COMPUTER ASSIGNMENT 04

U-net for image segmentation

In class, we talked about U-net for image segmentation. This assignment is intended to

- help you better understand the concept of U-net for image segmentation
- help you get started with designing networks in pytorch including loading data, network design, loss function, training and testing.

For this assignment, you will attempt to segment car images, which is a challenge hosted on Kaggle (https://www.kaggle.com/c/carvana-image-masking-challenge/data). The original data is available on the Kaggle website. We have extracted a small part of the dataset and uploaded it to the following link

https://drive.google.com/open?id=1gVSDa3eAJQ3DcSLVuQRYBgdxVhFvXEbR (https://drive.google.com/open?id=1gVSDa3eAJQ3DcSLVuQRYBgdxVhFvXEbR)

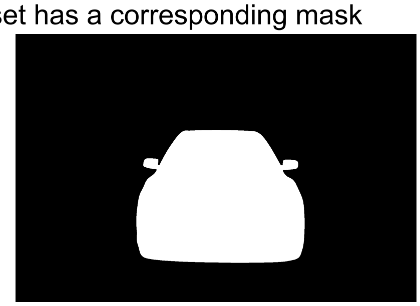
You should create a folder 'data/' in the current folder.

Then download train, train_mask, test dataset from the above link and extract them to 'data/'.

Or you can download the whole dataset from Kaggle website (https://www.kaggle.com/c/carvana-image-masking-challenge/data).

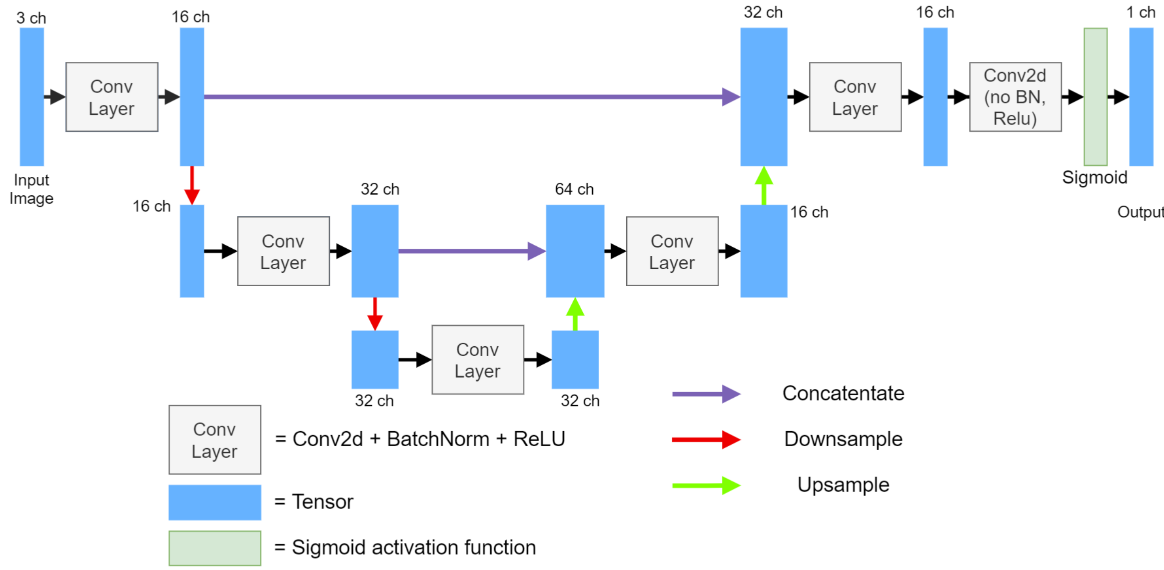
Let's first take a look at the images in the training dataset

Each image in the training dataset has a corresponding mask



You should

- Implement the U-net of the following architechure.



- Write function dice_coeff(input, target) for evaluation
- Load training dataset and testing dataset. Notice that you should rescale the images to a smaller size (for example 80x100). Otherwise it takes too long to train on cpu.
- Train your network for a few epochs.
- Test your model by feeding in a new image in testing dataset. Plot your result.

In [1]:
```
import torch
import torch.nn as nn
import torch.nn.functional as F
import random
import sys
import os
from optparse import OptionParser
import numpy as np
from torch import optim
from PIL import Image
from torch.autograd import Function, Variable
import matplotlib.pyplot as plt
import matplotlib
from torchvision import transforms
import glob
from tqdm import tqdm
import pickle
from torch.utils.data import Dataset
%matplotlib inline
import cv2
```

In [2]:
```
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print(device)
```

```
cuda:0
```

[TODO 1] First define following layers to be used later

- **Conv2d + BatchNorm2d + ReLu** as **single_conv layer** ,
- **down layer**: use **Maxpool2d** to downsample by a factor of 2

- **up layer**: takes two inputs of different dimensions. First use **nn.Upsample** to upsample the smaller input to be the same size as the larger, then **concatenate** the two along the channel dimension
- **outconv layer**: **Conv2d** followed by **sigmoid activation** to generate probability for each pixel

You can check out the documentation in this link to understand how to use the methods called in the provided template:

https://pytorch.org/docs/stable/nn.html (https://pytorch.org/docs/stable/nn.html)

