### 1 Introduction:

This is a programming assignment to create, train, and test a CNN for the task of semantic segmentation following the FCN32s. The network of this task is similar to VGG16. The dataset we use for this assignment is based on KITTI Road semantic segmentation dataset. Each image is a 352x1216 RGB image. In the folder named label, each file stores a (352,1216) numpy array In this dataset, 0 for Non-Road, 1 for Road, and -1 for Void.

# 2 Data Processing:

First of all, we need to do the data processing. This is a way to import data into our program.

```
def imageprocessing(path):
    img = utils.load image(path)
    batch = img.reshape((1, 352, 1216, 3))
def gtprocessing(path):
train gt list = os.listdir(train gt Path)
   test images.append(imageprocessing(test image Path+"/"+path))
   test labels.append(gtprocessing(test gt Path + "/" + path))
   train images.append(imageprocessing(train image Path+"/"+path))
```

#### Print the dataset:

```
print(train_images.shape)
print(validation_images.shape)
print(test_images.shape)
```

```
print(train_labels.shape)
print(validation_labels.shape)
print(test_labels.shape)

Print:
(199, 352, 1216, 3)
(45, 352, 1216, 3)
(45, 352, 1216, 3)
(199, 352, 1216)
(45, 352, 1216)
```

## 3 Architecture:

Construct a Fully Convolutional Network FCN-32s. FCN-32s network is based on VGG-16 network with some modifications:

Here are the codes for the architecture of FCN-32s. You can see that we changed the fully connected layers into fully convolutional network.

```
self.conv1 1 = self.conv layer(bgr, 3, 64, "conv1 1")
self.conv1^{-}2 = self.conv^{-}layer(self.conv1^{-}1, 64, 64, "conv1^{-}2")
self.conv2 1 = self.conv layer(self.pool1, 64, 128, "conv2 1")
self.conv2 2 = self.conv layer(self.conv2 1, 128, 128, "conv2 2")
self.conv3 1 = self.conv layer(self.pool2, 128, 256, "conv3 1")
self.conv3 2 = self.conv layer(self.conv3 1, 256, 256, "conv3 2")
self.conv4 1 = self.conv layer(self.pool3, 256, 512, "conv4 1")
self.conv4 2 = self.conv layer(self.conv4 1, 512, 512, "conv4 2")
self.conv4 3 = self.conv layer(self.conv4 2, 512, 512, "conv4 3")
self.conv5 1 = self.conv layer(self.pool4, 512, 512, "conv5 1")
self.conv5_2 = self.conv_1 ayer(self.conv5_1, 512, 512, "conv5_2")
self.conv5 3 = self.conv layer(self.conv5 2, 512, 512, "conv5 3")
self.conv6 = self.conv layer(self.pool5, 512, 4096, "conv6")
self.conv8 = self.conv layer(self.conv7, 4096, 1, "conv8")
self.conv9 = tf.layers.conv2d transpose(self.conv8, strides=(32,32),
self.data dict = None
```

# 4 Training and Validation:

For this part, we should configure the cross entropy (loss function). Shown as below:

```
# setup::::
Entropy = tf.nn.sigmoid_cross_entropy_with_logits(logits=fcn.conv9,
labels=true_out)
mask = tf.minimum(true_out,0)+1
costEntropy = tf.reduce_sum(Entropy*mask)/tf.reduce_sum(mask)
train =
tf.train.GradientDescentOptimizer(0.0001).minimize(costEntropy)
```

