CS_229_Vision_uncertainty_HW_2

May 12, 2023

0.0.1 Homework 2: Uncertainty and Vision

CS-229 Spring 2023

The goal of this assignment is to get familiar with training a computer vision task (Segmentation) with PyTorch, and to measure confidence calibration in your system.

[1]:
```
%matplotlib inline
import torch
import pandas as pd
import torch.nn as nn
import torch.optim as optim
import torchvision.transforms as transforms
import torchvision.datasets as datasets
from torchvision.models.segmentation import fcn_resnet50

import numpy as np
from PIL import Image
import matplotlib.pyplot as plt

# only needed for generating and storing results from grid search
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

[2]:
```
class ToIntTensor(transforms.ToTensor):
    """A custom transform that replaces "ToTensor". ToTensor always converts to␣
 ↪a
    a float in range [0,1]. This one converts to an integer, which can represent
    our class labels per pixel in an image segmentation problem"""
    def __call__(self, pic):
        tensor = super().__call__(pic)
        tensor = (tensor * 255).to(torch.int64)
        return tensor

def get_voc_dataloader(batch_size=4, resize_shape=(256,256)):
    """Get the VOC 2007 segmentation dataset and return PyTorch
    dataloaders for both training and validation.
```

```
    """
    # TODO: 2 points.
    # Define image transforms for both the input image AND the "label" image.
    # Remember, the labels are one category (integer) per pixel.
    # So, while the image_transform normalize the values to have mean zero and␣
↪unit standard deviation,
    # you shouldn't do that with the labels, which have to be integers.

    # I provided a "ToIntTensor" transform above to use for the label␣
↪transform, instead of ToTensor which always turns images to floats.
    # Also, we want to resize/crop images to be all the same size, a power of␣
↪2, and
    # we should transform the label and image in the same way when changing␣
↪size.
    # The size of images will drastically impact memory usage - I suggest␣
↪targeting 128 x 128
    # or even 64 x 64 if memory constraints are an issue.


    # error check for reshape size
    if type(resize_shape) is not tuple or len(resize_shape) != 2 or␣
↪resize_shape[0] != resize_shape[1] or resize_shape[0] not in␣
↪[2,4,8,16,32,64,128,256,512,1024]:
        raise Exception('Not valid reshape size')

    print ('Reshaping images to', resize_shape)

    # TODO
    image_transforms = transforms.Compose([
        transforms.Resize(resize_shape),
        transforms.ToTensor()
    ])

    label_transforms = transforms.Compose([
        transforms.Resize(resize_shape),
        ToIntTensor()
    ])

    # This downloads the data automatically and creates a "dataset" object that␣
↪applies the transforms
    # TODO: Specify path to save data
    data_dir = "./"
    train_dataset = datasets.VOCSegmentation(data_dir, year='2007',␣
↪image_set='train', download=True, transform=image_transforms,␣
↪target_transform=label_transforms)
```

```
    val_dataset = datasets.VOCSegmentation(data_dir, year='2007',␣
↪image_set='val', download=True, transform=image_transforms,␣
↪target_transform=label_transforms)
    test_dataset = datasets.VOCSegmentation(data_dir, year='2007',␣
↪image_set='test', download=True, transform=image_transforms,␣
↪target_transform=label_transforms)

    # Create data loaders for the datasets - necessary for efficient training
    train_dl = torch.utils.data.DataLoader(train_dataset,␣
↪batch_size=batch_size, shuffle=True)
    val_dl = torch.utils.data.DataLoader(val_dataset, batch_size=batch_size,␣
↪shuffle=False)
    test_dl = torch.utils.data.DataLoader(val_dataset, batch_size=batch_size,␣
↪shuffle=False)
    return train_dl, val_dl, test_dl
```

[3]:

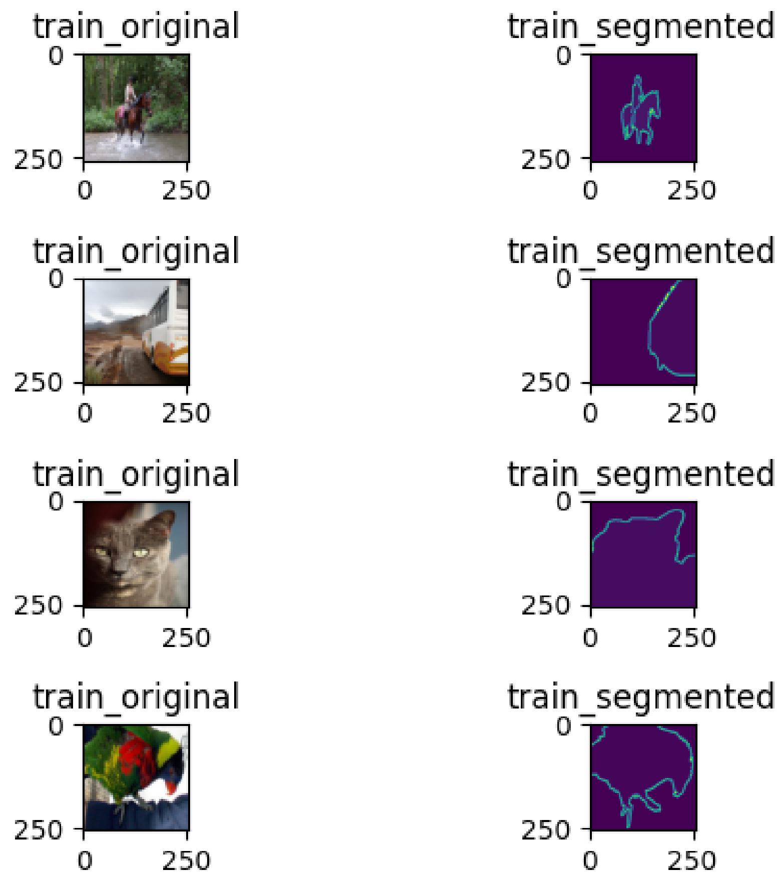
```
BATCH_SIZE = 4
train_dl_reshaped, val_dl_reshaped, test_dl_reshaped =␣
↪get_voc_dataloader(BATCH_SIZE, (256,256))
```

```
Reshaping images to (256, 256)
Downloading
http://host.robots.ox.ac.uk/pascal/VOC/voc2007/VOCtrainval_06-Nov-2007.tar to
./VOCtrainval_06-Nov-2007.tar

100%|      | 460032000/460032000 [00:36<00:00, 12506503.13it/s]

Extracting ./VOCtrainval_06-Nov-2007.tar to ./
Using downloaded and verified file: ./VOCtrainval_06-Nov-2007.tar
Extracting ./VOCtrainval_06-Nov-2007.tar to ./
Downloading
http://host.robots.ox.ac.uk/pascal/VOC/voc2007/VOCtest_06-Nov-2007.tar to
./VOCtest_06-Nov-2007.tar

100%|      | 451020800/451020800 [00:35<00:00, 12549012.50it/s]

