

# Convolutional Neural Networks

## Dog Identification App - data exploration

```
In [1]: import numpy as np
        from glob import glob

        # load filenames for human and dog images
        human_files = np.array(glob("lfw/**/*.jpg"))
        dog_files = np.array(glob("dogImages/**/*.jpg"))

        # print number of images in each dataset
        print('There are %d total human images.' % len(human_files))
        print('There are %d total dog images.' % len(dog_files))
```

There are 13233 total human images.  
There are 8351 total dog images.

## Step 1: Detect Humans

In this section, we use OpenCV's implementation of [Haar feature-based cascade classifiers](http://docs.opencv.org/trunk/d7/d8b/tutorial_py_face_detection.html) ([http://docs.opencv.org/trunk/d7/d8b/tutorial\\_py\\_face\\_detection.html](http://docs.opencv.org/trunk/d7/d8b/tutorial_py_face_detection.html)) to detect human faces in images.

OpenCV provides many pre-trained face detectors, stored as XML files on [github](https://github.com/opencv/opencv/tree/master/data/haarcascades) (<https://github.com/opencv/opencv/tree/master/data/haarcascades>). We have downloaded one of these detectors and stored it in the `haarcascades` directory. In the next code cell, we demonstrate how to use this detector to find human faces in a sample image.

```
In [2]: import cv2
import matplotlib.pyplot as plt
%matplotlib inline

# extract pre-trained face detector
face_cascade = cv2.CascadeClassifier('haarcascades/haarcascade_frontalface_
lt.xml')

# load color (BGR) image
img = cv2.imread(human_files[0])
# convert BGR image to grayscale
gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

# find faces in image
faces = face_cascade.detectMultiScale(gray)

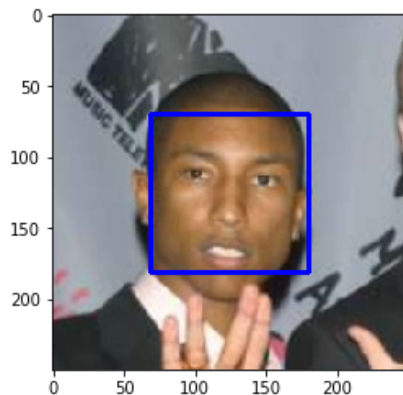
# print number of faces detected in the image
print('Number of faces detected:', len(faces))

# get bounding box for each detected face
for (x,y,w,h) in faces:
    # add bounding box to color image
    cv2.rectangle(img,(x,y),(x+w,y+h),(255,0,0),2)

# convert BGR image to RGB for plotting
cv_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

# display the image, along with bounding box
plt.imshow(cv_rgb)
plt.show()
```

Number of faces detected: 1



Before using any of the face detectors, it is standard procedure to convert the images to grayscale. The `detectMultiScale` function executes the classifier stored in `face_cascade` and takes the grayscale image as a parameter.

In the above code, `faces` is a numpy array of detected faces, where each row corresponds to a detected face. Each detected face is a 1D array with four entries that specifies the bounding box of the detected face. The first two entries in the array (extracted in the above code as `x` and `y`) specify the horizontal and vertical positions of the top left corner of the bounding box. The last two entries in the array (extracted here as `w` and `h`) specify the width and height of the box.

## Write a Human Face Detector

We can use this procedure to write a function that returns `True` if a human face is detected in an image and `False` otherwise. This function, aptly named `face_detector`, takes a string-valued file path to an image as input and appears in the code block below.

```
In [3]: # returns "True" if face is detected in image stored at img_path
def face_detector(img_path):
    img = cv2.imread(img_path)
    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
    faces = face_cascade.detectMultiScale(gray)
    return len(faces) > 0
```

### (IMPLEMENTATION) Assess the Human Face Detector

**Question 1:** Use the code cell below to test the performance of the `face_detector` function.

- What percentage of the first 100 images in `human_files` have a detected human face?
- What percentage of the first 100 images in `dog_files` have a detected human face?

Ideally, we would like 100% of human images with a detected face and 0% of dog images with a detected face. You will see that our algorithm falls short of this goal, but still gives acceptable performance. We extract the file paths for the first 100 images from each of the datasets and store them in the numpy arrays `human_files_short` and `dog_files_short`.

