CS 484/684 Computational Vision

credits: many thanks for the design of this assignemnt go to [Towaki Takikawa (https://tovacinni.github.io/)](https://tovacinni.github.io/)

Homework Assignment #5 - Supervised Deep Learning for Segmentation ¶

This assignment will test your understanding of applying deep learning by having you apply (fully supervised) deep learning to semantic segmentation, a well studied problem in computer vision.

You can get most of the work done using only CPU, however, the use of GPU will be helpful in later parts. Programming and debugging everything upto and including problem 5c should be fine on CPU. You will notice the benefit of GPU mostly in later parts (d-h) of problem 5, but they are mainly implemenmted and test your code written and debugged earlier. If you do not have a GPU readily accesible to you, we recommend that you use Google Colaboratory to get access to a GPU. Once you are satisfied with your code upto and including 5(c), simply upload this Jupyter Notebook to Google Colaboratory to run the tests in later parts of Problem 5.

Proficiency with PyTorch is required. Working through the PyTorch tutorials will make this assignment significantly easier. [https://pytorch.org/tutorials/ (https://pytorch.org/tutorials/)](https://pytorch.org/tutorials/)

In [1]:
```
%matplotlib inline

# It is best to start with USE_GPU = False (implying CPU). Switch USE_GPU to True only if you want to use GPU. However...
# we strongly recommend to wait until you are absolutely sure your CPU-based code works (at least on single image dataset)
USE_GPU = False
```

In [2]:
```
conda install pytorch torchvision -c pytorch
```

```
Collecting package metadata (current_repodata.json): done
Solving environment: done

# All requested packages already installed.


Note: you may need to restart the kernel to use updated packages.
```

In [3]:

```
# Python Libraries
import random
import math
import numbers
import platform
import copy

# Importing essential libraries for basic image manipulations.
import numpy as np
import PIL
from PIL import Image, ImageOps
import matplotlib.pyplot as plt
from tqdm import tqdm

# We import some of the main PyTorch and TorchVision libraries used for HW4.
# Detailed installation instructions are here: https://pytorch.org/get-started/locally/
# That web site should help you to select the right 'conda install' command to be run in 'Anaconda Pr
ompt'.
# In particular, select the right version of CUDA. Note that prior to installing PyTorch, you should
# install the latest driver for your GPU and CUDA (9.2 or 10.1), assuming your GPU supports it.
# For more information about pytorch refer to
# https://pytorch.org/docs/stable/nn.functional.html
# https://pytorch.org/docs/stable/data.html.
# and https://pytorch.org/docs/stable/torchvision/transforms.html
import torch
import torch.nn.functional as F
from torch import nn
from torch.utils.data import DataLoader
import torchvision.transforms as transforms
import torchvision.transforms.functional as tF

# We provide our own implementation of torchvision.datasets.voc (containing popular "Pascal" dataset)
# that allows us to easily create single-image datasets
from lib.voc import VOCSegmentation

# Note class labels used in Pascal dataset:
# 0:    background,
# 1-20: aeroplane, bicycle, bird, boat, bottle, bus, car, cat, chair, cow, diningtable, dog, horse, m
otorbike,
#       person, pottedplant, sheep, sofa, train, TV_monitor
# 255: "void", which means class for pixel is undefined
```

In [4]:
```
pip install -U numpy>=1.16.0
```

```
Note: you may need to restart the kernel to use updated packages.
```

In [5]:
```
pip install chainercv
```

```
Requirement already satisfied: chainercv in /Users/amber/opt/anaconda3/lib/python3.8/site-packages
(0.13.1)
Requirement already satisfied: chainer>=6.0 in /Users/amber/opt/anaconda3/lib/python3.8/site-package
s (from chainercv) (7.7.0)
Requirement already satisfied: Pillow in /Users/amber/opt/anaconda3/lib/python3.8/site-packages (fro
m chainercv) (7.2.0)
Requirement already satisfied: setuptools in /Users/amber/opt/anaconda3/lib/python3.8/site-packages
(from chainer>=6.0->chainercv) (49.2.0.post20200714)
Requirement already satisfied: numpy>=1.9.0 in /Users/amber/opt/anaconda3/lib/python3.8/site-package
s (from chainer>=6.0->chainercv) (1.20.2)
Requirement already satisfied: protobuf>=3.0.0 in /Users/amber/opt/anaconda3/lib/python3.8/site-pack
ages (from chainer>=6.0->chainercv) (3.15.8)
Requirement already satisfied: six>=1.9.0 in /Users/amber/opt/anaconda3/lib/python3.8/site-packages
(from chainer>=6.0->chainercv) (1.15.0)
Requirement already satisfied: filelock in /Users/amber/opt/anaconda3/lib/python3.8/site-packages (f
rom chainer>=6.0->chainercv) (3.0.12)
Requirement already satisfied: typing-extensions in /Users/amber/opt/anaconda3/lib/python3.8/site-pa
ckages (from chainer>=6.0->chainercv) (3.7.4.2)
Note: you may need to restart the kernel to use updated packages.
```

In [6]:
```python
# ChainerCV is a library similar to TorchVision, created and maintained by Preferred Networks.
# Chainer, the base library, inspired and led to the creation of PyTorch!
# Although Chainer and PyTorch are different, there are some nice functionalities in ChainerCV
# that are useful, so we include it as an excersice on learning other libraries.
# To install ChainerCV, normally it suffices to run "pip install chainercv" inside "Anaconda Prompt".
# For more detailed installation instructions, see https://chainercv.readthedocs.io/en/stable/instal
l.html
# For other information about ChainerCV library, refer to https://chainercv.readthedocs.io/en/stable/
from chainercv.evaluations import eval_semantic_segmentation
from chainercv.datasets import VOCSemanticSegmentationDataset
```

In [233]:
```
# This colorize_mask class takes in a numpy segmentation mask,
#  and then converts it to a PIL Image for visualization.
#  Since by default the numpy matrix contains integers from
#  0,1,...,num_classes, we need to apply some color to this
#  so we can visualize easier! Refer to:
#  https://pillow.readthedocs.io/en/4.1.x/reference/Image.html#PIL.Image.Image.putpalette
palette = [0, 0, 0, 128, 0, 0, 0, 128, 0, 128, 128, 0, 0, 0, 128, 128, 0, 128, 0, 128, 128,
           128, 128, 128, 64, 0, 0, 192, 0, 0, 64, 128, 0, 192, 128, 0, 64, 0, 128, 192, 0, 128,
           64, 128, 128, 192, 128, 128, 0, 64, 0, 128, 64, 0, 0, 192, 0, 128, 192, 0, 0, 64, 128]

def colorize_mask(mask):
    new_mask = Image.fromarray(mask.astype(np.uint8)).convert('P')
    new_mask.putpalette(palette)

    return new_mask
```

In [234]:

```python
# Below we will use a sample image-target pair from VOC training dataset to test your joint transform
s.
# Running this block will automatically download the PASCAL VOC Dataset (3.7GB) to DATASET_PATH if "d
ownload = True".
# The code below creates subdirectory "datasets" in the same location as the notebook file, but
# you can modify DATASET_PATH to download the dataset to any custom directory. Download takes a few m
inutes.
# On subsequent runs you may save time by setting "download = False" (the default value of this flag)

DATASET_PATH = 'datasets'

# Here, we obtain and visualize one sample (img, target) pair from VOC training dataset and one from
 validation dataset.
# Note that operator [...] extracts the sample corresponding to the specified index.
# Also, note the parameter download = True. Set this to False after you download to save time on late
r runs.
sample1 = VOCSegmentation(DATASET_PATH, image_set='train', download = False)[200]
sample2 = VOCSegmentation(DATASET_PATH, image_set='val')[20]

# We demonstrate two different (equivalent) ways to access image and target inside the samples.
img1, target1 = sample1
img2 = sample2[0]
target2 = sample2[1]

fig = plt.figure(figsize=(14,10))
ax1 = fig.add_subplot(2,2,1)
plt.title('sample1 - image')
ax1.imshow(img1)
ax2 = fig.add_subplot(2,2,2)
plt.title('sample1 - target')
ax2.imshow(target1)
ax3 = fig.add_subplot(2,2,3)
plt.title('sample2 - image')
ax3.imshow(img2)
ax4 = fig.add_subplot(2,2,4)
plt.title('sample2 - target')
ax4.imshow(target2)
print(img1.size)
print(type(target1))
```


```
(500, 375)
<class 'PIL.PngImagePlugin.PngImageFile'>
```

Problem 1

Implement a set of "Joint Transform" functions to perform data augmentation in your dataset.

Neural networks are typically applied to transformed images. There are several important reasons for this:

1. The image data should is in certain required format (i.e. consistent spacial resolution to batch). The images should also be normalized and converted to the "tensor" data format expected by pytorch libraries.
2. Some transforms are used to perform randomized image domain transformations with the purpose of "data augmentation".

In this exercise, you will implement a set of different transform functions to do both of these things. Note that unlike classification nets, training semantic segmentation networks requires that some of the transforms are applied to both image and the corresponding "target" (Ground Truth segmentation mask). We refer to such transforms and their compositions as "Joint". In general, your Transform classes should take as the input both the image and the target, and return a tuple of the transformed input image and target. Be sure to use critical thinking to determine if you can apply the same transform function to both the input and the output.

For this problem you may use any of the `torchvision.transforms.functional` functions. For inspiration, refer to:

[https://pytorch.org/tutorials/beginner/data_loading_tutorial.html (https://pytorch.org/tutorials/beginner/data_loading_tutorial.html)](https://pytorch.org/tutorials/beginner/data_loading_tutorial.html)

https://pytorch.org/docs/stable/torchvision/transforms.html#module-torchvision.transforms.functional

Example 1

This class takes a img, target pair, and then transform the pair such that they are in `Torch.Tensor()` format.