Then we can create a session and run it. Shown as below:

```
for epk in range(EPOCH):
    lossFTrain = []
        img1 true result = np.expand dims(train labels[i:i+1], -1)
img1 true result, train mode: True})
        lossF = sess.run(costEntropy, feed dict={images: img1,
true out: img1 true result, train mode: False})
        lossFTrain.append(lossF)
    lossTall = sum(lossFTrain)/len(lossFTrain)
    T.append(lossTall)
    lossFValidation = []
        img1 = validation images[i:i + 1]
        imq1 true result = np.expand dims(validation labels[i:i + 1],
```

```
# get prob and entropy
    prob = sess.run(fcn.prob, feed_dict={images: img1, true_out:
img1_true_result, train_mode: False})
    lossF = sess.run(costEntropy, feed_dict={images:
img1,true_out: img1_true_result, train_mode: False})

    lossFValidation.append(lossF)

    lossVall = sum(lossFValidation)/len(lossFValidation)
    V.append(lossVall)
    print("*****lossVall",lossVall)

# test_save

fcn.save_npy(sess, "C:/Users/yuhou/OneDrive/CSCI677/homework6/hw6/test-save-"+str(epk)+".npy")
```

You can see after each epoch, I saved all parameters (weight we have learned). The training process is very slow, so we should save the weight as soon as possible in case the process crash.

```
test-save-24.npy
 w6.py
ossCurve.png
                     test-save-12.npy
                                                                                                                                                      test-save-5.npy
                                                                                                                                test-save-44.npy
                                          test-save-19.npy
test-save-1.npy
                                                               test-save-25.npy
test-save-26.npy
                                                                                     test-save-31.npy
test-save-32.npy
                                                                                                          test-save-38.npy
test-save-39.npy
                     test-save-13.npy
                                                                                                                                test-save-45.npy
                                                                                                                                                      test-save-6.npy
                     test-save-14.npy
                                                               test-save-27.npy
                                                                                                          test-save-3.npy
prob.npv
                                          test-save-20.npy
                                                                                     test-save-33.npy
                                                                                                                                test-save-46.npy
                                                                                                                                                      test-save-7.npv
                     test-save-15.npy
                                          test-save-21.npy
                                                               test-save-28.npy
                                                                                     test-save-34.npy
                                                                                                          test-save-40.npy
                                                                                                                                test-save-47.npy
                                                                                                                                                      test-save-8.npy
                                                                                                         test-save-41.npy
                                                                                                                                test-save-48.npy
test-save-0.npy
                    test-save-16.npy
test-save-17.npy
                                                               test-save-29.npy
                                                                                    test-save-35.npy
test-save-36.npy
                                         test-save-22.npy
                                                                                                                                                     test-save-9.npv
                                                               test-save-2.npy
                                                                                                         test-save-42.npy
                                         test_save-23.npy
```

Figure 1

#### 5 Result:

#### 1- Loss Function Curve

I tried twice. For every training, I used learning rate as 0.0001 and 0.05. Only one of them got converged. I noticed that the instruction said the recommended learning rate should be 0.001, but I already started training, due to the long training time, I didn't stop it, but in order to see the influence of different learning rate, I tried 0.05 for the second time. I did not try a lot of times to train the network, because I did not use GPU on Azure and on my laptop. This also have an influence on my result of IoU and the visualization. The pictures below are my loss function curves. The epochs of them are both 50. The red line is training, and the blue line is validation.

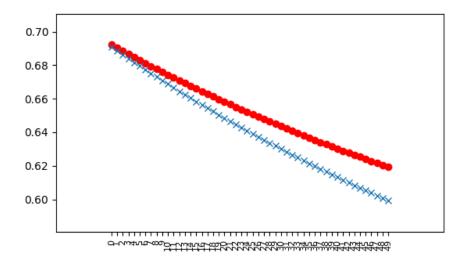


Figure 2 Learning rate as 0.001

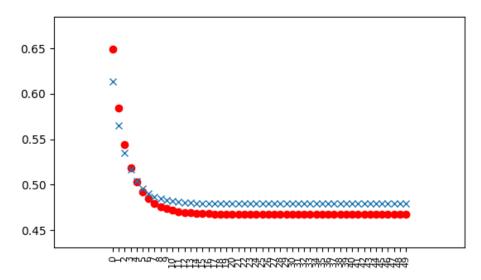


Figure 3 Learning rate as 0.05

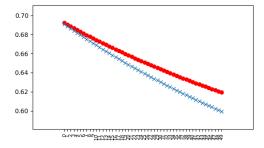
#### 2- IoU

We are going to use pixel-level intersection-over-union (IoU) metrics to evaluate the network output. Pixel-level IoU = TP/(TP+FP+FN), where TP, FP, and FN are the numbers of true positive, false positive, and false negative pixels, respectively. For the whole testing data. The overall IoU is 12.637%. This IoU is very low. I think there are something wrong with my code, the network learning nothing from the training set.

