Chapter_3_TL

January 26, 2022

1 Chapter 3: Transfer Learning - German Traffic Sign Recognition Benchmark (GTSRB)

Imports

[ ]:
```
#files
from glob import glob
import shutil
from pathlib import Path

# linalg
import numpy as np

# images
import cv2

# plotting
from matplotlib.ticker import MaxNLocator
import matplotlib.pyplot as plt
import seaborn as sns
from pylab import rcParams

# dataframes
import pandas as pd

# sklearn
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, classification_report

#progress bar
from tqdm import tqdm

# nice colors
import termcolor
from termcolor import colored

# pytorch
import torch, torchvision
```

```python
from torch import nn, optim

# functional
import torch.nn.functional as F

# utils
import torchvision.transforms as T
import PIL.Image as Image
from torch.optim import lr_scheduler
from collections import defaultdict

# datasets
from torchvision.datasets import ImageFolder
from torch.utils.data import DataLoader

# models
from torchvision import models
```

[ ]:
```python
# getting the specific device
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
dev_name = torch.cuda.get_device_name()
print(dev_name)
```

```
Tesla K80
```

[ ]:
```python
# setting the figure size
rcParams['figure.figsize'] = 12,8
```

Getting the GTSRB Dataset This dataset contains 42 classes of German traffic signs and we will use Transfer Learning to improve on a vainilla model.

[ ]:
```
!wget https://sid.erda.dk/public/archives/daaeac0d7ce1152aea9b61d9f1e19370/
↪GTSRB_Final_Training_Images.zip
```

```
--2022-01-26 18:26:49--  https://sid.erda.dk/public/archives/daaeac0d7ce1152aea9
b61d9f1e19370/GTSRB_Final_Training_Images.zip
Resolving sid.erda.dk (sid.erda.dk)… 130.225.104.13
Connecting to sid.erda.dk (sid.erda.dk)|130.225.104.13|:443… connected.
HTTP request sent, awaiting response… 200 OK
Length: 276294756 (263M) [application/zip]
Saving to: ‘GTSRB_Final_Training_Images.zip’

GTSRB_Final_Trainin 100%[===================>] 263.50M  11.1MB/s    in 26s

2022-01-26 18:27:16 (9.99 MB/s) - ‘GTSRB_Final_Training_Images.zip’ saved
[276294756/276294756]
```

```
[ ]: # Unzipping
     !unzip -qq "./GTSRB_Final_Training_Images.zip"
```

```
[ ]: # setting the path to the image folders
     IMG_FOLDER = '/content/GTSRB/Final_Training/Images'

     # getting all the classes
     train_folders = sorted(glob(IMG_FOLDER+'/*'))
     # number of classes
     print(f"We have {len(train_folders)} classes")
```

```
We have 43 classes
```