Solution:

In [303]:
```
class JointToTensor(object):
    def __call__(self, img, target):
        return tF.to_tensor(img), torch.from_numpy(np.array(target.convert('P'), dtype=np.int32)).long()
```

In [304]:
```python
# Check the transform by passing the image-target sample.

JointToTensor()(*sample1)
```

Out[304]:
```
(tensor([[[0.0431, 0.0510, 0.0353,  ..., 0.3137, 0.3725, 0.3490],
          [0.0196, 0.0431, 0.0235,  ..., 0.3294, 0.3569, 0.3294],
          [0.0392, 0.0510, 0.0471,  ..., 0.3412, 0.3765, 0.3608],
          ...,
          [0.9412, 0.9961, 1.0000,  ..., 0.9647, 0.9686, 0.9725],
          [1.0000, 0.9686, 0.9961,  ..., 0.9608, 0.9647, 0.9686],
          [1.0000, 0.9490, 1.0000,  ..., 0.9725, 0.9725, 0.9843]],

         [[0.0392, 0.0471, 0.0196,  ..., 0.1176, 0.1765, 0.1647],
          [0.0157, 0.0392, 0.0078,  ..., 0.1294, 0.1608, 0.1333],
          [0.0353, 0.0471, 0.0314,  ..., 0.1294, 0.1765, 0.1608],
          ...,
          [0.0157, 0.0667, 0.0706,  ..., 0.6549, 0.6588, 0.6588],
          [0.0784, 0.0431, 0.0667,  ..., 0.6510, 0.6510, 0.6549],
          [0.0745, 0.0235, 0.0784,  ..., 0.6627, 0.6627, 0.6706]],

         [[0.0314, 0.0392, 0.0157,  ..., 0.0118, 0.0706, 0.0549],
          [0.0078, 0.0314, 0.0039,  ..., 0.0235, 0.0549, 0.0275],
          [0.0275, 0.0392, 0.0275,  ..., 0.0275, 0.0706, 0.0549],
          ...,
          [0.0549, 0.0980, 0.0941,  ..., 0.2824, 0.2863, 0.2863],
          [0.1176, 0.0824, 0.0980,  ..., 0.2784, 0.2784, 0.2824],
          [0.1216, 0.0627, 0.1098,  ..., 0.2902, 0.2902, 0.2980]]]),
 tensor([[ 0,  0,  0,  ...,  0,  0,  0],
         [ 0,  0,  0,  ...,  0,  0,  0],
         [ 0,  0,  0,  ...,  0,  0,  0],
         ...,
         [15, 15, 15,  ...,  0,  0,  0],
         [15, 15, 15,  ...,  0,  0,  0],
         [15, 15, 15,  ...,  0,  0,  0]]))
```

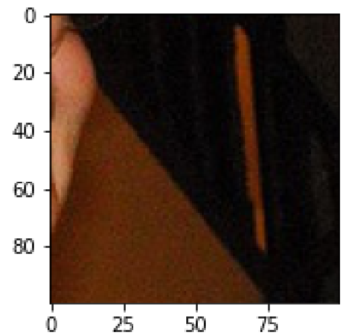
Example 2:

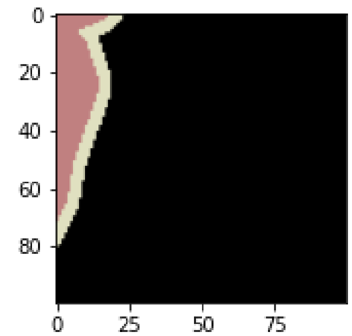
This class implements CenterCrop that takes an img, target pair, and then apply a crop about the center of the image such that the output resolution is $\text{size} \times \text{size}$.

Solution:

In [305]:

```
class JointCenterCrop(object):
    def __init__(self, size):
        """
        params:
            size (int) : size of the center crop
        """
        self.size = size

    def __call__(self, img, target):
        return (tF.five_crop(img, self.size)[4],
                tF.five_crop(target, self.size)[4])

img, target = JointCenterCrop(100)(*sample1)
fig = plt.figure(figsize=(12,6))
ax1 = fig.add_subplot(2,2,1)
ax1.imshow(img)
ax2 = fig.add_subplot(2,2,2)
ax2.imshow(target)
```





Out[305]: <matplotlib.image.AxesImage at 0x7f9010ca8610>

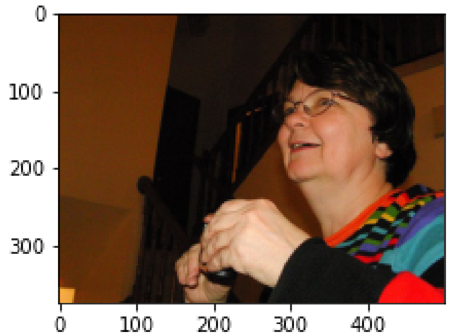
(a) Implement RandomFlip

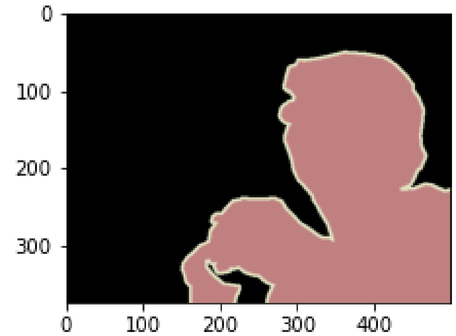
This class should take a img, target pair and then apply a horizontal flip across the vertical axis at random.

Solution:

In [310]:

```
class RandomFlip(object):
    def __call__(self, im, target):
        # we use a random number between 0 and 1 to decide if we should flip
        p = 0.5
        if random.uniform(0, 1) < 0.5:
            return (tF.hflip(im), tF.hflip(target))
        else:
            return (im,target)

# show result
im, target = RandomFlip()(*sample1)
fig = plt.figure(figsize=(12,6))
ax1 = fig.add_subplot(2,2,1)
ax1.imshow(im)
ax2 = fig.add_subplot(2,2,2)
ax2.imshow(target)
```





Out[310]: <matplotlib.image.AxesImage at 0x7f901168f1c0>

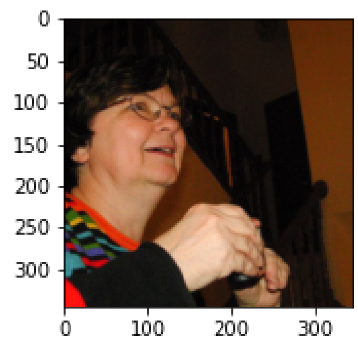
(b) Implement RandomResizeCrop

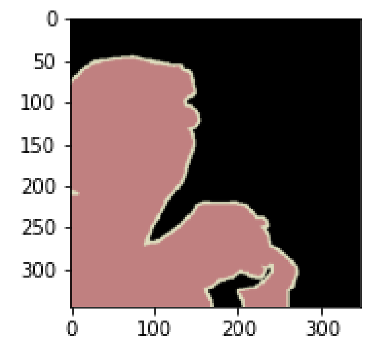
This class should take a img, target pair and then resize the images by a random scale between $[\mathrm{minimum\_scale}, \mathrm{maximum\_scale}]$, crop a random location of the image by $\min(\mathrm{size}, \mathrm{image\_height}, \mathrm{image\_width})$ (where the size is passed in as an integer in the constructor), and then resize to $\mathrm{size} \times \mathrm{size}$ (again, the size passed in). The crop box should fit within the image.

Solution:

In [311]:

```
class RandomResizeCorp(object):
    def __init__(self, minimum_scale, maximum_scale, size):
        self.min_scale = minimum_scale
        self.max_scale = maximum_scale
        self.size = size

    def __call__(self, im, target):
        # use function to get a random scale between self.min_scale and self.max_scale
        scale = np.random.uniform(self.min_scale, self.max_scale)
        # calculate the new size of the im after applying the scale
        new_hight = int(scale * im.size[1])
        new_width = int(scale * im.size[0])
        # resize the image
        im = tF.resize(im, (new_hight, new_width))
        target = tF.resize(target, (new_hight, new_width))
        # calculate the crop_size using min(size,image_height,image_width)
        crop_size = min(self.size, new_width, new_hight)
        # select a random crop location
        # from 0 to width - crop or height - crop(to let crop fit in im)
        crop_y = random.randint(0, new_hight - crop_size)
        crop_x = random.randint(0, new_width - crop_size)
        # tF.resized_crop(img, top, left, height, width, size)
        # note that top is the vertical component, left is the horizontol component
        return (tF.resized_crop(im, crop_y, crop_x, crop_size, crop_size, self.size),
                tF.resized_crop(target, crop_y, crop_x, crop_size, crop_size, self.size))

# show result
im, target = RandomResizeCorp(0.75, 1.5, 345)(*sample1)
fig = plt.figure(figsize=(12,6))
ax1 = fig.add_subplot(2,2,1)
ax1.imshow(im)
ax2 = fig.add_subplot(2,2,2)
ax2.imshow(target)
```





Out[311]: <matplotlib.image.AxesImage at 0x7f901993ff40>

(c) Implement Normalize

This class should take a img, target pair and then normalize the images by subtracting the mean and dividing variance.