In [3]:
```
################################################ [TODO] ########################
# DEFINE SINGLE_CONV CLASS
class single_conv(nn.Module):
    '''(conv => BN => ReLU) '''
    def __init__(self, in_ch, out_ch):
        super(single_conv, self).__init__()
        # Define the layers here
        # Note: for conv, use a padding of (1,1) so that size is maintained
        self.conv = nn.Conv2d(in_channels = in_ch, out_channels = out_ch, paddin
        self.bn = nn.BatchNorm2d(out_ch)
        self.relu = nn.ReLU()

    def forward(self, x):
        # define forward operation using the layers we have defined
        x = self.conv(x)
        x = self.bn(x)
        x = self.relu(x)

        return x

################################################ [TODO] ########################
# DEFINE DOWN CLASS
class down(nn.Module):
    def __init__(self):
        super(down, self).__init__()
        self.down = nn.MaxPool2d(2,2)  # use nn.MaxPool2d( )

    def forward(self, x):
        x = self.down(x)
        return x

################################################ [TODO] ########################
# DEFINE UP CLASS
# Note that this class will not only upsample x1, but also concatenate up-sample

class up(nn.Module):
    def __init__(self):
        super(up, self).__init__()
        self.up = nn.Upsample(scale_factor = 2, mode = 'bilinear')  # use nn.Ups

    def forward(self, x1, x2): # Takes in smaller x1 and larger x2
        # First we upsample x1 to be same size as x2
        x1 = self.up(x1)

        # This part is tricky so we've completed this
        # Notice that x2 and x1 may not have the same spatial size.
        # This is because when you downsample old_x2(say 25 by 25), you will get
        # Then you perform upsample to x1, you will get new_x1(24 by 24)
        # You should pad a new row and column so that new_x1 and x2 have the same
        diffY = x2.size()[2] - x1.size()[2]
        diffX = x2.size()[3] - x1.size()[3]
        x1 = F.pad(x1, (diffX // 2, diffX - diffX//2,
                        diffY // 2, diffY - diffY//2))

        # Now we concatenat x2 and x1 along channel dimension: torch.cat()
        # Note pytorch tensor shape correspond to: (batchsize, channel, x_dim, y_
```

```
        x = torch.cat((x2, x1), 1)
        #doubt: dimension =1 for channel?

        return x

################################################ [TODO] ########################
# DEFINE OUTCONV CLASS
class outconv(nn.Module):
    def __init__(self, in_ch, out_ch):
        super(outconv, self).__init__()
        # 1 conv layer
        self.conv = nn.Conv2d(in_ch, out_ch,kernel_size=(3,3))

    def forward(self, x):
        x = self.conv(x)
        # Apply sigmoid activation: torch.sigmoid()
        x = torch.sigmoid(x)
        return x
```

In [4]:
```
################################################ [TODO] #########################
# Build your network with predefined classes: single_conv, up, down, outconv
# The number of input and output channels should follow the U-Net Structure show
import torch.nn.functional as F
class UNet(nn.Module):
    def __init__(self, n_channels_in, n_channels_out):
        super(UNet, self).__init__()
        ## Define the necessary layers using the classes defined above
        self.conv1 = single_conv(n_channels_in, 16)
        self.downSampled1 = down()
        self.conv2 = single_conv(16, 32)
        self.downSampled2 = down()
        self.conv3 = single_conv(32,32)
        self.upSampled1 = up()
        self.conv4 = single_conv(64, 16)
        self.upSampled2 = up()
        self.conv5 = single_conv(32, 16)
        self.conv6 = outconv(16, n_channels_out)

    def forward(self, x):
        # Define forward pass
        x = self.conv1(x)
        cat1 = x
        x = self.downSampled1(x)
        x = self.conv2(x)
        cat2 = x

        x = self.downSampled2(x)
        x = self.conv3(x)

        x = self.upSampled1(cat2, x)
        x = self.conv4(x)

        x = self.upSampled2(cat1, x)

        x = self.conv5(x)
        x = self.conv6(x)
        return x
```

[TODO 2] Define evaluation function:

Dice coefficient is defined as

$$\text{DICE} = \frac{\text{area of } A \cap B}{\text{area of } A \cup B}$$

For the case of evaluating a Dice coefficient on predicted segmentation masks, we can approximate intersection of A and B as the element-wise multiplication between the prediction and target mask, and then sum the resulting matrix.

In order to quantify the area of A union B, some researchers use the simple sum whereas other researchers prefer to use the squared sum for this calculation. You can use either way.

In [5]:
```
################################################ [TODO] ########################
# define dice coefficient
class DiceCoeff(Function):
    """Dice coeff for one pair of input image and target image"""
    def forward(self, prediction, target):
        self.save_for_backward(prediction, target)
        eps = 0.0001 # in case union = 0
        ############################################ [TODO] ################
        # Calculate intersection and union.
        # You can convert a tensor into a vector with tensor.contiguous().view(-1
        # Then use torch.dot(A, B) to calculate the intersection.
        A = prediction.contiguous().view(-1) #doubt: what exactly to do?
        B = target.contiguous().view(-1)
        self.inter = torch.dot(A, B)
        #self.union = torch.sum(A + B) + eps # doubt: is sum correct?
        self.union = A.sum() + B.sum() + eps

        # Calculate DICE
        d = self.inter/self.union
        return d


################################################ [TODO] ########################
# Calculate dice coefficients for batches
def dice_coeff(prediction, target):
    """Dice coeff for batches"""
    s = torch.FloatTensor(1).zero_()

    # For each pair of input and target, call DiceCoeff().forward(prediction, tar
    # Then calculate average over all pairs
    for i, (a,b) in enumerate(zip(prediction, target)):
        s = s + DiceCoeff().forward(a, b)
    s = s / (i + 1)
    return s
```

Load images and masks

Load training imagse, normalize and resize them into smaller size so that you can perform training using a CPU. Split them into training and validation. Validation percent of 0.05 means 5% of training dataset is used as validation. In order to avoid repeated data preprocessing, we use the pickle tool to save the processed data.

