

0. Import Dependencies

In [1]:

```
from PIL import Image
import matplotlib.pyplot as plt
import torch
from torchvision import models
import numpy as np
import pandas as pd
import torchvision.transforms as T
from PIL import Image
import cv2
import sys
```

3. Semantic segmentation

Read paper Fully Convolutional Networks for Semantic Segmentation

(https://people.eecs.berkeley.edu/~jonlong/long_shelhamer_fcn.pdf). From the class drive download script segmentation.py, containing example how to use pretrained models for semantic segmentation.

main references:

<https://github.com/shelhamer/fcn.berkeleyvision.org>

https://github.com/mozhuqing/fcn/blob/f6213010926c561b3e4f35eb5ee59b7ccc6390ec/data_augmentation.ipynb

https://github.com/jedichien/ssd_keras/blob/b3008773d833501dalb7a21e8c37e6640e229d5f/T3_Assistances.ipynb

[https://github.com/zplab-](https://github.com/zplab-dev/Nicolette/blob/398be5b8a306972dfc4d530687b1a8ae290bcae5/image_analysis/analyze_images.py)

[dev/Nicolette/blob/398be5b8a306972dfc4d530687b1a8ae290bcae5/image_analysis/analyze_images.py](https://github.com/zplab-dev/Nicolette/blob/398be5b8a306972dfc4d530687b1a8ae290bcae5/image_analysis/analyze_images.py)

a) Briefly explain:

- i) How FCN upsamples predictions to match the original image size.
- ii) How had the authors improved the coarse predictions produced by the deepest layer.

Answer:

i) Different from classic CNNs that use fully connected layer after convolution to obtain fixed-length feature vectors for classification, FCN can accept input images of any size. Upsampling the feature map of the last convolutional layer using a deconvolution layer to revert to original size, so that prediction can be generated by pixels and retain the spatial information of input image. Finally, pixel-by-pixel classification is performed on the upsampled feature map.

However, upsampling cannot guarantee that the final pixelized prediction will be exactly the same as the original one. So, to ensure that the highest level of prediction, there will be a crop layer after the upsampling layer that crops the output results.

ii) The author discards the final classifier layer and converts all fully connected layers into convolutions and appends a 1×1 convolution to channel dimension 21 to roughly predict the rough result of each class. And he uses a deconvolution layer to perform coarse prediction and bilinear upsampling. Since the finer the prediction requires fewer layers, so he combined the semantic information from deeper coarse layers with the fine appearance information from shallower layers to produce accurate and detailed segmentation.

In [2]:

```
def decode_segmap(image, nc=21):
    label_colors = np.array([(0, 0, 0), # 0=background
                              # 1=aeroplane, 2=bicycle, 3=bird, 4=boat, 5=bottle
                              (128, 0, 0), (0, 128, 0), (128, 128, 0), (0, 0, 128), (128, 0, 128),
                              # 6=bus, 7=car, 8=cat, 9=chair, 10=cow
                              (0, 128, 128), (128, 128, 128), (64, 0, 0), (192, 0, 0), (64, 128, 0),
                              # 11=dining table, 12=dog, 13=horse, 14=motorbike, 15=person
                              (192, 128, 0), (64, 0, 128), (192, 0, 128), (64, 128, 128), (192, 128, 128),
                              # 16=potted plant, 17=sheep, 18=sofa, 19=train, 20=tv/monitor
                              (0, 64, 0), (128, 64, 0), (0, 192, 0), (128, 192, 0), (0, 64, 128)])

    r = np.zeros_like(image).astype(np.uint8)
    g = np.zeros_like(image).astype(np.uint8)
    b = np.zeros_like(image).astype(np.uint8)

    for l in range(0, nc):
        idx = image == l
        r[idx] = label_colors[l, 0]
        g[idx] = label_colors[l, 1]
        b[idx] = label_colors[l, 2]

    rgb = np.stack([r, g, b], axis=2)
    return rgb
```

In [3]:

```
def apply_mask(im, im_pred):
    """
    Overlays the predicted class labels onto an image using the alpha channel.
    This function assumes that the background label is the black color.
    This function is provided as an inspiration for the masking function you should write.
    """
    r_channel, g_channel, b_channel = cv2.split(im_pred)
    alpha_channel = 127 * np.ones(b_channel.shape, dtype=b_channel.dtype)
    # Make background pixels fully transparent
    alpha_channel -= 127 * np.all(im_pred == np.array([0, 0, 0]), axis=2).astype(b_channel.dtype)
    im_pred = cv2.merge((r_channel, g_channel, b_channel, alpha_channel))
    mask = Image.fromarray(im_pred, mode='RGBA')
    masked_img = Image.fromarray(im)
    masked_img.paste(mask, box=None, mask=mask)
    return np.array(masked_img)
```

In [4]:

```
# define the model
fcn = models.segmentation.fcn_resnet101(pretrained=True).eval()
```

b) Download YourEmail.png and take a class index assigned to you from classes.csv. Modify segmentation.py so that you predict segmentation mask of this class (by FCN model) on the image given to you and highlight prediction via red mask blended with the original image. Submit this image as YourEmail_predicted.png.

