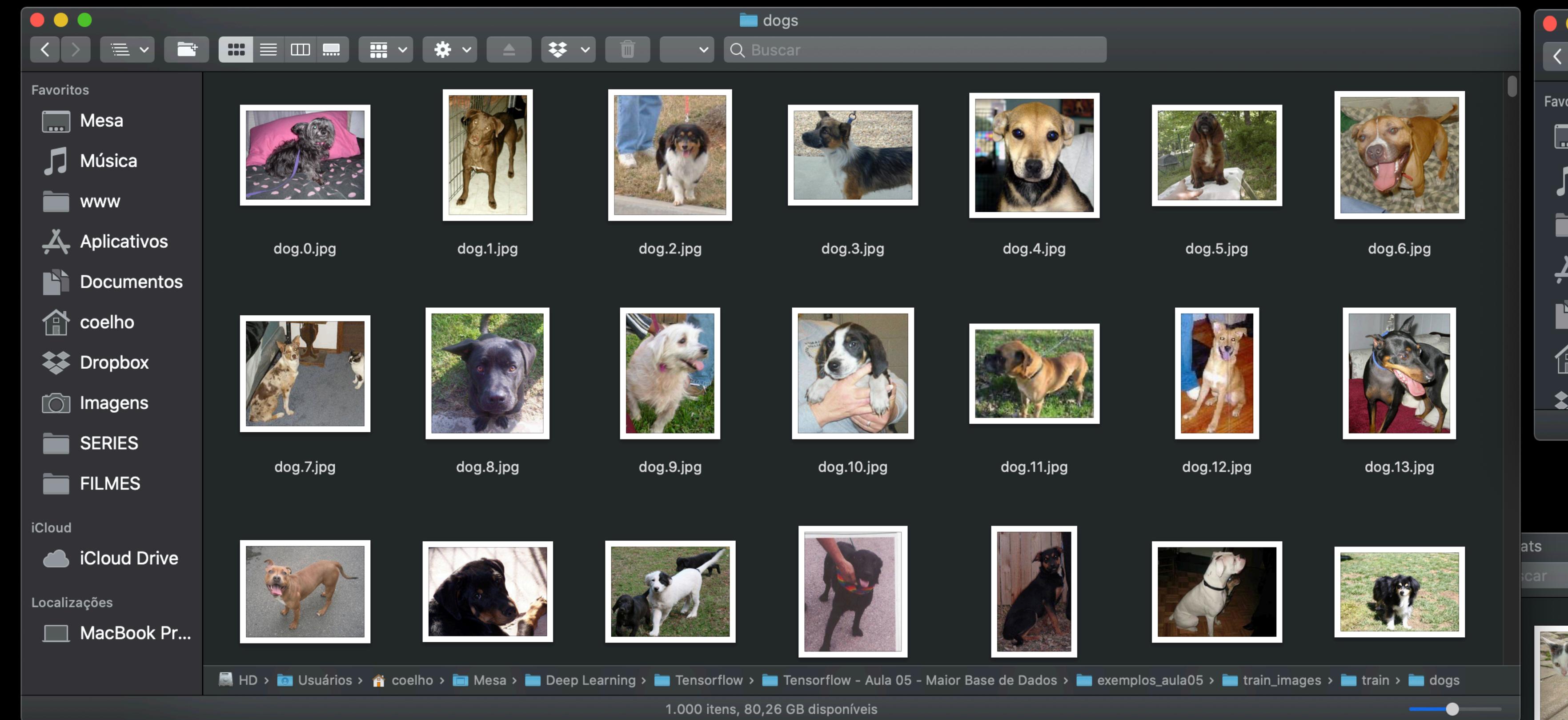
Big Data



0) DOWNLOAD DA BASE DE DADOS

- https://storage.googleapis.com/mledu-datasets/cats_and_dogs_filtered.zip
- A base de dados contém 25.000 imagens, sendo metade de cachorros (label 1) e metade de gatos (label 0).





Temos duas pastas:
uma para treino
e outra para validação.

1) IMPORTANDO A BASE DE DADOS

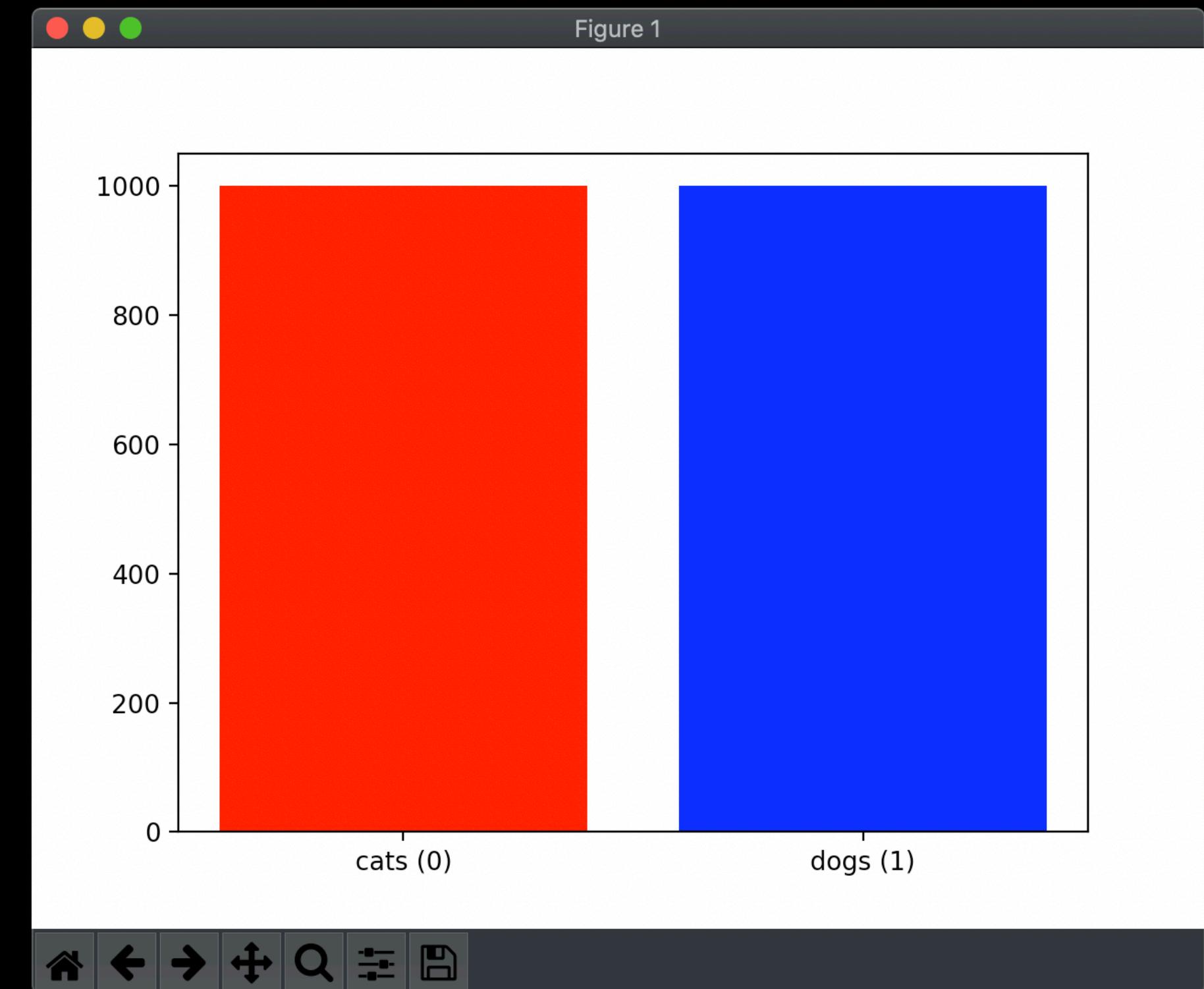
```
17
18 def main():
19     # 1 - loading data
20     base_dir = './train_images/'
21     train_dir = os.path.join(base_dir, 'train')
22     validation_dir = os.path.join(base_dir, 'validation')
23     # Directory with our training cat/dog pictures
24     train_cats_dir = os.path.join(train_dir, 'cats')
25     train_dogs_dir = os.path.join(train_dir, 'dogs')
26     # Directory with our validation cat/dog pictures
27     validation_cats_dir = os.path.join(validation_dir, 'cats')
28     validation_dogs_dir = os.path.join(validation_dir, 'dogs')
29     train_cat_fnames = os.listdir(train_cats_dir)
30     train_dog_fnames = os.listdir(train_dogs_dir)
31     print(train_cat_fnames[:10])
32     print(train_dog_fnames[:10])
33     print('total training cat images :', len(os.listdir(train_cats_dir)))
34     print('total training dog images :', len(os.listdir(train_dogs_dir)))
35     print('total validation cat images :', len(os.listdir(validation_cats_dir)))
36     print('total validation dog images :', len(os.listdir(validation_dogs_dir)))
```

```
['cat.952.jpg', 'cat.946.jpg', 'cat.6.jpg', '
['dog.775.jpg', 'dog.761.jpg', 'dog.991.jpg',
total training cat images : 1000
total training dog images : 1000
total validation cat images : 500
total validation dog images : 500
```