**Answer:** (You can print out your results and/or write your percentages in this cell)

```
In [4]: %matplotlib inline
```

```
In [5]: # from tqdm import tqdm

human_files_short = human_files[:100]
dog_files_short = dog_files[:100]

### Do NOT modify the code above this line. ###

## TODO: Test the performance of the face_detector algorithm
## on the images in human_files_short and dog_files_short.

fig, ax = plt.subplots(2,4, figsize = (14,8))

for k, files in enumerate([human_files, dog_files]):
    count = 0
    for i in range(4):
        # Random selection
        j = np.random.randint(len(files))

        # Is there a face
        facelog = face_detector(files[j])

        count += 1*facelog
        # Plot the image and set the title accordingly
        img = cv2.imread(files[j])
        cv_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

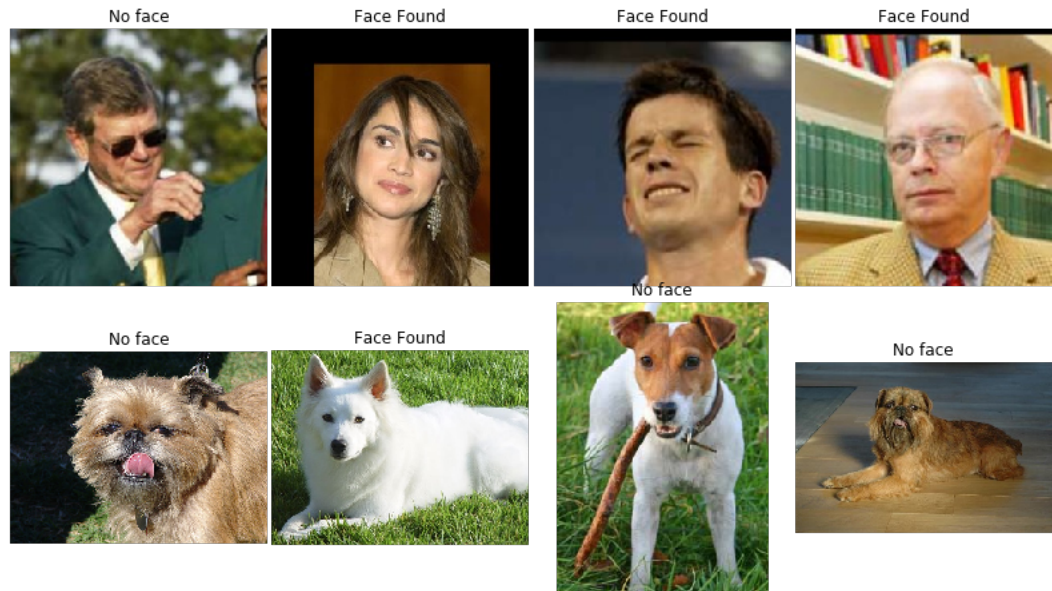
        ax[k,i].imshow(cv_rgb)
        if facelog:
            ax[k,i].set_title('Face Found')
        else:
            ax[k,i].set_title('No face')
        ax[k,i].set_axis_off()

fig.subplots_adjust(wspace=0.02, hspace=0)

for k, files in enumerate([human_files_short, dog_files_short]):
    count = 0
    for file in files:
        # Is there a face
        facelog = face_detector(file)
        count+= facelog*1

    if k == 0:
        print('In {}% of human images, it found a face'.format(int(count*100/len(human_files_short))))
    else:
        print('In {}% of dog images, it found a face'.format(int(count*100/len(dog_files_short))))
```

In 99% of human images, it found a face  
 In 13% of dog images, it found a face



## Dog dataset - study

```
In [6]: dog_files_test = np.array(glob("dogImages/test/*"))
dog_files_valid = np.array(glob("dogImages/valid/*/*"))
dog_files_train = np.array(glob("dogImages/train/*/*"))
print('Number of files training, validation, test = ', len(dog_files_train),
      len(dog_files_valid), len(dog_files_test))
```

Number of files training, validation, test = 6680 835 133

```
In [7]: ltotal = len(dog_files)
print('Fraction of files training, validation, test = ', len(dog_files_train)
      /ltotal, len(dog_files_valid)/ltotal, len(dog_files_test)/ltotal)
```

Fraction of files training, validation, test = 0.7999042030894503 0.09998802  
 538618129 0.01592623637887678

