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Homework #5

1. Source code

a) Dataset: For his class I passed as arguments the root directory and two transformations one for the image we are going to train and a target_transformation which resizes the output and the ground truth. Image.open was used to open the file as an Image tensor.

```
class KittiDataset(Dataset): # Pytorch dataset class
# important functions len and getitem
# Load data in an efficient way, like multiple CPUs
# To speed up process in training specially for HD images so it can have
multithreading features
    """Face Landmarks dataset."""

    def __init__(self, root_dir, transform=None, target_transform=None):
        """
        Args:
            root_dir (string): Directory with all the images.
        """
        self.root_dir = root_dir
        self.transform = transform
        self.target_transform = target_transform

        self.images = os.listdir(os.path.join(root_dir, 'image_2'))
        self.labels = os.listdir(os.path.join(root_dir, 'semantic'))
        self.gt = os.listdir(os.path.join(root_dir, 'semantic_rgb'))

    def __len__(self):
      return len(self.images)

    def __getitem__(self, idx):
      if torch.is_tensor(idx):
            idx = idx.tolist()

      img_path = os.path.join(self.root_dir + '/image_2', self.images[idx])
      label_path = os.path.join(self.root_dir + '/semantic', self.images[idx])
      gt_path = os.path.join(self.root_dir + '/semantic_rgb', self.images[idx])

      image = pil_loader(img_path)
      label = Image.open(label_path)
      gt = Image.open(gt_path)

      sample = {'image': image, 'label': label, 'gt': gt}

      if self.transform:
            sample['image'] = self.transform(sample['image'])
```

```
            sample['label'] = self.target_transform(sample['label'])
            sample['gt'] = self.target_transform(sample['gt'])

      return sample
```

b) Models: Uses additional Conv layers to get better classification and at the end we add a fully connected layer with Dropouts to increase variance in the distribution.

FCN 32: Use as described in homework with a slight modification of filter size of 224 in the last layer, since I was not able to make it work with filter_size of 64 or 32, probably I need to add some padding in the previous layer to make it work with such filter size.

```
num_classes = 35

class FCN32(nn.Module):
  def __init__(self):
    super(FCN32, self).__init__()
    self.features = vgg16.features
    self.classifier = nn.Sequential(
      nn.Conv2d(512, 4096, 7),
      nn.ReLU(inplace=True),
      nn.Dropout2d(),
      nn.Conv2d(4096, 4096, 1),
      nn.ReLU(inplace=True),
      nn.Dropout2d(),
      nn.Conv2d(4096, num_classes, 1),
      nn.ConvTranspose2d(num_classes, num_classes, 224, stride=32)
    )

  def forward(self, x):
    x = self.features(x)
    x = self.classifier(x)
    return x

fcn = FCN32()
fcn.to(device)
```

FCN 16: Implemented as described in the homework

```
num_classes = 35

class FCN16(nn.Module):
  def __init__(self):
    super(FCN16, self).__init__()
    self.features = vgg16.features
    self.classifier = nn.Sequential(
      nn.Conv2d(512, 4096, 7),
      nn.ReLU(inplace=True),
      nn.Conv2d(4096, 4096, 1),
```

```
      nn.ReLU(inplace=True),
      nn.Conv2d(4096, num_classes, 1)
    )
    self.score_pool4 = nn.Conv2d(512, num_classes, 1)
    self.upscore2 = nn.ConvTranspose2d(num_classes, num_classes, 14, stride=2,
bias=False)
    self.upscore16 = nn.ConvTranspose2d(num_classes, num_classes, 16, stride=16,
bias=False)

  def forward(self, x):
    pool4 = self.features[:-7](x)
    pool5 = self.features[-7:](pool4)
    pool5_upscored = self.upscore2(self.classifier(pool5))
    pool4_scored = self.score_pool4(pool4)
    combined = pool4_scored + pool5_upscored
    res = self.upscore16(combined)
    return res

fcn = FCN16()
fcn.to(device)
```

c) Loss Function and Optimizer

```
criterion = nn.CrossEntropyLoss()
betas = (0.5, 0.999)

optimizer = optim.Adam(fcn.parameters(), lr=0.001, betas=betas)
```

d) Optimizer

```
optimizer = optim.Adam(net.parameters(), lr=0.001)
```

e) Evaluation: To calculate mean IoU I used the confusion matrix data which pixel-level IoU easy to calculate since the intersection is calculated using the diagonal of the confusion matrix (TP) and the union (TP+PN+FN) is calculated by the summation in axis 1 + the summation in axis 0 – intersection.

```
overall_conf_mat = np.zeros((35, 35))
with torch.no_grad():
  for k, dat1 in enumerate(test_loader):
    # Get image, label pair
    inputs1, labels1 = dat1['image'], dat1['label']

    # Using GPU
    inputs1 = inputs1.to(device)
    labels1 = labels1.to(device)

    # Predicting segmentation for val inputs
```

```python
    outputs1 = model(inputs1)

    preds = torch.argmax(outputs1, dim=1).detach().cpu().numpy()
    gt = labels1.detach().cpu().numpy()

    # Compute confusion matrix
    conf_mat = confusion_matrix(y_pred=preds.flatten(), y_true=gt.flatten(),
labels=list(range(35)))
    overall_conf_mat += conf_mat

mean_iou, iou = get_mean_iou(conf_mat=overall_conf_mat)
print('IOU: {}'.format(iou))
print('Mean IOU: {}'.format(np.round(mean_iou, 2)))


with torch.no_grad():
  for k, dat in enumerate(test_loader):
    # Get image, label pair
    inputs, labels, gt = dat['image'], dat['label'], dat['gt']

    # Using GPU
    inputs = inputs.to(device)
    labels = labels.to(device)

    outputs = model(inputs)
    pred = torch.argmax(outputs.squeeze(), dim=0).detach().cpu().numpy()

    # Getting the segmentation
    segmentation = decode_segmap(pred)

    unorm = UnNormalize(mean=(0.485, 0.456, 0.406), std=(0.229, 0.224, 0.225))
    unnormalized_image = unorm(inputs[0].cpu())
    image_array = np.transpose(unnormalized_image.numpy(), (1, 2, 0))
    # gt_array = np.transpose(gt, (1, 2, 0))

    plt.imshow(image_array); plt.axis('off');
    plt.show()

    plt.imshow(segmentation);  plt.axis('off');
    plt.show()

    plt.imshow(gt[0]);  plt.axis('off');
    plt.show()

    if k == 20:
        break
```

f) Training Loop: It is split in two parts: the first part for the training where it calculates the loss and IoU in each iteration and once the epoch is completed it calculates the average IoU and average loss, the second part iterates over the validation loader, calculates average IoU and loss, and stores the best model to use it in the evaluation with the test set.

```
best_loss = 1000000000
num_epochs = 140

train_loss_history = []
val_loss_history = []
train_iou_history = []
val_iou_history = []

for epoch in range(num_epochs):
  val_running_iou = 0
  val_running_loss = 0
  train_running_iou = 0
  train_running_loss = 0
  j = 0
  fcn.train()
  for i, dat in enumerate(train_loader):

    j += 1
    # Get image, label pair
    inputs, labels = dat['image'], dat['label']

    # Using GPU
    inputs = inputs.to(device)
    labels = labels.to(device)

    # Set parameter gradients to 0
    optimizer.zero_grad()

    # Forward pass for a batch
    outputs = fcn(inputs)
    preds = torch.argmax(outputs, dim=1).detach().cpu().numpy()
    gt = labels.detach().cpu().numpy()

    # Compute loss
    loss = criterion(outputs, labels)
    train_running_loss += loss

    # Compute confusion matrix
    conf_mat = confusion_matrix(y_pred=preds.flatten(), y_true=gt.flatten(),
labels=list(range(35)))
    mean_iou = get_mean_iou(conf_mat=conf_mat)
    train_running_iou += mean_iou

    # Backpropagate
    loss.backward()
```