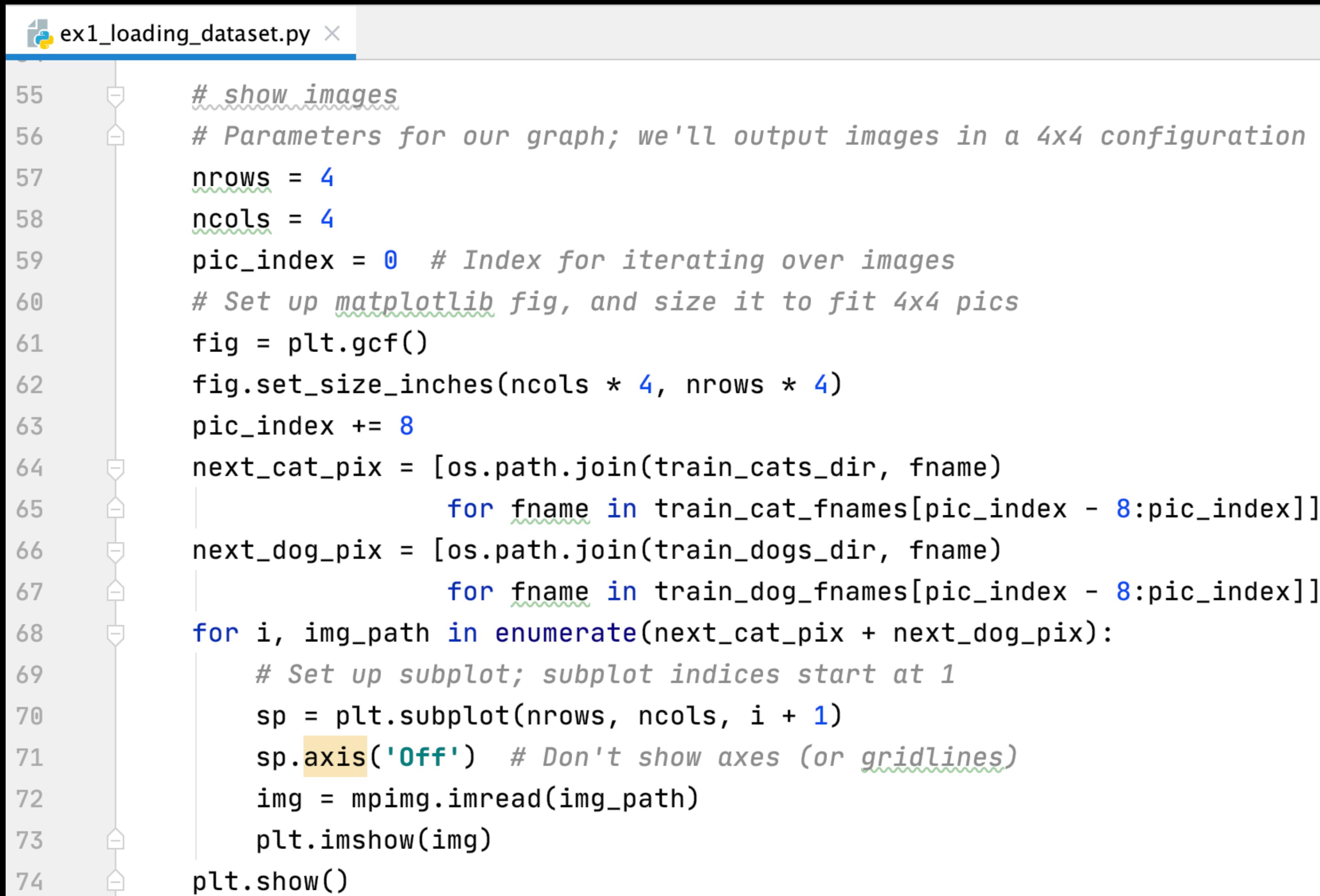
1) IMPORTANDO A BASE DE DADOS

```
ex1_loading_dataset.py ×

37
38     # show the images quantity
39     categories = []
40     filenames = []
41     load_images(train_dogs_dir, categories, filenames)
42     load_images(train_cats_dir, categories, filenames)
43     #    load_images(validation_cats_dir, categories, filenames)
44     #    load_images(validation_dogs_dir, categories, filenames)
45     df = pd.DataFrame({
46         'filename': filenames,
47         'category': categories
48     })
49     print(df.head())
50     plt.bar(['cats (0)', 'dogs (1)'], df['category'].value_counts(), color=['r', 'b'])
51     plt.show()
```