Solution:

In [312]:

```
norm = ([0.485, 0.456, 0.406],
        [0.229, 0.224, 0.225])

class JointNormalize(object):
    def __init__(self, mean, variance):
        self.mean = mean
        self.variance = variance

    def __call__(self, tensor, target):
        # normalize the image but do not change the target
        return (tF.normalize(tensor, self.mean, self.variance), target)

# show result
tensor = JointToTensor()(*sample1)
JointNormalize(*norm)(*tensor)
```

```
Out[312]: (tensor([[[-1.9295, -1.8953, -1.9638,  ..., -0.7479, -0.4911, -0.5938],
            [-2.0323, -1.9295, -2.0152,  ..., -0.6794, -0.5596, -0.6794],
            [-1.9467, -1.8953, -1.9124,  ..., -0.6281, -0.4739, -0.5424],
            ...,
            [ 1.9920,  2.2318,  2.2489,  ...,  2.0948,  2.1119,  2.1290],
            [ 2.2489,  2.1119,  2.2318,  ...,  2.0777,  2.0948,  2.1119],
            [ 2.2489,  2.0263,  2.2489,  ...,  2.1290,  2.1290,  2.1804]],

           [[-1.8606, -1.8256, -1.9482,  ..., -1.5105, -1.2479, -1.3004],
            [-1.9657, -1.8606, -2.0007,  ..., -1.4580, -1.3179, -1.4405],
            [-1.8782, -1.8256, -1.8957,  ..., -1.4580, -1.2479, -1.3179],
            ...,
            [-1.9657, -1.7381, -1.7206,  ...,  0.8880,  0.9055,  0.9055],
            [-1.6856, -1.8431, -1.7381,  ...,  0.8704,  0.8704,  0.8880],
            [-1.7031, -1.9307, -1.6856,  ...,  0.9230,  0.9230,  0.9580]],

           [[-1.6650, -1.6302, -1.7347,  ..., -1.7522, -1.4907, -1.5604],
            [-1.7696, -1.6650, -1.7870,  ..., -1.6999, -1.5604, -1.6824],
            [-1.6824, -1.6302, -1.6824,  ..., -1.6824, -1.4907, -1.5604],
            ...,
            [-1.5604, -1.3687, -1.3861,  ..., -0.5495, -0.5321, -0.5321],
            [-1.2816, -1.4384, -1.3687,  ..., -0.5670, -0.5670, -0.5495],
            [-1.2641, -1.5256, -1.3164,  ..., -0.5147, -0.5147, -0.4798]]]),
 tensor([[ 0,  0,  0,  ...,  0,  0,  0],
         [ 0,  0,  0,  ...,  0,  0,  0],
         [ 0,  0,  0,  ...,  0,  0,  0],
         ...,
         [15, 15, 15,  ...,  0,  0,  0],
         [15, 15, 15,  ...,  0,  0,  0],
         [15, 15, 15,  ...,  0,  0,  0]]))
```

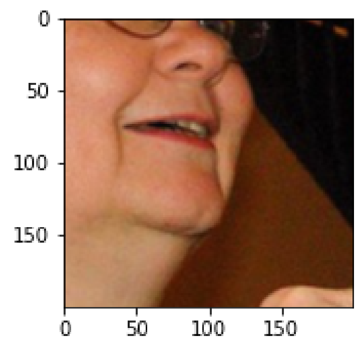
(d) Compose the transforms together:

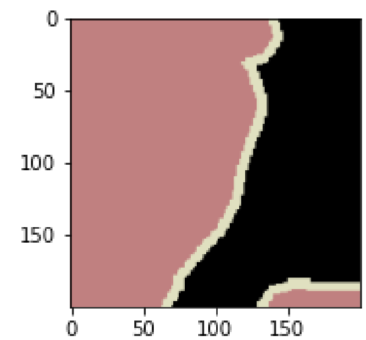
Use `JointCompose` (fully implemeted below) to compose the implemented transforms together in some random order. Verify the output makes sense and visualize it.

In [313]:
```
# This class composes transofrmations from a given list of image transforms (expected in the argumen
t). Such compositions
# will be applied to the dataset during training. This cell is fully implemented.

class JointCompose(object):
    def __init__(self, transforms):
        """
        params:
           transforms (list) : list of transforms
        """
        self.transforms = transforms

    # We override the __call__ function such that this class can be
    # called as a function i.e. JointCompose(transforms)(img, target)
    # Such classes are known as "functors"
    def __call__(self, img, target):
        """
        params:
            img (PIL.Image)    : input image
            target (PIL.Image) : ground truth label
        """
        assert img.size == target.size
        for t in self.transforms:
            img, target = t(img, target)
        return img, target
```

In [316]:

```
# Student Answer:
# First example use JointCenterCrop and RandomResizeCorp
# in this example, the image should not flip
trans1 = [RandomResizeCorp(0.75, 1.5, 600), JointCenterCrop(200)]
im01, target01 = JointCompose(trans1)(*sample1)
fig = plt.figure(figsize=(12,6))
ax1 = fig.add_subplot(2,2,1)
ax1.imshow(im01)
ax2 = fig.add_subplot(2,2,2)
ax2.imshow(target01)

# Second example: use RandomResizeCorp and RandomFlip
trans2 = [RandomResizeCorp(0.75, 1.5, 345), RandomFlip()]
im02, target02 = JointCompose(trans2)(*sample1)
fig = plt.figure(figsize=(12,6))
ax1 = fig.add_subplot(2,2,1)
ax1.imshow(im02)
ax2 = fig.add_subplot(2,2,2)
ax2.imshow(target02)
```


0
50
100
150
0
50
100
150


0
50
100
150
0
50
100
150


```
Out[316]: <matplotlib.image.AxesImage at 0x7f901f67afa0>
```

(e) Compose the transforms together: use `JointCompose` to compose the implemented transforms for:

1. A sanity dataset that will contain 1 single image. Your objective is to overfit on this 1 image, so choose your transforms and parameters accordingly.

2. A training dataset that will contain the training images. The goal here is to generalize to the validation set, which is unseen.

3. A validation dataset that will contain the validation images. The goal here is to measure the 'true' performance.

In [317]:

```
# Student Answer:

# since we overfit the image, we simply transfer it to tensor and then nomalize it
sanity_joint_transform = JointCompose([JointToTensor(),
                                       JointNormalize(*norm)])

# we need to resize the image, crop it and then transform it to tensor
# and finally normalize it
# makesure we make all training image have the same size
train_joint_transform =  JointCompose([ RandomResizeCorp(0.8, 1.2, 300),
                                       JointToTensor(),
                                       JointNormalize(*norm)])

val_joint_transform = JointCompose([JointToTensor(),
                                    JointNormalize(*norm)])
```

This code below will then apply `train_joint_transform` to the entire dataset.

In [318]:

```
# Apply the Joint-Compose transformations above to create three datasets and the
# corresponding Data-Loaders.
# This cell is fully implemented.

# This single image data(sub)set can help to better understand and to debug the network training proc
ess.
# Optional integer parameter 'sanity_check' specifies the index of the image-target pair and creates
 a single image dataset.
# Note that we use the same image (index=200) as used for sample1.
sanity_data = VOCSegmentation(
    DATASET_PATH,
    image_set = 'train',
    transforms = sanity_joint_transform,
    sanity_check = 200
)

# This is a standard VOC data(sub)set used for training semantic segmentation networks
train_data = VOCSegmentation(
    DATASET_PATH,
    image_set = 'train',
    transforms = train_joint_transform
)

# This is a standard VOC data(sub)set used for validating semantic segmentation networks
val_data = VOCSegmentation(
    DATASET_PATH,
    image_set='val',
    transforms = val_joint_transform
)

# Increase TRAIN_BATCH_SIZE if you are using GPU to speed up training.
# When batch size changes, the learning rate may also need to be adjusted.
# Note that batch size maybe limited by your GPU memory, so adjust if you get "run out of GPU memory"
error.
TRAIN_BATCH_SIZE = 4

# If you are NOT using Windows, set NUM_WORKERS to anything you want, e.g. NUM_WORKERS = 4,
# but Windows has issues with multi-process dataloaders, so NUM_WORKERS must be 0 for Windows.
NUM_WORKERS = 0

sanity_loader = DataLoader(sanity_data, batch_size=1, num_workers=NUM_WORKERS, shuffle=False)
train_loader = DataLoader(train_data, batch_size=TRAIN_BATCH_SIZE, num_workers=NUM_WORKERS, shuffle=T
```

```
rue)
val_loader = DataLoader(val_data, batch_size=1, num_workers=NUM_WORKERS, shuffle=False)
```

Problem 2

(a) Implement encoder/decoder segmentation CNN using PyTorch.

You must follow the general network architecture specified in the image below. Note that since convolutional layers are the main building blocks in common network architectures for image analysis, the corresponding blocks are typically unlabeled in the network diagrams. The network should have 5 (pre-trained) convolutional layers (residual blocks) from "resnet" in the encoder part, two upsampling layers, and one skip connection. For the layer before the final upsampling layer, lightly experiment with some combination of Conv, ReLU, BatchNorm, and/or other layers to see how it affects performance.

You should choose specific parameters for all layers, but the overall structure should be restricted to what is shown in the illustration above. For inspiration, you can refer to papers in the citation section of the following link to DeepLab (e.g. specific parameters for each layer): [http://liangchiehchen.com/projects/DeepLab.html (http://liangchiehchen.com/projects/DeepLab.html)](http://liangchiehchen.com/projects/DeepLab.html). The first two papers in the citation section are particularly relevant.

In your implementation, you can use a base model of choice (you can use `torchvision.models` as a starting point), but we suggest that you learn the properties of each base model and choose one according to the computational resources available to you.

Note: do not apply any post-processing (such as DenseCRF) to the output of your net.

Solution:

In [319]:

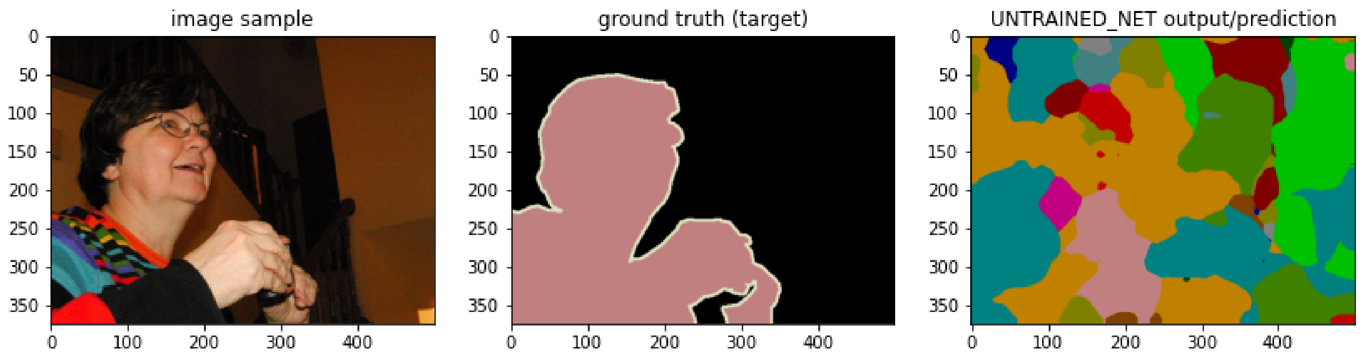
```
import torchvision.models as models

class MyNet(nn.Module):
    def __init__(self, num_classes, criterion=None):
        super(MyNet, self).__init__()
        self.num_class = num_classes
        self.criterion = criterion
        # we use ResNet34 for our model
        # ResNet-34 model from “Deep Residual Learning for Image Recognition”.
        self.used_net = models.resnet34(pretrained=True,progress=True)
        # torch.nn.Conv2d(in_channels, out_channels, kernel_size,stride=1)
        # some cov and bn layers
        # conv layers
        # kernel size is 7*7, stride is 3
        # note: 576 is 512(size of resnet34) + 64(size after applying layers in resnet34)
        # we use 576 since we need to apply concat
        self.conv1 = nn.Conv2d(576, 250, 7, stride=3,dilation=1)
        #self.conv1 = nn.Conv2d(512, 250, 7, stride=3,dilation=1)
        self.conv2 = nn.Conv2d(250, self.num_class, 1, stride=1,dilation=1)
        # Normalization Layer
        self.bn2d = nn.BatchNorm2d(250)

    # note both upsampling, we use bilinear mode
    def forward(self, inp, gts=None):
        original_shape = inp.shape
        # use the resnet
        inp = self.used_net.conv1(inp)
        inp = self.used_net.bn1(inp)
        inp = self.used_net.relu(inp)
        inp = self.used_net.maxpool(inp)
        # get the copy of inp(used later in concatention)
        original_inp = inp;
        # get the shape of inp before applying layers (used in the first upsampling)
        inp_shape = inp.shape
        # use the layers of used_net
        inp = self.used_net.layer1(inp)
        inp = self.used_net.layer2(inp)
        inp = self.used_net.layer3(inp)
        inp = self.used_net.layer4(inp)
        # do the first upsampling
        # upsample so that we can apply concatention
        upsample1 = nn.UpsamplingBilinear2d((inp_shape[2],inp_shape[3]))
```

```
        inp = upsample1(inp)
        # do concatention
        inp = torch.cat((original_inp,inp),1)
        # applying some layers of conv, relu and bn
        inp = self.conv1(inp)
        inp = F.relu(inp)
        inp = self.bn2d(inp)
        inp = self.conv2(inp)
        inp = F.relu(inp)
        # upsample for decoder using bininear interpolation
        # this time, we upsample to the original size
        inp = F.interpolate(inp, size = (original_shape[2], original_shape[3]),
                            mode = 'bilinear')
        # update the final result
        lfinal = inp
        # the given code (donot modify)
        if self.training:
            # Return the loss if in training mode
            return self.criterion(lfinal, gts)
        else:
            # Return the actual prediction otherwise
            return lfinal
```

(b) Create UNTRAINED_NET and run on a sample image

In [320]:

```
untrained_net = MyNet(21).eval()
sample_img, sample_target = JointNormalize(*norm)(*JointToTensor()(*sample1))
untrained_output = untrained_net.forward(sample_img[None])

fig = plt.figure(figsize=(14,10))
ax = fig.add_subplot(1,3,1)
plt.title('image sample')
ax.imshow(sample1[0])
ax = fig.add_subplot(1,3,2)
plt.title('ground truth (target)')
ax.imshow(sample1[1])
ax = fig.add_subplot(1,3,3)
plt.title('UNTRAINED_NET output/prediction')
ax.imshow(colorize_mask(torch.argmax(untrained_output, dim=1).numpy()[0]))
```



Out[320]: <matplotlib.image.AxesImage at 0x7f9021c5f250>

Problem 3

(a) Implement the loss function (Cross Entropy Loss). Do not use already implemented versions of this loss function.

Feel free to use functions like `F.log softmax` and `F.nll loss` (if you want to, or you can just implement the math).

In [321]:
```
# Student Answer:
class MyCrossEntropyLoss():
    def __init__(self, ignore_index):
        self.ignore_index = ignore_index

    def __call__(self, untrained_output, sample_target):
        # F.log_softmax(input, dim=None, _stacklevel=3, dtype=None)
        # F.nll_loss(input, target, weight=None, size_average=None,
        #            ignore_index=-100, reduce=None, reduction='mean')
        softmax = F.log_softmax(untrained_output, dim = 1)
        return F.nll_loss(softmax, sample_target, ignore_index = self.ignore_index)
```

(b) Compare against the existing CrossEntropyLoss function on your sample output from your neural network.

In [322]:
```
criterion = nn.CrossEntropyLoss(ignore_index=255)

print(criterion(untrained_output, sample_target[None]))

my_criterion = MyCrossEntropyLoss(ignore_index=255)

print(my_criterion(untrained_output, sample_target[None]))
```

```
tensor(3.0670, grad_fn=<NllLoss2DBackward>)
tensor(3.0670, grad_fn=<NllLoss2DBackward>)
```

Problem 4

(a) Use standard function `eval_semantic_segmentation` (already imported from chainerCV) to compute "mean intersection over union" for the output of UNTRAINED_NET on sample1 (`untrained_output`) using the target for sample1. Read documentations for function `eval_semantic_segmentation` to properly set its input parameters.

In [323]:

```
# Write code to propely compute 'pred' and 'gts' as arguments for function 'eval_semantic_segemntatio
n'
# note that at the begining we define img1, target1 = sample1
#img1, target1 = sample1

print(untrained_output.shape)
# Note class labels used in Pascal dataset:
# 0:    background,
# 1-20: aeroplane, bicycle, bird, boat, bottle, bus, car, cat, chair, cow,
#       diningtable, dog, horse, motorbike,
#       person, pottedplant, sheep, sofa, train, TV_monitor
# 255: "void", which means class for pixel is undefined
labels = {
    0: 'background',
    1: 'aeroplane',
    2: 'bicycle',
    3: 'bird',
    4: 'boat',
    5: 'bottle',
    6: 'bus',
    7: 'cat',
    8: 'car',
    9: 'chair',
    10: 'cow',
    11: 'diningtable',
    12: 'dog',
    13: 'horse',
    14: 'motorbike',
    15: 'person',
    16: 'pottedplant',
    17: 'sheep',
    18: 'sofa',
    19: 'train',
    20: 'TV_monitor',
    255: "void"
}

# calculate the predict labels and gt labels
# 1. predict labels
pred = torch.argmax(untrained_output, dim=1).numpy()[0]

# 2. gt labels
```

```
# calculate the same in Q5(c)
gts = torch.from_numpy(np.array(sample1[1].convert('P'), dtype=np.int32)).long().numpy()
gts[gts == 255] = -1
conf = eval_semantic_segmentation(pred[None], gts[None])

print("mIoU for the sample image / ground truth pair: {}".format(conf['miou']))
```

```
torch.Size([1, 21, 375, 500])
mIoU for the sample image / ground truth pair: 0.009401026708788052
```

(b) Write the validation loop.

In [324]:
```
def validate(val_loader, net):

    iou_arr = []
    net.eval()
    val_loss = 0

    with torch.no_grad():
        for i, data in enumerate(val_loader):

            inputs, masks = data

            if USE_GPU:
                # use GPU
                inputs = inputs.cuda()
                masks = masks.cuda()
                net = net.cuda()
            else:
                # use CPU
                inputs = inputs.cpu()
                masks = masks.cpu()
                net = net.cpu()


            # Write me
            # same as in Classification_Notebook_CS484_UW.ipynb
            output = net(inputs)
            val_loss += MyCrossEntropyLoss(ignore_index=255)(output,masks)
            preds = torch.argmax(output, dim = 1).numpy()
            gts = torch.from_numpy(np.array(masks, dtype = np.int32)).long().numpy()
            gts[gts == 255] = -1

            # Hint: make sure the range of values of the ground truth is what you expect

            conf = eval_semantic_segmentation(preds, gts)

            iou_arr.append(conf['miou'])

    return val_loss, (sum(iou_arr) / len(iou_arr))
```

(c) Run the validation loop for UNTRAINED_NET against the sanity validation dataset.

In [325]:
```
%%time
print("mIoU over the sanity dataset:{}".format(validate(sanity_loader, untrained_net)[1]))
```

```
mIoU over the sanity dataset:0.009401026708788052
CPU times: user 1.08 s, sys: 122 ms, total: 1.21 s
Wall time: 1.1 s
```

Problem 5

(a) Define an optimizer to train the given loss function.

Feel free to choose your optimizer of choice from [https://pytorch.org/docs/stable/optim.html (https://pytorch.org/docs/stable/optim.html)](https://pytorch.org/docs/stable/optim.html).

In [326]:
```
def get_optimizer(net):
    # use the sampe optimizer as in Classification_Notebook_CS484_UW.ipynb
    optimizer = torch.optim.SGD(net.parameters(),
                                lr=0.001,
                                weight_decay=1e-5,
                                momentum=0.5,
                                nesterov=False)
    return optimizer
```

(b) Write the training loop to train the network.

In [327]:
```
def train(train_loader, net, optimizer, loss_graph):

    for i, data in enumerate(train_loader):

        inputs, masks = data

        if USE_GPU:
            inputs = inputs.cuda()
            net = net.cuda()
            mask = mask.cuda()

        # Write me
        # same as in Classification_Notebook_CS484_UW.ipynb
        optimizer.zero_grad()
        main_loss = net(inputs, gts=masks)
        loss_graph.append(main_loss.item())
        main_loss.backward()
        optimizer.step()

        # loss_graph.append() Populate this list to graph the loss

    return main_loss
```