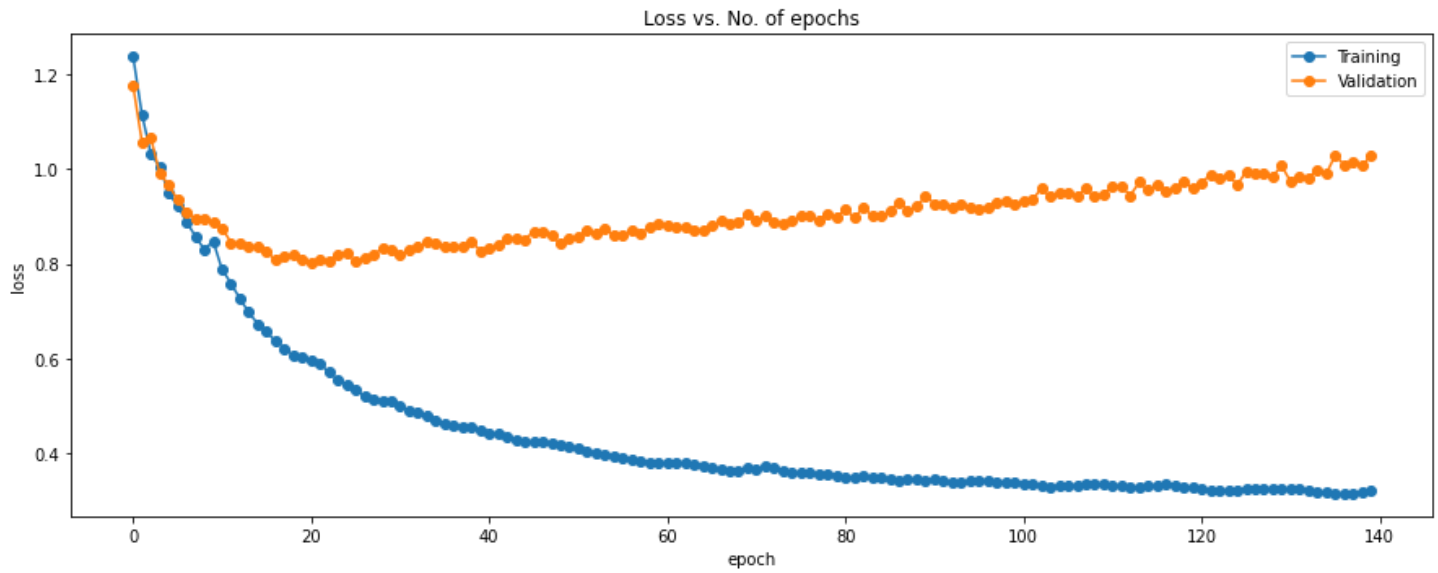
```
    # Update the weights
    optimizer.step()

  # Averaging loss and scores
  avg_train_loss = float(train_running_loss)/(j)
  avg_train_iou = float(train_running_iou)/(j)

  train_loss_history.append(avg_train_loss)
  train_iou_history.append(avg_train_iou)

  fcn.eval()
  with torch.no_grad():
    for k, dat1 in enumerate(val_loader):
      # Get image, label pair
      inputs1, labels1 = dat1['image'], dat1['label']

      # # Using GPU
      inputs1 = inputs1.to(device)
      labels1 = labels1.to(device)

      # Predicting segmentation for val inputs
      outputs1 = fcn(inputs1)

      # Compute CE loss and aggregate it
      loss1 = criterion(outputs1, labels1)
      val_running_loss += loss1

      # Reshaping prediction segmentations and actual segmentations for iou and dice
score
      preds = torch.argmax(outputs1, dim=1).detach().cpu().numpy()
      gt = labels1.detach().cpu().numpy()

      # Compute confusion matrix
      conf_mat = confusion_matrix(y_pred=preds.flatten(), y_true=gt.flatten(),
labels=list(range(35)))

      # Computing iou and dice scores and aggregating them
      mean_iou = get_mean_iou(conf_mat=conf_mat)
      val_running_iou += mean_iou

    avg_val_loss = float(val_running_loss)/(k+1)
    avg_val_iou = float(val_running_iou)/(k+1)

    val_loss_history.append(avg_val_loss)
    val_iou_history.append(avg_val_iou)

    if avg_val_loss < best_loss:
      best_loss = avg_val_loss
      torch.save(fcn.state_dict(), '/content/best_model_fcn16.pth.tar')
```

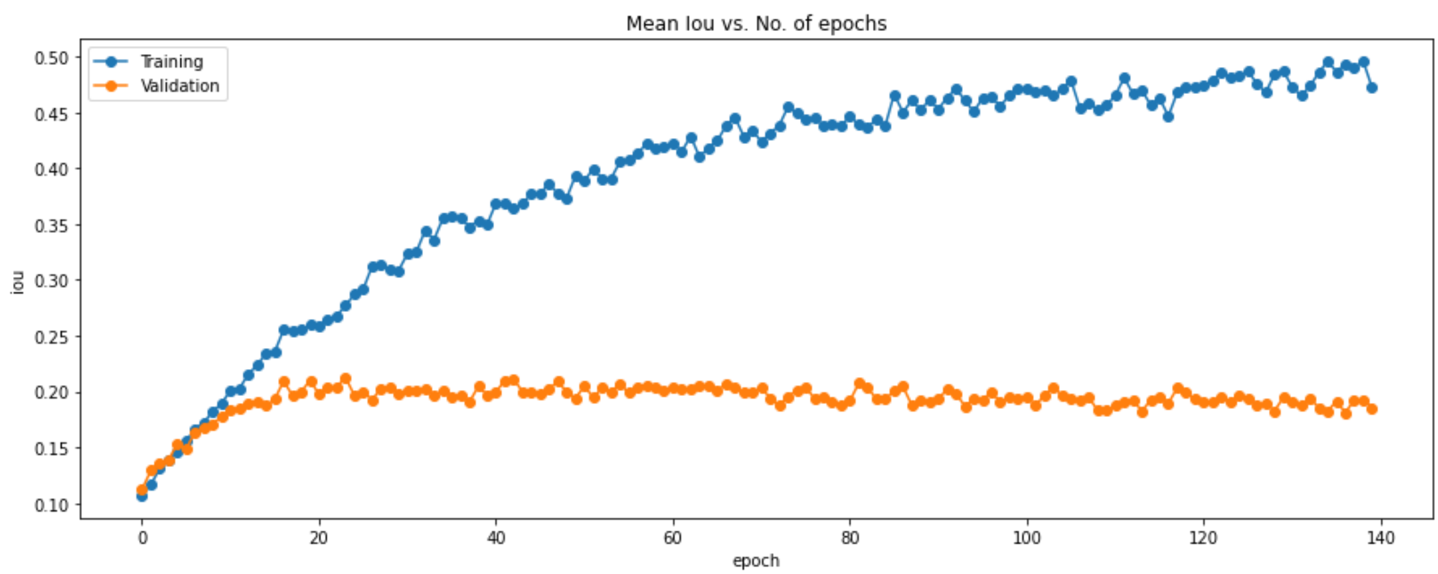
```
    # Visualizations for batch wise metrics
    print('epoch {}, training loss: {}, iou score: {}'.format(epoch+1,
avg_train_loss, avg_train_iou))
    print('epoch {}, validation loss: {}, iou score: {}'.format(epoch+1,
avg_val_loss, avg_val_iou))

print('Finished Training')
```

Please see appendix for rest of utility functions, transformations and more.