1) IMPORTANDO A BASE DE DADOS



The image shows a screenshot of a code editor with a dark theme. The file being edited is named "ex1_loading_dataset.py". The code itself is a Python script designed to show images from a dataset. It uses the `os`, `mpimg`, and `matplotlib` libraries. The script starts by importing these libraries and defining parameters for displaying images in a 4x4 grid. It then sets up a `matplotlib` figure and its size. The script iterates over image paths, combining them into two lists: one for cat images and one for dog images. These lists are then combined and iterated over to create a 4x4 grid of images. Each subplot is set to have no axes or gridlines. The script concludes with a call to `plt.show()` to display the images.

```
55     # show images
56     # Parameters for our graph; we'll output images in a 4x4 configuration
57     nrows = 4
58     ncols = 4
59     pic_index = 0 # Index for iterating over images
60     # Set up matplotlib fig, and size it to fit 4x4 pics
61     fig = plt.gcf()
62     fig.set_size_inches(ncols * 4, nrows * 4)
63     pic_index += 8
64     next_cat_pix = [os.path.join(train_cats_dir, fname)
65                     for fname in train_cat_fnames[pic_index - 8:pic_index]]
66     next_dog_pix = [os.path.join(train_dogs_dir, fname)
67                     for fname in train_dog_fnames[pic_index - 8:pic_index]]
68     for i, img_path in enumerate(next_cat_pix + next_dog_pix):
69         # Set up subplot; subplot indices start at 1
70         sp = plt.subplot(nrows, ncols, i + 1)
71         sp.axis('Off') # Don't show axes (or gridlines)
72         img = mpimg.imread(img_path)
73         plt.imshow(img)
74     plt.show()
```

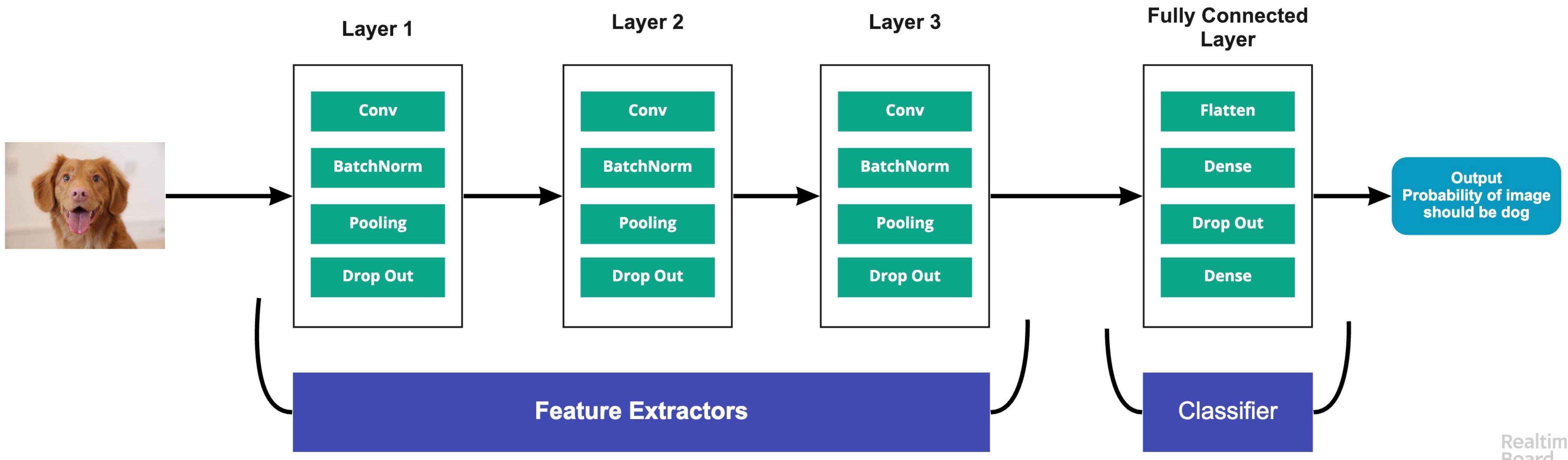
1) IMPORTANDO A BASE DE DADOS

```
ex1_loading_dataset.py x
```

```
55     # show images
56     # Parameters for displaying images
57     nrows = 4
58     ncols = 4
59     pic_index = 0    # Index of image in flattened list of images
60
61     # Set up matplotlib
62     fig = plt.gcf()
63     fig.set_size_inches(4*ncols, 4*nrows)
64     pic_index += 8
65
66     next_cat_pix = [os.path.join('..', 'dataset/cats', f)
67                      for f in next_cat_pix]
68
69     next_dog_pix = [os.path.join('..', 'dataset/dogs', f)
70                      for f in next_dog_pix]
71
72     for i, img_path in enumerate(next_cat_pix + next_dog_pix):
73         # Set up subplot
74         sp = plt.subplot(nrows, ncols, i+1)
75         sp.axis('Off')
76         img = mpimg.imread(img_path)
77         plt.imshow(img)
78
79         if pic_index < len(next_cat_pix):
80             plt.title('Cat')
81         else:
82             plt.title('Dog')
83
84         plt.show()
```