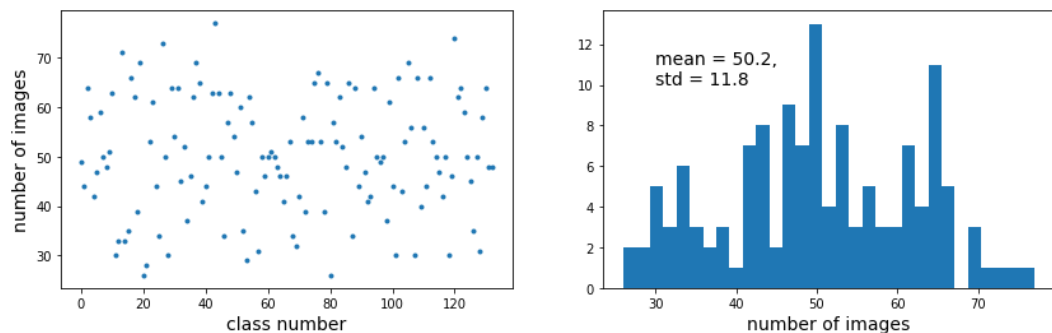
```
In [8]: folders1 = []
folders2 = []
for file in dog_files:
    folders1.append(file.split('/')[1])
    folders2.append(file.split('/')[2])

f1 = set(folders1)
f2 = set(folders2)

numberfiles = np.zeros(len(f2))
for i, folder in enumerate(f2):
    files_train = np.array(glob("dogImages/train/"+folder+"/*"))
    numberfiles[i] = len(files_train)
```

```
In [12]: fig, ax = plt.subplots(1,2 , figsize = (14,4))
ax[0].plot(numberfiles, '.')
ax[0].set_xlabel('class number', fontsize = 14)
ax[0].set_ylabel('number of images', fontsize = 14)
ax[1].hist(numberfiles,31)
ax[1].set_xlabel('histogram', fontsize = 14)
ax[1].set_ylabel('number of images', fontsize = 14)
ax[1].text(30.,10,
          'mean = {:.1f},\nstd = {:.1f}'.format(np.mean(numberfiles),
          np.std(numberfiles)),
          fontsize = 14)
print('mean, std = ',np.mean(numberfiles), np.std(numberfiles))
print('breed less represented:',list(f2)[numberfiles.argmin()],numberfiles.m
in())
print('breed most represented:',list(f2)[numberfiles.argmax()],numberfiles.m
ax())
```

```
mean, std = 50.225563909774436 11.81919971169211
breed less represented: 132.Xoloitzcuintli 26.0
breed most represented: 005.Alaskan_malamute 77.0
```



```
In [13]: h = np.histogram(numberfiles,31)
print('Fraction of breeds with less than 40 images = {:.3f}'.format(
      sum(h[0][h[1][1:]<40])/sum(h[0])))

print('Fraction of breeds with more than 60 images = {:.3f}'.format(
      sum(h[0][h[1][: -1]>60])/sum(h[0])))
```

```
Fraction of breeds with less than 40 images = 0.195
Fraction of breeds with more than 60 images = 0.256
```

```
In [14]: dog_files_ext = ['dogImages/train/005.Alaskan_malamute/Alaskan_malamute_00304.jpg',  
                        'dogImages/train/132.Xoloitzcuintli/Xoloitzcuintli_08288.jpg']  
  
fig, ax = plt.subplots(1,2, figsize = (8,8))  
files = dog_files_ext  
for i in range(2):  
    img = cv2.imread(files[i])  
    cv_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)  
  
    ax[i].imshow(cv_rgb)  
    ax[i].set_axis_off()
```



We suggest the face detector from OpenCV as a potential way to detect human images in your algorithm, but you are free to explore other approaches, especially approaches that make use of deep learning :). Please use the code cell below to design and test your own face detection algorithm. If you decide to pursue this *optional* task, report performance on `human_files_short` and `dog_files_short`.

---

## Step 2: Detect Dogs

In this section, we use a [pre-trained model \(http://pytorch.org/docs/master/torchvision/models.html\)](http://pytorch.org/docs/master/torchvision/models.html) to detect dogs in images.

### Obtain Pre-trained mobilenetv2

The code cell below downloads the mobilenetv2 model, along with weights that have been trained on [ImageNet \(http://www.image-net.org/\)](http://www.image-net.org/), a very large, very popular dataset used for image classification and other vision tasks. ImageNet contains over 10 million URLs, each linking to an image containing an object from one of [1000 categories \(https://gist.github.com/yrevar/942d3a0ac09ec9e5eb3a\)](https://gist.github.com/yrevar/942d3a0ac09ec9e5eb3a).

```
In [21]: import torch  
import torchvision.models as models  
# check if CUDA is available  
use_cuda = False
```

```
In [22]: import torch
import torchvision.models as models

# define VGG16 model
mobilenetv2 = models.mobilenet_v2(pretrained=True)

# move model to GPU if CUDA is available
if use_cuda:
    mobilenetv2 = mobilenetv2.cuda()
```

```
In [34]: import imagenet1000_clsidx_to_labels as labels
classes = labels.classes
```

**Before writing function**, let us understand how to provide input data to the network, and what kind of output we receive. As usual the documentation is a bit confusing, but on the web there are some resources where they do go around small details for single image processing:

- We first load the image with Pillow
- Then we construct the transformation for preprocessing:
  - Resize image
  - Crop the central part
  - Transform it to a tensor
  - Normalize according to documentation
  - Unsqueeze the array to copy it to the network
  - Move it to the cuda device
- We put mobilenetv2 in evaluation mode
- Then, we evaluate it and take it back to the cpu
- Finally, we need to detach the tensor to forget about the derivatives and transform it into numpy
- The largest value is the label



```
In [94]: #https://www.learnopencv.com/pytorch-for-beginners-image-classification-using-pre-trained-models/
from PIL import Image
import torchvision.transforms as transforms

idx_dog = 101
img = Image.open(dog_files[idx_dog])

normalize = transforms.Normalize(mean = [0.485, 0.456, 0.406],
                                std = [0.229, 0.224, 0.225])

transform = transforms.Compose([transforms.Resize(256),
                                transforms.CenterCrop(224),
                                transforms.ToTensor(),
                                normalize])

imgtd = transform(img)
batch = torch.unsqueeze(imgtd, 0)
mobilenetv2.eval()

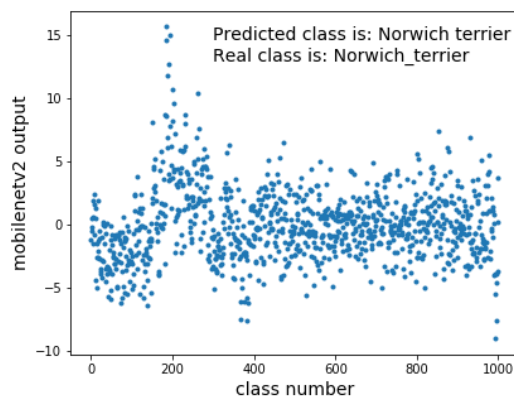
output = mobilenetv2(batch)
outputnp = output.detach().numpy()
fig, ax = plt.subplots(1,2, figsize = (14,5))

ax[0].plot(outputnp.flatten(),'.')
ax[0].set_xlabel('class number', fontsize = 14)
ax[0].set_ylabel('mobilenetv2 output', fontsize = 14)

img = cv2.imread(dog_files[idx_dog])
cv_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
ax[1].imshow(cv_rgb)
ax[1].set_axis_off()
#ax[1].hist(numberfiles,31)
#ax[1].set_xlabel('histogram', fontsize = 14)
#ax[1].set_xlabel('number of images', fontsize = 14)
real_class = dog_files[idx_dog].split('/')[2].split('.')[1]
print(real_class)
ax[0].text(300,13,'Predicted class is: {} \n Real class is: {}'.format(
    classes[outputnp.argmax()],
    real_class), fontsize = 14)
```

Norwich\_terrier

Out[94]: Text(300, 13, 'Predicted class is: Norwich terrier \n Real class is: Norwich\_terrier')



Now, we are ready to write it

```

In [51]: from PIL import Image
import torchvision.transforms as transforms

# Set PIL to be tolerant of image files that are truncated.
from PIL import ImageFile
ImageFile.LOAD_TRUNCATED_IMAGES = True

In [61]: def mobilenet_predict(img_path):
    """
    Use pre-trained mobilenet model to obtain index corresponding to
    predicted ImageNet class for image at specified path

    Args:
        img_path: path to an image

    Returns:
        Index corresponding to VGG-16 model's prediction
    """

    ## TODO: Complete the function.
    ## Load and pre-process an image from the given img_path
    ## Return the *index* of the predicted class for that image

    img = Image.open(img_path)

    # Preprocessing
    # Defining function
    normalize = transforms.Normalize(mean = [0.485, 0.456, 0.406],
                                     std = [0.229, 0.224, 0.225])
    transform = transforms.Compose([transforms.Resize(256),
                                    transforms.CenterCrop(224),
                                    transforms.ToTensor(),
                                    normalize])

    # Transforming
    imgtd = transform(img)
    batch = torch.unsqueeze(imgtd, 0)
    if use_cuda:
        batch = batch.cuda()

    # Network evaluation
    mobilenetv2.eval()

    output = mobilenetv2(batch).cpu()
    outputnp = output.detach().numpy()

    return outputnp.argmax() # predicted class index

```

## Dog Detector

While looking at the [dictionary](https://gist.github.com/yrevar/942d3a0ac09ec9e5eb3a) (<https://gist.github.com/yrevar/942d3a0ac09ec9e5eb3a>), you will notice that the categories corresponding to dogs appear in an uninterrupted sequence and correspond to dictionary keys 151-268, inclusive, to include all categories from 'Chihuahua' to 'Mexican hairless'. Thus, in order to check to see if an image is predicted to contain a dog by the pre-trained VGG-16 model, we need only check if the pre-trained model predicts an index between 151 and 268 (inclusive).

Use these ideas to complete the `dog_detector` function below, which returns `True` if a dog is detected in an image (and `False` if not).

```
In [69]: ### returns "True" if a dog is detected in the image stored at img_path
def dog_detector(img_path):
    ## TODO: Complete the function.
    imgclass = mobilenet_predict(img_path)
    isdog = False
    if imgclass>150 and imgclass<269:
        isdog = True

    return isdog # true/false
```