2 Discussion

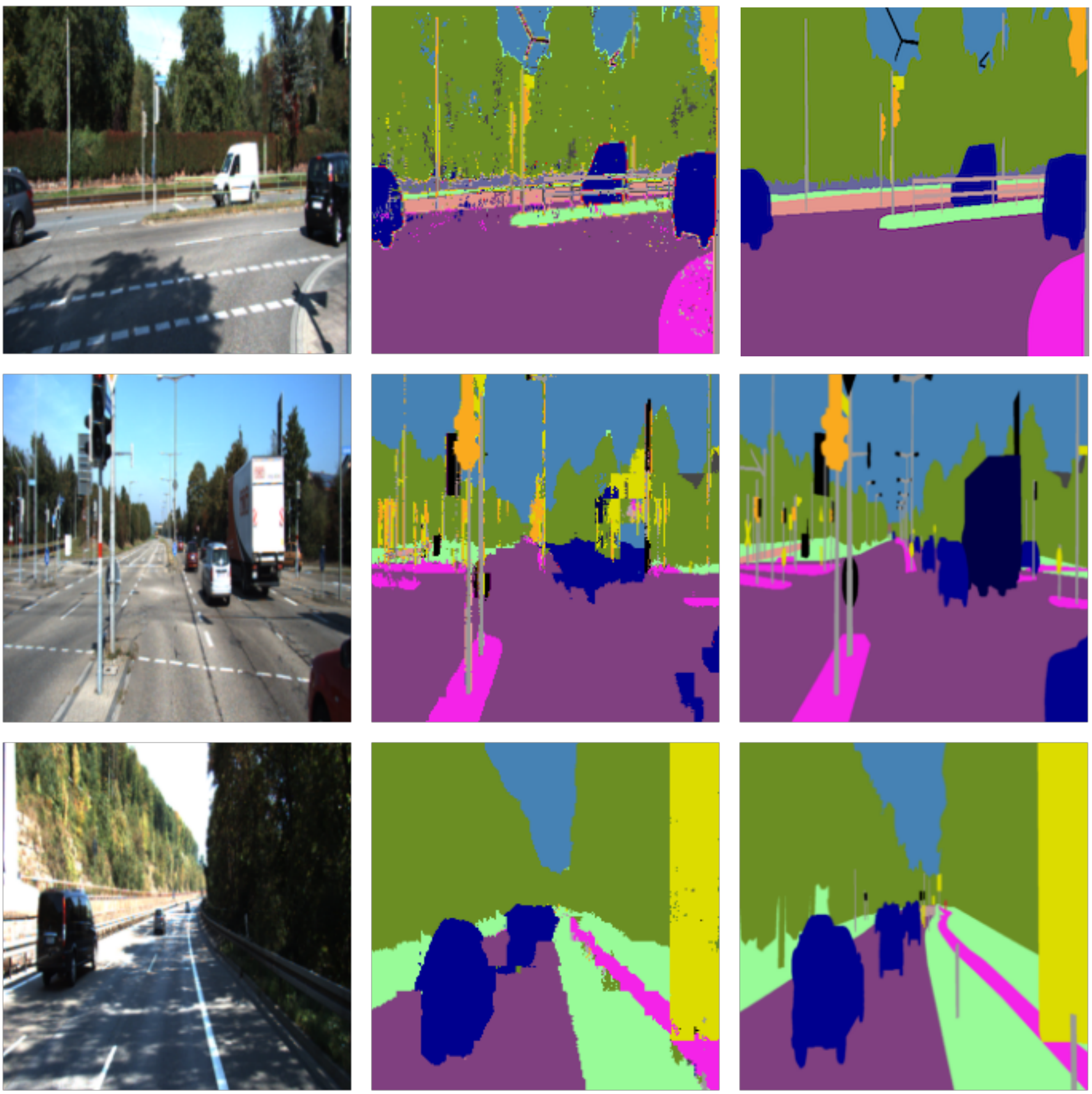
2.1 Evolution of training losses and validation losses with FCN 16 using Adam as optimizer, learning rate = 0.001, betas = (0.5, 0.999) after 140 epochs