Figure 1

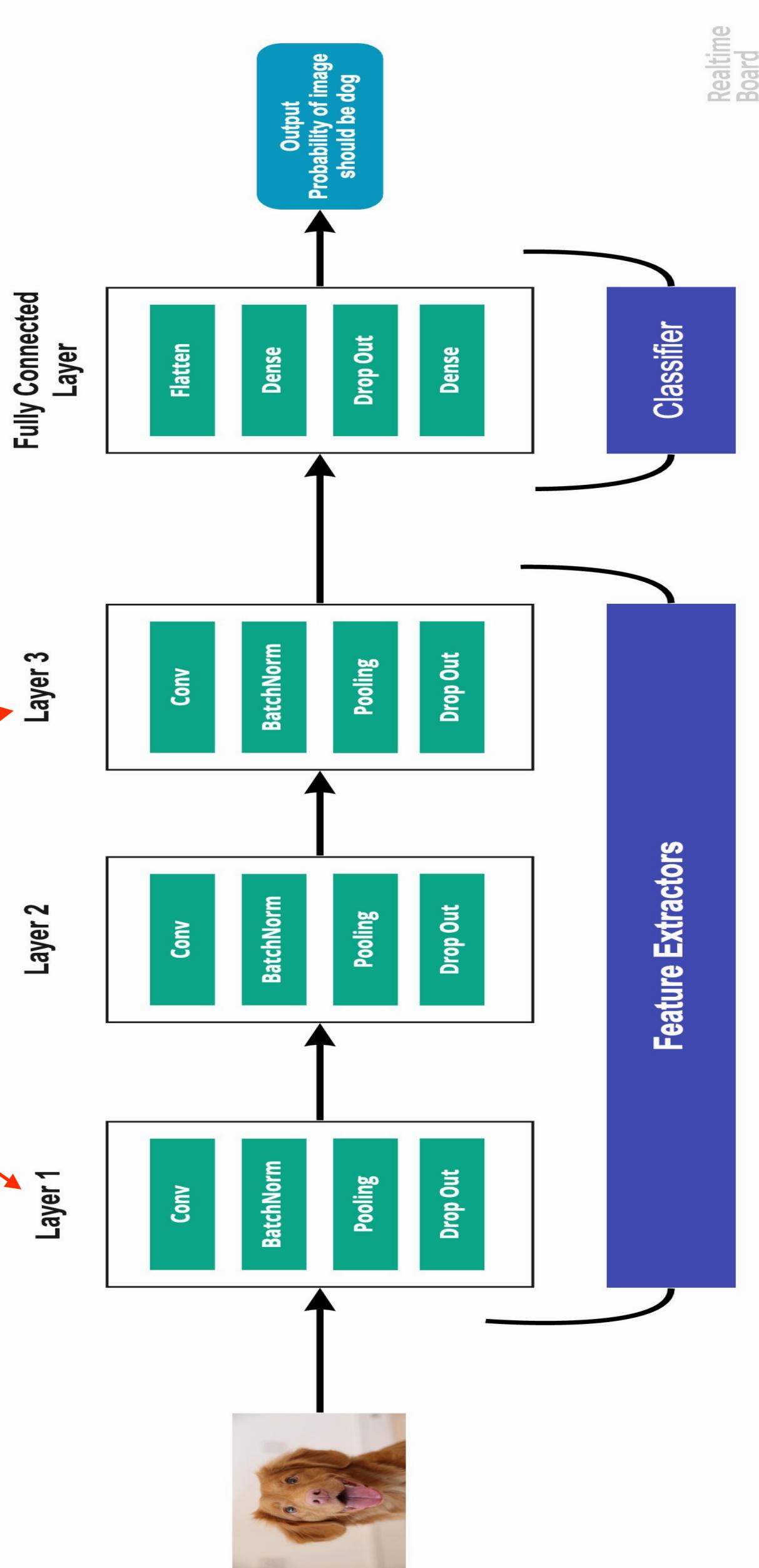
2) DEFININDO O MODELO DA REDE NEURAL



- **Layer 1(Input):** representa os dados de imagem de entrada. Reformata cada imagem para vetor unidimensional. Ex: A imagem tem $64 \times 64 = 4096$, e é convertida em um vetor $(4096, 1)$.
- **Layer 2 (Convolutional):** Extrai características (features) da imagem.
- **Layer 3 (Pooling):** Reduz o volume espacial da imagem após a convulação.
- **Fully Connected Layer:** Faz a classificação.
- **Output Layer:** Apresenta como saída a probabilidade de ser a imagem de um cachorro.

2) DEFININDO O MODELO DA REDE NEURAL

```
28 # define the model
29 model = Sequential()
30
31     model.add(Conv2D(32, (3, 3), activation='relu',
32                      input_shape=(IMAGE_WIDTH, IMAGE_HEIGHT, IMAGE_CHANNELS)))
33     model.add(BatchNormalization())
34     model.add(MaxPooling2D(pool_size=(2, 2)))
35     model.add(Dropout(0.25))
36
37     model.add(Conv2D(64, (3, 3), activation='relu'))
38     model.add(BatchNormalization())
39     model.add(MaxPooling2D(pool_size=(2, 2)))
40     model.add(Dropout(0.25))
41
42     model.add(Conv2D(128, (3, 3), activation='relu'))
43     model.add(BatchNormalization())
44     model.add(MaxPooling2D(pool_size=(2, 2)))
45     model.add(Dropout(0.25))
46
47     model.add(Flatten())
48     model.add(Dense(512, activation='relu'))
49     model.add(BatchNormalization())
50     model.add(Dropout(0.5))
51     model.add(Dense(1, activation='sigmoid'))
52
53     model.compile(loss='binary_crossentropy', optimizer=RMSprop(lr=0.001), metrics=['accuracy'])
```

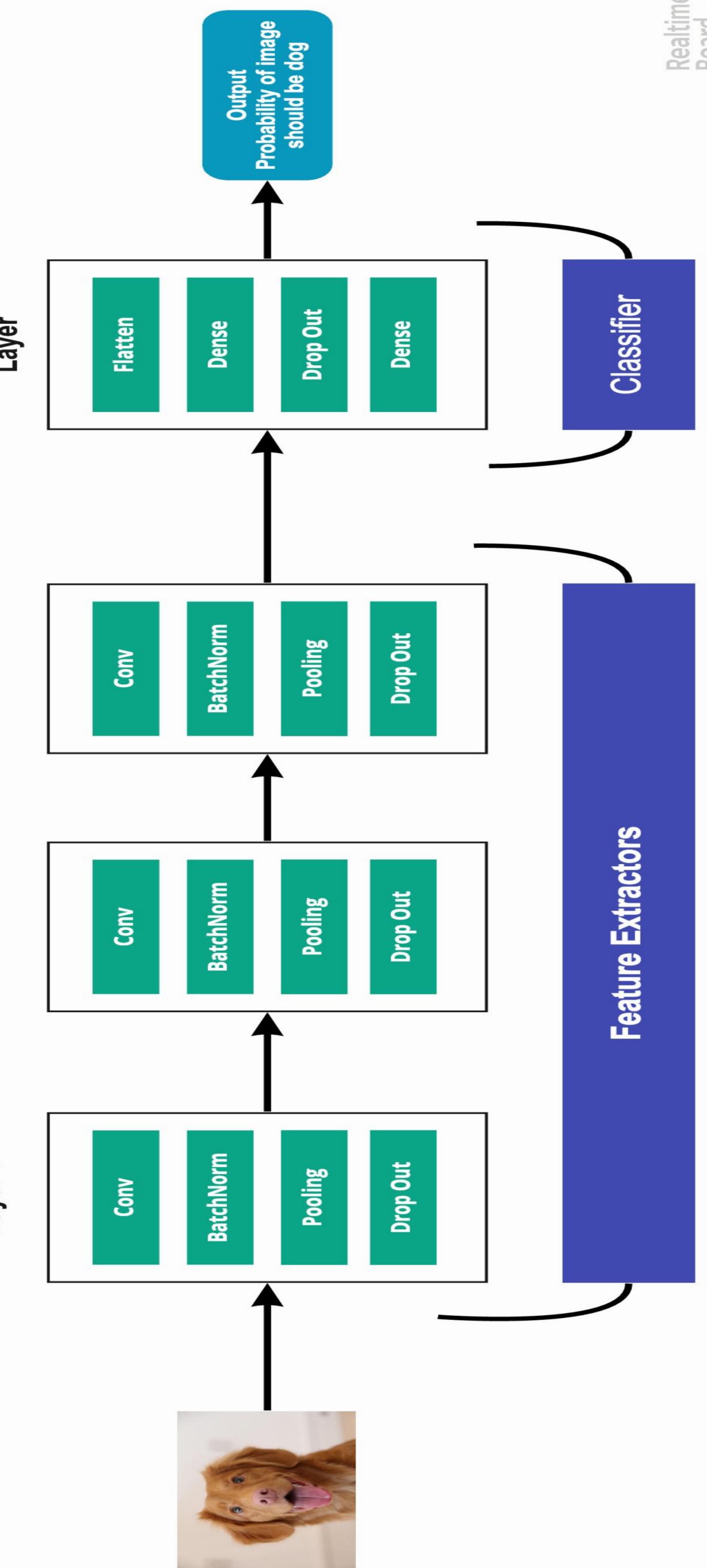


Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 148, 148, 32)	896
batch_normalization_1 (Batch Normalization)	(None, 148, 148, 32)	128
max_pooling2d_1 (MaxPooling2D)	(None, 74, 74, 32)	0
dropout_1 (Dropout)	(None, 74, 74, 32)	0
conv2d_2 (Conv2D)	(None, 72, 72, 64)	18496
batch_normalization_2 (Batch Normalization)	(None, 72, 72, 64)	256
max_pooling2d_2 (MaxPooling2D)	(None, 36, 36, 64)	0
dropout_2 (Dropout)	(None, 36, 36, 64)	0
conv2d_3 (Conv2D)	(None, 34, 34, 128)	73856
batch_normalization_3 (Batch Normalization)	(None, 34, 34, 128)	512
max_pooling2d_3 (MaxPooling2D)	(None, 17, 17, 128)	0
dropout_3 (Dropout)	(None, 17, 17, 128)	0
flatten_1 (Flatten)	(None, 36992)	0
dense_1 (Dense)	(None, 512)	18940416
batch_normalization_4 (Batch Normalization)	(None, 512)	2048
dropout_4 (Dropout)	(None, 512)	0
dense_2 (Dense)	(None, 1)	513