This part has been done for you. But please read through so that you learn the general processing steps.

In [6]:
```
# try to split the whole train dataset into train and validation, and match the i
# corresponding label path
def split_train_val(image_paths, mask_paths, train_size):
    img_paths_dic = {}
    mask_paths_dic = {}
    len_data = len(image_paths)
    print('total len:', len_data)
    for i in range(len(image_paths)):
        img_paths_dic[os.path.basename(image_paths[i])[:-4]] = image_paths[i]

    for i in range(len(mask_paths)):
        mask_paths_dic[os.path.basename(mask_paths[i])[:-9]] = mask_paths[i]

    img_mask_list = []
    for key in img_paths_dic:
        img_mask_list.append((img_paths_dic[key], mask_paths_dic[key]))

    train_img_mask_paths = img_mask_list[:int(len_data*train_size)]
    val_img_mask_paths = img_mask_list[int(len_data*train_size):]
    return train_img_mask_paths, val_img_mask_paths

# read in the image and label pair, and then resize them from 1280*1918 to 80*10(
# your computer memory limitation
def preprocess_image(image_mask_paths):
    img_mask_list = []
    new_h, new_w = 80, 100

    for i in tqdm(range(len(image_mask_paths))):
        # cv2 cannot read .gif files
        # Use Image.open() to open image and mask, then convert them to np arrays
        # For images use float32, mask use uint8
        # Normalize img to range (0,1)
        img = np.array(Image.open(image_mask_paths[i][0]), np.float32) / 255.0
        mask = np.array(Image.open(image_mask_paths[i][1]), np.uint8)

        # Use cv2 to resize images to 80x100, use INTER_CUBIC interpolation
        img_resize = cv2.resize(img, dsize=(new_w, new_h), interpolation=cv2.INTE
        mask_resize = np.uint8(cv2.resize(mask, dsize=(new_w, new_h), interpolati

        img_mask_list.append((img_resize, mask_resize))
    return img_mask_list

# save the data into pickle file and you can just reload this file, which can hel
# file again in the future, since reading in image file from hard drive would tak
def pickle_store(file_name,save_data):
    fileObj = open(file_name,'wb')
    pickle.dump(save_data,fileObj)
    fileObj.close()
```

In [7]:
```
# get all the image and mask path and number of images
image_paths = glob.glob("data/train/*.jpg")
mask_paths = glob.glob("data/train_masks/*.gif")

# split these path using a certain percentage
train_size = 0.95
print('original image shape: {}'.format(np.array(Image.open(image_paths[0])).sha
print('orginal mask shape: {}'.format(np.array(Image.open(mask_paths[0])).shape)

train_img_mask_paths, val_img_mask_paths = split_train_val(image_paths, mask_pat

print('train len: {}, val len: {}'.format(len(train_img_mask_paths),len(val_img_
```

```
original image shape: (1280, 1918, 3)
orginal mask shape: (1280, 1918)
total len: 5088
train len: 4833, val len: 255
```

In [8]:
```
## This part preprocess the images and save them to pickle files.
## If the pickle file already exists, this part will not run
## IMPORTANT: If you made any change to the prepreprocess function,
## you need to delete the pickle files before you rerun this part
train_img_masks_save_path = './data/train_img_masks.pickle'
if os.path.exists(train_img_masks_save_path):
    with open(train_img_masks_save_path,'rb') as f:
        train_img_masks = pickle.load(f)
    f.close()
else:
    train_img_masks = preprocess_image(train_img_mask_paths)
    pickle_store(train_img_masks_save_path,train_img_masks)
print('train len: {}'.format(len(train_img_masks)))
```

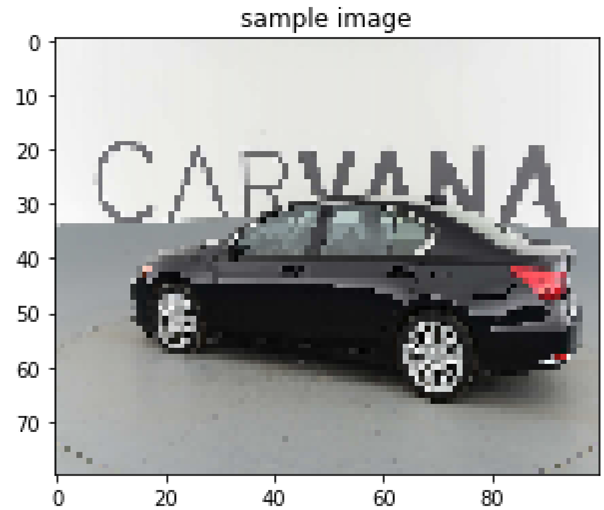
```
train len: 4833
```

In [9]:
```
val_img_masks_save_path = './data/val_img_masks.pickle'
if os.path.exists(val_img_masks_save_path):
    with open(val_img_masks_save_path,'rb') as f:
        val_img_masks = pickle.load(f)
    f.close()
else:
    val_img_masks = preprocess_image(val_img_mask_paths)
    pickle_store(val_img_masks_save_path,val_img_masks)
print('val len: {}'.format(len(val_img_masks)))
```