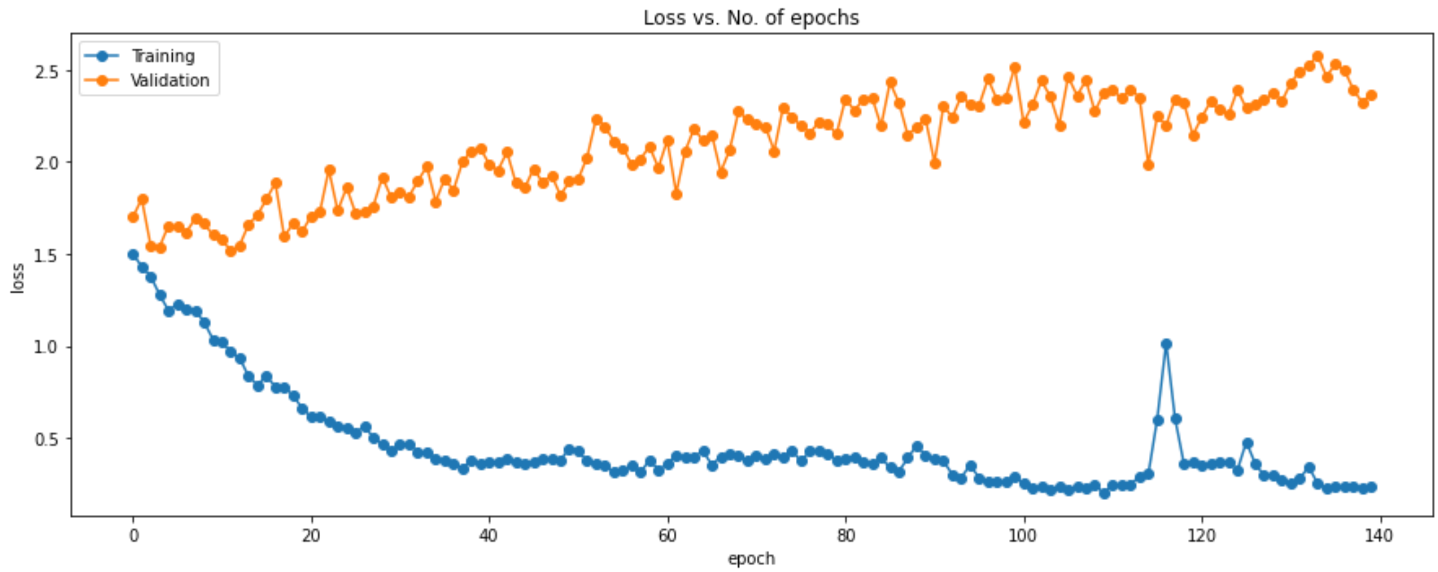
2.1.1 Evaluation metric on test data

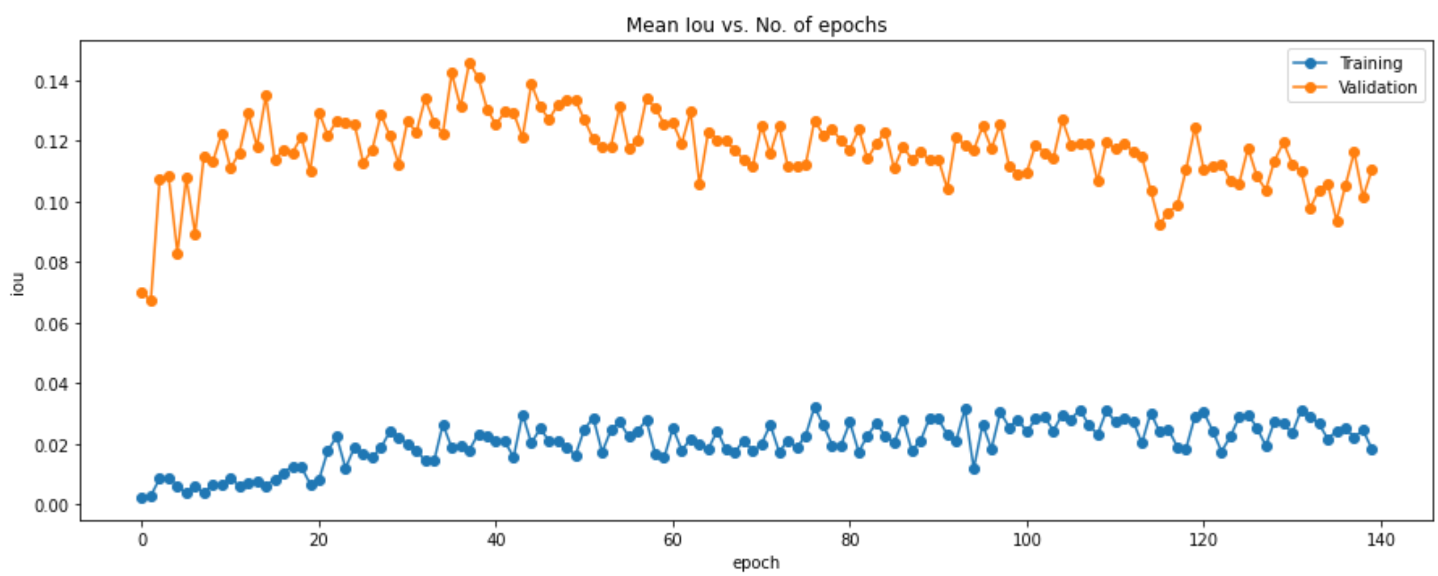
```
Mean IOU: 0.3

Pixel-level IOU: [0.         0.         0.         0.         0.421875   0.05075758
 0.2601626  0.87887102 0.55460552 0.31881262 0.37165304 0.7448051
 0.19798761 0.09071496 0.4253857  0.00647715 0.00618673 0.11895879
 0.03682688 0.13758515 0.27939644 0.79163026 0.61728869 0.79067183
 0.00425894 0.00504881 0.76342157 0.05257423 0.69709763 0.20661157
 0.57954545 0.276      0.0083682  0.373297          nan]

*nan values seem related to category -1
```



Examples: left original image, center predicted image, right ground truth

2.1.2 Evolution of training losses and validation losses with FCN 32 using Adam as optimizer, learning rate = 0.001, betas = (0.5, 0.999) after 140 epochs