Helper Functions

```
[ ]: # Helper functions - 3 total !

     # 1 - loading the image
     def load_image(PATH, resize=True,size=(64,64)):
       '''
       Helper function to load the image and resize it to 64x64 in case that is␣
      ↪needed, or one can also
       define the specific shape
       '''
       # loading the image and loading it into RGB
       img = cv2.cvtColor(cv2.imread(PATH), cv2.COLOR_BGR2RGB)

       # resizing and interpolate
       if resize:
         img = cv2.resize(img, (size[0], size[1]), interpolation=cv2.INTER_AREA)

       return img


     # 2 - show image
     def show_img(PATH):
       '''
       Helper function to visualize an image
       '''
       # loading the image with the previous function
       img = load_image(PATH)
       # showing the image
       plt.imshow(img)
       plt.axis('off')


     # 3 - make grid with different signs
```

```
def make_traffic_grid(PATHS):
  '''
  Helper function which makes a grid to visualize 11 * 4 images (44 total)
  '''
  # loop through the paths we give it and load the images + make into array
  loaded_images = np.array([load_image(img) for img in PATHS])
  # convert it to tensors
  loaded_images = torch.as_tensor(loaded_images)
  # permuting them - changing the RGB --> BGR
  loaded_images = loaded_images.permute(0,3,1,2)
  # make a grid
  img_grid = torchvision.utils.make_grid(loaded_images, nrow=11)
  # make the figure for the grid
  plt.figure(figsize=(24,12))
  # show the image
  plt.imshow(img_grid.permute(1,2,0))
  # turning off the axis
  plt.axis('off')


def make_folders_data(CLASS,DATA_DIR, DATA_SETS):
  '''
  Helper function which makes a folder for the specific classes and the
  specific phase (train, test, val )

  '''
  # data directory
  ddir = Path(DATA_DIR)

  # looping
  for k in DATA_SETS:
    for y in CLASS:
      (ddir/k/y).mkdir(parents=True, exist_ok=True)

def split_data(CLASS_INDECES,CLASSES, DATA_SET, TRAIN_RATIO, VAL_RATIO,␣
↪DEBUG=True, FILE_BUG=False):
  '''
  Helper function to split the data into 10% testing and validation and 80%␣
↪training

  '''

  # looping through the index of the classes we chose
  for idx, class_idx in enumerate(CLASS_INDECES):
    # making the image path an array
    img_path = np.array(glob(f"{train_folders[class_idx]}/*.ppm"))
    # getting the specified class name
```

```python
    class_name = CLASSES[idx]
    # debugging
    if DEBUG:
      print(f"\nThe class {class_name} has {len(img_path)} images.")
    # shuffling them
    np.random.shuffle(img_path)
    # defining the ratios given the image path length (number of images)
    RATIOS = (int(TRAIN_RATIO*len(img_path)), int(VAL_RATIO*len(img_path)))
    # splitting them
    data_split = np.split(
                          img_path,
                          indices_or_sections=[RATIOS[0], RATIOS[1]]
                          )
    # zipping
    dataset_data = zip(DATA_SET,data_split)
    #ddir
    data_directory = Path('data')
    # moving the specified images
    for d, imgs in dataset_data:
      for paths in imgs:
        shutil.copy(paths, f"{data_directory}/{d}/{class_name}")
        if FILE_BUG:
          print(f"Moved {paths} successfully !!!")


def show_image(INPUT,title=None):
  '''
  Helper function to visualize the transformations that were done

  '''
  # transposing the image
  input = INPUT.numpy().transpose((1,2,0))
  # reverting the normalization
  means = np.array([meanies])
  st_dev = np.array([stds])
  # de-normalize
  input = st_dev * input + means
  # clipping
  input = np.clip(input, 0, 1)
  # showing
  plt.imshow(input)
  if title is not None:
    plt.title(title)
  plt.axis('off')
```

Visualize the Dataset

[ ]:
```python
# lets visualize a single example
CLASS = 9
sample_image = glob(train_folders[CLASS] + '/*ppm')[0]
show_img(sample_image)
```

[ ]:
```python
# get the random ramples
sample_images = [np.random.choice(glob(f"{x}/*ppm")) for x in train_folders]
print(f"Number of samples : {len(sample_images)}")

# now let's make a grid for these
make_traffic_grid(sample_images)
```

```
Number of samples : 43
```

Sepparating the Images

[ ]:
```
# we will use specific classes for this
classes = ['priority_road','give_way','stop','no_entry']

# and their corresponding indices
class_index = [12,13,14,17]

# datasets - train test val
DATASETS = ['train','test','val']

# making folders
make_folders_data(classes, 'data',DATASETS)

# splitting the data
split_data(class_index, classes, DATASETS,0.8, 0.9, DEBUG=True,FILE_BUG=False)
```

```
The class priority_road has 2100 images.

The class give_way has 2160 images.

The class stop has 780 images.

The class no_entry has 1110 images.
```