Extracting ./VOCtest_06-Nov-2007.tar to ./
```

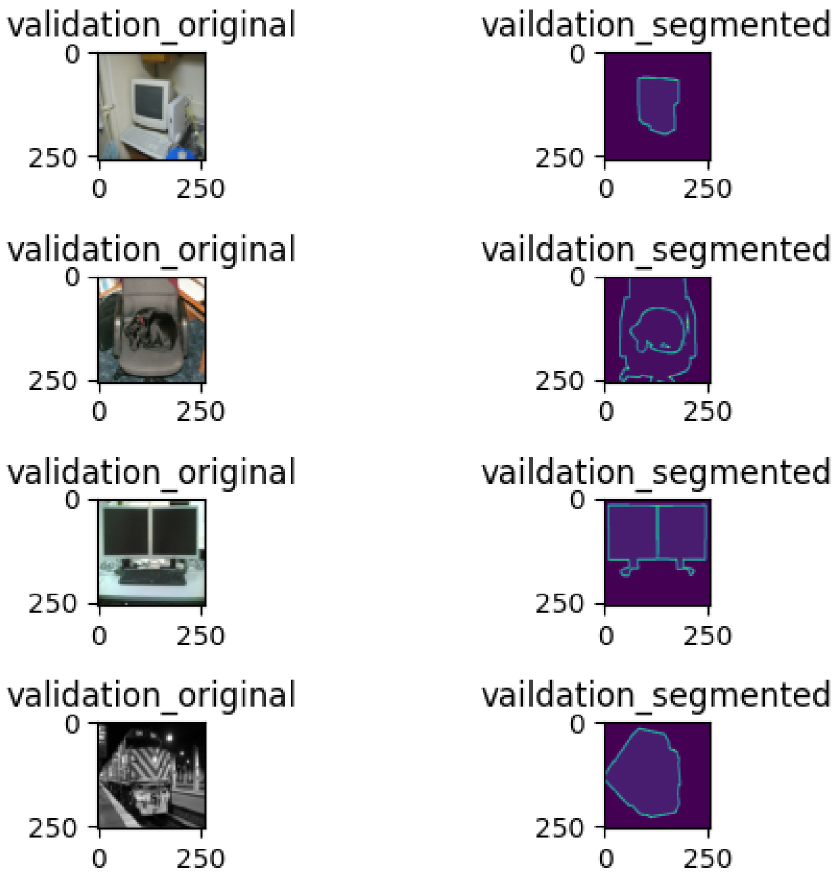
[4]:

```
for _, (images,labels) in enumerate(train_dl_reshaped):
    fig, axs = plt.subplots(BATCH_SIZE, 2)

    for i in range(BATCH_SIZE):
        axs[i, 0].imshow(images[i].permute(1,2,0))
        axs[i, 0].set_title("train_original")

        axs[i, 1].imshow(labels[i].permute(1,2,0))
        axs[i, 1].set_title("train_segmented")
```

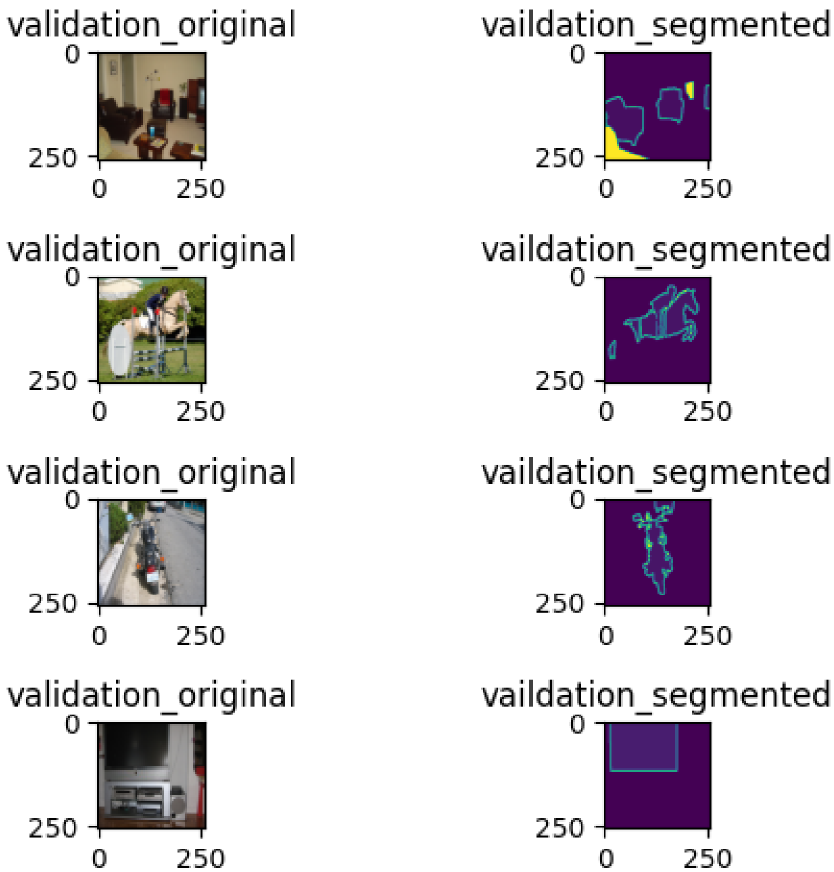
```python
    fig.tight_layout()
    plt.show()
    break
```



[5]:
```python
# plot a few validation samples
for _, (images,labels) in enumerate(val_dl_reshaped):
    fig, axs = plt.subplots(BATCH_SIZE, 2)

    for i in range(BATCH_SIZE):
        axs[i, 0].imshow(images[i].permute(1,2,0))
        axs[i, 0].set_title("validation_original")

        axs[i, 1].imshow(labels[i].permute(1,2,0))
        axs[i, 1].set_title("vaildation_segmented")

    fig.tight_layout()
    plt.show()
    break
```



[6]:
```python
# plot a few validation samples
for _, (images,labels) in enumerate(train_dl_reshaped):
    fig, axs = plt.subplots(BATCH_SIZE, 2)

    for i in range(BATCH_SIZE):
        axs[i, 0].imshow(images[i].permute(1,2,0))
        axs[i, 0].set_title("validation_original")

        axs[i, 1].imshow(labels[i].permute(1,2,0))
        axs[i, 1].set_title("vaildation_segmented")

    fig.tight_layout()
    plt.show()
    break
```




```
[7]: def train_epoch(model, train_dl, val_dl, optimizer, device):
         """
         Train one epoch of model with optimizer, using data from train_dl.
         Do training on "device".
         Return the train and validation loss and validation accuracy.
         """

         # We'll use the cross entropy loss. There's a nice feature that it
         # allows you to "ignore_index". In this case index 255 is the mask to ignore
         # recommend to use in constructing loss
         criterion = nn.CrossEntropyLoss(ignore_index=255)

         # TODO: Train (3 points)
         # Iterate over the train dataloader
         # Put data batch on same device as model
         # "Forward pass" - run data through model, and use output to calculate loss.
     ↪
         # "backward pass"
         # Remember to keep track of training loss during loop.
```

```
    # Train Step
    model.train()
    train_loss = 0

    for _, (images,labels) in enumerate(train_dl):

        optimizer.zero_grad()
        images = images.to(device)
        labels = labels.to(device)
        labels = labels.squeeze(1)

        # Forward pass
        output = model(images)['out']
        loss = criterion(output, labels)

        # Store loss
        with torch.no_grad():
            train_loss += loss.item()

        # Backward and optimize
        loss.backward()
        optimizer.step()

    # TODO: Validation loss and accuracy (2 points)
    # Estimate the loss on the validation dataset
    # The network should be in "eval" mode (remember to go back to train mode␣
↪for training)
    # Turn off grad tracking for speed
    # Accuracy on validation datais very helpful to output -
    # 69(nice! :D) percent of pixels are "background" - we hope to get better␣
↪accuracy than that!