# 6 Effects of parameter choices:

Due to the long duration of training, we just tested two sessions. We tried learning rate as 0.001 and 0.05 to see the difference. We can see if learning rate is 0.05 (higher), the loss function will

be smaller than the learning rate as 0.001. Also, the loss function can drop down soon. Shown as figure 4 and figure 5. They are the same to the figure 2 and figure 3.



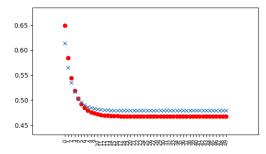


Figure 4 Learning rate as 0.001

Figure 5 Learning rate as 0.05

## 7 Visualization and Discussion:

In order to make sure we can get the result before the training crash. We saved the sigmoid function into a ".npy" file. We can use this file to visualize result.

```
# visualization of data
prob = np.load("./prob.npy")

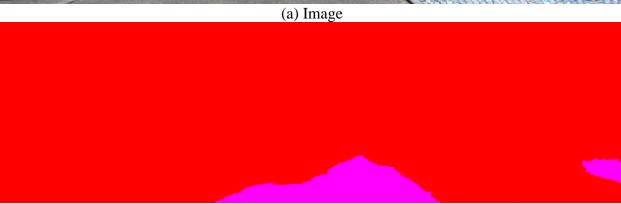
# which image you want to check
number = 15
print(prob.shape)  # (45, 352, 1216, 1)
x = prob[15][0]

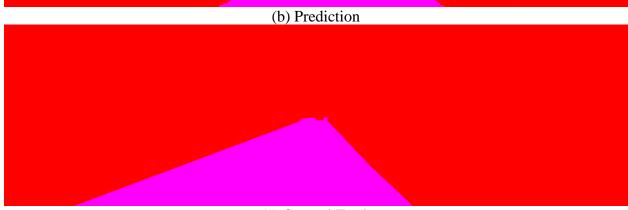
# This is for B chanel, cuz R and G chanel are the same
x[x>0.5] = 255
x[x<=0.5] = 0
x = np.squeeze(x, axis=2)
print(x.shape)
# This is for R chanel
R = np.zeros([352,1216],dtype=np.uint8)
R.fill(255) # or img[:] = 255
print(R.shape)
# This is for G chanel
G = np.zeros([352,1216],dtype=np.uint8)
G.fill(0) # or img[:] = 255
print(G.shape)

# Create the image
img = [x,G,R]
img = np.array(img)
img = np.swapaxes(np.swapaxes(img,0,2),0,1) # shape (3,352,1216)->>
(352, 1216, 3)
print(img.shape)
```

However, in this homework, we did not get a good result. I just present two failure examples. It seems that few things the code have learned from the training, so it predicted a bad result from the testing data.

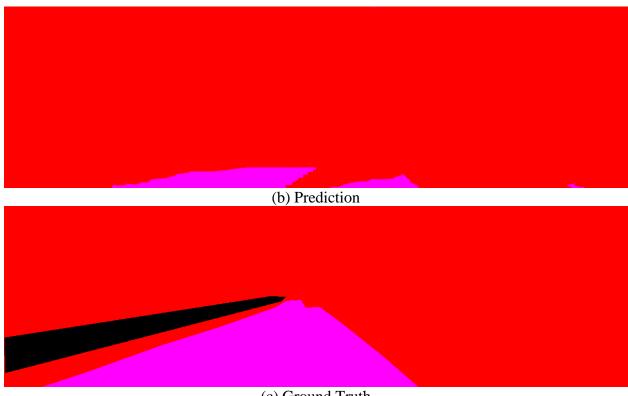






(c) Ground Truth
Figure 6 uu\_000003.png (IoU = 25.295%)