Total params: 19,037,121
Trainable params: 19,035,649
Non-trainable params: 1,472

SUMÁRIO DO MODELO



3) PREPARANDO OS DADOS

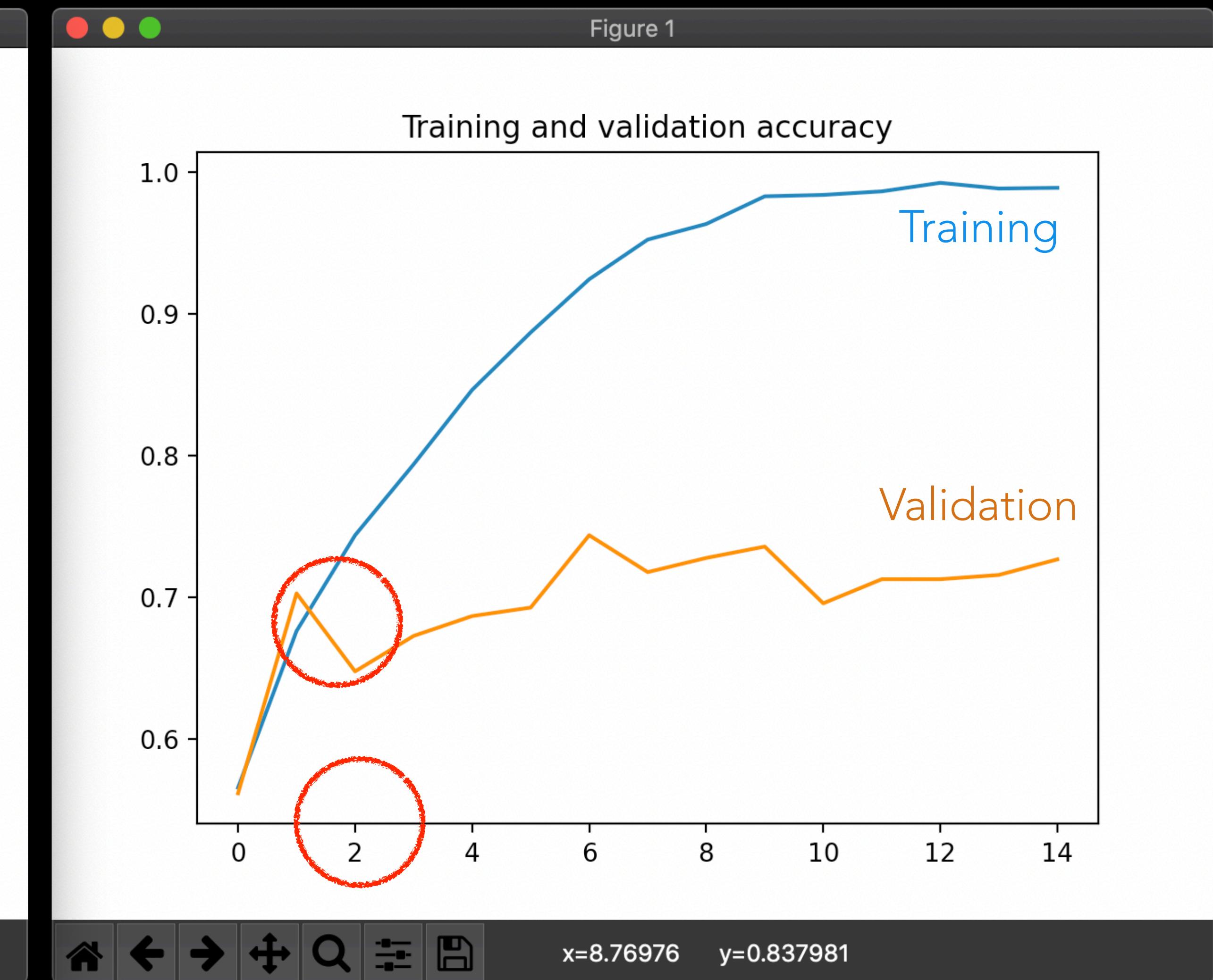
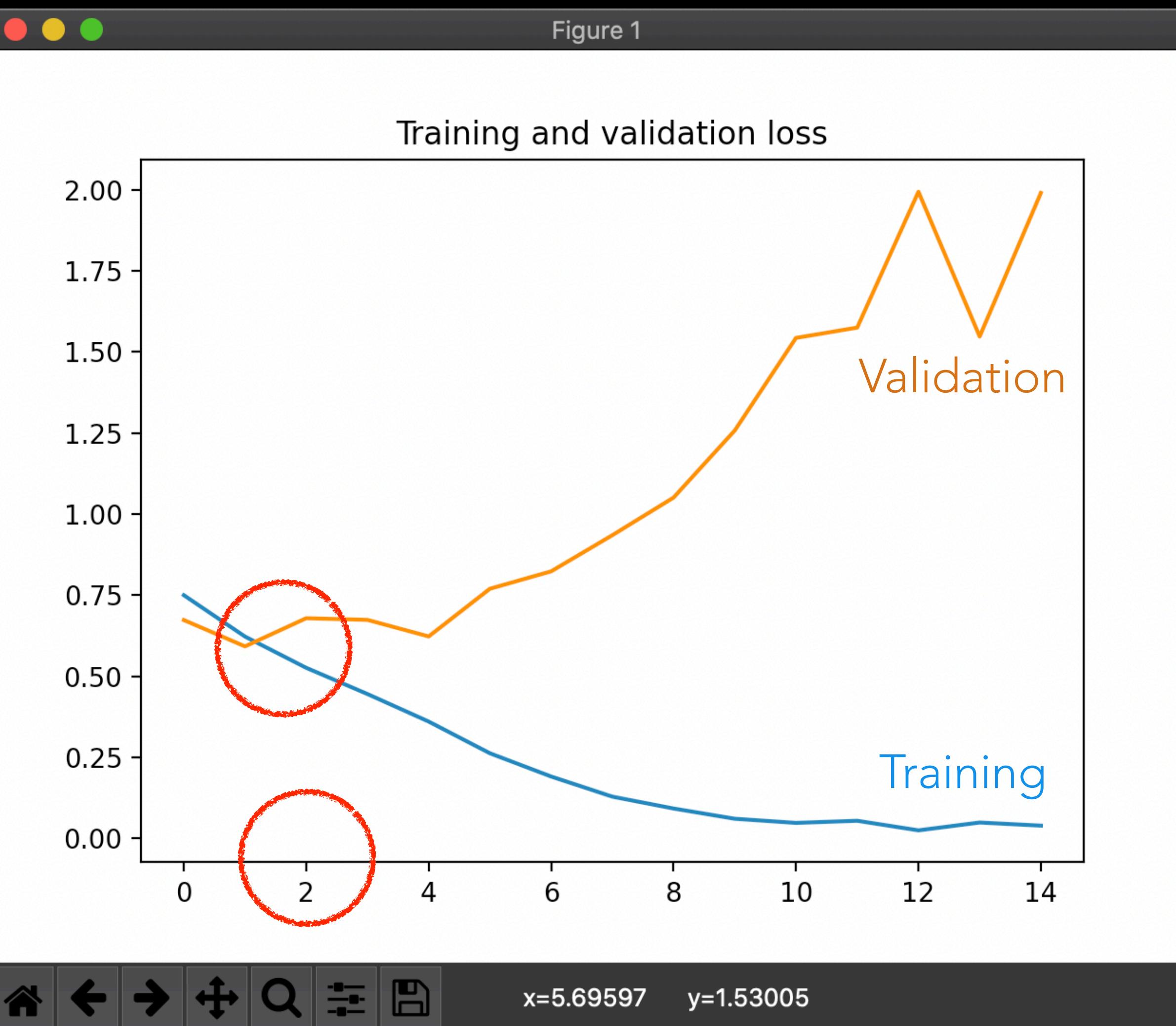
```
ex3_prepare_data.py ×

70      # 3 - preparing data (preprocessing)
71      # All images will be rescaled by 1./255.
72      train_datagen = ImageDataGenerator(rescale=1.0 / 255.)
73      test_datagen = ImageDataGenerator(rescale=1.0 / 255.)
74      # -----
75      # Flow training images in batches of 20 using train_datagen generator
76      # -----
77      train_generator = train_datagen.flow_from_directory(train_dir,
78                                              batch_size=batch_size,
79                                              class_mode='binary',
80                                              target_size=(IMAGE_WIDTH, IMAGE_HEIGHT))
81      # -----
82      # Flow validation images in batches of 20 using test_datagen generator
83      # -----
84      validation_generator = test_datagen.flow_from_directory(validation_dir,
85                                              batch_size=batch_size,
86                                              class_mode='binary',
87                                              target_size=(IMAGE_WIDTH, IMAGE_HEIGHT))
```