Image Transformations

[ ]:
```
# we will use the standard deviations and means that are given by torchvision
# means
meanies = [0.485,0.456,0.406]
# standard deviations
stds = [0.229, 0.224, 0.225]
```

```
# making a transformations dictionary
# transformations included:
# - Random Resized crop
# - Random Rotation
# - Center Crop
# - Normalization
transforms = {
              "train":T.Compose([
                                  T.RandomResizedCrop(size=256),
                                  T.RandomRotation(degrees=15),
                                  T.RandomHorizontalFlip(),
                                  T.ToTensor(),
                                  T.Normalize(meanies, stds)
                                  ]),

              "val":T.Compose([
                               T.Resize(size=256),
                                T.CenterCrop(size=224),
                                T.ToTensor(),
                                T.Normalize(meanies, stds)
                               ]),

              "test":T.Compose([
                                 T.Resize(size=256),
                                 T.CenterCrop(size=224),
                                 T.ToTensor(),
                                 T.Normalize(meanies, stds)
                                 ])
              }
```

Making the datasets

```
[ ]: data_dir = Path('data')
# create a pytorch dataset for each of the images
image_datasets = {
                  k: ImageFolder(f"{data_dir}/{k}",transforms[k]) for k in␣
 ↪DATASETS
                  }
# make a dataloader out of the datasets
data_loaders = {
                o: DataLoader(image_datasets[o],batch_size=4,␣
 ↪shuffle=True,num_workers=2) for o in DATASETS
                }

# we can extract the size of the dataset
size_ds = {d: len(image_datasets[d]) for d in DATASETS}
```

```
# also the class names
class_names = image_datasets['train'].classes
```

Visualizing the Image Transformations

[ ]:
```
# iterate over one of the dataloaders
targets, labels = next(iter(data_loaders['train']))
# make a grid
out_grid = torchvision.utils.make_grid(targets)
# lets show the images
show_image(out_grid, title=[class_names[x] for x in labels])
```

['give_way', 'stop', 'no_entry', 'priority_road']

Making the model - Transfer Learning

[ ]:
```
# make model function
def make_model(n_classes):
    '''
    Helper function to use a pretrained model with the GTSRB
    '''
    model = models.resnet34(pretrained=True)
    # stating the number of features
    n_features = model.fc.in_features
    # chaning the model fully connected
    model.fc = nn.Linear(n_features, n_classes)
    return model.to(device)

# number of classes
NUM_CLASSES = len(class_names)
# making the base model
base_model = make_model(NUM_CLASSES)
```

```
Downloading: "https://download.pytorch.org/models/resnet34-b627a593.pth" to
/root/.cache/torch/hub/checkpoints/resnet34-b627a593.pth

  0%|          | 0.00/83.3M [00:00<?, ?B/s]
```

Training - Testing - Validation Helper Functions

2 TRAINING

[ ]:
```
def train_loop(MODEL, DATA_LOADER, LOSS_FUNCTION, OPTIMIZER, DEVICE, SCHEDULER,␣
↪EXAMPLES):
  '''
  Helper function which trains the model with the given loss function,␣
↪optimizer, and scheduler.
  Training on the specified DATA_LOADER and with number of examples
  '''
  # putting into training mode
  model = MODEL.train()
  # accumulate the losses
  running_loss = []
  # correctly predicted counter
  correct_preds = 0
  # going over out dataloader
  for inputs, targets in DATA_LOADER:
    # sending to device
    inputs = inputs.to(DEVICE)
    targets = targets.to(DEVICE)
    # predicting an output
    y_pred = MODEL(inputs)
    # getting the max
    _, preds = torch.max(y_pred, dim=1)
    # getting the loss
    loss = LOSS_FUNCTION(y_pred, targets)
    # correct prediction
    correct_preds+= torch.sum(preds == targets)
    # appending the loss
    running_loss.append(loss.item())
    # zeroing grads
    OPTIMIZER.zero_grad()
    # sending the loss backwards
    loss.backward()
    # stepping
    OPTIMIZER.step()
    #print(num_corr, avg_loss)
  # step the scheduler
  SCHEDULER.step()
  # number correct
  num_corr = correct_preds.double()/EXAMPLES
  avg_loss = np.mean(running_loss)

  return num_corr, avg_loss
```