## Assess the Dog Detector

**Question 2:** Use the code cell below to test the performance of your `dog_detector` function.

- What percentage of the images in `human_files_short` have a detected dog?
- What percentage of the images in `dog_files_short` have a detected dog?

```
In [70]: %time
### TODO: Test the performance of the dog_detector function
### on the images in human_files_short and dog_files_short.
print('Performance with Mobilenet v2')

failures = np.zeros(100)
for k, files in enumerate([human_files_short, dog_files_short]):
    count = 0
    for i, file in enumerate(files):
        # Is it a dog?
        isdog = dog_detector(file)
        count+= isdog*1
        failures[i] = isdog*1

    if k == 0:
        failures_humans = failures
        print('It classified {}% of human images as dogs'.format(int(count*100/len(human_files_short))))
    else:
        failures_dogs = 1-failures
        print('It classified {}% of dogs images as dogs'.format(int(count*100/len(dog_files_short))))

Performance with Mobilenet v2
It classified 0% of human images as dogs
It classified 100% of dogs images as dogs
CPU times: user 35.2 s, sys: 155 ms, total: 35.4 s
Wall time: 6.09 s
```

```
In [67]: dog_files_short[failures_dogs.argmax()]
```

```
Out[67]: 'dogImages/valid/090.Italian_greyhound/Italian_greyhound_06157.jpg'
```

```

In [91]: idx_dog = 24
img = Image.open(dog_files_short[idx_dog])

normalize = transforms.Normalize(mean = [0.485, 0.456, 0.406],
                                std = [0.229, 0.224, 0.225])

transform = transforms.Compose([transforms.Resize(256),
                                transforms.CenterCrop(224),
                                transforms.ToTensor(),
                                normalize])

imgtd = transform(img)
batch = torch.unsqueeze(imgtd, 0)
mobilenetv2.eval()

output = mobilenetv2(batch)
outputnp = output.detach().numpy()
fig, ax = plt.subplots(1,2, figsize = (14,5))

ax[0].plot(outputnp.flatten(),'.')
ax[0].set_xlabel('class number', fontsize = 14)
ax[0].set_ylabel('mobilenetv2 output', fontsize = 14)

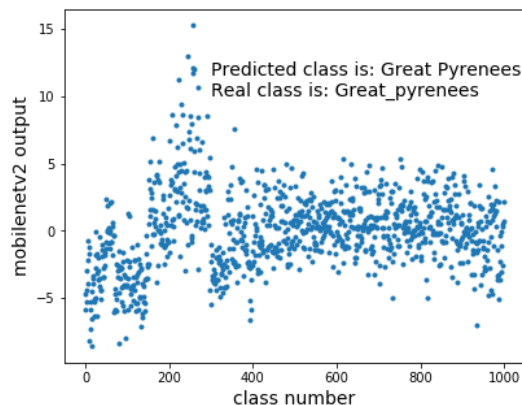
img = cv2.imread(dog_files[idx_dog])
cv_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
ax[1].imshow(cv_rgb)
ax[1].set_axis_off()

real_class = dog_files_short[idx_dog].split('/')[2].split('.')[1]
print(real_class)
ax[0].text(300,10,'Predicted class is: {} \n Real class is: {}'.format(
    classes[outputnp.argmax()],
    real_class), fontsize = 14)

```

Great\_pyrenees

Out[91]: Text(300, 10, 'Predicted class is: Great Pyrenees\nReal class is: Great\_pyrenees')



```
In [147]: count = 0.0
for idx_dog in range(100):
    img = Image.open(dog_files_short[idx_dog])

    normalize = transforms.Normalize(mean = [0.485, 0.456, 0.406],
                                     std = [0.229, 0.224, 0.225])

    transform = transforms.Compose([transforms.Resize(256),
                                    transforms.CenterCrop(224),
                                    transforms.ToTensor(),
                                    normalize])

    imgtd = transform(img)
    batch = torch.unsqueeze(imgtd, 0)
    mobilenetv2.eval()

    output = mobilenetv2(batch)
    outputnp = output.detach().numpy()
    real_class = dog_files_short[idx_dog].split('/')[2].split('.')[1].replace("_", "").lower()
    predicted_class = classes[outputnp.argmax()].lower()
    print(real_class, ',', predicted_class, 1*(real_class==predicted_class))
    count += 1*(real_class==predicted_class)

print(count)
```