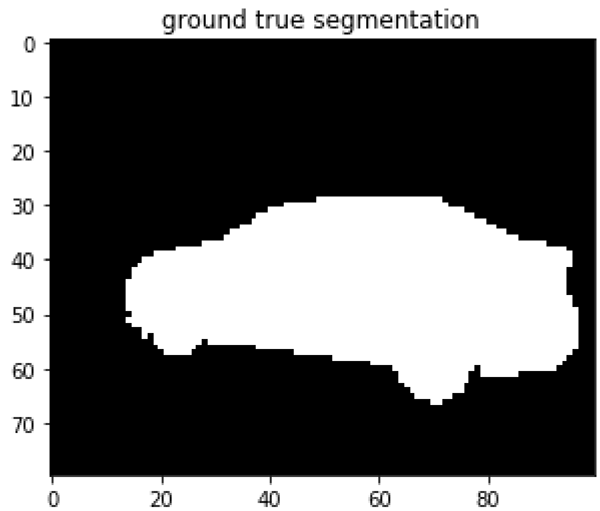
```
val len: 255
```

In [10]:
```
#### Let us display some of the images to make sure the data loading and process
### the original size of the image is: 1280*1918, but we resize the image to 80*
### training the segmentation network
img_num = 5
plt.imshow(train_img_masks[img_num][0])
plt.title("sample image")
plt.show()
```

```
Clipping input data to the valid range for imshow with RGB data ([0..1] for flo
ats or [0..255] for integers).
```



In [11]:
```
plt.imshow(train_img_masks[img_num][1], cmap='gray')
plt.title("ground true segmentation")
plt.show()
```



Create datasets in the format that you can later use Torch "DataLoader" during training and define data augmentation

In [12]:
```
#### define transform classes for  data augmentation
class Flip(object):
    """
    Flip the image left or right for data augmentation, but prefer original image
    """
    def __init__(self,ori_probability=0.60):
        self.ori_probability = ori_probability

    def __call__(self, sample):
        if random.uniform(0,1) < self.ori_probability:
            return sample
        else:
            img, label = sample['img'], sample['label']
            img_flip = img[:,:,::-1]
            label_flip = label[:,::-1]

            return {'img': img_flip, 'label': label_flip}

class ToTensor(object):
    """
    Convert ndarrays in sample to Tensors.
    """
    def __init__(self):
        pass

    def __call__(self, sample):
        image, label = sample['img'], sample['label']

        return {'img': torch.from_numpy(image.copy()).type(torch.FloatTensor),
                'label': torch.from_numpy(label.copy()).type(torch.FloatTensor)}
```

In [13]:
```
# the dataset class
class CustomDataset(Dataset):
    def __init__(self, image_masks, transforms=None):

        self.image_masks = image_masks
        self.transforms = transforms

    def __len__(self):  # return count of sample we have

        return len(self.image_masks)

    def __getitem__(self, index):

        image = self.image_masks[index][0] # H, W, C
        mask = self.image_masks[index][1]

        image = np.transpose(image, axes=[2, 0, 1]) # C, H, W

        sample = {'img': image, 'label': mask}

        if transforms:
            sample = self.transforms(sample)

        return sample

train_dataset = CustomDataset(train_img_masks, transforms=transforms.Compose([Fl
val_dataset = CustomDataset(val_img_masks, transforms=transforms.Compose([Flip()
```

[TODO 3] Start training your network

In [14]:
```
################################################ [TODO] #########################
# This function is used to evaluate the network after each epoch of training
# Input: network and validation dataset
# Output: average dice_coeff
def eval_net(net, dataset):
    # set net mode to evaluation
    net.eval()
    tot = 0
    for i, b in enumerate(dataset):
        img = b['img'].to(device)
        B = img.shape[0]
        true_mask = b['label'].to(device)
        ################################################ [TODO] #################
        # Feed the image to network to get predicted mask
        mask_pred = net(img)
        mask_pred = nn.functional.interpolate(mask_pred, size=(80,100), mode='bi

        # For all pixels in predicted mask, set them to 1 if larger than 0.5. Oth
        mask_pred[mask_pred>0.5] = 1
        mask_pred[mask_pred<=0.5] = 0
        #mask_pred

        # calculate dice_coeff()
        # note that you should add all the dice_coeff in validation/testing datas
        # call dice_coeff() here
        tot += dice_coeff(mask_pred, true_mask)
        # Return average dice_coeff()
    return tot / (i + 1)
```