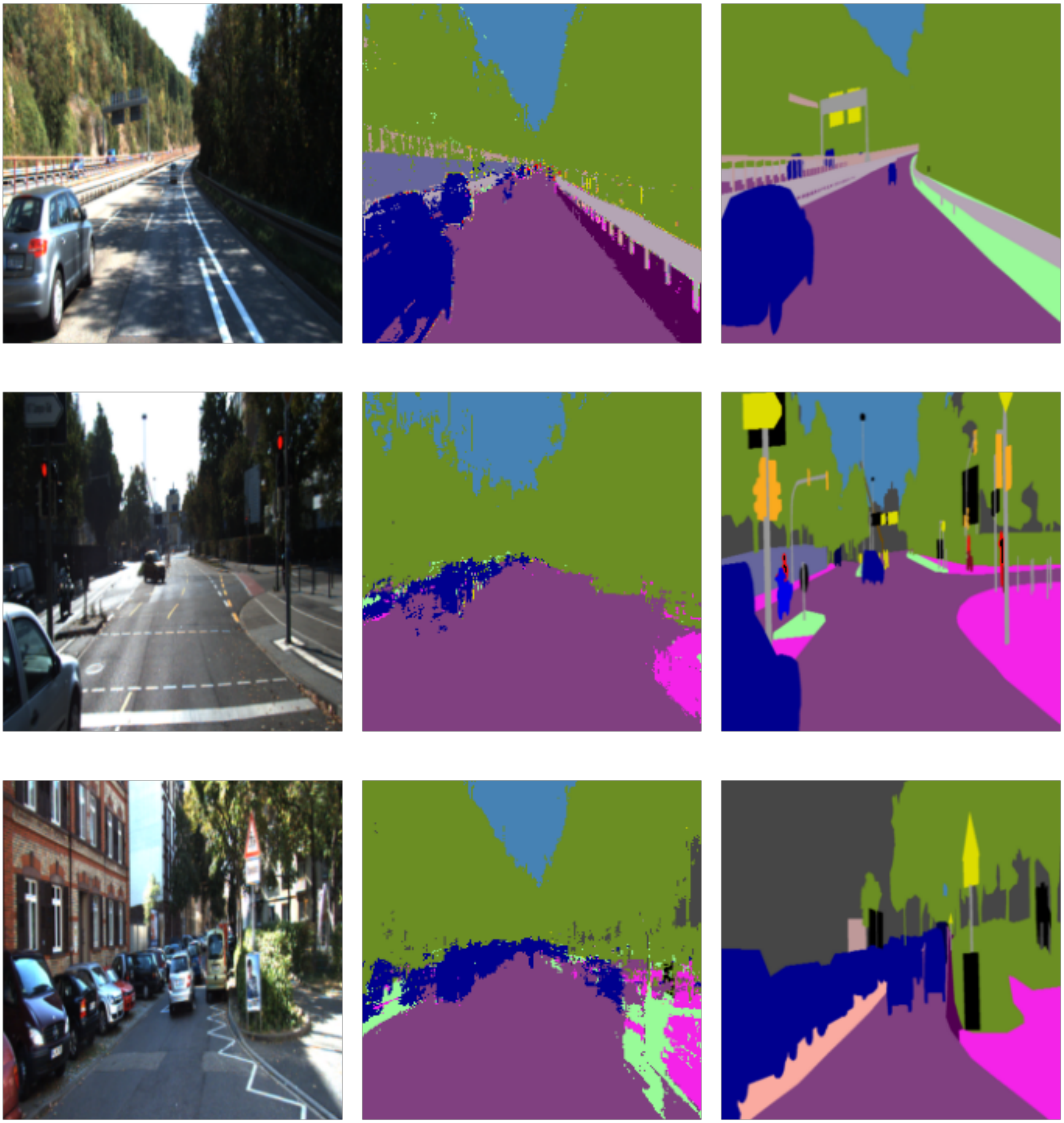




2.1.3 Evaluation metric on test data FCN 32

```
Mean IOU: 0.12

Pixel-level IOU: [0.00000000e+00 0.00000000e+00 0.00000000e+00 0.00000000e+00
 2.68901912e-01 5.55144338e-02 3.84732206e-03 6.77009575e-01
 1.54676162e-01 9.13115246e-02 1.29398210e-02 1.88490698e-01
 8.81080202e-02 1.87995994e-02 1.81493183e-01 1.15283267e-02
 8.59950860e-03 1.13996254e-01 4.69784768e-02 9.04286128e-02
 3.19874779e-02 5.70181738e-01 4.17274856e-01 4.85156984e-01
 3.56576862e-03 4.88102502e-03 2.87682197e-01 0.00000000e+00
 5.64334086e-04 0.00000000e+00 9.09090909e-03 2.18340611e-01
 0.00000000e+00 0.00000000e+00            nan]
```

Examples of FCN 32



As it can be appreciated FCN 32 failed to recognize small and medium size object. I believe this is due to the large filter size at the end of the classifier layers.

2.2 Effects of parameter choices

The most important parameters to have a good semantic segmentation network are without a doubt the optimizer and apply the correct transformations and normalization. Rest of parameters were applied as suggested in homework instructions.

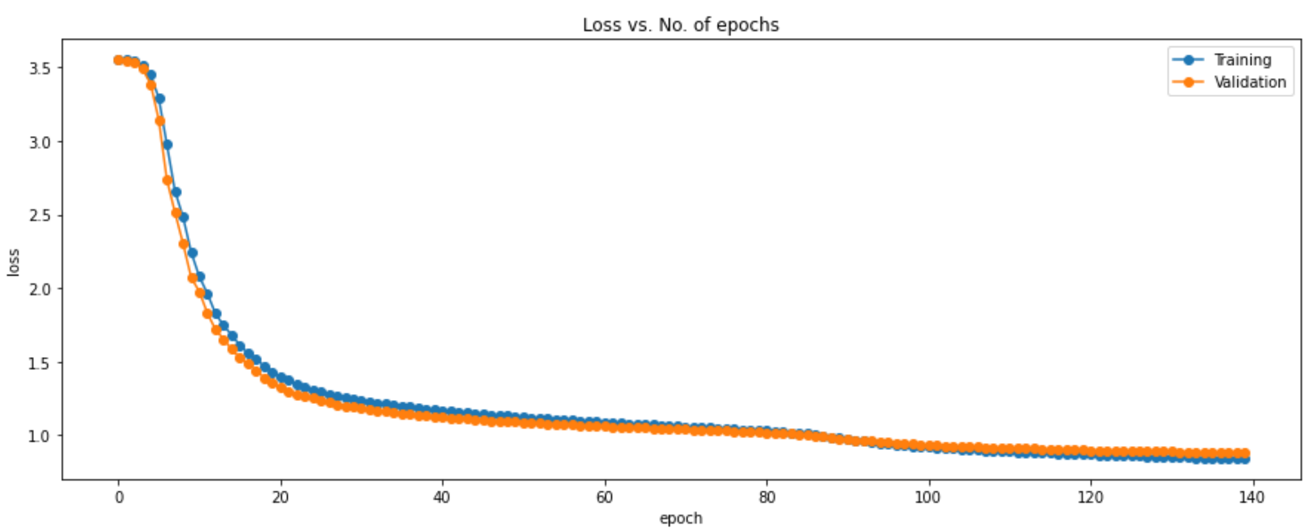
```
params = {'batch_size': 5,
          'shuffle': True,
          'num_workers': 4}

data_mean = [0.485, 0.456, 0.406]
data_std = [0.229, 0.224, 0.225]
```

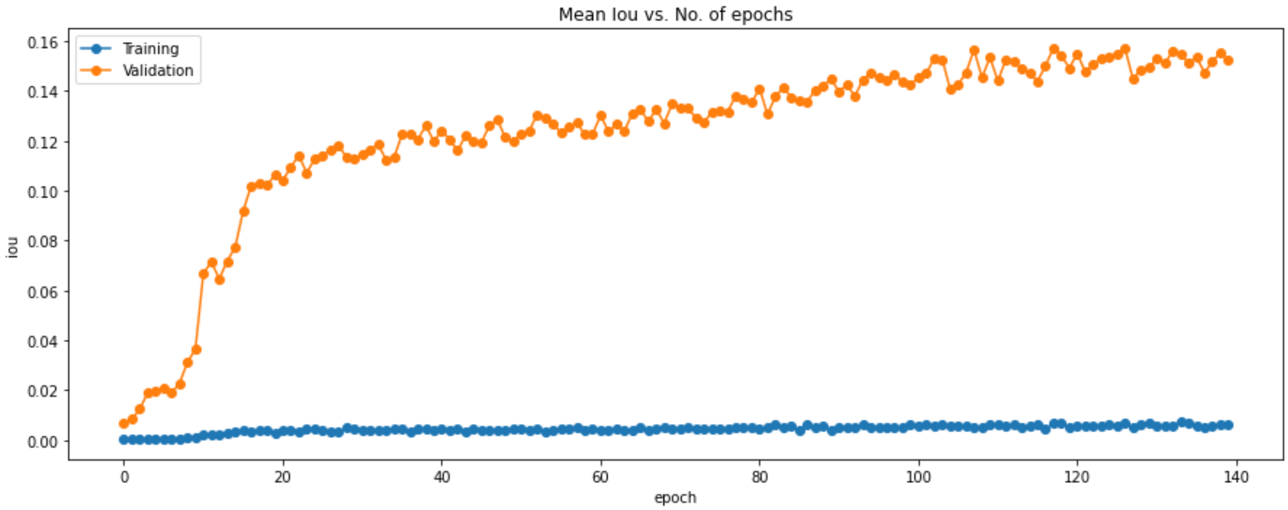
The following transformations were applied to the three data sets:

```
img_transform = transforms.Compose([
    transforms.Resize(input_size),
    transforms.ToTensor(),
    transforms.Normalize(mean=data_mean, std=data_std)
]) # Applied to input

target_transform = transforms.Compose([
    transforms.Resize(input_size),
    ConvertToBackground()
]) # Applied to output and ground_truth
```