    # Test Step
    model.eval()
    with torch.no_grad():

        val_loss = 0
        all_preds = []
        all_masks = []

        for  _, (images,labels) in enumerate(val_dl):
            images = images.to(device)
            labels = labels.to(device)
            labels = labels.squeeze(1)

            # Forward
```

```
            outputs = model(images)['out']
            loss = nn.CrossEntropyLoss(ignore_index=255)(outputs, labels)
            val_loss += loss.item()

            # Make prediction
            preds = torch.argmax(outputs, dim=1)
            all_preds.append(preds)
            all_masks.append(labels)

        # Concatenate all preds from X,4,Y,Z to 4X,Y,Z
        all_preds = torch.concatenate(all_preds)
        all_masks = torch.concatenate(all_masks)

        # Reshape to get single vector instead of tensor
        all_preds = all_preds.reshape(-1,1)
        all_masks = all_masks.reshape(-1,1)

        # calculate accuracy
        val_acc = torch.sum(all_preds == all_masks)/all_masks.shape[0]

    return train_loss, val_loss, val_acc.item()
```

0.0.2 Main loop

[8]:
```
def main_loop(batch_size=32, learning_rate=0.01, momentum=0.1, weight_decay=0.
 ↪01, epochs=60, resize_shape=(256,256), early_stopping=False, patience=5):

    print ('-----------------------------------------------------')
    print ('batch_size = {}, learning_rate = {}, momentum = {}, weight_decay =␣
 ↪{}, epochs = {}, resize_shape = {}'.format(batch_size, learning_rate,␣
 ↪momentum, weight_decay, epochs, resize_shape))

    # Load model and data
    n_class = 21  # The class labels are 0...20. The label "255" is interpreted␣
 ↪as a "mask" meant to be ignored
    model = fcn_resnet50(n_class=n_class).to(device)
    train_dl, val_dl, _ = get_voc_dataloader(batch_size=batch_size,␣
 ↪resize_shape=resize_shape)

    # Training loop
    optimizer = optim.SGD(model.parameters(), lr=learning_rate,␣
 ↪momentum=momentum, weight_decay=weight_decay)

    patience_ctr = 0
```

```
best_acc = -1
train_losses, val_losses, val_accuracies = [], [], []
for epoch in range(epochs):
    train_loss, val_loss, val_accuracy = train_epoch(model, train_dl,␣
↪val_dl, optimizer, device)

    # Print the loss, and store for plotting
    train_losses.append(train_loss)
    val_losses.append(val_loss)
    val_accuracies.append(val_accuracy)
    print('Epoch %d: Train loss: %.3f | Val loss: %.3f | Acc: %.3f' %␣
↪(epoch+1, train_loss, val_loss, val_accuracy))

    # early stopping
    if best_acc <= val_accuracy:
        patience_ctr = 0
        best_acc = val_accuracy
    else:
        patience_ctr += 1
        if patience_ctr >= patience and early_stopping == True:
            print ('Early Stopping as accuracy decreases')
            break




plt.figure(1)
plt.plot(torch.arange(len(train_losses)), train_losses, label='train_loss')
plt.plot(torch.arange(len(val_losses)), val_losses, label='val_loss')
plt.title('Train and Validation loss')
plt.ylabel('loss')
plt.xlabel('n_epochs')
plt.grid()
plt.legend()
plt.show()

plt.figure(1)
plt.plot(torch.arange(len(val_accuracies)), val_accuracies,␣
↪label='val_accuracy')
plt.title('Validation Accuracy')
plt.ylabel('accuracy')
plt.xlabel('n_epochs')
plt.grid()
plt.legend()
plt.show()
```

```
    return sum(train_losses)/len(train_losses), sum(val_losses)/
↪len(val_losses), sum(val_accuracies)/len(val_accuracies), model, train_dl,␣
↪val_dl
```

0.0.3 Grid Search For hyper parameters

[9]:
```
# # results from this will be linked below. do not run this, it will run for␣
↪~50 hrs

# device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
# device = torch.device('mps') if torch.backends.mps.is_available() else device

# # Search some optimal hyperparameters
# results = []
# # for epoch in [20, 40]:
# #     for learning_rate in [0.01, 0.001, 0.0001]:
# #         for batch_size in [16, 32, 64]:
# #             for resize_shape in [(128,128), (256,256)]:
# #                 for weight_decay in [0, 0.1, 0.01]:
# #                     for momentum in [0., 0.1, 0.5, 0.9, 1.]:

#                         if (batch_size == 64 and resize_shape == (256,256)):
#                           continue

#                         train_loss, val_loss, val_acc, _, _, _ =␣
↪main_loop(batch_size, learning_rate, weight_decay, momentum, epoch,␣
↪resize_shape)

#                         results.append({
#                             'batch_size':batch_size,
#                             'learning_rate':learning_rate,
#                             'epoch':epoch,
#                             'resize_shape':resize_shape,
#                             'weight_decay':weight_decay,
#                             'momentum':momentum,
#                             'train_loss':train_loss,
#                             'val_loss':val_loss,
#                             'val_acc':val_acc,
#                         })

#                         df = pd.DataFrame.from_records(results)
#                         path_to_store = f'/content/drive/MyDrive/UCR/
↪results_{iter}.csv'
#                         with open(path_to_store, 'w', encoding = 'utf-8-sig')␣
↪as f:
#                             df.to_csv(f)
```

[10]:

```
# The results from grid search are stored in the csv.
from urllib import request
request.urlretrieve('https://d1u36hdvoy9y69.cloudfront.net/cs-229-ml/results.
↪csv','results.csv')

df = pd.read_csv('results.csv')
df = df.sort_values(by=['val_acc'], ascending=False)
df.head(10)
```

[10]:

```
     epoch  learning_rate  batch_size resize_shape  weight_decay  momentum  \
125     40           0.01          16   (256, 256)          0.10       0.0
130     40           0.01          16   (256, 256)          0.01       0.0
160     40           0.01          32   (256, 256)          0.01       0.0
155     40           0.01          32   (256, 256)          0.10       0.0
150     40           0.01          32   (256, 256)          0.00       0.0
20      20           0.01          16   (256, 256)          0.10       0.0
131     40           0.01          16   (256, 256)          0.01       0.1
120     40           0.01          16   (256, 256)          0.00       0.0
156     40           0.01          32   (256, 256)          0.10       0.1
161     40           0.01          32   (256, 256)          0.01       0.1