3 EVALUTATION

[ ]:
```
# Evaluate the model
def val_loop(MODEL, DATA_LOADER, LOSS_FUNCTION, DEVICE, EXAMPLES):
  '''
  Helper function to evaluate the model

  '''
  # setting into eval mode
  model = MODEL.eval()
  # accumulate the loss and predictions
  running_loss = []
  corr_preds = 0
  # loop
  with torch.no_grad():
    for inputs, targets in DATA_LOADER:
      # sending to deivce
      inputs = inputs.to(DEVICE)
      targets = targets.to(DEVICE)
      # prediction
      y_pred = MODEL(inputs)
      # max vls
      _, preds = torch.max(y_pred, dim=1)
      #loss
      loss = LOSS_FUNCTION(y_pred, targets)
      # correct predictions
      corr_preds += torch.sum(preds == targets)
      # keep track of loss
      running_loss.append(loss.item())
      # correct
      num_corr = corr_preds.double() / EXAMPLES
      avg_loss = np.mean(running_loss)
  return num_corr, avg_loss
```

4 TRAINING LOOP

[ ]:
```
def train_model(MODEL, DATA_LOADER, DATASET_SIZES, DEVICE, EPOCHS=3):
  '''
  Helper Function to train the model with the training and evaluation loop

  '''
  # defin our optimizer
  optimizer = optim.SGD(MODEL.parameters(), lr = 0.001, momentum=0.9)
  # define our scheduler
  scheduler = lr_scheduler.StepLR(optimizer, step_size=7, gamma=0.1)
  # define our loss function
```

```
  loss_fn = nn.CrossEntropyLoss().to(DEVICE)
  # history
  history = defaultdict(list)
  best_acc = 0
  for epoch in range(EPOCHS):
    # keep track of epochs
    print(f"\nEpoch: {epoch+1}/{EPOCHS}")
    # TRAINING
    train_acc, train_loss = train_loop(MODEL, DATA_LOADER['train'], loss_fn,␣
↪optimizer, DEVICE, scheduler, DATASET_SIZES['train'])
    train_txt = f"\nTRAINING: LOSS:{train_loss} ACCURACY: {train_acc}"
    print(colored(train_txt, 'red','on_white'))
    # VALIDATION
    val_acc, val_loss = val_loop(MODEL, DATA_LOADER['val'], loss_fn, DEVICE,␣
↪DATASET_SIZES['val'])
    val_txt = f"\nVALIDATION: LOSS:{val_loss} ACCURACY: {val_acc}"
    print(colored(val_txt, 'green','on_grey'))
    # keeping track of the data
    history['train_acc'].append(train_acc)
    history['train_loss'].append(train_loss)
    history['val_acc'].append(val_acc)
    history['val_loss'].append(val_loss)
    # keeping the best accuracy so far
    if val_acc > best_acc:
      torch.save(MODEL.state_dict(), "best_model_state.bin")
      best_acc = val_acc
  print(f"\nTHE BEST ACCURACY: {best_acc}")
    # loading the best model
  MODEL.load_state_dict(torch.load('best_model_state.bin'))
  return MODEL, history
```