In [5]:

```
csv=pd.read_csv('classes.csv',header=18)
csv.head(0)
#9=chair
```

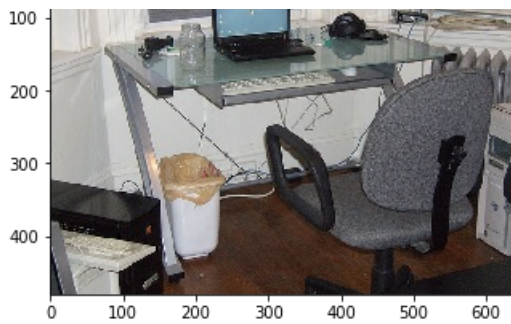
Out[5]:

XZHANG6@TCD.IE 9

In [6]:

```
# load an image
img = Image.open('./XZHANG6@TCD.IE.png')
plt.imshow(img)
plt.show()
```





In [7]:

```
# transform the image
trf = T.Compose([T.ToTensor(),
                 T.Normalize(mean = [0.485, 0.456, 0.406],
                             std = [0.229, 0.224, 0.225])])
inp = trf(img).unsqueeze(0)
```

In [8]:

```
# pass the input through the net
out = fcn(inp)['out']
print (out.shape)
```

torch.Size([1, 21, 480, 640])

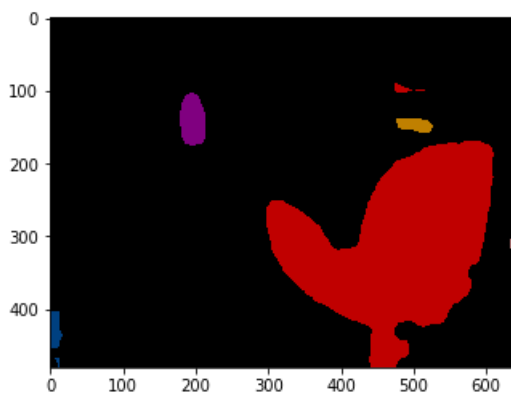
In [9]:

```
# calculate labels
om = torch.argmax(out.squeeze(), dim=0).detach().cpu().numpy()
print (np.unique(om))
```

[0 5 9 11 15 20]

In [10]:

```
# show segmentation output
rgb = decode_segmap(om)
plt.imshow(rgb)
plt.show()
```



In [11]:

```
# show red mask blended with the original image output
img = cv2.imread('XZHANG6@TCD.IE.png', cv2.IMREAD_COLOR)
rgb1 = rgb[:, :, :-1]
mask = apply_mask(img, rgb1)
cv2.imwrite("XZHANG6@TCD.IE_predicted.png", mask)
```

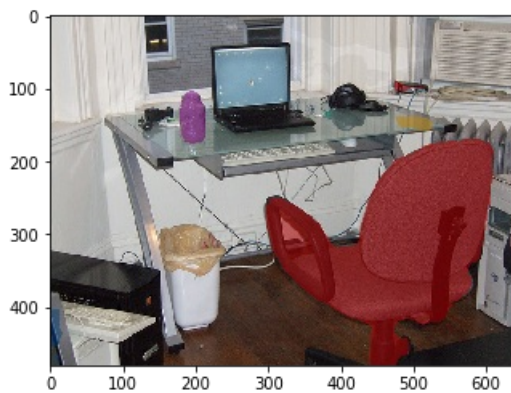
Out[11]:

-

True

In [12]:

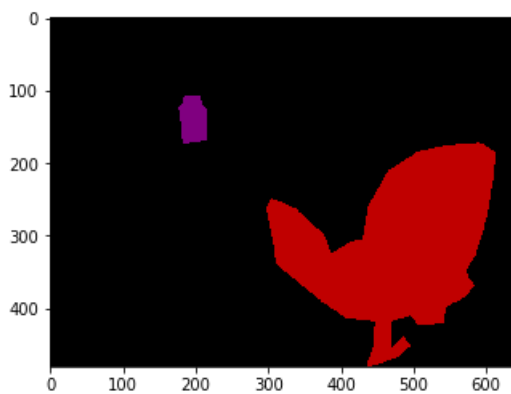
```
merge = cv2.imread('XZHANG6@TCD.IE_predicted.png', cv2.IMREAD_COLOR)
merge = merge[:, :, :-1]
plt.imshow(merge)
plt.show()
```



c) Decode the groundtruth image YourEmail_mask.png and calculate intersection over union (IOU) with the prediction for the class assigned to you. Report IOU in file YourEmail_iou.csv.

In [13]:

```
# load an mask
ground = Image.open('./XZHANG6@TCD.IE_mask.png')
plt.imshow(ground)
plt.show()
```



In [14]:

```
def calculate_iou(prediction, ground_truth, plot_val=False, save_val=False, save_dir=None, pyr=False):
    """Find intersection over union for 2 images
    Prediction and ground_truth are boolean arrays
    """
    #intersect and union
    intersect = (prediction & ground_truth)
    union = (prediction|ground_truth)
    IoU=intersect.sum()/union.sum()

    return intersect.sum()/union.sum()
```

In [15]:

```
calculate_iou(rgb, ground)
```

Out[15]:

0.8864340045282527

0.8864342045382537

In [16]:

```
final=pd.DataFrame(data={
    'IoU':calculate_iou(rgb, ground)},index=[0])
final.to_csv('XZHANG6@TCD.IE_iou.csv',header=None,index=None)
```