     train_loss  val_loss   val_acc
125    4.660566  7.666572  0.803307
130    4.925307  7.856535  0.803028
160    2.540164  4.093119  0.802137
155    2.376173  3.996474  0.801836
150    2.531680  4.089894  0.799998
20     5.910290  8.202301  0.799369
131    6.041143  8.584558  0.798994
120    4.831833  7.916957  0.798457
156    2.741209  4.296331  0.797684
161    2.830769  4.313980  0.797613
```

0.0.4 Main Loop Training with Optimal Hyperparameters

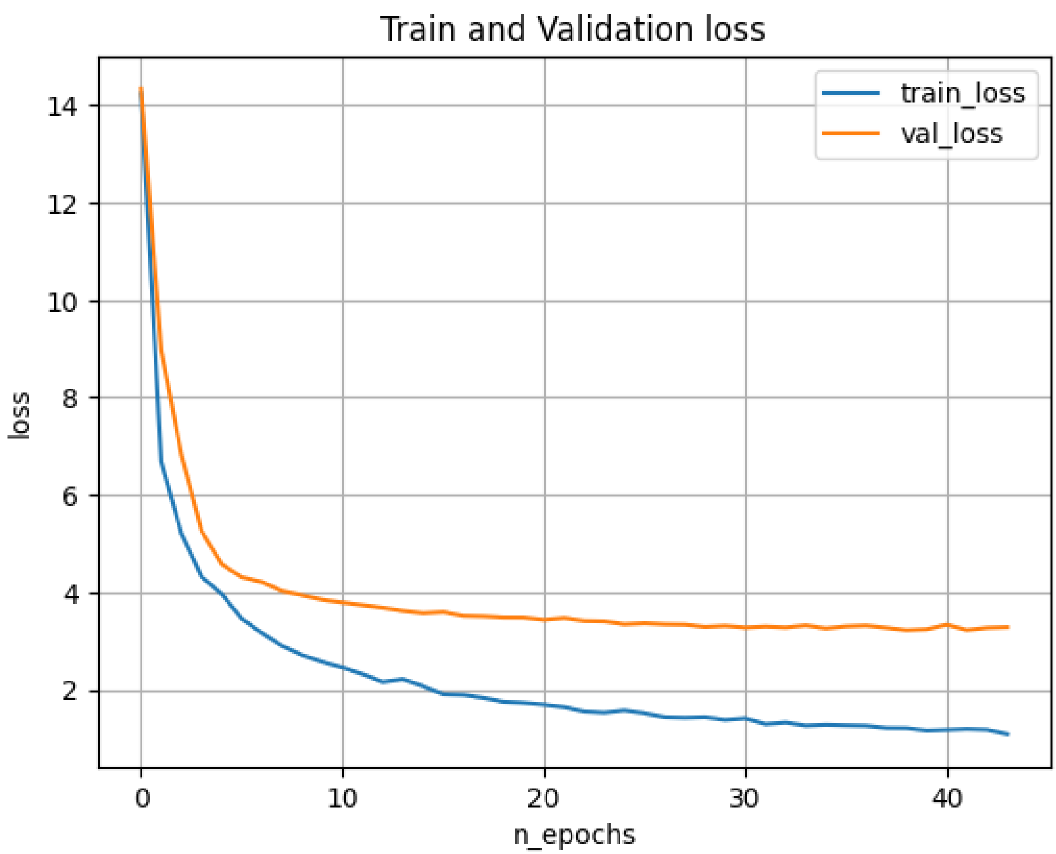
[11]:

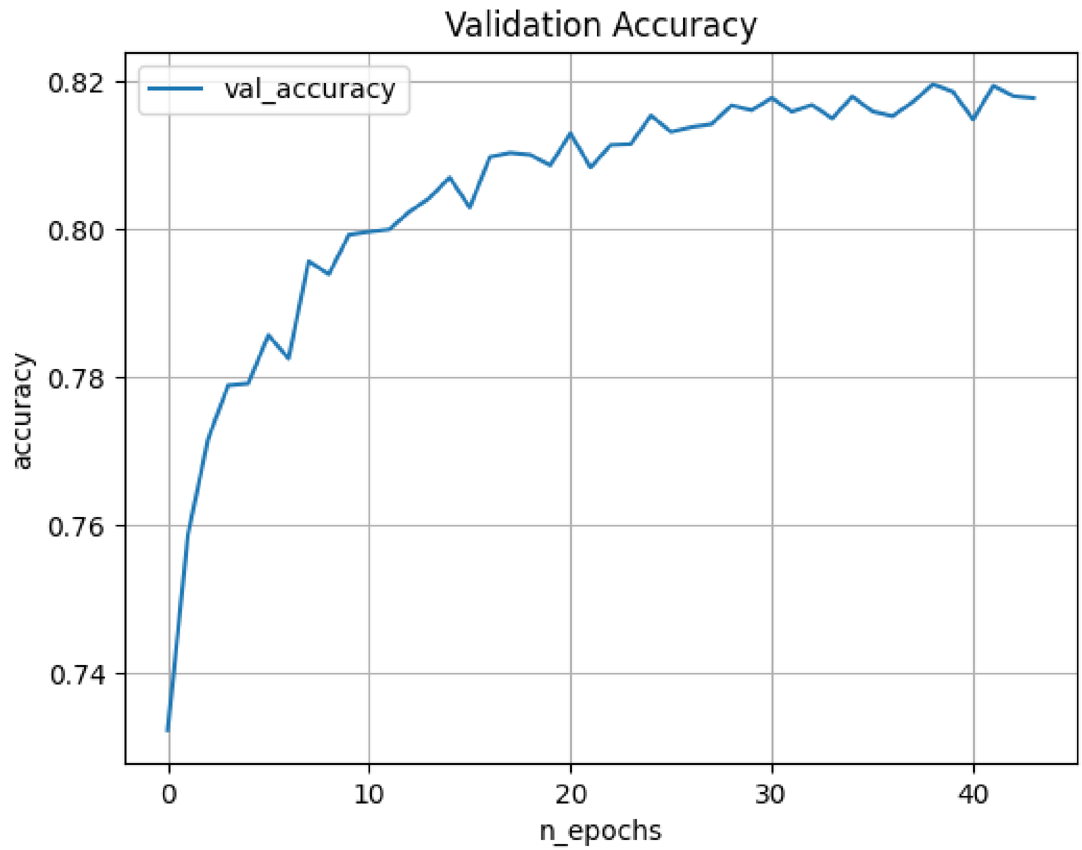
```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
device = torch.device('mps') if torch.backends.mps.is_available() else device

# Define some hyperparameters
epochs = 60
learning_rate = 0.01
n_class = 21  # The class labels are 0...20. The label "255" is interpreted as␣
↪a "mask" meant to be ignored
batch_size = 32  # Adjust batch size to make maximal use of GPU without running␣
↪out of memory
resize_shape = (256,256)
weight_decay = 0.1
```

```
momentum = 0.01
early_stopping = True
patience = 5

train_loss, val_loss, val_acc, model, train_dl, val_dl = main_loop(batch_size,
 ↪learning_rate, weight_decay, momentum, epochs, resize_shape, early_stopping,
 ↪patience)
```

```
----------------------------------------------------
batch_size = 32, learning_rate = 0.01, momentum = 0.1, weight_decay = 0.01,
epochs = 60, resize_shape = (256, 256)

Downloading: "https://download.pytorch.org/models/resnet50-0676ba61.pth" to
/root/.cache/torch/hub/checkpoints/resnet50-0676ba61.pth
100%|      | 97.8M/97.8M [00:00<00:00, 204MB/s]

Reshaping images to (256, 256)
Using downloaded and verified file: ./VOCtrainval_06-Nov-2007.tar
Extracting ./VOCtrainval_06-Nov-2007.tar to ./
Using downloaded and verified file: ./VOCtrainval_06-Nov-2007.tar
Extracting ./VOCtrainval_06-Nov-2007.tar to ./
Using downloaded and verified file: ./VOCtest_06-Nov-2007.tar
Extracting ./VOCtest_06-Nov-2007.tar to ./
Epoch 1: Train loss: 14.236 | Val loss: 14.338 | Acc: 0.732
Epoch 2: Train loss: 6.677 | Val loss: 8.967 | Acc: 0.759
Epoch 3: Train loss: 5.207 | Val loss: 6.830 | Acc: 0.772
Epoch 4: Train loss: 4.318 | Val loss: 5.259 | Acc: 0.779
Epoch 5: Train loss: 3.964 | Val loss: 4.573 | Acc: 0.779
Epoch 6: Train loss: 3.453 | Val loss: 4.306 | Acc: 0.786
Epoch 7: Train loss: 3.157 | Val loss: 4.207 | Acc: 0.782
Epoch 8: Train loss: 2.899 | Val loss: 4.025 | Acc: 0.796
Epoch 9: Train loss: 2.707 | Val loss: 3.937 | Acc: 0.794
Epoch 10: Train loss: 2.569 | Val loss: 3.844 | Acc: 0.799
Epoch 11: Train loss: 2.454 | Val loss: 3.786 | Acc: 0.800
Epoch 12: Train loss: 2.316 | Val loss: 3.734 | Acc: 0.800
Epoch 13: Train loss: 2.155 | Val loss: 3.679 | Acc: 0.802
Epoch 14: Train loss: 2.213 | Val loss: 3.616 | Acc: 0.804
Epoch 15: Train loss: 2.069 | Val loss: 3.569 | Acc: 0.807
Epoch 16: Train loss: 1.903 | Val loss: 3.593 | Acc: 0.803
Epoch 17: Train loss: 1.891 | Val loss: 3.514 | Acc: 0.810
Epoch 18: Train loss: 1.828 | Val loss: 3.505 | Acc: 0.810
Epoch 19: Train loss: 1.748 | Val loss: 3.481 | Acc: 0.810
Epoch 20: Train loss: 1.727 | Val loss: 3.479 | Acc: 0.809
Epoch 21: Train loss: 1.689 | Val loss: 3.429 | Acc: 0.813
Epoch 22: Train loss: 1.639 | Val loss: 3.469 | Acc: 0.808
Epoch 23: Train loss: 1.549 | Val loss: 3.409 | Acc: 0.811
Epoch 24: Train loss: 1.527 | Val loss: 3.401 | Acc: 0.811
Epoch 25: Train loss: 1.572 | Val loss: 3.340 | Acc: 0.815
```