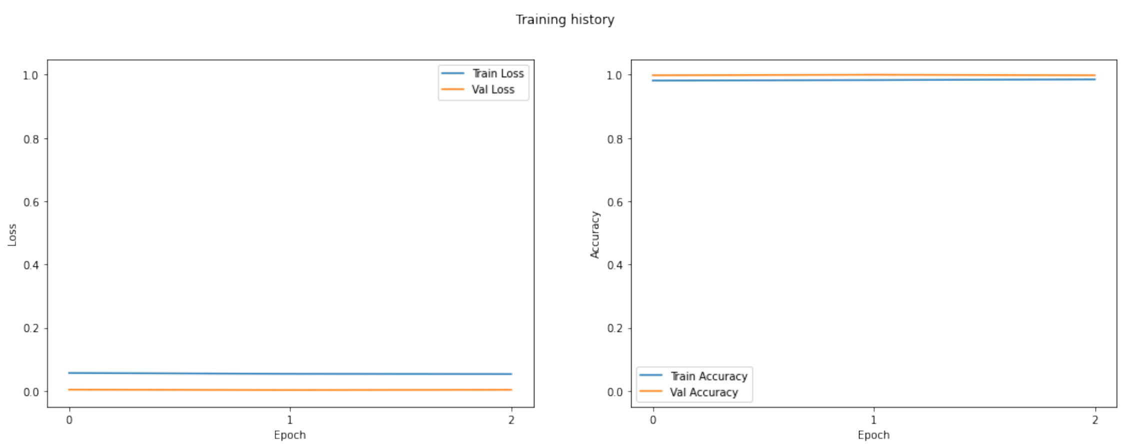
[ ]:
```
base_model, history = train_model(base_model, data_loaders, size_ds, device)
```

```
Epoch: 1/3
TRAINING: LOSS:0.05681165572400275 ACCURACY: 0.9817073170731707
VALIDATION: LOSS:0.004216150927070821 ACCURACY: 0.9983739837398374

Epoch: 2/3
TRAINING: LOSS:0.054183467861499905 ACCURACY: 0.983130081300813
VALIDATION: LOSS:0.0028477875562376307 ACCURACY: 1.0

Epoch: 3/3
TRAINING: LOSS:0.0534301981483763 ACCURACY: 0.9853658536585366
VALIDATION: LOSS:0.0037492613879549423 ACCURACY: 0.9983739837398374

THE BEST ACCURACY: 1.0
```

Visualize the History

[ ]:
```
def plot_history(HISTORY,SIZE=(18,6)):
    # creating the figure
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=SIZE)
    # LOSS
    ax1.plot(history['train_loss'], label='Train Loss')
    ax1.plot(history['val_loss'], label='Val Loss')
    # setting the ticks
    ax1.xaxis.set_major_locator(MaxNLocator(integer=True))
    ax1.set_ylim([-0.05, 1.05])
    ax1.legend()
    # labels
    ax1.set_ylabel('Loss')
    ax1.set_xlabel('Epoch')
    # ACCURACY
    ax2.plot(history['train_acc'], label='Train Accuracy')
    ax2.plot(history['val_acc'], label='Val Accuracy')
    # setting the ticks
    ax2.xaxis.set_major_locator(MaxNLocator(integer=True))
    ax2.set_ylim([-0.05, 1.05])
    ax2.legend()
    # lables
    ax2.set_ylabel('Accuracy')
    ax2.set_xlabel('Epoch')
    #Title
    fig.suptitle('Training history')
```

[ ]:
```
plot_history(history)
```



Visualize Predictions

[ ]:
```python
# we are going to show predictions on the test set now
def show_predictions(MODEL, CLASS_NAMES, N_IMAGES=6):
  # eval mode
  MODEL.eval()
  # counter
  imgs = 0
  # create a figure
  plt.figure()

  # with no grad
  with torch.no_grad():
    for idx, (inputs, targets) in enumerate(data_loaders['test']):
      # to device
      inputs = inputs.to(device)
      targets = targets.to(device)
      #preds
      outputs = MODEL(inputs)
      # getting the max
      _, pred = torch.max(outputs, dim=1)
      # now let's check the predictions
      for k in range(inputs.shape[0]):
        imgs+=1
        ax = plt.subplot(2, N_IMAGES//2, imgs)
        ax.set_title(f"Predicted: {class_names[pred[k]]}")
        show_image(inputs.cpu().data[k])
        ax.axis('off')
        if imgs == N_IMAGES:
          return
```