(c) Ground Truth Figure 7 nm\_000014.png (IoU = 19.436%)

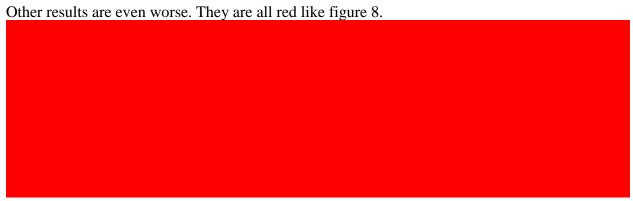


Figure 8 failure examples

There are some reasons I got the bad results in this homework. I think the main reason is that the training is not enough. For the first session, it even did not converge. On the other hand, the second session got converged, but I guess it falls into a local optimization.

# 8 Appendix (code):

1-util.py

import skimage
import skimage.io

```
import skimage.transform
import numpy as np

# [height, width, depth]

def load_image(path):
    # load image
    img = skimage.io.imread(path)
    img = img / 255.0
    assert (0 <= img).all() and (img <= 1.0).all()
    # print "Original Image Shape: ", img.shape
    # we crop image from center
    short_edge = min(img.shape[:2])
    yy = int((img.shape[0] - short_edge) / 2)
    xx = int((img.shape[1] - short_edge) / 2)
    crop_img = img[yy: yy + short_edge, xx: xx + short_edge]
    resized_img = skimage.transform.resize(crop_img, (352, 1216))
    return resized_img

if __name__ == "__main__":
    test()</pre>
```

2- fcn32\_trainable.py

```
11 11 11
rgb scaled = rgb * 255.0
assert red.get shape().as list()[1:] == [352, 1216, 1]
assert green.get shape().as list()[1:] == [352, 1216, 1]
assert blue.get_shape().as_list()[1:] == [352, 1216, 1]
bgr = tf.concat(axis=3, values=[
    green - FCN MEAN[1],
    red - FCN MEAN[2],
assert bgr.get shape().as list()[1:] == [352, 1216, 3]
self.conv1 1 = self.conv layer(bgr, 3, 64, "conv1 1")
self.conv1 2 = self.conv layer(self.conv1 1, 64, 64,
self.pool1 = self.max pool(self.conv1 2, 'pool1')
self.conv2 1 = self.conv layer(self.pool1, 64, 128, "conv2 1")
self.conv2 2 = self.conv layer(self.conv2 1, 128, 128,
self.conv3 1 = self.conv layer(self.pool2, 128, 256,
self.conv3 2 = self.conv layer(self.conv3 1, 256, 256,
self.conv3 3 = self.conv layer(self.conv3 2, 256, 256,
self.conv4 1 = self.conv layer(self.pool3, 256, 512,
self.conv4 2 = self.conv layer(self.conv4 1, 512, 512,
self.conv4 3 = self.conv layer(self.conv4 2, 512, 512,
self.conv5 1 = self.conv layer(self.pool4, 512, 512,
self.conv5 2 = self.conv layer(self.conv5 1, 512, 512,
self.conv5 3 = self.conv layer(self.conv5 2, 512, 512,
self.pool5 = self.max pool(self.conv5 3, 'pool5')
self.conv6 = self.conv layer(self.pool5, 512, 4096, "conv6")
```

```
self.conv7 = self.conv layer(self.conv6, 4096, 4096, "conv7")
        self.conv8 = self.conv layer(self.conv7, 4096, 1, "conv8")
       self.conv9 = tf.layers.conv2d transpose(self.conv8,
    def avg pool(self, bottom, name):
    def max pool(self, bottom, name):
   def conv layer(self, bottom, in channels, out channels, name):
        with tf.variable scope(name):
            filt, conv biases = self.get conv var(3, in channels,
out channels, name)
            bias = tf.nn.bias add(conv, conv biases)
   def fc layer(self, bottom, in size, out size, name):
        with tf.variable scope(name):
            weights, biases = self.get fc var(in size, out size, name)
            fc = tf.nn.bias add(tf.matmul(x, weights), biases)
   def get conv var(self, filter size, in channels, out channels,
        filters = self.get var(initial value, name, 0, name +
        initial value = tf.truncated normal([out channels], .0, .001)
        biases = self.get var(initial value, name, 1, name +
```

```
return filters, biases
def get fc var(self, in size, out size, name):
def get var(self, initial value, name, idx, var name):
    if self.trainable:
    assert var.get shape() == initial value.get shape()
def save npy(self, sess, npy path="./save.npy"):
        var out = sess.run(var)
    np.save(npy path, data dict)
    print(("file saved", npy path))
def get var count(self):
    for v in list(self.var dict.values()):
```