```
Epoch 26: Train loss: 1.514 | Val loss: 3.361 | Acc: 0.813
Epoch 27: Train loss: 1.432 | Val loss: 3.340 | Acc: 0.814
Epoch 28: Train loss: 1.421 | Val loss: 3.333 | Acc: 0.814
Epoch 29: Train loss: 1.432 | Val loss: 3.285 | Acc: 0.817
Epoch 30: Train loss: 1.378 | Val loss: 3.307 | Acc: 0.816
Epoch 31: Train loss: 1.410 | Val loss: 3.272 | Acc: 0.818
Epoch 32: Train loss: 1.290 | Val loss: 3.293 | Acc: 0.816
Epoch 33: Train loss: 1.323 | Val loss: 3.274 | Acc: 0.817
Epoch 34: Train loss: 1.259 | Val loss: 3.317 | Acc: 0.815
Epoch 35: Train loss: 1.276 | Val loss: 3.255 | Acc: 0.818
Epoch 36: Train loss: 1.265 | Val loss: 3.297 | Acc: 0.816
Epoch 37: Train loss: 1.257 | Val loss: 3.313 | Acc: 0.815
Epoch 38: Train loss: 1.210 | Val loss: 3.267 | Acc: 0.817
Epoch 39: Train loss: 1.207 | Val loss: 3.216 | Acc: 0.820
Epoch 40: Train loss: 1.157 | Val loss: 3.236 | Acc: 0.818
Epoch 41: Train loss: 1.172 | Val loss: 3.332 | Acc: 0.815
Epoch 42: Train loss: 1.189 | Val loss: 3.219 | Acc: 0.819
Epoch 43: Train loss: 1.175 | Val loss: 3.267 | Acc: 0.818
Epoch 44: Train loss: 1.085 | Val loss: 3.280 | Acc: 0.818
Early Stopping as accuracy decreases
```





0.1 Post training visualization and analysis

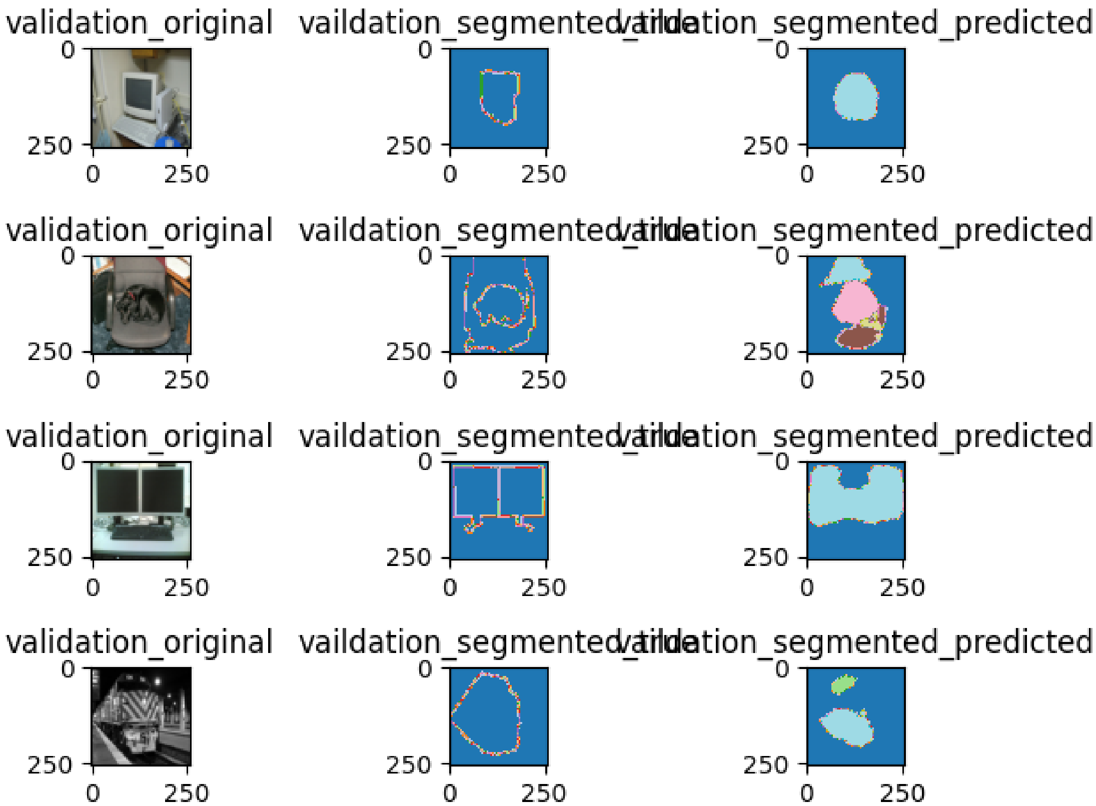
[12]:
```
# TODO: Train and test loss plot
# TODO: Print out an example image, true segmentation, and predicted␣
 ↪segmentation (1 point)
# Use a colormap to get good visualizations of the segmentation classes
# cmap = plt.cm.get_cmap('tab20', n_class + 1)  # tab20 is a colormap with 20␣
 ↪distinct colors
# cmap(numpy class array) outputs something with nice colors

train_dl, val_dl, test_dl = get_voc_dataloader(batch_size=5,␣
 ↪resize_shape=(256,256))

# tab20 is a colormap with 20 distinct colors
cmap = plt.cm.get_cmap('tab20', n_class + 1)
BATCH_SIZE_temp = 4
# plot a few validation samples
for _, (images,labels) in enumerate(val_dl):
    plt.figure(figsize=(40,40))
```