In [15]:
```
################################################ [TODO] ########################
# Create a UNET object from the class defined above. Input channels = 3, output c
net = UNet(3,1)
net = net.to(device)
# run net.to(device) if using GPU
# If continuing from previously saved model, use
# net.load_state_dict(torch.load('PATH TO SAVED MODEL FILE'))
print(net)

# This shows the number of parameters in the network
n_params = sum(p.numel() for p in net.parameters() if p.requires_grad)
print('Number of parameters in network: ', n_params)
```

```
UNet(
  (conv1): single_conv(
    (conv): Conv2d(3, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (bn): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_s
tats=True)
    (relu): ReLU()
  )
  (downSampled1): down(
    (down): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode
=False)
  )
  (conv2): single_conv(
    (conv): Conv2d(16, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (bn): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_s
tats=True)
    (relu): ReLU()
  )
  (downSampled2): down(
    (down): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode
=False)
  )
  (conv3): single_conv(
    (conv): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (bn): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_s
tats=True)
    (relu): ReLU()
  )
  (upSampled1): up(
    (up): Upsample(scale_factor=2.0, mode=bilinear)
  )
  (conv4): single_conv(
    (conv): Conv2d(64, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (bn): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_s
tats=True)
    (relu): ReLU()
  )
  (upSampled2): up(
    (up): Upsample(scale_factor=2.0, mode=bilinear)
  )
  (conv5): single_conv(
    (conv): Conv2d(32, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (bn): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_s
```

```
tats=True)
    (relu): ReLU()
  )
  (conv6): outconv(
    (conv): Conv2d(16, 1, kernel_size=(3, 3), stride=(1, 1))
  )
)
Number of parameters in network:  28561
```

In [16]:
```
################################################ [TODO] ##########################
# Specify number of epochs, image scale factor, batch size and learning rate
epochs = 10          # e.g. 10, or more until dice converge  #doubt: how many epo
batch_size = 16    # e.g. 16
lr =  0.01           # e.g. 0.01
N_train = len(train_img_masks)
model_save_path = './model/'  # directory to same the model after each epoch.

################################################ [TODO] ##########################
# Define an optimizer for your model.
# Pytorch has built-in package called optim. Most commonly used methods are alrea
# Here we use stochastic gradient descent to optimize
# For usage of SGD, you can read https://pytorch.org/docs/stable/_modules/torch/o
# Also you can use ADAM as the optimizer
# For usage of ADAM, you can read https://www.programcreek.com/python/example/926

optimizer = optim.SGD(net.parameters(), momentum=0.9, weight_decay=0.0005, lr=lr)
#suggested parameter settings: momentum=0.9, weight_decay=0.0005

# The loss function we use is binary cross entropy: nn.BCELoss()
criterion = nn.BCELoss()
# note that although we want to use DICE for evaluation, we use BCELoss for train

################################################ [TODO] ##########################
# Start training  #This part takes very long time to run if using CPU
for epoch in range(epochs):
    print('Starting epoch {}/{}.'.format(epoch + 1, epochs))
    net.train()
    # Reload images and masks for training and validation and perform random shuf
    train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=batch_si
    val_loader = torch.utils.data.DataLoader(val_dataset, batch_size=batch_size,

    epoch_loss = 0
    count = 0
    for i, b in enumerate(train_loader):
        ################################################ [TODO] ##################
        # Get images and masks from each batch

        imgs = b['img'].to(device)
        #imgs = np.moveaxis(imgs, 2, 0)
        true_masks = b['label'].to(device)

        ################################################ [TODO] ##################
        # Feed your images into the network

        masks_pred = net(imgs)
        masks_pred = nn.functional.interpolate(masks_pred, size=(80,100), mode='b
        # Flatten the predicted masks and true masks. For example, A_flat = A.vie
        masks_probs_flat = masks_pred.view(-1)
        true_masks_flat = true_masks.view(-1)
        ################################################ [TODO] ##################
        # Calculate the loss by comparing the predicted masks vector and true mas
        # And sum the losses together
        loss = criterion(masks_probs_flat,true_masks_flat)
        epoch_loss += loss.item()
        if count % 20 == 0:  #Print status every 20 batch
```

```
            print('{0:.4f} --- loss: {1:.6f}'.format(i * batch_size / N_train, lo
        count = count + 1
        # optimizer.zero_grad() clears x.grad for every parameter x in the optimi
        # It’s important to call this before loss.backward(), otherwise you’ll ac
        optimizer.zero_grad()
        # loss.backward() computes dloss/dx for every parameter x which has requi
        # These are accumulated into x.grad for every parameter x
        loss.backward()
        # optimizer.step updates the value of x using the gradient x.grad.
        optimizer.step()

    print('Epoch finished ! Loss: {}'.format(epoch_loss / i))
    ################################################ [TODO] #####################
    # Perform validation with eval_net() on the validation data
    val_dice = eval_net(net, val_loader)
    print('Validation Dice Coeff: {}'.format(val_dice))

    # Save the model after each epoch
    if os.path.isdir(model_save_path):
        torch.save(net.state_dict(),model_save_path + 'Car_Seg_Epoch{}.pth'.forma
    else:
        os.makedirs(model_save_path, exist_ok=True)
        torch.save(net.state_dict(),model_save_path + 'Car_Seg_Epoch{}.pth'.forma
    print('Checkpoint {} saved !'.format(epoch + 1))
```

```
0.0000 --- loss: 0.045751
0.0662 --- loss: 0.046345
0.1324 --- loss: 0.045236
0.1986 --- loss: 0.047309
0.2648 --- loss: 0.049113
0.3311 --- loss: 0.049279
0.3973 --- loss: 0.047866
0.4635 --- loss: 0.048755
0.5297 --- loss: 0.048515
0.5959 --- loss: 0.049885
0.6621 --- loss: 0.047396

0.7283 --- loss: 0.047778
0.7945 --- loss: 0.047331
0.8607 --- loss: 0.046575
0.9270 --- loss: 0.049102
0.9932 --- loss: 0.051005
Epoch finished ! Loss: 0.04892559215081054
Validation Dice Coeff: tensor([0.4748], grad_fn=<DivBackward0>)
Checkpoint 9 saved !
```