4) TREINANDO A REDE

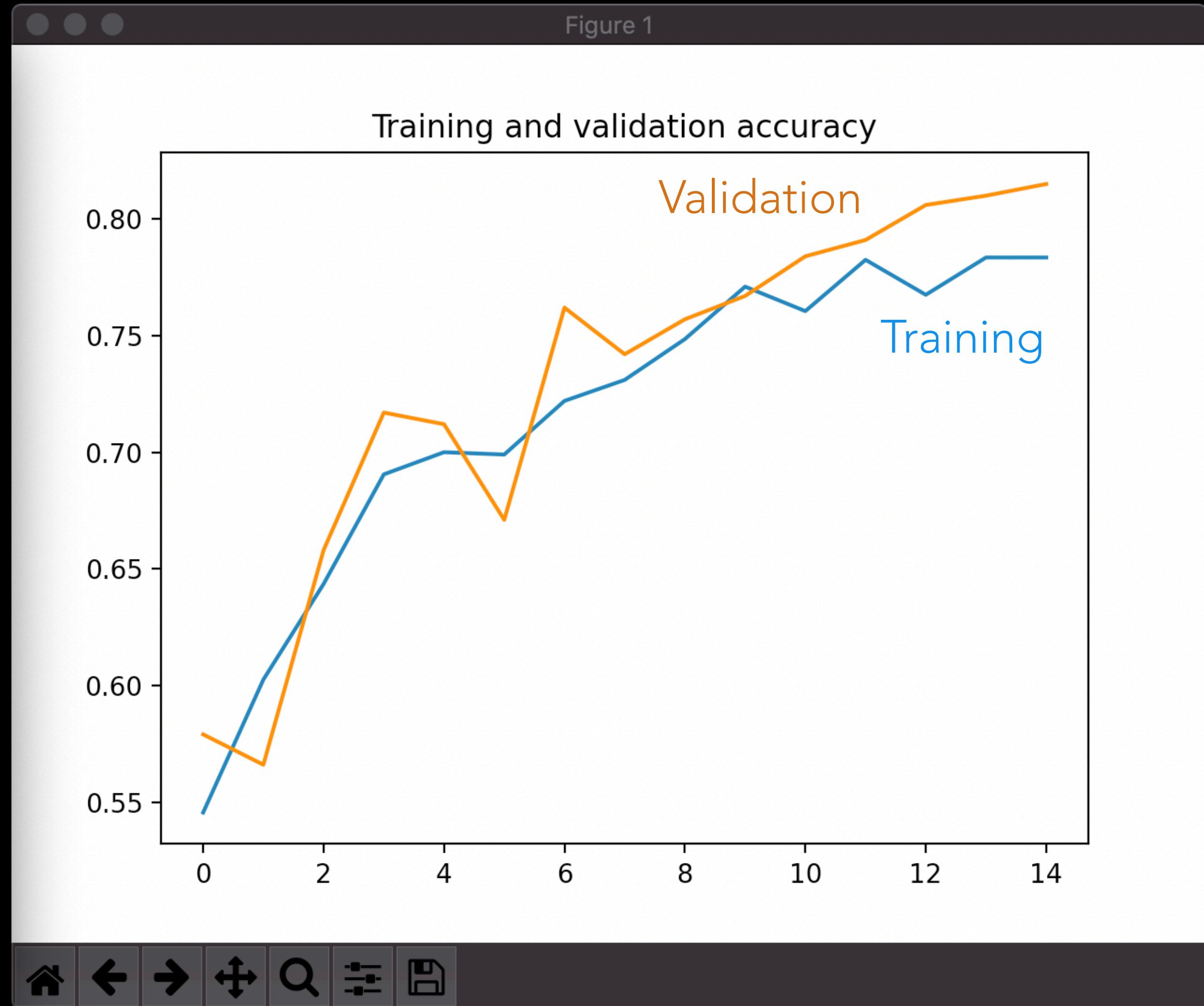
```
105     # 4 - train the network
106     history = model.fit(train_generator,
107                           validation_data=validation_generator,
108                           steps_per_epoch=100,
109                           epochs=15,
110                           validation_steps=50,
111                           verbose=2)
112     print(history)
113
114     # -----
115     # Retrieve a list of list results on training and test data
116     # sets for each training epoch
117     #
118     acc = history.history['accuracy']
119     val_acc = history.history['val_accuracy']
120     loss = history.history['loss']
121     val_loss = history.history['val_loss']
122     epochs = range(len(acc)) # Get number of epochs
123
124     # -----
125     # Plot training and validation accuracy per epoch
126     #
127     plt.plot(epochs, acc, color='b')
128     plt.plot(epochs, val_acc, color='r')
129     plt.title('Training and validation accuracy')
130     plt.show()
131
132     # -----
133     # Plot training and validation loss per epoch
134     #
135     plt.plot(epochs, loss, color='b')
136     plt.plot(epochs, val_loss, color='r')
137     plt.title('Training and validation loss')
138     plt.show()
```

7) RESULTADOS



A partir de duas épocas, não aprendemos nada mais (overtraining).