```
    fig, axs = plt.subplots(BATCH_SIZE_temp, 3)

    images = images.to(device)
    labels = labels.to(device)

    with torch.no_grad():
      outputs = model(images)['out']
      preds = torch.argmax(outputs, dim=1)
      preds = preds.unsqueeze(1)

    for i in range(BATCH_SIZE_temp):
        axs[i, 0].imshow(torch.permute(images[i].to('cpu'), (1,2,0)))
        axs[i, 0].set_title("validation_original")

        axs[i, 1].imshow(torch.permute(labels[i].to('cpu'), (1,2,0)), cmap=cmap)
        axs[i, 1].set_title("vaildation_segmented_true")

        axs[i, 2].imshow(torch.permute(preds[i].to('cpu'), (1,2,0)), cmap=cmap)
        axs[i, 2].set_title("vaildation_segmented_predicted")

    fig.tight_layout()
    plt.show()
    break
```

```
Reshaping images to (256, 256)
Using downloaded and verified file: ./VOCtrainval_06-Nov-2007.tar
Extracting ./VOCtrainval_06-Nov-2007.tar to ./
Using downloaded and verified file: ./VOCtrainval_06-Nov-2007.tar
Extracting ./VOCtrainval_06-Nov-2007.tar to ./
Using downloaded and verified file: ./VOCtest_06-Nov-2007.tar
Extracting ./VOCtest_06-Nov-2007.tar to ./
```

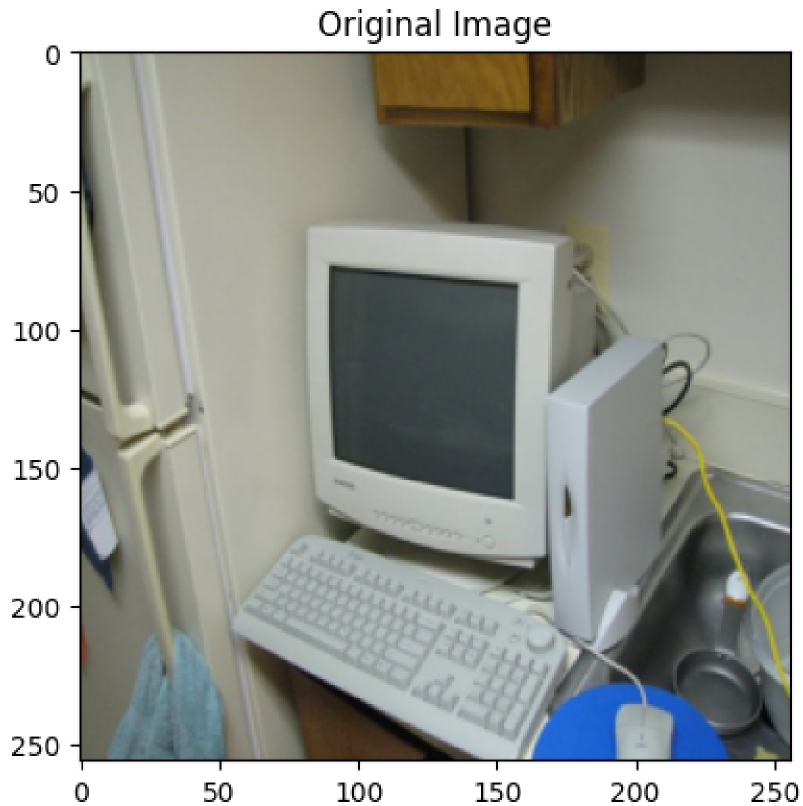
```
<ipython-input-12-aaa50a9cebda>:10: MatplotlibDeprecationWarning: The get_cmap
function was deprecated in Matplotlib 3.7 and will be removed two minor releases
later. Use ``matplotlib.colormaps[name]`` or
``matplotlib.colormaps.get_cmap(obj)`` instead.
  cmap = plt.cm.get_cmap('tab20', n_class + 1)
```

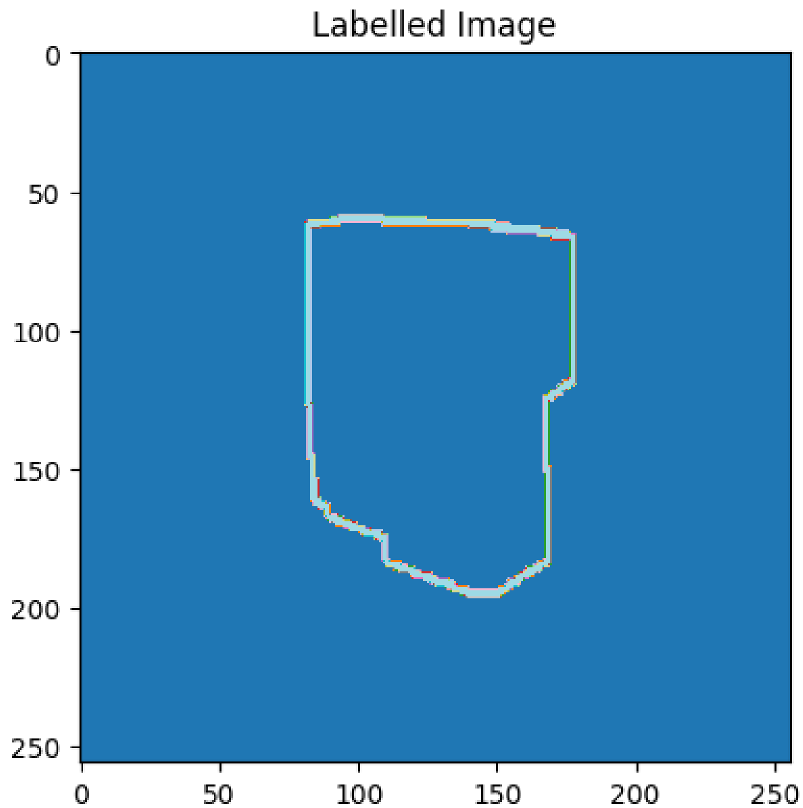
```
<Figure size 4000x4000 with 0 Axes>
```

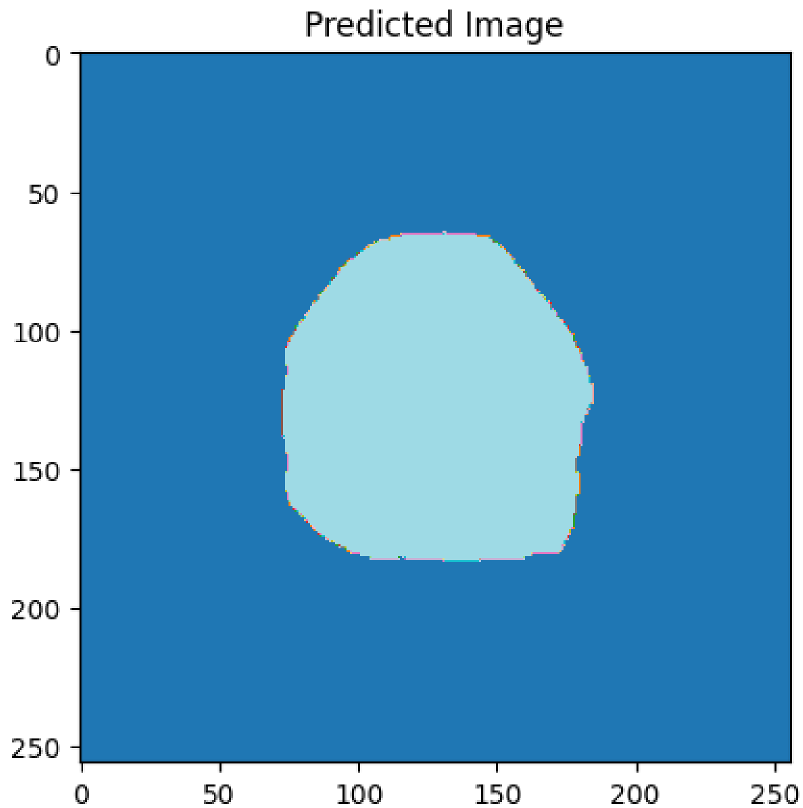


[13]:
```python
# Plot 1 set of images from validation set
first_batch = next(iter(val_dl))
images = first_batch[0].to(device)
labels = first_batch[1].to(device)

with torch.no_grad():
  outputs = model(images)['out']
  preds = torch.argmax(outputs, dim=1)
  preds = preds.unsqueeze(1)

plt.figure(1)
plt.title('Original Image')
plt.imshow(torch.permute(images[0].to('cpu'), (1,2,0)), cmap=cmap)
plt.show()
print ()

plt.figure(2)
plt.title('Labelled Image')
plt.imshow(torch.permute(labels[0].to('cpu'), (1,2,0)), cmap=cmap)
plt.show()
print ()
```