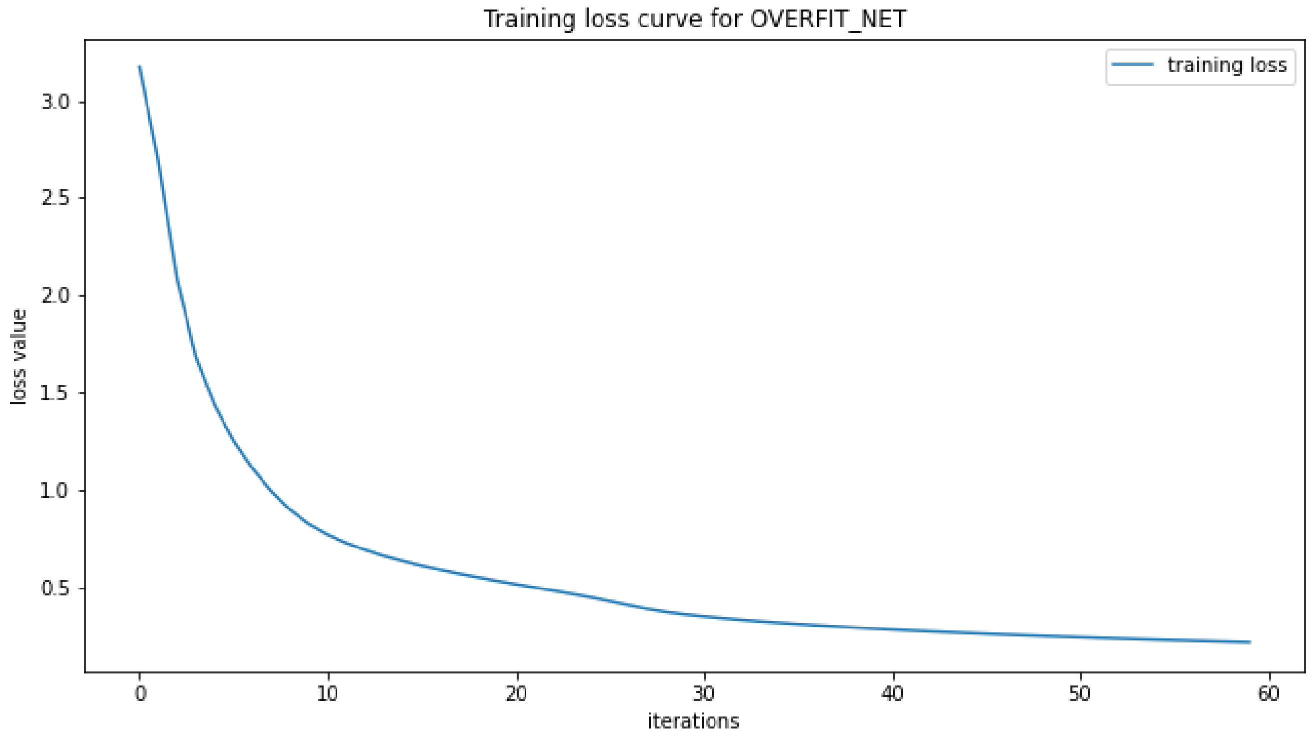
(c) Create OVERFIT_NET and train it on the single image dataset.

Single image training is helpful for debugging and hyper-parameter tuning (e.g. learning rate, etc.) as it is fast even on a single CPU. In particular, you can work with a single image until your loss function is consistently decreasing during training loop and the network starts producing a reasonable output for this training image. Training on a single image also teaches about overfitting, particualrly when comparing it with more thorough forms of network training.

In [328]:
```
%%time
%matplotlib notebook

# The whole training on a single image (20-40 epochs) should take only a minute or two on a CPU (and
 a few seconds on GPU).
# Below we create a (deep) copy of untrained_net and train it on a single training image (leading to
 gross overfitting).
# Later, we will create a separate (deep) copy of untrained_net to be trained on full training datase
t.
# NOTE: Normally, one can create a new net via declaration new_net = MyNet(21). But, randomization of
weights when new nets
# are declared that way creates *different* untrained nets. This notebook compares different versions
of network training.
# For this comparison to be direct and fair, it is better to train (deep) copies of the exact same un
trained_net.
overfit_net = copy.deepcopy(untrained_net)

# set loss function for the net
overfit_net.criterion = nn.CrossEntropyLoss(ignore_index=255)

# You can change the number of EPOCHS
EPOCH = 60

# switch to train mode (original untrained_net was set to eval mode)
overfit_net.train()

optimizer = get_optimizer(overfit_net)

print("Starting Training...")

loss_graph = []

fig = plt.figure(figsize=(12,6))
plt.subplots_adjust(bottom=0.2,right=0.85,top=0.95)
ax = fig.add_subplot(1,1,1)

for e in range(EPOCH):
    loss = train(sanity_loader, overfit_net, optimizer, loss_graph)
    ax.clear()
    ax.set_xlabel('iterations')
    ax.set_ylabel('loss value')
    ax.set_title('Training loss curve for OVERFIT_NET')
```

```
    ax.plot(loss_graph, label='training loss')
    ax.legend(loc='upper right')
    fig.canvas.draw()
    print("Epoch: {} Loss: {}".format(e, loss))

%matplotlib inline
```

```
Starting Training...
```



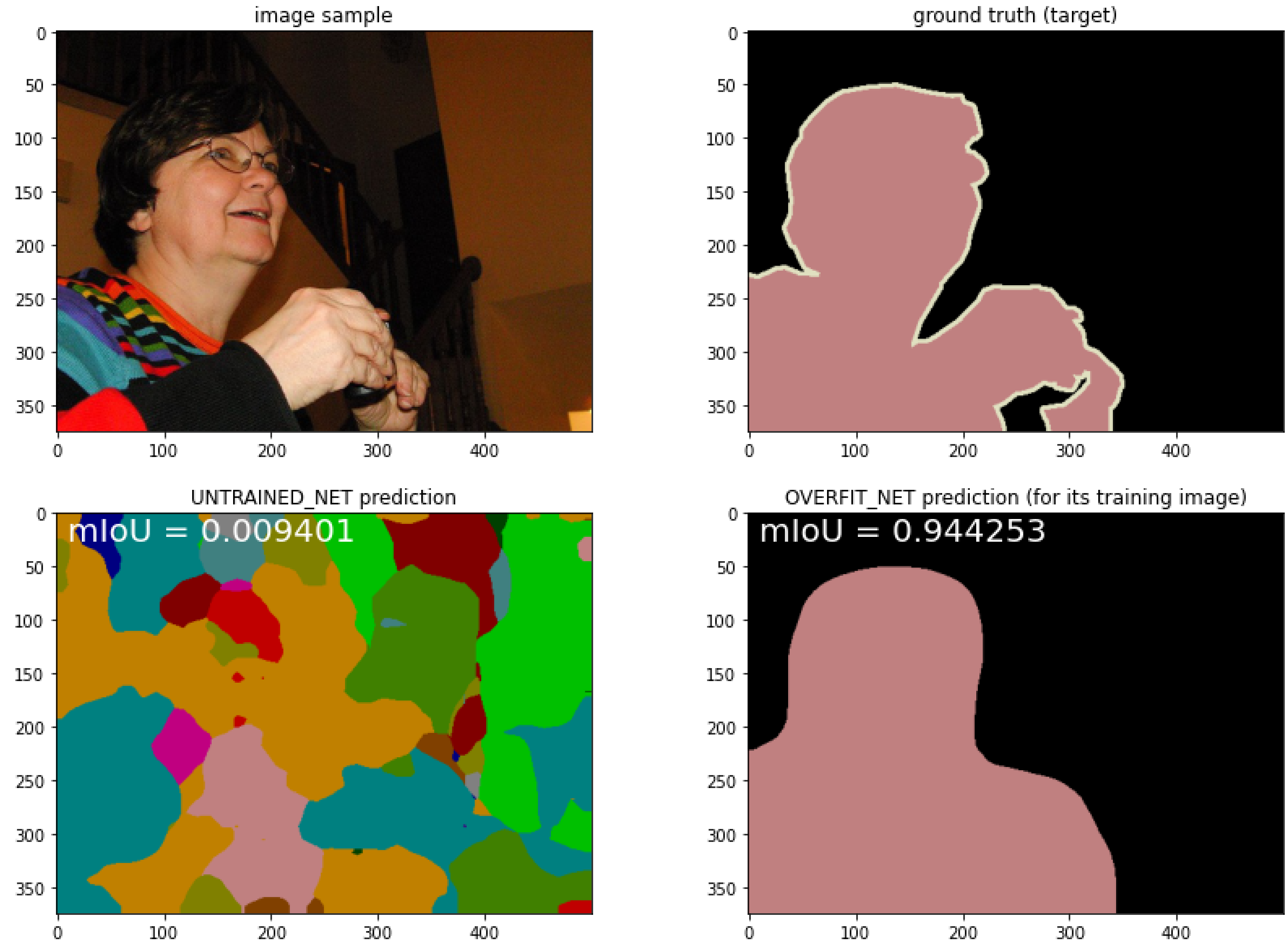
```
Epoch: 0 Loss: 3.1733756065368652
Epoch: 1 Loss: 2.6907355785369873
Epoch: 2 Loss: 2.0817627906799316
Epoch: 3 Loss: 1.6824922561645508
Epoch: 4 Loss: 1.4351547956466675
Epoch: 5 Loss: 1.2521353960037231
Epoch: 6 Loss: 1.1106537580490112
Epoch: 7 Loss: 0.9932776689529419
Epoch: 8 Loss: 0.8978433012962341
Epoch: 9 Loss: 0.8248823285102844
Epoch: 10 Loss: 0.769737184047699
Epoch: 11 Loss: 0.7267917394638062
Epoch: 12 Loss: 0.6909821629524231
Epoch: 13 Loss: 0.6608249545097351
Epoch: 14 Loss: 0.6344200968742371
Epoch: 15 Loss: 0.6107886433601379
Epoch: 16 Loss: 0.589042067527771
Epoch: 17 Loss: 0.5689800977706909
Epoch: 18 Loss: 0.5502417683601379
Epoch: 19 Loss: 0.5321215391159058
Epoch: 20 Loss: 0.5151316523551941
Epoch: 21 Loss: 0.4989590644836426
Epoch: 22 Loss: 0.4823892116546631
Epoch: 23 Loss: 0.46586501598358154
Epoch: 24 Loss: 0.44832929968833923
Epoch: 25 Loss: 0.4290023148059845
Epoch: 26 Loss: 0.40822023153305054
Epoch: 27 Loss: 0.38912713527679443
Epoch: 28 Loss: 0.37254148721694946
Epoch: 29 Loss: 0.36018481850624084
Epoch: 30 Loss: 0.3498188257217407
Epoch: 31 Loss: 0.34047365188598633
Epoch: 32 Loss: 0.3319617509841919
Epoch: 33 Loss: 0.32418569922447205
Epoch: 34 Loss: 0.31704211235046387
Epoch: 35 Loss: 0.3103388249874115
Epoch: 36 Loss: 0.3040645122528076
Epoch: 37 Loss: 0.2981868088245392
Epoch: 38 Loss: 0.29262739419937134
Epoch: 39 Loss: 0.2873102128505707
Epoch: 40 Loss: 0.28230491280555725
Epoch: 41 Loss: 0.2775735557079315
Epoch: 42 Loss: 0.27311018109321594
```

```
Epoch: 43 Loss: 0.2688719928264618
Epoch: 44 Loss: 0.26479098200798035
Epoch: 45 Loss: 0.2608250081539154
Epoch: 46 Loss: 0.2569998502731323
Epoch: 47 Loss: 0.25335195660591125
Epoch: 48 Loss: 0.24979938566684723
Epoch: 49 Loss: 0.24638037383556366
Epoch: 50 Loss: 0.24310088157653809
Epoch: 51 Loss: 0.23995885252952576
Epoch: 52 Loss: 0.23689556121826172
Epoch: 53 Loss: 0.23388046026229858
Epoch: 54 Loss: 0.2309613674879074
Epoch: 55 Loss: 0.228174090385437
Epoch: 56 Loss: 0.22547639906406403
Epoch: 57 Loss: 0.22288623452186584
Epoch: 58 Loss: 0.22036488354206085
Epoch: 59 Loss: 0.2178536057472229
CPU times: user 3min 39s, sys: 21.4 s, total: 4min
Wall time: 3min 40s
```

Qualitative and quantitative evaluation of predictions (untrained vs overfit nets) - fully implemented.