[TODO 4] load one image from testing dataset and plot output mask

In [27]:
```
############################################### [TODO] ########################
# Define a function for prediction/testing
def predict_img(net,full_img,out_threshold=0.5):
    # set the mode of your network to evaluation
    net.eval()

    # convert from Height*Width*Channel TO Channel*Height*Width
    full_img = np.moveaxis(full_img, -1, 0)

    # convert numpy array to torch tensor, normalize to range (0,1)
    X_img = torch.from_numpy(full_img)/255.0
    X_img = X_img.unsqueeze(0)

    with torch.no_grad():
        ############################################### [TODO] ################
        # predict the masks
        X_img = X_img.to(device)
        output_img = net(X_img)
        out_probs = output_img.squeeze(0).squeeze(0)
        # threshold the probability to generate mask: mask=1 if prob > out_thresl
        # change back to numpy, set to uint8
        out_mask_np = (out_probs > out_threshold).float()
        if torch.cuda.is_available():
            out_mask_np = out_mask_np.cpu()
        out_mask_np = out_mask_np.numpy().astype('uint8')

    return out_mask_np
```

In [28]:
```
############################################### [TODO] ########################
# Load an image from testing dataset
test_img_paths = glob.glob("data/test/*.jpg")
test_img = np.array(Image.open(test_img_paths[0]))

orig_shape = test_img.shape

# Resize image to (80,100)
img_resize = cv2.resize(test_img,(80, 100), cv2.INTER_CUBIC )

############################################### [TODO] ########################
# Predict the mask
mask = predict_img(net, img_resize)
# Rescale the mask back to original image size
mask =  cv2.resize(np.array(mask), (orig_shape[1], orig_shape[0]), cv2.INTER_CUBI
```

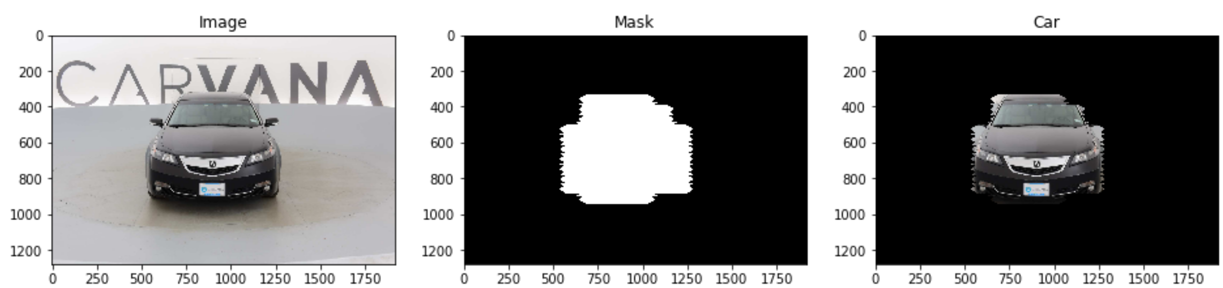
```
C:\ProgramData\Anaconda3\lib\site-packages\torch\nn\functional.py:2506: UserWar
ning: Default upsampling behavior when mode=bilinear is changed to align_corner
s=False since 0.4.0. Please specify align_corners=True if the old behavior is d
esired. See the documentation of nn.Upsample for details.
  "See the documentation of nn.Upsample for details.".format(mode))
```

In [29]:
```
## Extract the car from the image using the predicted mask
img_seg = test_img.copy()
for i in range(3):
    img_seg[:, :, i] =  test_img[:, :, i] * mask
```

Plot original image and mask image

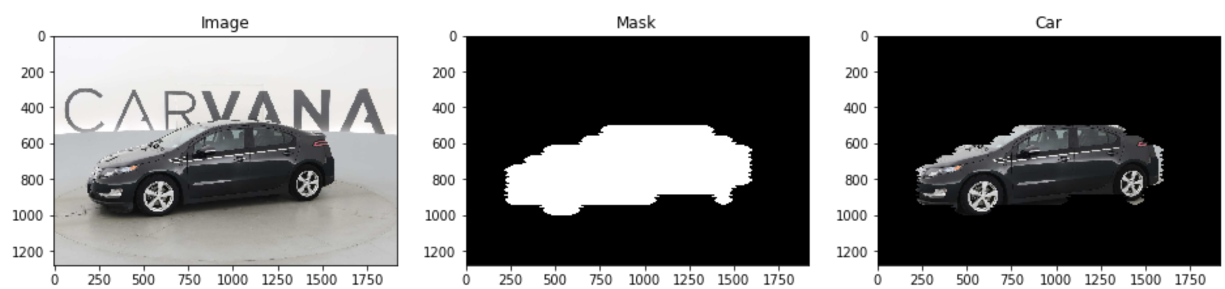
In [30]:
```
############################################### [TODO] #########################
# Plot original images and masks and segmented part
plt.figure(figsize = (16,48))
plt.subplot(1,3,1)
plt.imshow(test_img)
plt.title('Image')
plt.subplot(1,3,2)
plt.imshow(mask,cmap='gray')
plt.title('Mask')
plt.subplot(1,3,3)
plt.imshow(img_seg)
plt.title('Car')
```