```
plt.figure(3)
plt.title('Predicted Image')
plt.imshow(torch.permute(preds[0].to('cpu'), (1,2,0)), cmap=cmap)
print ()
```




Labelled Image
0
50
100
150
200
250
0
50
100
150
200
250



0.1.1 Confidence Calibration for Validation Set

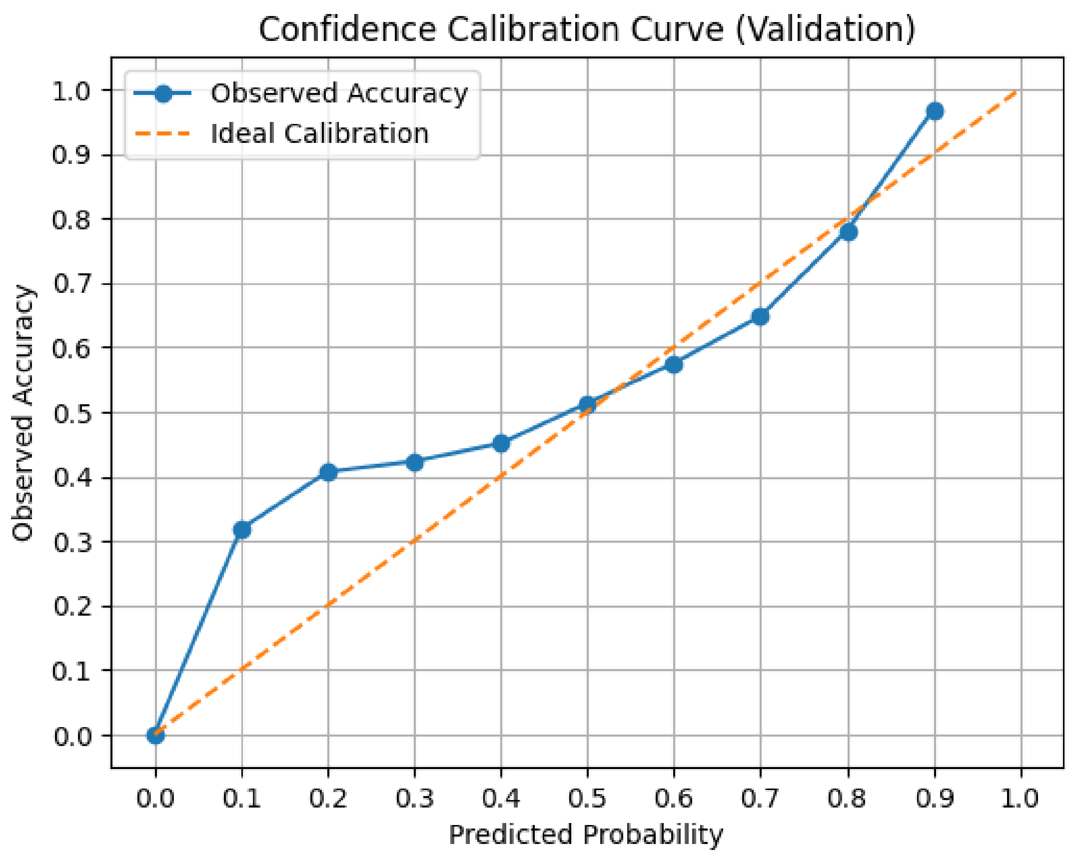
[14]:
```
# Feel free to use the outputs of my code for the confidence calibration plot
↪and ECE
# Here I run the model on all points in the validation set.
# I collect predictions on all pixels, excluding masks, and flatten them.

model.eval()
with torch.no_grad():
    all_acc = []
    all_conf = []
    for i, (inputs, labels) in enumerate(val_dl):

        # move data to device
        inputs, labels = inputs.to(device), labels.to(device)

        # get predictions
        outputs = model(inputs)['out']

        # reshape y_true to column vector
```

```
        labels = labels.squeeze(1).flatten(start_dim=1)  # batch, h, w  - integer values 0..20 or 255 for mask

        # generate y_pred from model output and convert y_pred to column vector
        predicted_label = outputs.argmax(axis=1).flatten(start_dim=1)  # batch, h, w, integer 0...20

        # generate probabilities from outputs
        probs = outputs.softmax(axis=1)  # batch, n_class, h, w

        # get max probability value for each pixel
        confidence = probs.max(axis=1).values.flatten(start_dim=1)  # Confidence in predicted label

        # get accuracy
        accuracy = (predicted_label == labels)

        # get only samples that are less than mask
        accuracy_filter = accuracy[labels < 255]

        # get only samples that are less than mask
        confidence_filter = confidence[labels < 255]

        all_acc.append(accuracy_filter)
        all_conf.append(confidence_filter)

# accuracy to predict pixel class across all pixels and images, excluding masks
all_acc = torch.cat(all_acc).cpu().numpy()

# confidence of prediction for each pixel and image, excluding masks
all_conf = torch.cat(all_conf).cpu().numpy()


# Get the average confidence and accuracy for points within different confidence ranges
bins = 10

# Generate intervals from 0 to 1 inclusive at a step of 0.1
bin_boundaries = np.linspace(0, 1, bins + 1)
bin_lowers = bin_boundaries[:-1]
bin_uppers = bin_boundaries[1:]
bin_centers = 0.5*(bin_lowers+bin_uppers)

bin_acc = np.zeros(bins)  # Store accuracy within each bin
bin_conf = np.zeros(bins)  # Store confidence within each bin
bin_frac = np.zeros(bins)  # Store the fraction of data in included in each bin
```

```
# find how many points lie in which bins based on confidence value
# for each bin at index
for i in range(bins):
    # point lies in bin if the confidence in less than max of the bin and␣
 ↪higher than the min of the bin
    in_bin = np.logical_and(all_conf >= bin_lowers[i], all_conf < bin_uppers[i])

    # find the fraction of points that lie in the bin
    bin_frac[i] = np.sum(in_bin) / len(all_conf)

    if bin_frac[i] > 0.:
        # average accuracy in this bin
        bin_acc[i] = all_acc[in_bin].mean()
        # average confidence in this bin
        bin_conf[i] = all_conf[in_bin].mean()
    else:
        # If no points are in this bin, they don't contribute to ECE anyway
        bin_acc[i], bin_conf[i] = 0, 0
```

[15]:
```
# TODO: Plot confidence calibration curve and calculate expected calibration␣
 ↪error (1 point)

# plot the calibration curve
fig, ax = plt.subplots()
ax.plot(bin_lowers, bin_acc, marker='o', label='Observed Accuracy')
ax.plot([0, 1], [0, 1], linestyle='--', label='Ideal Calibration')
ax.set_xlabel('Predicted Probability')
ax.set_ylabel('Observed Accuracy')
ax.set_title('Confidence Calibration Curve (Validation)')
plt.xticks(np.arange(0, 1.1, 0.1))
plt.yticks(np.arange(0, 1.1, 0.1))
plt.grid()
ax.legend()
```

[15]:
```
<matplotlib.legend.Legend at 0x7effd68963e0>
```



[16]:
```
# Calculate ECE
ece = np.sum(np.abs(bin_acc - bin_lowers) * bin_frac)
print("ECE: ", ece)
```