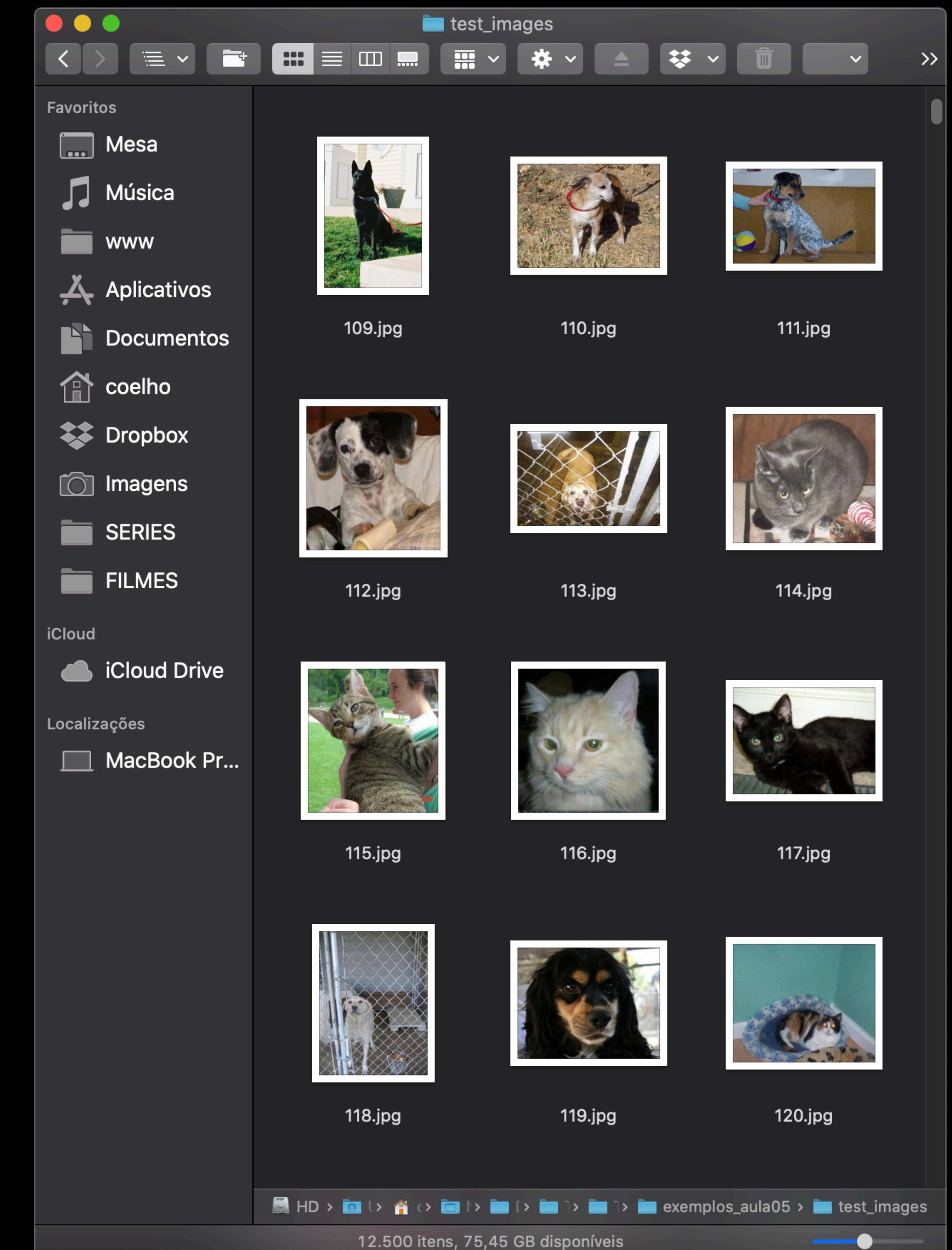
E SE USARMOS UMA BASE DADOS MAIOR?



Usando os dados totais do BD de gatos e cachorros do Kaggle (25.000 imagens)

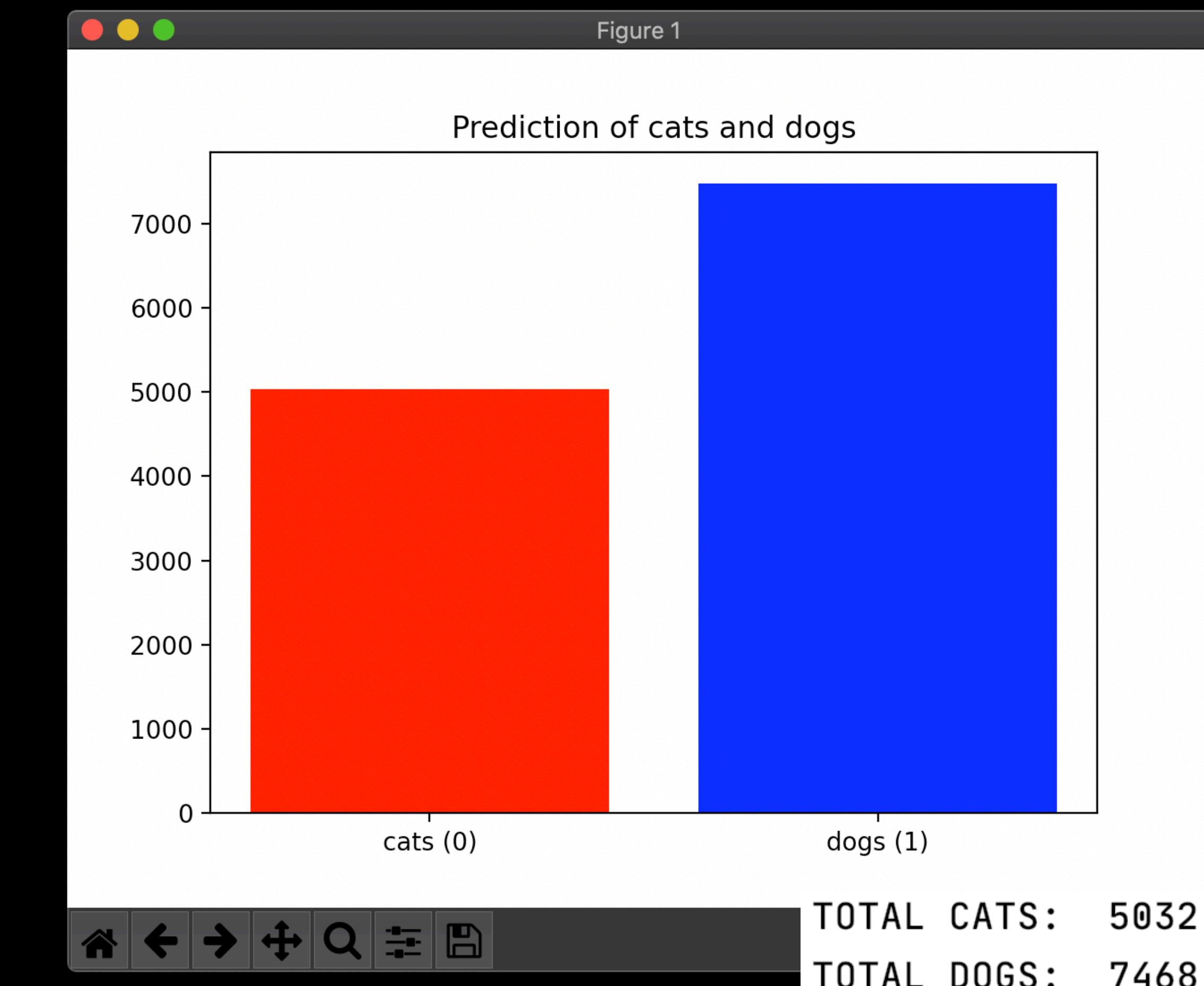
5) PREDIÇÃO

```
102      # 5 - predict
103      files = [os.path.join(dp, f)
104          for dp, dn, filenames in os.walk(test_dir)
105              for f in filenames
106                  if os.path.splitext(f)[1] == '.jpg']
107      print(files)
108      cats = 0
109      dogs = 0
110      index = 0
111      plt.figure(figsize=(12, 24))
112      for fn in files:
113          img = load_img(fn, target_size=image_size)
114          y = image.img_to_array(img)
115          x = np.expand_dims(y, axis=0)
116          images = np.vstack([x])
117          classes = model.predict(images, batch_size=10)
118          print(classes[0])
119          category = "dog"
120          if classes[0] > 0.5:
121              print(fn + " is a dog")
122              dogs += 1
123          else:
124              category = "cat"
125              print(fn + " is a cat")
126              cats += 1
127          plt.subplot(6, 3, index + 1)
128          plt.imshow(img)
129          plt.xlabel(fn + ' (' + "{}".format(category) + ')')
130          index += 1
131          print('TOTAL CATS: ', cats)
132          print('TOTAL DOGS: ', dogs)
133          # 6 - plot results
134          plt.tight_layout()
135          plt.show() # show previous figure
136          plt.title("Prediction of cats and dogs")
137          plt.bar(['cats (0)', 'dogs (1)'], [cats, dogs], color=['r', 'b'])
138          plt.show()
```