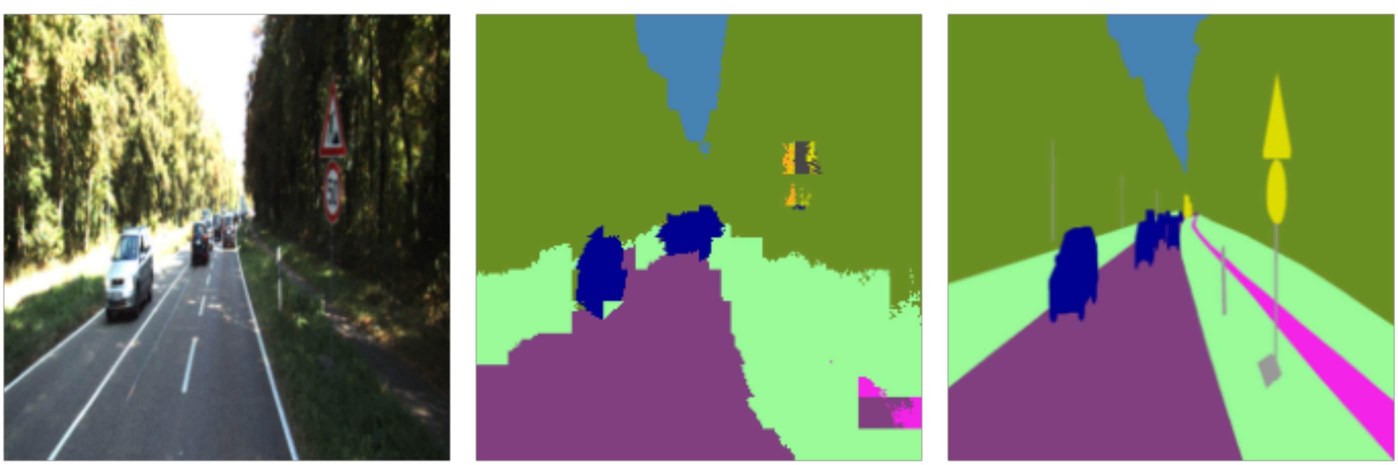
2.2.1 SGD Optimizer with learning rate of 0.001, momentum 0.99 and 140 epochs

As it can be appreciated in the following images a different optimizer such as SGD produces worse results than using Adam (lower mIoU and higher loss)

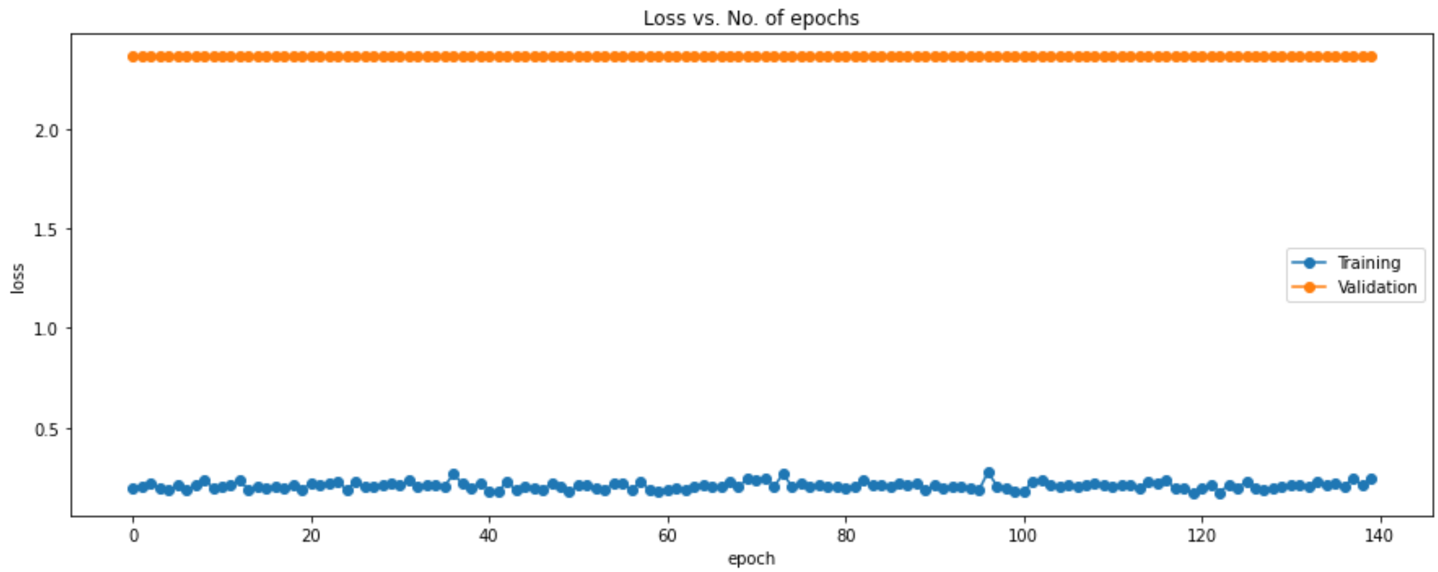


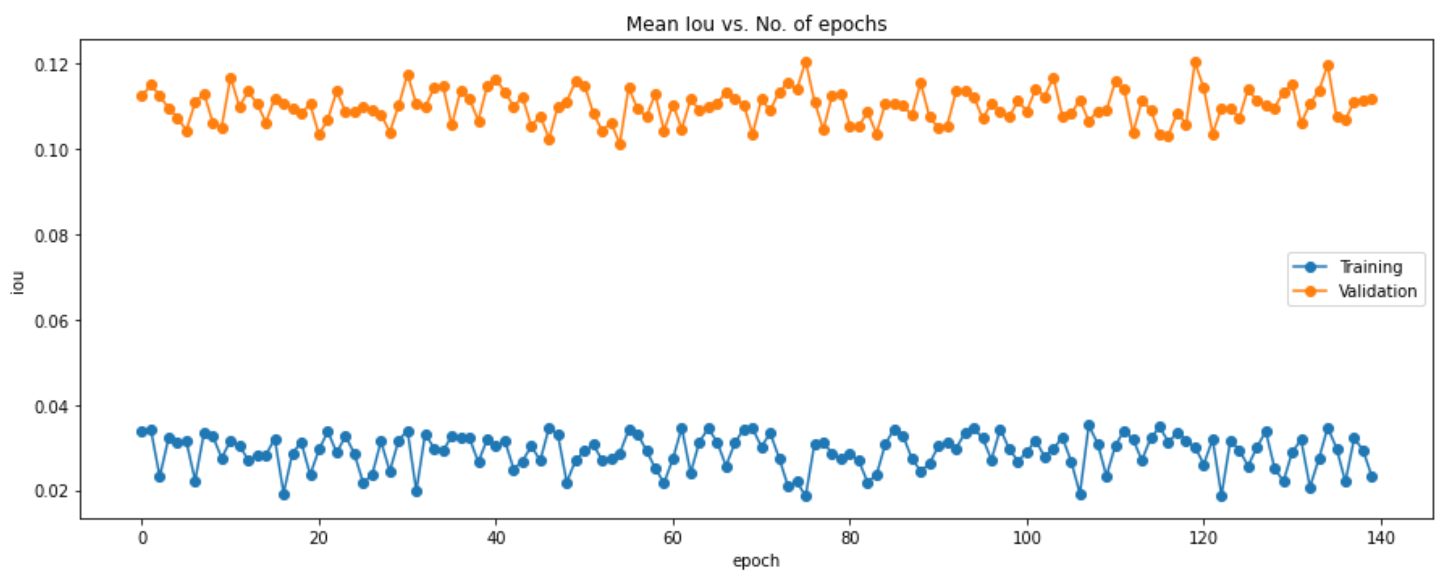



```
Test set:

Mean IOU: 0.13

Pixel level-IOU: [0.         0.         0.         0.00673905 0.
 0.         0.77584447 0.24534817 0.00775155 0.05853094 0.35657824
 0.07689936 0.00583242 0.18200398 0.         0.         0.01159069
 0.         0.02248423 0.01655507 0.72896022 0.50053674 0.80410127
 0.         0.         0.54987353 0.         0.         0.
 0.         0.         0.         0.                nan]
```