```
ECE:  0.06005434410458268
```

Confidence Calibration for TEST Set

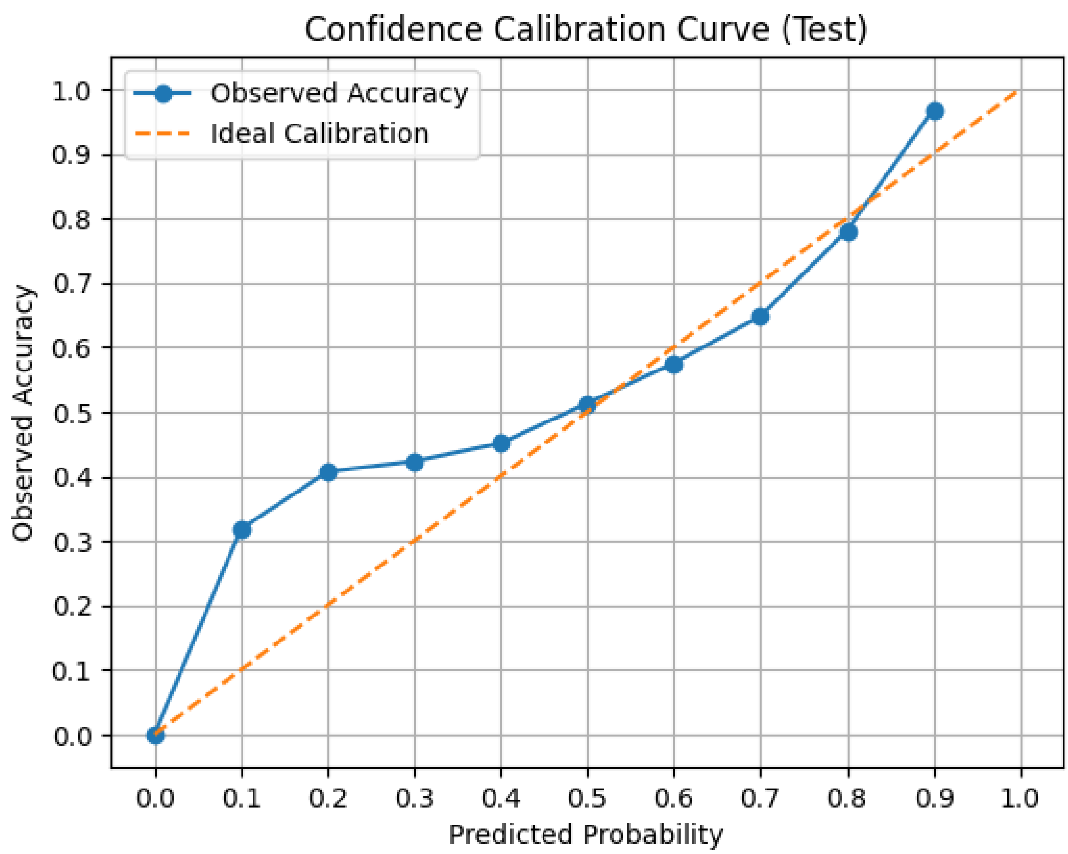
[17]:
```
# Feel free to use the outputs of my code for the confidence calibration plot␣
↪and ECE
# Here I run the model on all points in the validation set.
# I collect predictions on all pixels, excluding masks, and flatten them.

model.eval()
with torch.no_grad():
    all_acc = []
    all_conf = []
    for i, (inputs, labels) in enumerate(test_dl):

        # move data to device
        inputs, labels = inputs.to(device), labels.to(device)
```

```
        # get predictions
        outputs = model(inputs)['out']

        # reshape y_true to column vector
        labels = labels.squeeze(1).flatten(start_dim=1)  # batch, h, w  -␣
 ↪integer values 0..20 or 255 for mask

        # generate y_pred from model output and convert y_pred to column vector
        predicted_label = outputs.argmax(axis=1).flatten(start_dim=1)  # batch,␣
 ↪h, w, integer 0...20

        # generate probabilities from outputs
        probs = outputs.softmax(axis=1)  # batch, n_class, h, w

        # get max probability value for each pixel
        confidence = probs.max(axis=1).values.flatten(start_dim=1)  #␣
 ↪Confidence in predicted label

        # get accuracy
        accuracy = (predicted_label == labels)

        # get only samples that are less than mask
        accuracy_filter = accuracy[labels < 255]

        # get only samples that are less than mask
        confidence_filter = confidence[labels < 255]

        all_acc.append(accuracy_filter)
        all_conf.append(confidence_filter)

# accuracy to predict pixel class across all pixels and images, excluding masks
all_acc = torch.cat(all_acc).cpu().numpy()

# confidence of prediction for each pixel and image, excluding masks
all_conf = torch.cat(all_conf).cpu().numpy()


# Get the average confidence and accuracy for points within different␣
 ↪confidence ranges
bins = 10

# Generate intervals from 0 to 1 inclusive at a step of 0.1
bin_boundaries = np.linspace(0, 1, bins + 1)
bin_lowers = bin_boundaries[:-1]
bin_uppers = bin_boundaries[1:]
bin_centers = 0.5*(bin_lowers+bin_uppers)
```

```
bin_acc = np.zeros(bins)  # Store accuracy within each bin
bin_conf = np.zeros(bins)  # Store confidence within each bin
bin_frac = np.zeros(bins)  # Store the fraction of data in included in each bin

# find how many points lie in which bins based on confidence value
# for each bin at index
for i in range(bins):
    # point lies in bin if the confidence in less than max of the bin and␣
↪higher than the min of the bin
    in_bin = np.logical_and(all_conf >= bin_lowers[i], all_conf < bin_uppers[i])

    # find the fraction of points that lie in the bin
    bin_frac[i] = np.sum(in_bin) / len(all_conf)

    if bin_frac[i] > 0.:
        # average accuracy in this bin
        bin_acc[i] = all_acc[in_bin].mean()
        # average confidence in this bin
        bin_conf[i] = all_conf[in_bin].mean()
    else:
        # If no points are in this bin, they don't contribute to ECE anyway
        bin_acc[i], bin_conf[i] = 0, 0
```

[18]:
```
# TODO: Plot confidence calibration curve and calculate expected calibration␣
↪error (1 point)

# plot the calibration curve
fig, ax = plt.subplots()
ax.plot(bin_lowers, bin_acc, marker='o', label='Observed Accuracy')
ax.plot([0, 1], [0, 1], linestyle='--', label='Ideal Calibration')
ax.set_xlabel('Predicted Probability')
ax.set_ylabel('Observed Accuracy')
ax.set_title('Confidence Calibration Curve (Test)')
plt.xticks(np.arange(0, 1.1, 0.1))
plt.yticks(np.arange(0, 1.1, 0.1))
plt.grid()
ax.legend()
```

[18]: <matplotlib.legend.Legend at 0x7effd63bf130>



[19]:
```
# Calculate ECE
ece = np.sum(np.abs(bin_acc - bin_lowers) * bin_frac)
print("ECE: ", ece)
```

```
ECE:  0.060054344410458268
```

[20]:
```
# !sudo apt-get update
# !sudo apt-get install texlive-xetex texlive-fonts-recommended
# !jupyter nbconvert --log-level CRITICAL --to pdf␣
↪CS_229_Vision_uncertainty_HW_2.ipynb
```