[ ]:
```python
show_predictions(base_model, class_names, N_IMAGES=8)
```

Getting the actual predictions

[ ]:
```
def get_preds(MODEL, DATA_LOADER):
  model = MODEL.eval()
  predictions = []
  real_vals = []
  with torch.no_grad():
    for inputs, targets in DATA_LOADER:
      inputs = inputs.to(device)
      targets = targets.to(device)
      outputs=model(inputs)
      _, preds = torch.max(outputs, dim=1)
      predictions.extend(preds)
      real_vals.extend(targets)
  predictions = torch.as_tensor(predictions).cpu()
  real_vals = torch.as_tensor(real_vals).cpu()
  return predictions, real_vals
```

[ ]:
```
y_pred, y_test = get_preds(base_model, data_loaders['test'])
```

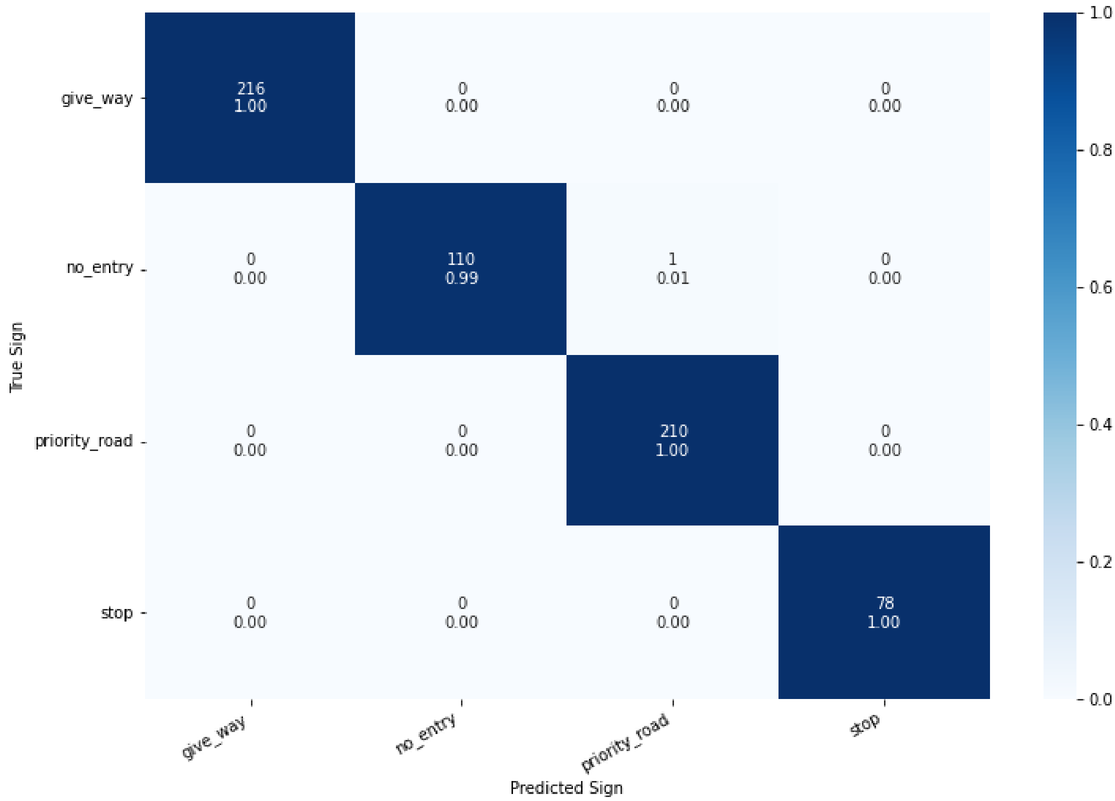
Classification Report + Matrix

[ ]:
```
# classification report
cr = classification_report(y_test, y_pred, target_names=class_names)
print(cr)
```

```
                precision    recall  f1-score   support

    give_way       1.00      1.00      1.00       216
    no_entry       1.00      0.99      1.00       111
priority_road       1.00      1.00      1.00       210
        stop       1.00      1.00      1.00        78

    accuracy                           1.00       615
   macro avg       1.00      1.00      1.00       615
weighted avg       1.00      1.00      1.00       615
```