#### 3- test.py

```
import collections
import pickle
import numpy as np
import utils
import matplotlib.pyplot as plt
SOFTMAX = True
def imageprocessing(path):
    img = utils.load image(path)
    batch = img.reshape((1, 352, 1216, 3))
def gtprocessing(path):
test qt Path =
train gt Path =
# data list
test image list = os.listdir(test image Path)
train image list = os.listdir(train image Path)
test gt list = os.listdir(test gt Path)
```

```
train images = []
train labels = []
    test images.append(imageprocessing(test image Path+"/"+path))
   test labels.append(gtprocessing(test gt Path + "/" + path))
   train images.append(imageprocessing(train image Path+"/"+path))
    train labels.append(gtprocessing(train gt Path + "/" + path))
with tf.device('/cpu:0'):
   EPOCH = 50
    sess = tf.Session()
    fcn = fcn32.Fcn32()
    fcn.build(images, train mode)
tf.nn.sigmoid cross entropy with logits(logits=fcn.conv9,
_abels=true out)
    costEntropy = tf.reduce sum(Entropy*mask)/tf.reduce sum(mask)
tf.train.GradientDescentOptimizer(0.0001).minimize(costEntropy)
    for epk in range(EPOCH):
```

```
lossFTrain = []
        for i in range(len(train images)):
            sess.run(train, feed dict={images: img1, true out:
            lossF = sess.run(costEntropy, feed dict={images: img1,
            lossFTrain.append(lossF)
        lossTall = sum(lossFTrain)/len(lossFTrain)
        T.append(lossTall)
        print("*****lossFall", lossTall)
        lossFValidation = []
        for i in range(len(validation images)):
            prob = sess.run(fcn.prob, feed dict={images: img1,
            lossF = sess.run(costEntropy, feed dict={images:
img1,true out: img1 true result, train mode: False})
            lossFValidation.append(lossF)
        lossVall = sum(lossFValidation)/len(lossFValidation)
        V.append(lossVall)
```

```
fcn.save npy(sess, "C:/Users/yuhou/OneDrive/桌面
   print("T",T)
   plt.figure()
   plt.plot(E,T,'ro')
   plt.subplots adjust(bottom=0.3)
    plt.savefig('C:/Users/yuhou/OneDrive/桌面
    fcn.save npy(sess, "C:/Users/yuhou/OneDrive/桌面
    lossTTValidation = []
    PROB = []
        img1 true result = np.expand dims(test labels[i:i + 1], -1)
img1 true result, train mode: False})
        PROB.append(prob)
        lossF = sess.run(costEntropy, feed dict={images: img1,
        lossTTValidation.append(lossF)
    lossVall = sum(lossTTValidation) / len(lossTTValidation)
    print("*****lossVall", lossVall)
```

## np.save('C:/Users/yuhou/OneDrive/臬面 /CSCI677/homework6/hw6/prob.npy',np.array(PROB)

## 9 Reference:

- [1] https://www.youtube.com/watch?v=JuRQAi5RR3A
- [2] https://docs.opencv.org/3.0-
- beta/doc/py\_tutorials/py\_gui/py\_image\_display/py\_image\_display.html
- [3] https://www.tensorflow.org/api\_docs/python/tf/initializers/local\_variables
- [4] https://www.tensorflow.org/api\_docs/python/tf/convert\_to\_tensor