In [329]:
```python
# switch back to evaluation mode
overfit_net.eval()

sample_img, sample_target = JointNormalize(*norm)(*JointToTensor()(*sample1))
if USE_GPU:
    sample_img = sample_img.cuda()
sample_output_O = overfit_net.forward(sample_img[None])
sample_output_U = untrained_net.forward(sample_img[None])

# computing mIOU (quantitative measure of accuracy for network predictions)
if USE_GPU:
    pred_O = torch.argmax(sample_output_O, dim=1).cpu().numpy()[0]
    pred_U = torch.argmax(sample_output_U, dim=1).cpu().numpy()[0]
else:
    pred_O = torch.argmax(sample_output_O, dim=1).numpy()[0]
    pred_U = torch.argmax(sample_output_U, dim=1).numpy()[0]

gts = torch.from_numpy(np.array(sample1[1].convert('P'), dtype=np.int32)).long().numpy()
gts[gts == 255] = -1
conf_O = eval_semantic_segmentation(pred_O[None], gts[None])
conf_U = eval_semantic_segmentation(pred_U[None], gts[None])


fig = plt.figure(figsize=(14,10))
ax1 = fig.add_subplot(2,2,1)
plt.title('image sample')
ax1.imshow(sample1[0])
ax2 = fig.add_subplot(2,2,2)
plt.title('ground truth (target)')
ax2.imshow(sample1[1])
ax3 = fig.add_subplot(2,2,3)
plt.title('UNTRAINED_NET prediction')
ax3.text(10, 25, 'mIoU = {:_>8.6f}'.format(conf_U['miou']), fontsize=20, color='white')
ax3.imshow(colorize_mask(torch.argmax(sample_output_U, dim=1).cpu().numpy()[0]))
ax4 = fig.add_subplot(2,2,4)
plt.title('OVERFIT_NET prediction (for its training image)')
ax4.text(10, 25, 'mIoU = {:_>8.6f}'.format(conf_O['miou']), fontsize=20, color='white')
ax4.imshow(colorize_mask(torch.argmax(sample_output_O, dim=1).cpu().numpy()[0]))
```

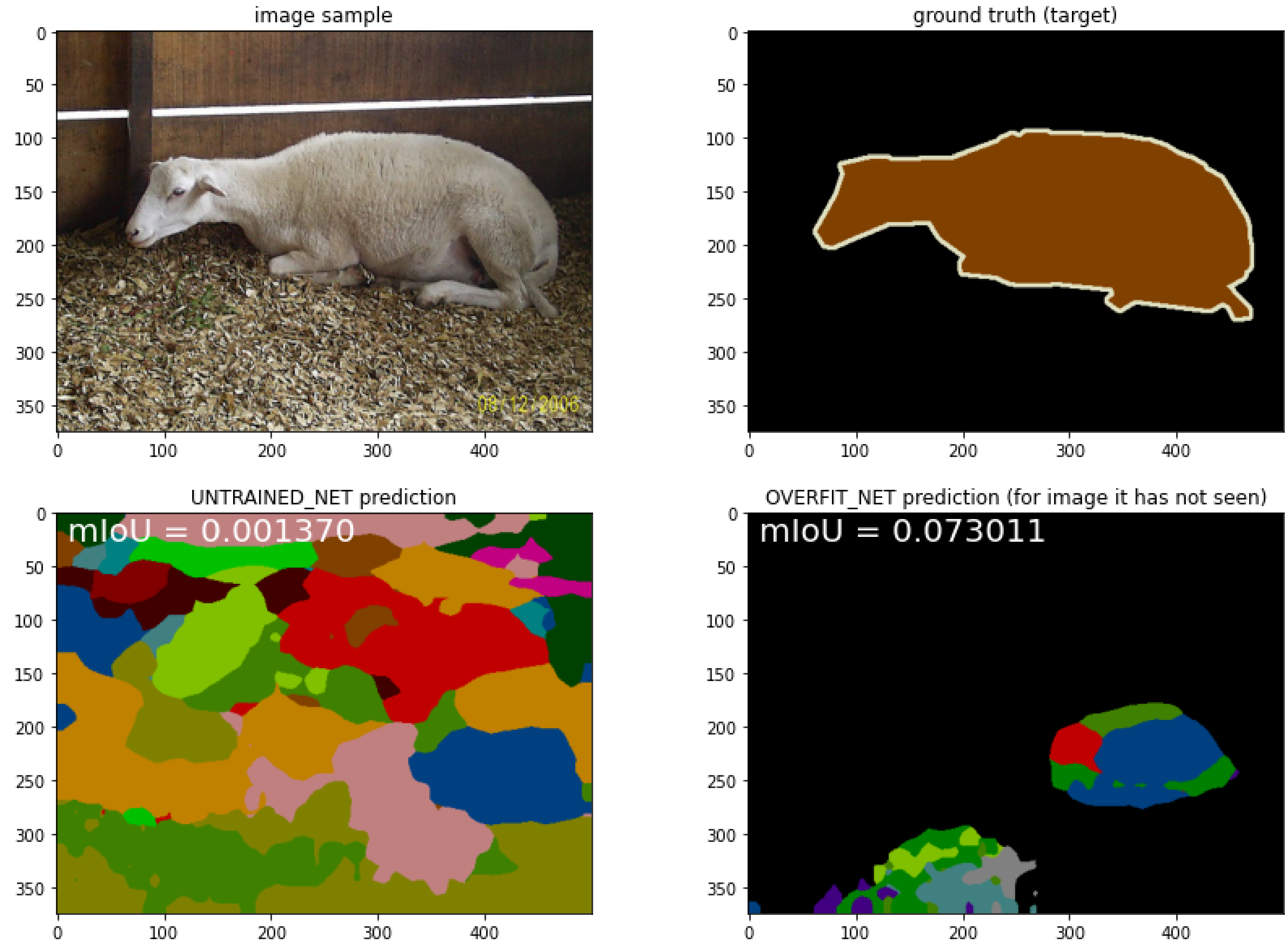
```
Out[329]: <matplotlib.image.AxesImage at 0x7f901d6ccdf0>
```



In [330]:

```python
sample_img, sample_target = JointNormalize(*norm)(*JointToTensor()(*sample2))
if USE_GPU:
    sample_img = sample_img.cuda()
sample_output_O = overfit_net.forward(sample_img[None])
sample_output_U = untrained_net.forward(sample_img[None])

# computing mIOU (quantitative measure of accuracy for network predictions)
if USE_GPU:
    pred_O = torch.argmax(sample_output_O, dim=1).cpu().numpy()[0]
    pred_U = torch.argmax(sample_output_U, dim=1).cpu().numpy()[0]
else:
    pred_O = torch.argmax(sample_output_O, dim=1).numpy()[0]
    pred_U = torch.argmax(sample_output_U, dim=1).numpy()[0]

gts = torch.from_numpy(np.array(sample2[1].convert('P'), dtype=np.int32)).long().numpy()
gts[gts == 255] = -1
conf_O = eval_semantic_segmentation(pred_O[None], gts[None])
conf_U = eval_semantic_segmentation(pred_U[None], gts[None])

fig = plt.figure(figsize=(14,10))
ax1 = fig.add_subplot(2,2,1)
plt.title('image sample')
ax1.imshow(sample2[0])
ax2 = fig.add_subplot(2,2,2)
plt.title('ground truth (target)')
ax2.imshow(sample2[1])
ax3 = fig.add_subplot(2,2,3)
plt.title('UNTRAINED_NET prediction')
ax3.text(10, 25, 'mIoU = {:_>8.6f}'.format(conf_U['miou']), fontsize=20, color='white')
ax3.imshow(colorize_mask(torch.argmax(sample_output_U, dim=1).cpu().numpy()[0]))
ax4 = fig.add_subplot(2,2,4)
plt.title('OVERFIT_NET prediction (for image it has not seen)')
ax4.text(10, 25, 'mIoU = {:_>8.6f}'.format(conf_O['miou']), fontsize=20, color='white')
ax4.imshow(colorize_mask(torch.argmax(sample_output_O, dim=1).cpu().numpy()[0]))
```

```
Out[330]: <matplotlib.image.AxesImage at 0x7f9018eb2be0>
```



Run the validation loop for OVERFIT_NET against the sanity dataset (an image it was trained on) - fully implemented

In [331]:
```
%%time
print("mIoU for OVERFIT_NET over its training image:{}".format(validate(sanity_loader, overfit_net)[1
]))
```

```
mIoU for OVERFIT_NET over its training image:0.9442527581761997
CPU times: user 1.26 s, sys: 156 ms, total: 1.42 s
Wall time: 1.68 s
```

WARNING: For the remaining part of the assignment (below) it is advisable to switch to GPU mode as running each validation and training loop on the whole training set takes over an hour on CPU (there are several such loops below). Note that GPU mode is helpful only if you have a sufficiently good NVIDIA gpu (not older than 2-3 years) and cuda installed on your computer. If you do not have a sufficiently good graphics card available, you can still finish the remaining part in CPU mode (takes a few hours), as the cells below are mostly implemented and test your code written and debugged in the earlier parts above. You can also switch to Google Colaboratory to run the remaining parts below.