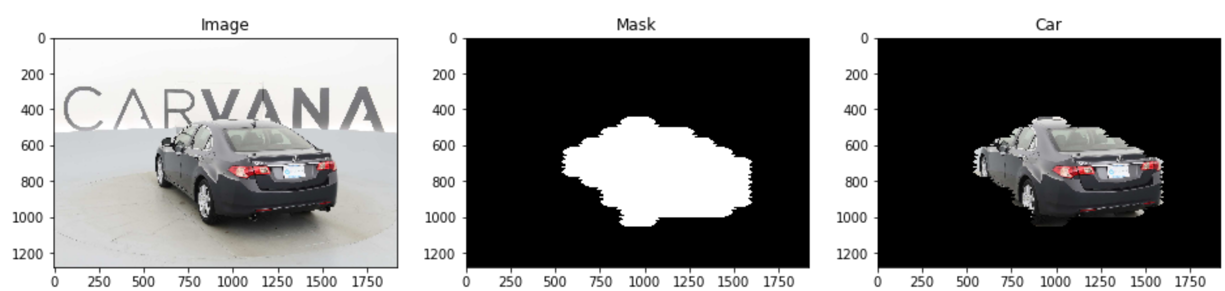
Out[30]: Text(0.5, 1.0, 'Car')



In [26]:

```
################################################ [TODO] ##########################
# Display ten more of test samples
length = len(test_img_paths)
count = 0
while(count < 10):
    k = np.random.randint(0, length)
    test_img = np.array(Image.open(test_img_paths[k]))

    orig_shape = test_img.shape

    # Resize image to (80,100)
    img_resize = cv2.resize(test_img,(80, 100), cv2.INTER_CUBIC )

    ################################################ [TODO] #####################
    # Predict the mask
    mask = predict_img(net, img_resize)
    # Rescale the mask back to original image size
    mask =  cv2.resize(np.array(mask), (orig_shape[1], orig_shape[0]), cv2.INTER_
    temp = test_img.copy()
    for i in range(3):
        temp[:, :, i] =  test_img[:, :, i] * mask
    plt.figure(figsize = (16,48))
    plt.subplot(1,3,1)
    plt.imshow(test_img)
    plt.title('Image')
    plt.subplot(1,3,2)
    plt.imshow(mask,cmap='gray')
    plt.title('Mask')
    plt.subplot(1,3,3)
    plt.imshow(temp)
    plt.title('Car')

    count += 1
```