belgian malinois , malinois 0  
belgian malinois , malinois 0  
belgian malinois , malinois 0  
belgian malinois , malinois 0  
belgian malinois , malinois 0  
belgian malinois , malinois 0  
belgian malinois , malinois 0  
parson russell terrier , wire-haired fox terrier 0  
parson russell terrier , borzoi, russian wolfhound 0  
parson russell terrier , italian greyhound 0  
parson russell terrier , toy terrier 0  
norwegian elkhound , norwegian elkhound, elkhound 0  
norwegian elkhound , norwegian elkhound, elkhound 0  
norwegian elkhound , norwegian elkhound, elkhound 0  
norwegian elkhound , norwegian elkhound, elkhound 0  
norwegian elkhound , norwegian elkhound, elkhound 0  
norwegian elkhound , norwegian elkhound, elkhound 0  
doberman pinscher , doberman, doberman pinscher 0  
doberman pinscher , doberman, doberman pinscher 0  
doberman pinscher , doberman, doberman pinscher 0  
doberman pinscher , doberman, doberman pinscher 0  
doberman pinscher , doberman, doberman pinscher 0  
doberman pinscher , doberman, doberman pinscher 0  
great pyrenees , great pyrenees 1  
great pyrenees , kuvasz 0  
great pyrenees , great pyrenees 1  
great pyrenees , great pyrenees 1  
great pyrenees , kuvasz 0  
great pyrenees , great pyrenees 1  
great pyrenees , great pyrenees 1  
belgian sheepdog , groenendael 0  
belgian sheepdog , groenendael 0  
belgian sheepdog , groenendael 0  
belgian sheepdog , groenendael 0  
belgian sheepdog , groenendael 0  
belgian sheepdog , groenendael 0  
belgian sheepdog , groenendael 0  
dandie dinmont terrier , dandie dinmont, dandie dinmont terrier 0  
dandie dinmont terrier , dandie dinmont, dandie dinmont terrier 0  
dandie dinmont terrier , dandie dinmont, dandie dinmont terrier 0  
dandie dinmont terrier , dandie dinmont, dandie dinmont terrier 0  
dandie dinmont terrier , dandie dinmont, dandie dinmont terrier 0  
dandie dinmont terrier , dandie dinmont, dandie dinmont terrier 0  
belgian tervuren , german shepherd, german shepherd dog, german police dog, a  
lsatian 0  
belgian tervuren , german shepherd, german shepherd dog, german police dog, a  
lsatian 0  
belgian tervuren , leonberg 0  
belgian tervuren , groenendael 0  
belgian tervuren , german shepherd, german shepherd dog, german police dog, a  
lsatian 0  
belgian tervuren , german shepherd, german shepherd dog, german police dog, a  
lsatian 0  
mastiff , bull mastiff 0  
mastiff , bull mastiff 0  
mastiff , bull mastiff 0  
mastiff , bull mastiff 0  
mastiff , bull mastiff 0  
mastiff , bull mastiff 0  
mastiff , bull mastiff 0  
neapolitan mastiff , bloodhound, sleuthhound 0  
neapolitan mastiff , labrador retriever 0  
neapolitan mastiff , great dane 0  
neapolitan mastiff , bull mastiff 0  
petit basset griffon vendeen , soft-coated wheaten terrier 0  
petit basset griffon vendeen , otterhound, otter hound 0

33 % accuracy being generous

## Statistical features of images

```
In [102]: imgstats = np.zeros((100,4))
          for i, file in enumerate(dog_files_short):
              # Is there a face
              img = cv2.imread(file)
              gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
              imgstats[i,:] = *img.mean(axis = (0,1))/255.0, gray.mean()/255.0
```

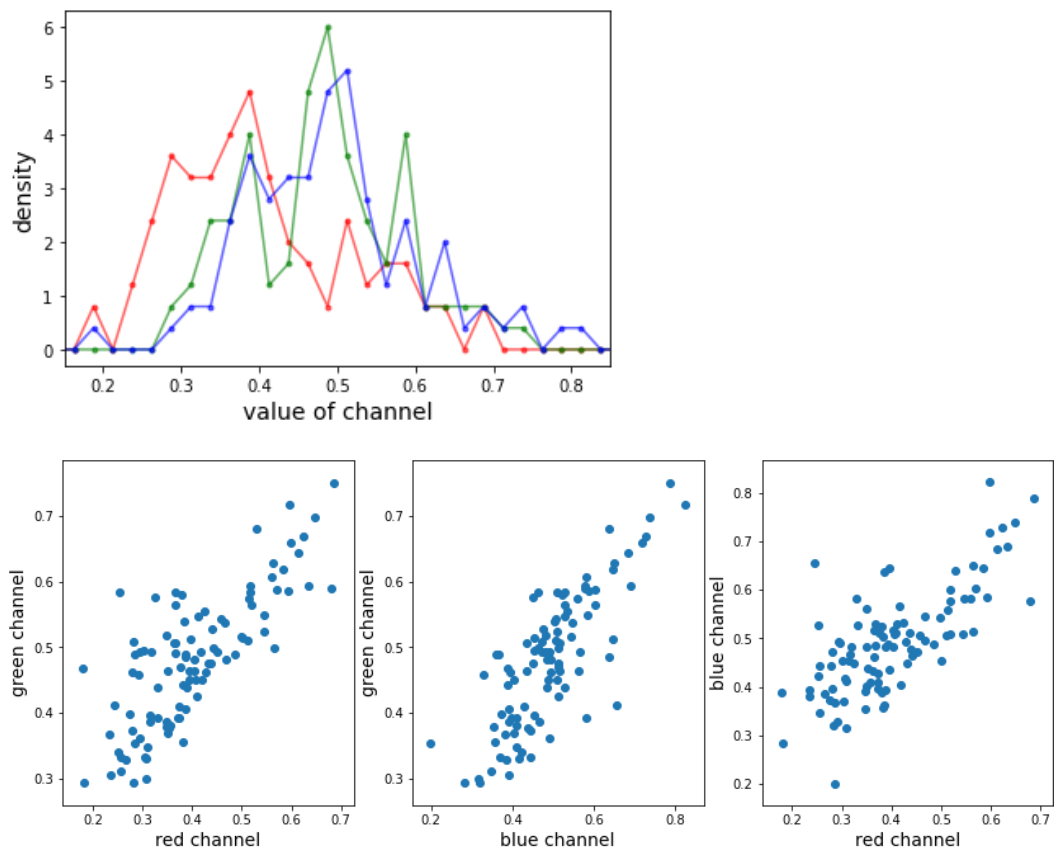
```

In [113]: bins = np.linspace(0,1,41)
xb = (bins[1:]+bins[:-1])*0.5
hr = np.histogram(imgstats[:,0],bins,density = True)[0]
hg = np.histogram(imgstats[:,1],bins,density = True)[0]
hb = np.histogram(imgstats[:,2],bins,density = True)[0]
plt.plot(xb, hr, 'r.-', alpha = 0.6)
plt.plot(xb, hg, 'g.-', alpha = 0.6)
plt.plot(xb, hb, 'b.-', alpha = 0.6)
plt.xlim(0.15,0.85)
plt.xlabel('value of channel', fontsize = 14)
plt.ylabel('density', fontsize = 14)

fig,ax = plt.subplots(1,3, figsize = (14,5))
ax[0].scatter(imgstats[:,0], imgstats[:,1])
ax[1].scatter(imgstats[:,2], imgstats[:,1])
ax[2].scatter(imgstats[:,0], imgstats[:,2])
ax[0].set_xlabel('red channel', fontsize = 14)
ax[2].set_xlabel('red channel', fontsize = 14)
ax[1].set_xlabel('blue channel', fontsize = 14)
ax[0].set_ylabel('green channel', fontsize = 14)
ax[1].set_ylabel('green channel', fontsize = 14)
ax[2].set_ylabel('blue channel', fontsize = 14)