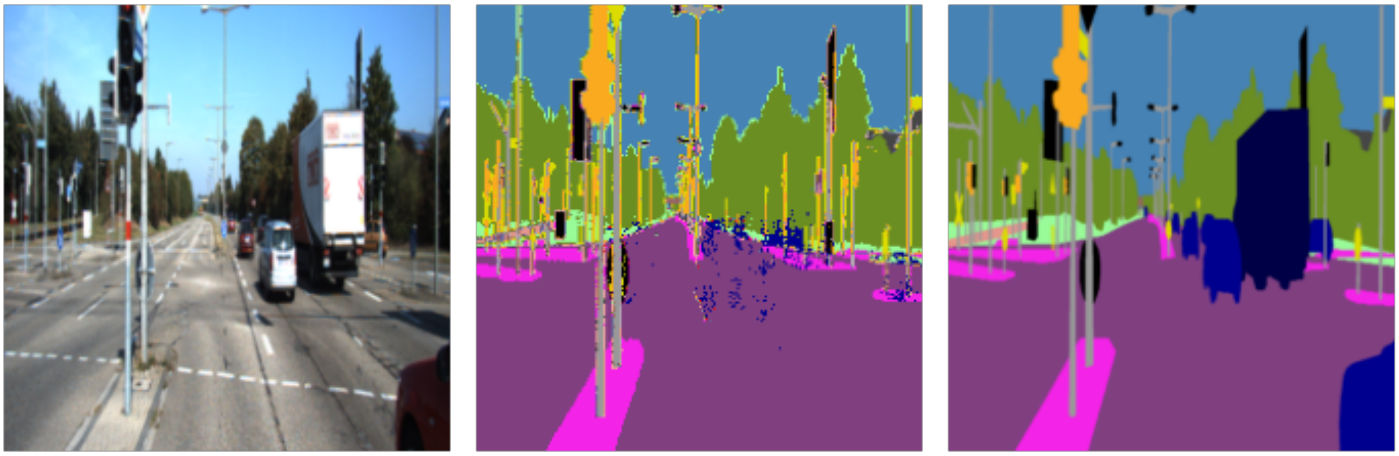


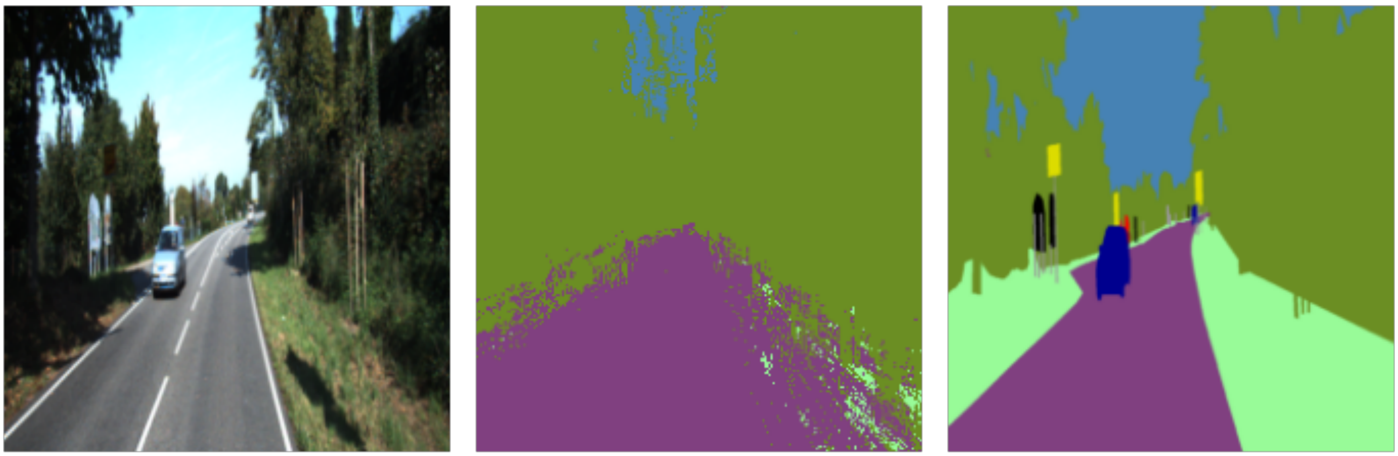
Training classifier parameters only. Adam optimizer, learning rate = 0.001, betas = (0.5, 0.999) after 140 epochs





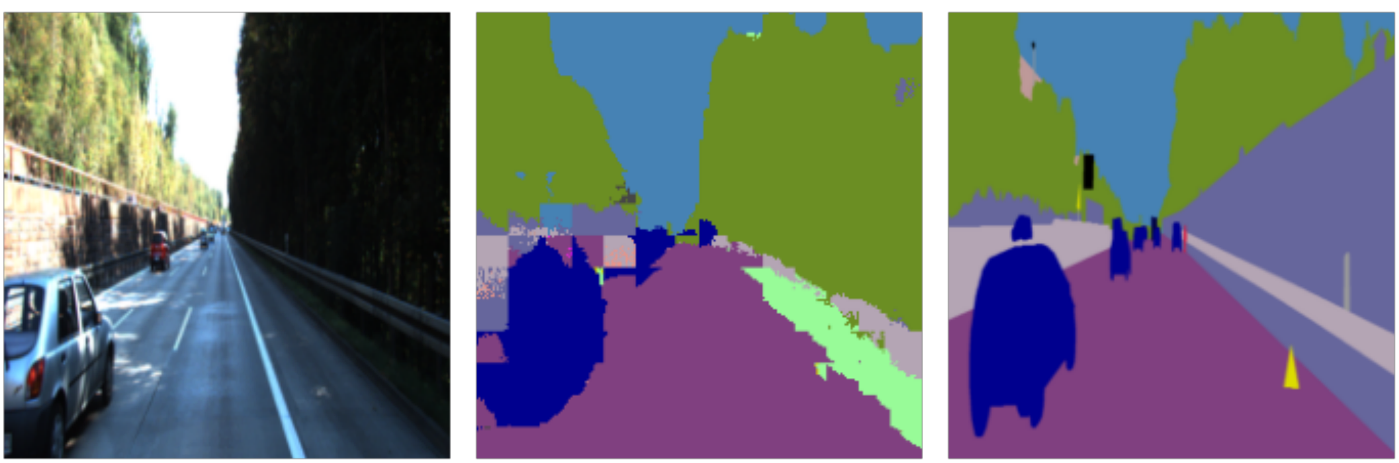

```
Test set:

Mean IOU: 0.11

Pixel-level IOU: [0.         0.         0.         0.         0.28793388 0.05206349
 0.01512478 0.66271618 0.22499368 0.0575155  0.0733171  0.18720653
 0.04215263 0.0217372  0.15904752 0.01124663 0.00980232 0.06606124
 0.04008252 0.09322671 0.04233366 0.54269537 0.42301755 0.50308682
 0.00745474 0.00648618 0.22163123 0.00782998 0.11574279 0.00813008
 0.00381679 0.00429185 0.         0.00275482        nan]
```