You can use validation-data experiments below to tune your hyper-parameters. Normally, validation data is used exactly for this purpose. For actual competitions, testing data is not public and you can not tune hyper-parameters on in.

(d) Evaluate UNTRAINED_NET and OVERFIT_NET on validation dataset.

Run the validation loop for UNTRAINED_NET against the validation dataset:

In [332]:
```
%%time
# This will be slow on CPU (around 1 hour or more). On GPU it should take only a few minutes (dependi
ng on your GPU).
print("mIoU for UNTRAINED_NET over the entire dataset:{}".format(validate(val_loader, untrained_net)[
1]))
```

```
mIoU for UNTRAINED_NET over the entire dataset:0.0027920566160010477
CPU times: user 25min 30s, sys: 3min, total: 28min 31s
Wall time: 26min 54s
```

Run the validation loop for OVERFIT_NET against the validation dataset (it has not seen):

In [333]:
```
%%time
# This will be slow on CPU (around 1 hour or more). On GPU it should take only a few minutes (dependi
ng on your GPU).
print("mIoU for OVERFIT_NET over the validation dataset:{}".format(validate(val_loader, overfit_net)[
1]))
```

```
mIoU for OVERFIT_NET over the validation dataset:0.08192394698794468
CPU times: user 24min 47s, sys: 2min 51s, total: 27min 38s
Wall time: 25min 13s
```

(e) Explain in a few sentences the quantitative results observed in (c) and (d):

Student answer:\ Part(C):\ For untrained net, since we do not train the net, the mIoU for both image1 and image2 are very low\ For overfit net, since we train this net completely on image1, we can notice that the mIoU for image one fits very well. Also, since we train this net on image1, the mIoU for image2 does not fit well

Part(D):\ For untrained net, since we do not do any training, the mIoU over entire dataset is very low.\ For overfit net, since we only train it on image1, it only fit well on image one. This lead to the result that the mIoU for overfit net cannot behave well on the data it has not seen.

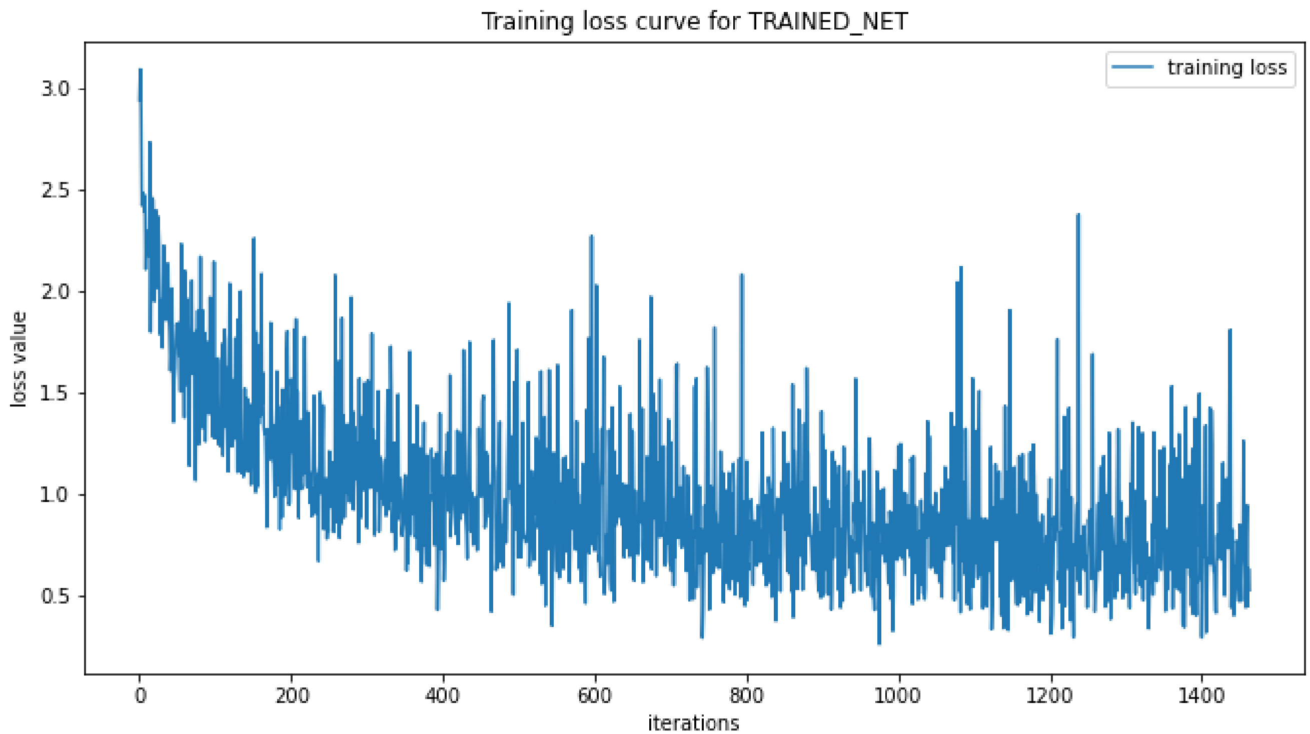
(f) Create TRAINED_NET and train it on the full training dataset:

In [334]:

```
%%time
%matplotlib notebook

# This training will be very slow on a CPU (>1hour per epoch). Ideally, this should be run in GPU mod
e (USE_GPU=True)
# taking only a few minutes per epoch (depending on your GPU and batch size). Thus, before proceeding
with this excercise,
# it is highly advisable that you first finish debugging your net code. In particular, make sure that
OVERFIT_NET behaves
# reasonably, e.g. its loss monotonically decreases during training and its output is OK (for the ima
ge it was trained on).
# Below we create another (deep) copy of untrained_net. Unlike OVERFIT_NET it will be trained on a fu
ll training dataset.
trained_net = copy.deepcopy(untrained_net)

# set loss function for the net
trained_net.criterion = nn.CrossEntropyLoss(ignore_index=255)


# You can change the number of EPOCHS below. Since each epoch for TRAINED_NET iterates over all train
ing dataset images,
# the number of required epochs could be smaller compared to OFERFIT_NET where each epoch iterates ov
er one-image-dataset)
EPOCH = 4

# switch to train mode (original untrained_net was set to eval mode)
trained_net.train()

optimizer = get_optimizer(trained_net)

print("Starting Training...")

loss_graph = []

fig = plt.figure(figsize=(12,6))
plt.subplots_adjust(bottom=0.2,right=0.85,top=0.95)
ax = fig.add_subplot(1,1,1)

for e in range(EPOCH):
    loss = train(train_loader, trained_net, optimizer, loss_graph)
    ax.clear()
    ax.set_xlabel('iterations')
```

```python
    ax.set_ylabel('loss value')
    ax.set_title('Training loss curve for TRAINED_NET')
    ax.plot(loss_graph, label='training loss')
    ax.legend(loc='upper right')
    fig.canvas.draw()
    print("Epoch: {} Loss: {}".format(e, loss))

%matplotlib inline
```

```
Starting Training...
```



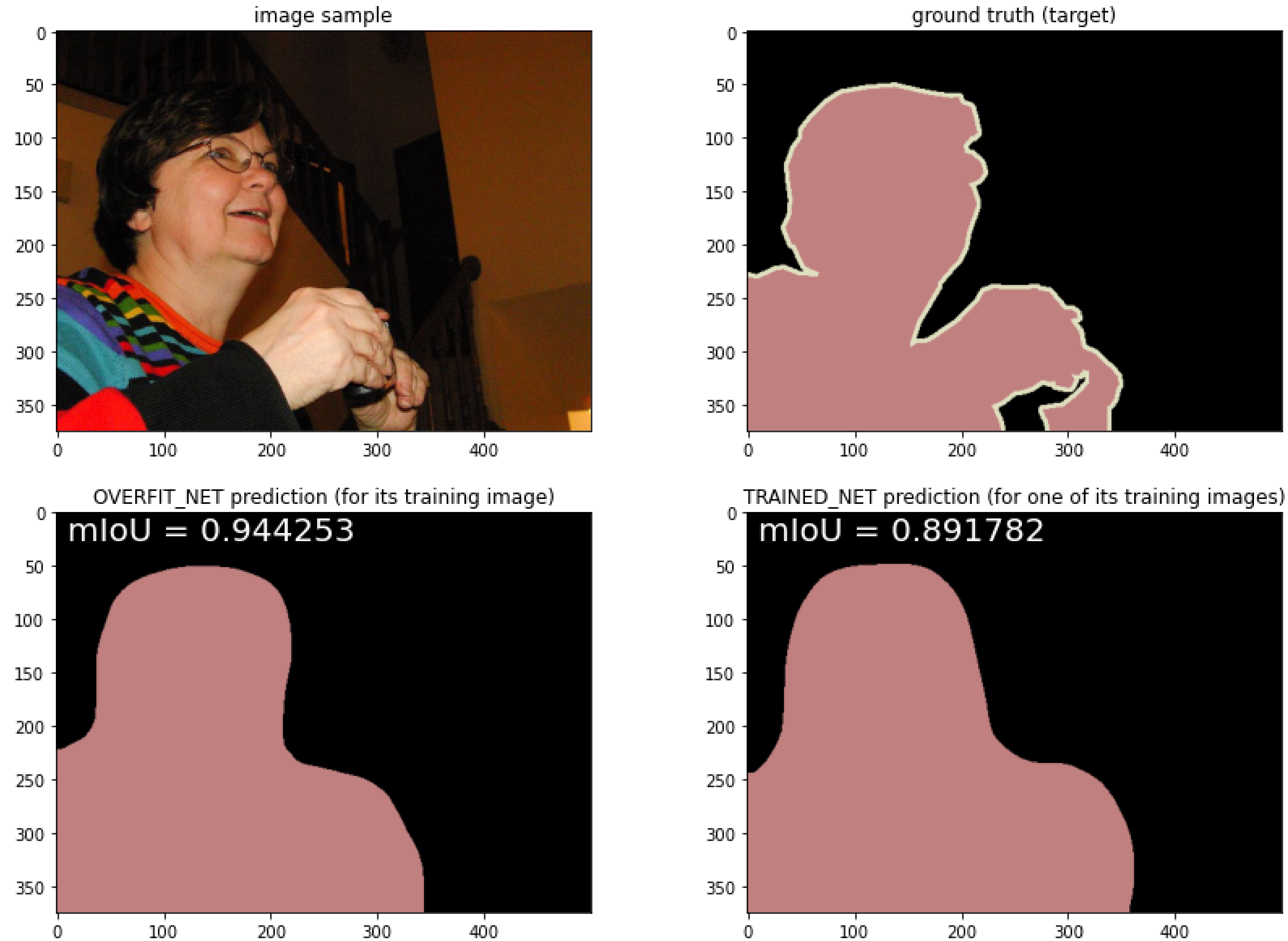

```
Epoch: 0 Loss: 0.806950569152832
Epoch: 1 Loss: 1.0074036121368408
Epoch: 2 Loss: 0.9855901002883911
Epoch: 3 Loss: 0.529554545879364
CPU times: user 2h 31min 6s, sys: 13min 19s, total: 2h 44min 25s
Wall time: 4h 47min 31s
```