```

Out[113]: Text(0, 0.5, 'blue channel')



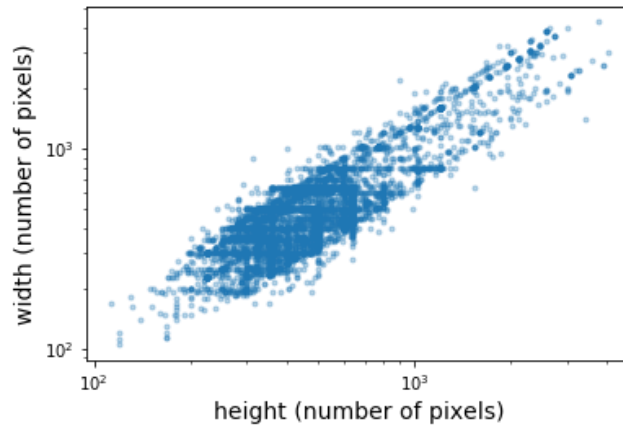
```

In [174]: imgsizes = np.zeros((len(dog_files),3))
for i, file in enumerate(dog_files):
    # Is there a face
    img = cv2.imread(file)
    imgsizes[i,:] = img.shape

```



```
In [185]: plt.plot(imgsizes[:,0],imgsizes[:,1],'.', alpha = 0.3)
plt.xlabel('height (number of pixels)', fontsize = 14)
plt.ylabel('width (number of pixels)', fontsize = 14)
plt.xscale('log')
plt.yscale('log')
plt.savefig('sizeimgs.png',dpi = 200)
```



```
In [177]: imgstats = np.zeros((len(dog_files),4))
for i, file in enumerate(dog_files):
    # Is there a face
    img = cv2.imread(file)
    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
    imgstats[i,:] = *img.mean(axis = (0,1))/255.0, gray.mean()/255.0
```

```

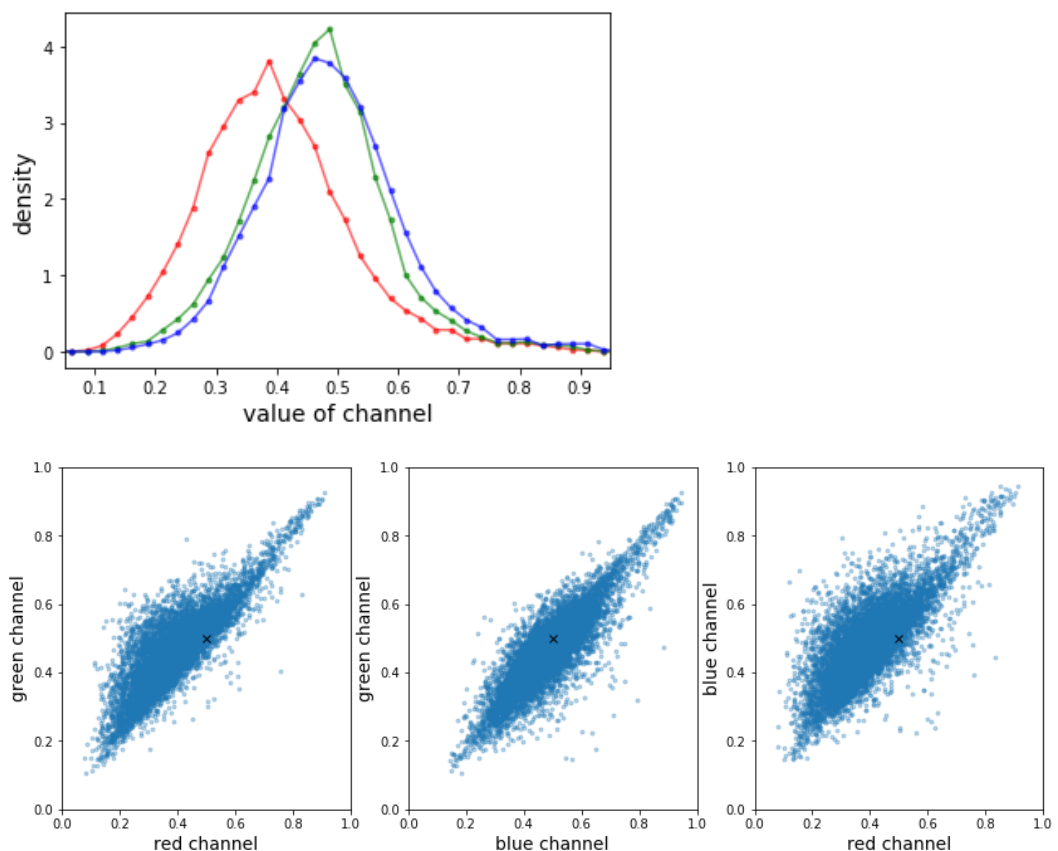
In [182]: bins = np.linspace(0,1,41)
xb = (bins[1:]+bins[:-1])*0.5
hr = np.histogram(imgstats[:,0],bins,density = True)[0]
hg = np.histogram(imgstats[:,1],bins,density = True)[0]
hb = np.histogram(imgstats[:,2],bins,density = True)[0]
plt.plot(xb, hr, 'r.-', alpha = 0.6)
plt.plot(xb, hg, 'g.-', alpha = 0.6)
plt.plot(xb, hb, 'b.-', alpha = 0.6)
plt.xlim(0.05,0.95)
plt.xlabel('value of channel', fontsize = 14)
plt.ylabel('density', fontsize = 14)

plt.savefig('channels0.png', dpi = 200)

fig,ax = plt.subplots(1,3, figsize = (14,5))
ax[0].plot(imgstats[:,0], imgstats[:,1],'.', alpha = 0.3)
ax[1].plot(imgstats[:,2], imgstats[:,1],'.', alpha = 0.3)
ax[2].plot(imgstats[:,0], imgstats[:,2],'.', alpha = 0.3)
ax[0].set_xlabel('red channel', fontsize = 14)
ax[2].set_xlabel('red channel', fontsize = 14)
ax[1].set_xlabel('blue channel', fontsize = 14)
ax[0].set_ylabel('green channel', fontsize = 14)
ax[1].set_ylabel('green channel', fontsize = 14)