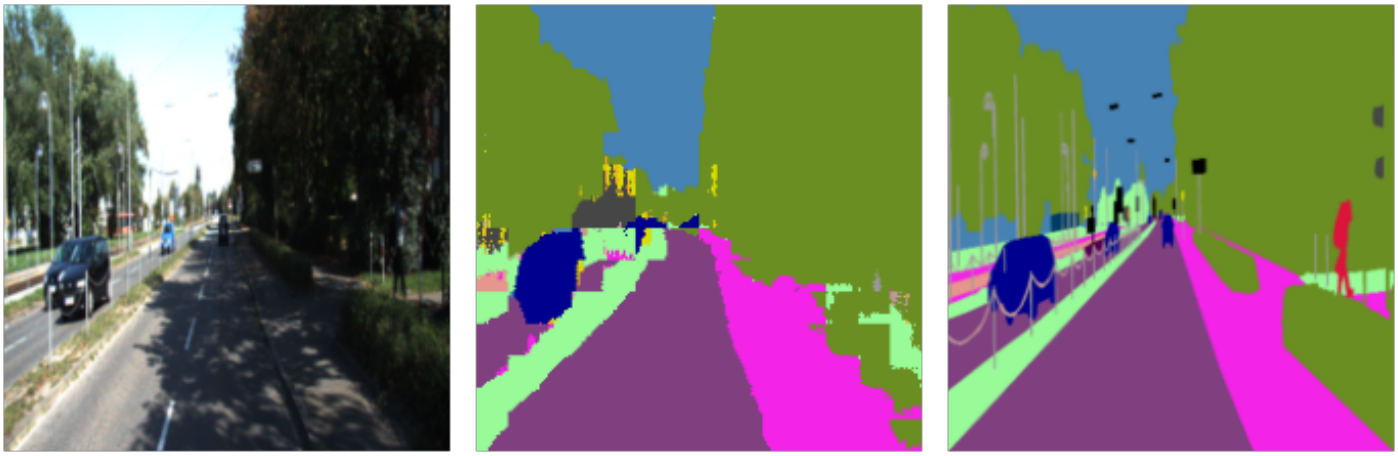




Training only vgg16.features.parameters seems to produce good results in some object like roads, sidewalks, light bulbs, trees and sky, but it performs poorly classifying cars and trucks.

2.3 Example of failed cases





It is worth mentioning that in circumstances where there is plenty of shadow even the model with highest average IoU fails to classify the object under the right category. In the first example it was not able to segment the wall and in the second everything many things in the right side were predicted incorrectly. Additionally, some thin object also fails to segment like the protection between the opposite sides of the road in the second example.

3. Conclusions

In general, a customized VGG16 network produces acceptable results for semantic segmentation, but a proper data preprocessing and tunning of hyper parameters is necessary to obtain good results such as freezing/unfreezing convolution layers, pretraining or not VGG16, transformations, normalization, batch size, to name a few. In this experiment it is hard to tell under which circumstances FCN 16 is preferable over FCN 32 and the other way around since in all my experiments FCN 16 performed better than FCN 32 but most probably it was because of an improper configuration of FCN 32 which I believe could be fixed by using some padding in the convolutional layers or adding intermediate layers between the classifier and the deconvolutional layer.

It is also worth mentioning that in both FCN 16 and FCN 32 with Adam optimizer reach their optimal capacity around 20 epochs and then the generalization gap starts increasing so it might be worth to do more fine tuning and try to apply other transformations to the output to try to reduce overfitting but for matters of time it was not possible to do more experiments.

Appendix:

Code to use Google Drive in Colab instead of downloading data every time

```
from google.colab import drive
ROOT = "/content/drive"
drive.mount(ROOT)
```

Utility function to transform image array into tensor

```
class ConvertToBackground(object):
  def __call__(self, img):
    img = np.asarray(img, dtype=np.long)
    img[img == 255] = 0
    img = torch.from_numpy(img)
    return img
```

Utility function to unnormalize input to display it along output and ground truth

```
class UnNormalize(object):
    def __init__(self, mean, std):
        self.mean = mean
        self.std = std

    def __call__(self, tensor):
        """
        Args:
            tensor (Tensor): Tensor image of size (C, H, W) to be normalized.
        Returns:
            Tensor: Normalized image.
        """
        for t, m, s in zip(tensor, self.mean, self.std):
            t.mul_(s).add_(m)
            # The normalize code -> t.sub_(m).div_(s)
        return tensor
```

Utility function to assign values to output image based in predictions

```
def decode_segmap(image, nc=35):

  label_colors = np.array([(0, 0, 0),
              (0, 0, 0), (0, 0, 0), (0, 0, 0), (0, 0, 0), (111, 74,  0),
              ( 81,  0, 81), (128, 64,128), (244, 35,232), (250,170,160),
(230,150,140),
              ( 70, 70, 70), (102,102,156), (190,153,153), (180,165,180),
(150,100,100),
              (150,120, 90), (153,153,153), (153,153,153), (250,170, 30),
(220,220,0),
```

```
              (107,142, 35), (152,251,152), (70,130,180), (220, 20, 60), (255,  0,
0),
              (  0,  0,142), (  0,  0, 70), (  0, 60,100), (  0,  0, 90), (  0,
0,110),
              (  0, 80,100), (  0,  0,230), (119, 11, 32), (  0,  0,142)])

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

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

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

Code to download pretrained vgg16 model

```
vgg16 = models.vgg16(pretrained=True)
```

Code to freeze convolution layers

```
for param in vgg16.features.parameters():
  param.requires_grad = False
```

Utility function to calculate Pixel level IoU and Mean IoU taking as input a confusion matrix

```
def get_mean_iou(conf_mat, multiplier=1.0):
  cm = conf_mat.copy()
  np.fill_diagonal(cm, np.diag(cm) * multiplier)
  inter = np.diag(cm)
  gt_set = cm.sum(axis=1)
  pred_set = cm.sum(axis=0)
  union_set =  gt_set + pred_set - inter
  iou = inter.astype(float) / union_set
  mean_iou = np.nanmean(iou)
  return mean_iou, iou
```

Code to visualize input, output and ground truth

```
with torch.no_grad():
  for k, dat in enumerate(test_loader):
    # Get image, label pair
    inputs, labels, gt = dat['image'], dat['label'], dat['gt']
```

```
    # Using GPU
    inputs = inputs.to(device)
    labels = labels.to(device)

    outputs = model(inputs)
    pred = torch.argmax(outputs.squeeze(), dim=0).detach().cpu().numpy()

    # Getting the segmentation
    segmentation = decode_segmap(pred)

    unorm = UnNormalize(mean=(0.485, 0.456, 0.406), std=(0.229, 0.224, 0.225))
    unnormalized_image = unorm(inputs[0].cpu())
    image_array = np.transpose(unnormalized_image.numpy(), (1, 2, 0))
    # gt_array = np.transpose(gt, (1, 2, 0))

    plt.imshow(image_array); plt.axis('off');
    plt.show()

    plt.imshow(segmentation);  plt.axis('off');
    plt.show()

    plt.imshow(gt[0]);  plt.axis('off');
    plt.show()

    if k == 30:
        break
```