[ ]:
```
# classification matrix
def show_cm(CM, NAMES):
  # copying the confustion matrix
  cm = CM.copy()
  # counts
  cell_counts = cm.flatten()
  # normalize
  cm_row_norm = cm / cm.sum(axis=1)[:, np.newaxis]
  #percentages
  row_percentages = ["{0:.2f}".format(value) for value in cm_row_norm.flatten()]
  # labels
  cell_labels = [f"{cnt}\n{per}" for cnt, per in zip(cell_counts,␣
↪row_percentages)]
  cell_labels = np.asarray(cell_labels).reshape(cm.shape[0], cm.shape[1])
  # dataframe
  df = pd.DataFrame(cm_row_norm, index=NAMES, columns=NAMES)
  #heatmap
  hmap = sns.heatmap(df, annot=cell_labels, fmt="", cmap="Blues")
  # ticks
  hmap.yaxis.set_ticklabels(hmap.yaxis.get_ticklabels(), rotation=0, ha='right')
  hmap.xaxis.set_ticklabels(hmap.xaxis.get_ticklabels(), rotation=30,␣
↪ha='right')
  # labels
  plt.ylabel('True Sign')
  plt.xlabel('Predicted Sign')
```

[ ]:
```
# make the confusion matrix
cm = confusion_matrix(y_test, y_pred)
# showing it
show_cm(cm,class_names)
```



5 Predict on Unseen Images

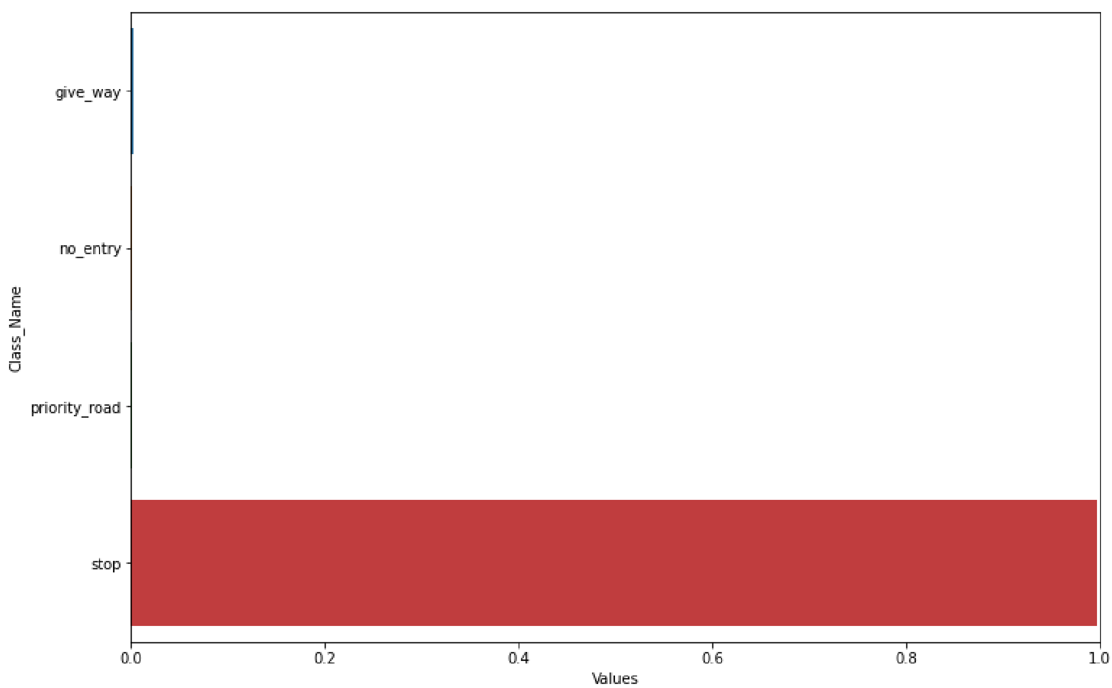
[ ]:
```
# we need to get the probabilities for each of the classes
def get_pred_proba(MODEL, PATH):
  # reading and converting the images
  img = Image.open(PATH)
  img = img.convert('RGB')
  img = transforms['test'](img).unsqueeze(0)
  img = img.to(device)
  # predicting
  pred = MODEL(img)
  pred = F.softmax(pred, dim=1)
  pred = pred.detach().cpu().numpy().flatten()
  return pred

# define another function to plot it as it returns an array
def plot_pred_proba(PRED, NAMES):
  pred_df = pd.DataFrame(
                        {
                          'Class_Name':NAMES,
```

```
                        'Values':PRED
                        })
  sns.barplot(x='Values',y='Class_Name',data=pred_df,orient='h')
  plt.xlim([0,1])
  plt.show()
```