ax[2].set_ylabel('blue channel', fontsize = 14)
ax[0].set_xlim(0,1)
ax[0].set_ylim(0,1)
ax[1].set_xlim(0,1)
ax[1].set_ylim(0,1)
ax[2].set_xlim(0,1)
ax[2].set_ylim(0,1)
ax[0].plot(0.5,0.5,'kx')
ax[1].plot(0.5,0.5,'kx')
ax[2].plot(0.5,0.5,'kx')

```

Out[182]: [<matplotlib.lines.Line2D at 0x7f2814a11518>]



```
In [184]: print(imgstats.mean(0))
```

```
[0.39679833 0.46614418 0.48672974 0.46440096]
```

**More images!**

```
In [124]: ncol = 4
fig, ax = plt.subplots(2,ncol, figsize = (14,8))

files = human_files
count = 0
k = 0
for i in range(ncol):
    # Random selection
    j = np.random.randint(len(files))

    name = files[j].split('/')[1]
    print(name)
    print(img.shape)
    # Plot the image and set the title accordingly
    img = cv2.imread(files[j])
    cv_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

    ax[k,i].imshow(cv_rgb)
    ax[k,i].set_title(name,fontsize = 14)
    ax[k,i].set_axis_off()

k = 1
files = dog_files
count = 0
for i in range(ncol):
    # Random selection
    j = np.random.randint(len(files))
    dogbreed =files[j].split('/')[2].split('.')[1]

    # Plot the image and set the title accordingly
    img = cv2.imread(files[j])
    cv_rgb = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    print(img.shape)
    ax[k,i].imshow(cv_rgb)
    ax[k,i].set_title(dogbreed,fontsize = 14)

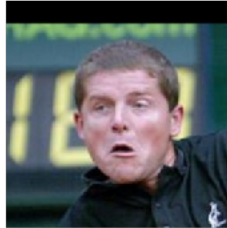
    ax[k,i].set_axis_off()
```

Ellen\_Pompeo  
(894, 895, 3)  
Jiri\_Novak  
(250, 250, 3)  
Kurt\_Hellstrom  
(250, 250, 3)  
Laurel\_Clark  
(250, 250, 3)  
(500, 311, 3)  
(532, 800, 3)  
(2320, 3484, 3)  
(240, 240, 3)

Ellen\_Pompeo



Jiri\_Novak



Kurt\_Hellstrom



Laurel\_Clark



Dandie\_dinmont\_terrier



Labrador\_retriever



Beauceron



Bouvier\_des\_flandres