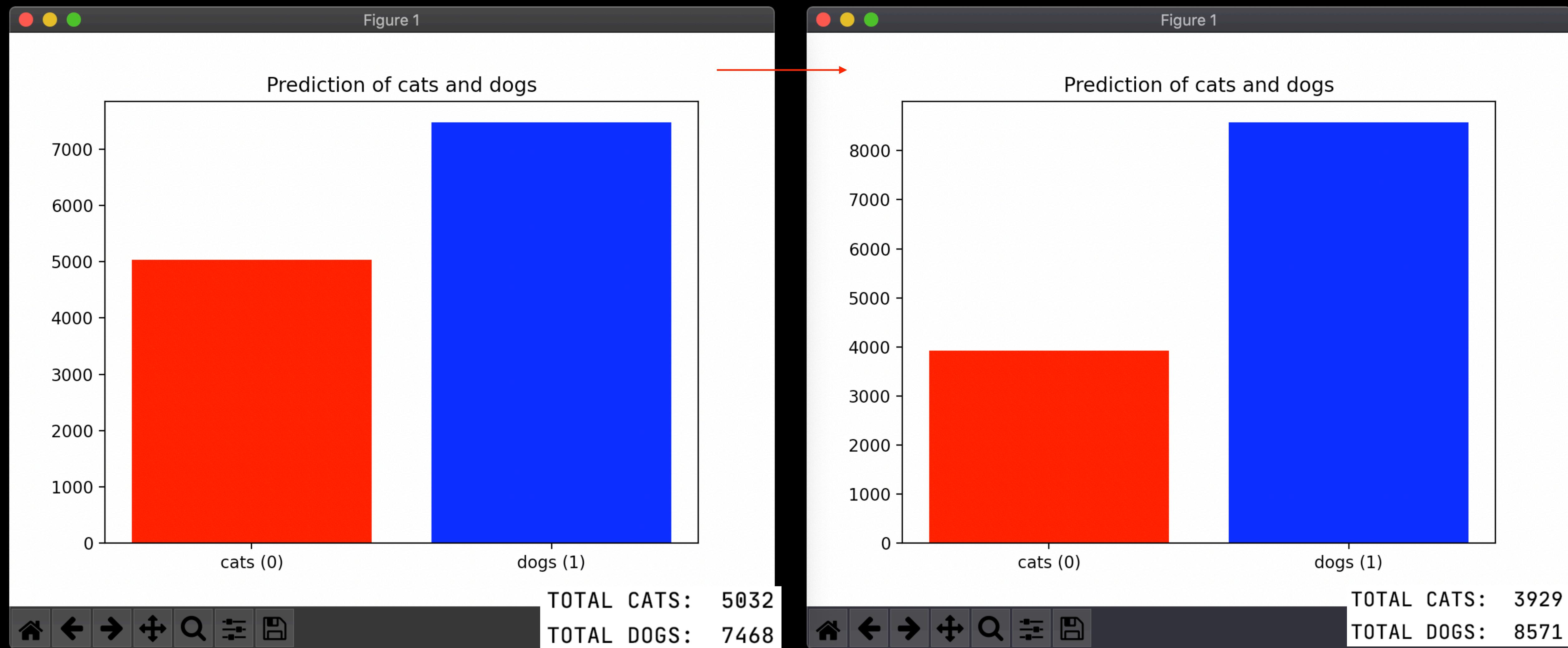


6) RESULTADOS

```
102      # 5 - predict
103      files = [os.path.join(dp, f)
104          for dp, dn, filenames in os.walk(test_dir)
105          for f in filenames
106          if os.path.splitext(f)[1] == '.jpg']
107      print(files)
108      cats = 0
109      dogs = 0
110      index = 0
111      plt.figure(figsize=(12, 24))
112      for fn in files:
113          img = load_img(fn, target_size=image_size)
114          y = image.img_to_array(img)
115          x = np.expand_dims(y, axis=0)
116          images = np.vstack([x])
117          classes = model.predict(images, batch_size=10)
118          print(classes[0])
119          category = "dog"
120          if classes[0] > 0.5:
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124              category = "cat"
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131      print('TOTAL CATS: ', cats)
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136      plt.title("Prediction of cats and dogs")
137      plt.bar(['cats (0)', 'dogs (1)'], [cats, dogs], color=['r', 'b'])
138      plt.show()
```



6) RESULTADOS



Usando os dados totais do BD de gatos e cachorros do Kaggle (25.000 imagens)

LINKS ÚTEIS

- <https://www.kaggle.com/c/dogs-vs-cats>
- <https://www.kaggle.com/uysimty/keras-cnn-dog-or-cat-classification>
- <https://colab.research.google.com/github/lmoroney/dlaicourse/blob/master/Course%202%20-%20Part%202%20-%20Lesson%202%20-%20Notebook.ipynb#scrollTo=H4XHh2xSfgie>

EXERCÍCIO

Tente usar as 25.000 imagens!!

[https://ojqugrhayuzyvbkearhjak.coursera-apps.org/notebooks/week1/
Exercise_1_Cats_vs_Dogs_Question-FINAL.ipynb](https://ojqugrhayuzyvbkearhjak.coursera-apps.org/notebooks/week1/Exercise_1_Cats_vs_Dogs_Question-FINAL.ipynb)

DÚVIDAS?

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