(g) Qualitative and quantitative evaluation of predictions (OVERFIT_NET vs TRAINED_NET):

In [335]:

```
# switch back to evaluation mode
trained_net.eval()

sample_img, sample_target = JointNormalize(*norm)(*JointToTensor()(*sample1))
if USE_GPU:
    sample_img = sample_img.cuda()
sample_output_O = overfit_net.forward(sample_img[None])
sample_output_T = trained_net.forward(sample_img[None])

# computing mIOU (quantitative measure of accuracy for network predictions)
pred_T = torch.argmax(sample_output_T, dim=1).cpu().numpy()[0]
pred_O = torch.argmax(sample_output_O, dim=1).cpu().numpy()[0]
gts = torch.from_numpy(np.array(sample1[1].convert('P'), dtype=np.int32)).long().numpy()
gts[gts == 255] = -1
conf_T = eval_semantic_segmentation(pred_T[None], gts[None])
conf_O = eval_semantic_segmentation(pred_O[None], gts[None])


fig = plt.figure(figsize=(14,10))
ax1 = fig.add_subplot(2,2,1)
plt.title('image sample')
ax1.imshow(sample1[0])
ax2 = fig.add_subplot(2,2,2)
plt.title('ground truth (target)')
ax2.imshow(sample1[1])
ax3 = fig.add_subplot(2,2,3)
plt.title('OVERFIT_NET prediction (for its training image)')
ax3.text(10, 25, 'mIoU = {:_>8.6f}'.format(conf_O['miou']), fontsize=20, color='white')
ax3.imshow(colorize_mask(torch.argmax(sample_output_O, dim=1).cpu().numpy()[0]))
ax4 = fig.add_subplot(2,2,4)
plt.title('TRAINED_NET prediction (for one of its training images)')
ax4.text(10, 25, 'mIoU = {:_>8.6f}'.format(conf_T['miou']), fontsize=20, color='white')
ax4.imshow(colorize_mask(torch.argmax(sample_output_T, dim=1).cpu().numpy()[0]))
```

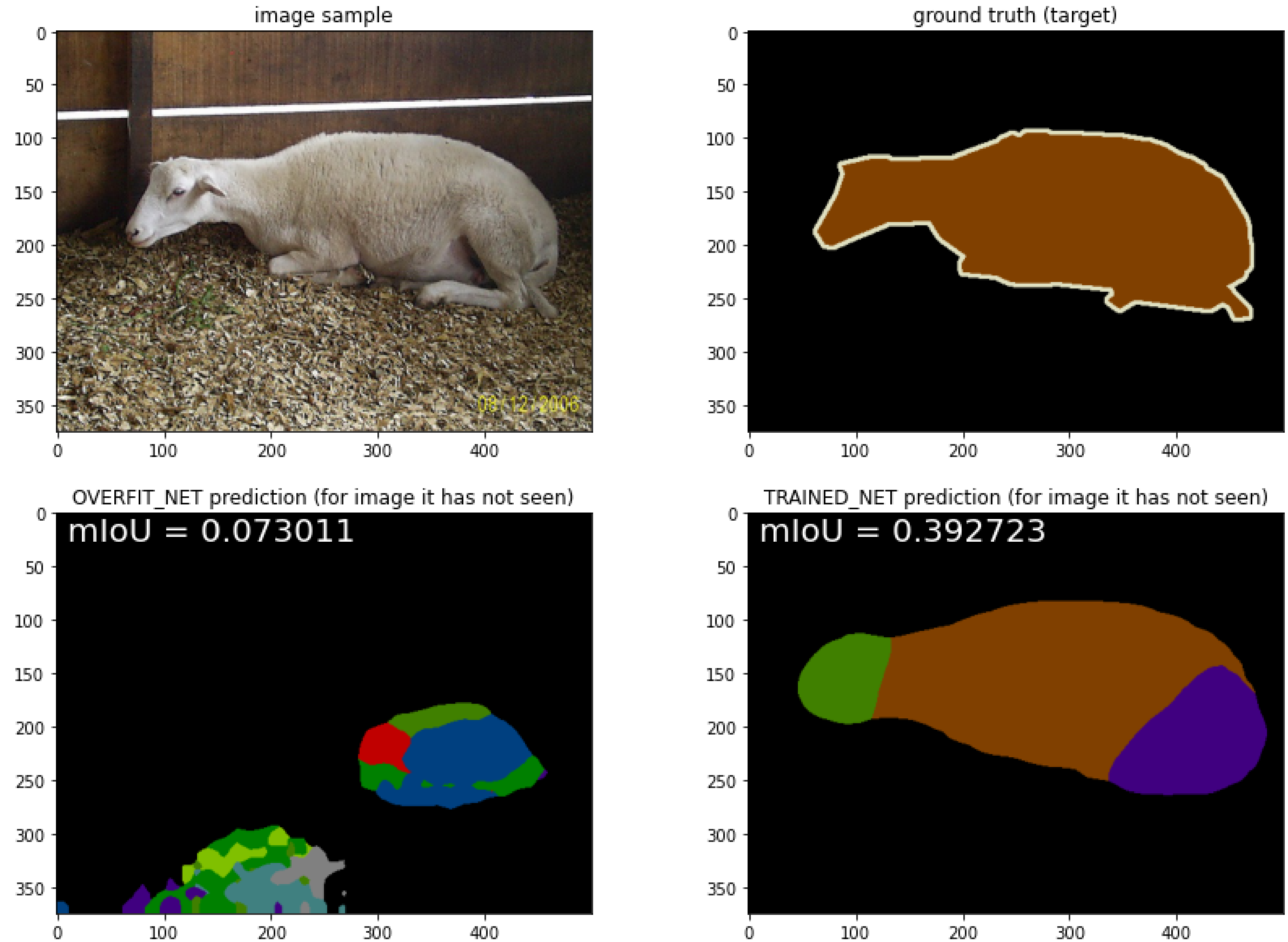
Out[335]: <matplotlib.image.AxesImage at 0x7f902050a2b0>



In [336]:

```
sample_img, sample_target = JointNormalize(*norm)(*JointToTensor()(*sample2))
if USE_GPU:
    sample_img = sample_img.cuda()
sample_output_O = overfit_net.forward(sample_img[None])
sample_output_T = trained_net.forward(sample_img[None])

# computing mIOU (quantitative measure of accuracy for network predictions)
pred_O = torch.argmax(sample_output_O, dim=1).cpu().numpy()[0]
pred_T = torch.argmax(sample_output_T, dim=1).cpu().numpy()[0]
gts = torch.from_numpy(np.array(sample2[1].convert('P'), dtype=np.int32)).long().numpy()
gts[gts == 255] = -1
conf_O = eval_semantic_segmentation(pred_O[None], gts[None])
conf_T = eval_semantic_segmentation(pred_T[None], gts[None])


fig = plt.figure(figsize=(14,10))
ax1 = fig.add_subplot(2,2,1)
plt.title('image sample')
ax1.imshow(sample2[0])
ax2 = fig.add_subplot(2,2,2)
plt.title('ground truth (target)')
ax2.imshow(sample2[1])
ax3 = fig.add_subplot(2,2,3)
plt.title('OVERFIT_NET prediction (for image it has not seen)')
ax3.text(10, 25, 'mIoU = {:_>8.6f}'.format(conf_O['miou']), fontsize=20, color='white')
ax3.imshow(colorize_mask(torch.argmax(sample_output_O, dim=1).cpu().numpy()[0]))
ax4 = fig.add_subplot(2,2,4)
plt.title('TRAINED_NET prediction (for image it has not seen)')
ax4.text(10, 25, 'mIoU = {:_>8.6f}'.format(conf_T['miou']), fontsize=20, color='white')
ax4.imshow(colorize_mask(torch.argmax(sample_output_T, dim=1).cpu().numpy()[0]))
```

Out[336]: <matplotlib.image.AxesImage at 0x7f9022a4ca00>



(h) Evaluate TRAINED_NET on validation dataset.

Run the validation loop for TRAINED_NET against the validation dataset (it has not seen):

In [337]:
```
%%time
# This will be slow on CPU (around 1 hour). On GPU it should take only a few minutes (depending on yo
ur GPU).
print("mIoU for TRAINED_NET over the validation dataset:{}".format(validate(val_loader, trained_net)[
1]))
```

```
mIoU for TRAINED_NET over the validation dataset:0.49457657380386366
CPU times: user 24min 46s, sys: 2min 53s, total: 27min 39s
Wall time: 44min 22s
```

Problem 6

For the network that you implemented, write a paragraph or two about limitations / bottlenecks about the work. What could be improved? What seems to be some obvious issues with the existing works?

The limitation is the parameters. We use the parameters of kernel size and sampling rate in paper "DeepLab: Semantic Image Segmentation with Deep Convolutional Nets, Atrous Convolution, and Fully Connected CRFs". The model used in this paper is VGG-16, but we use model resnet-34. The parameters works ok, but may not make the best performance.\ The obvious issue is that the resnet model we use requires a long time for training, which makes it practically infeasible for some applications.