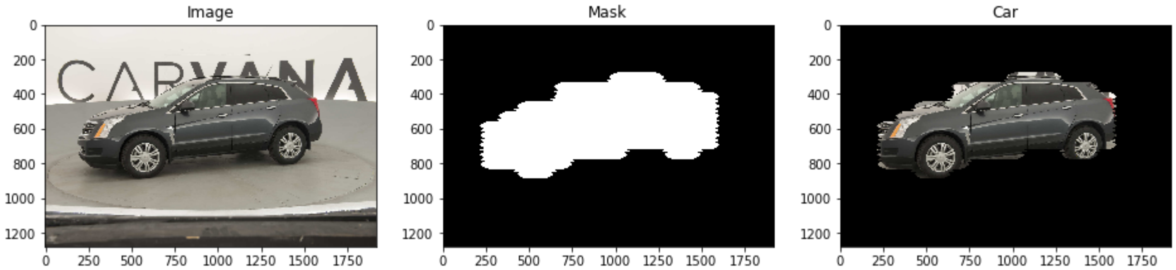


Image
Mask
Car
0
200
400
600
800
1000
1200
0 250 500 750 1000 1250 1500 1750

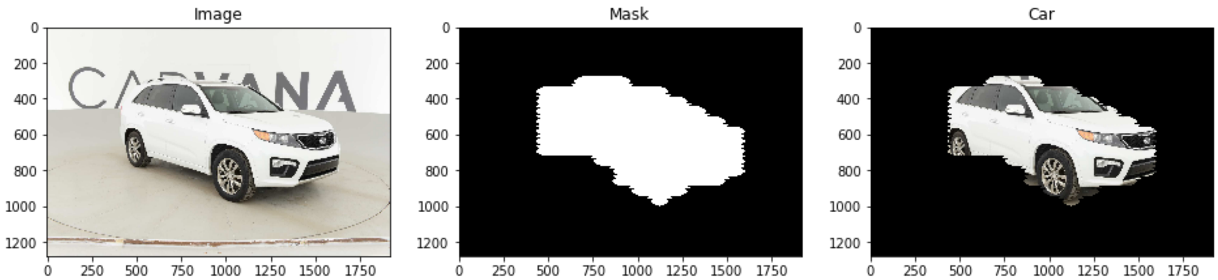


Image
Mask
Car
0
200
400
600
800
1000
1200
0 250 500 750 1000 1250 1500 1750

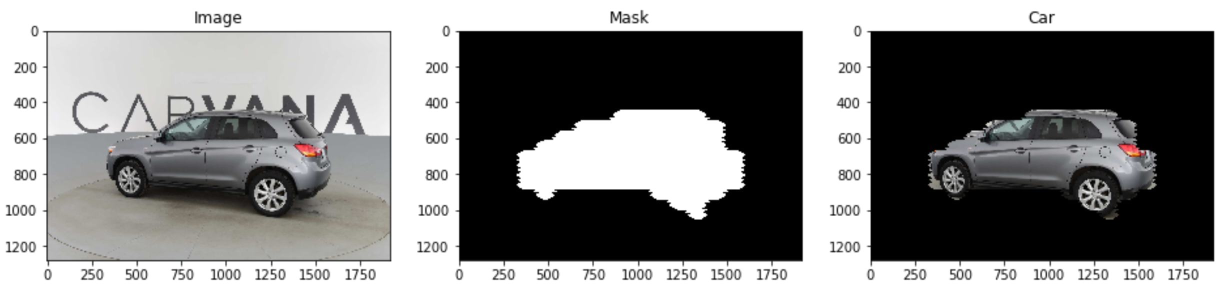


Image
Mask
Car
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200
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600
800
1000
1200
0 250 500 750 1000 1250 1500 1750


Image
Mask
Car
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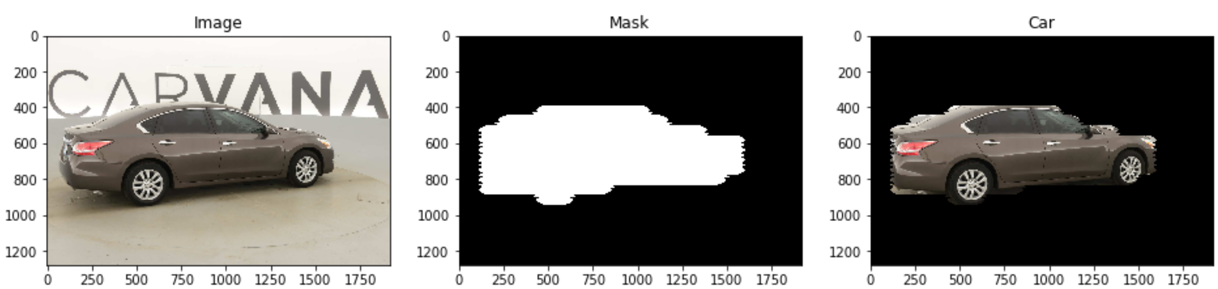
Image
Mask
Car
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200
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0 250 500 750 1000 1250 1500 1750

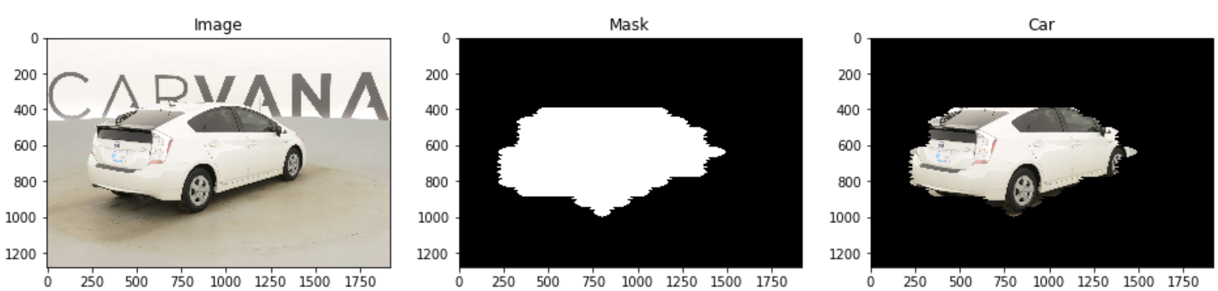
Image
Mask
Car
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200
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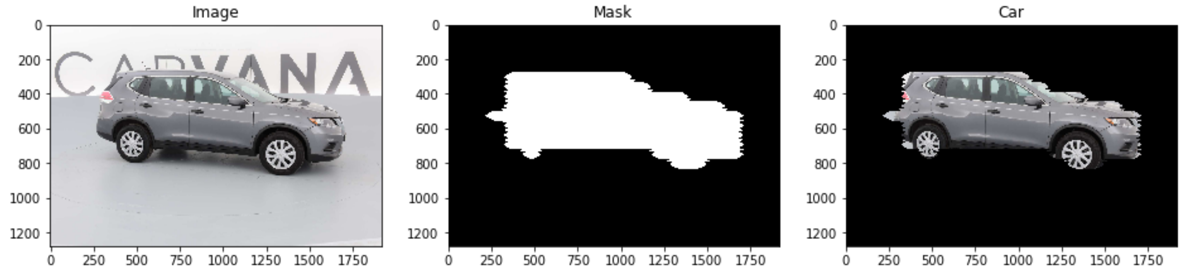
600
800
1000
1200
0 250 500 750 1000 1250 1500 1750




```
In [ ]:
```