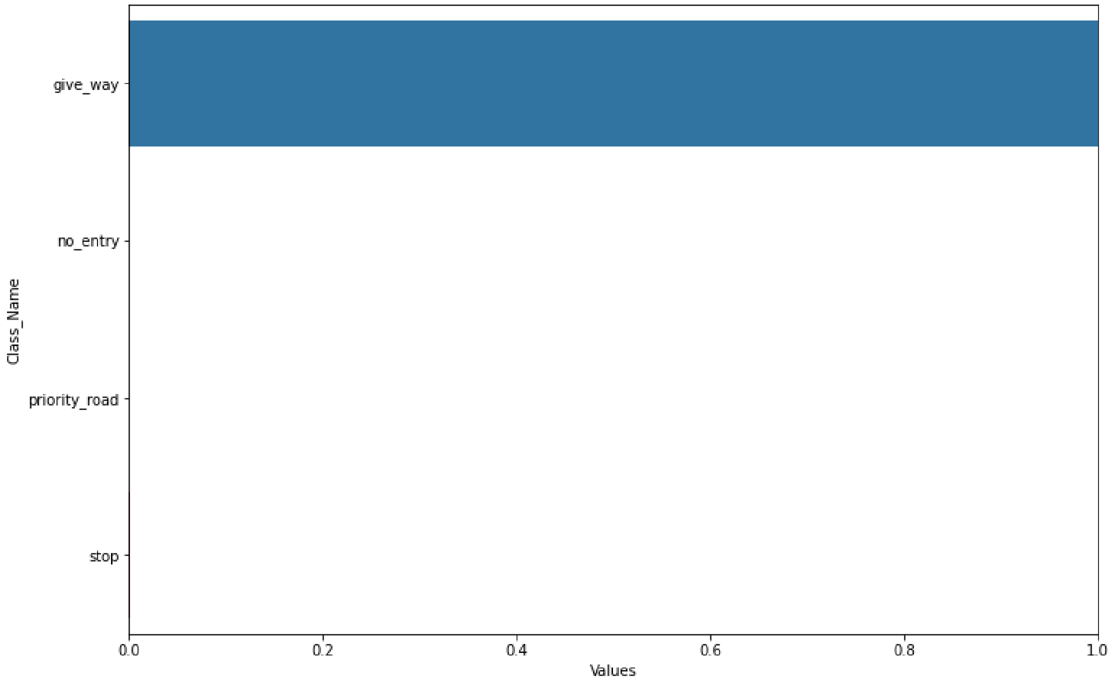
[ ]:
```
!gdown --id 19Qz3a61Ou_QSHsLeTznx8LtDBu4tbqHr
!gdown --id 1F61-iNhlJk-yKZRGcu6S9P29HxDFxF0u
```

```
Downloading…
From: https://drive.google.com/uc?id=19Qz3a61Ou_QSHsLeTznx8LtDBu4tbqHr
To: /content/stop-sign.jpg
100% 77.3k/77.3k [00:00<00:00, 73.7MB/s]
Downloading…
From: https://drive.google.com/uc?id=1F61-iNhlJk-yKZRGcu6S9P29HxDFxF0u
To: /content/unknown-sign.jpg
100% 41.4k/41.4k [00:00<00:00, 16.1MB/s]
```

[ ]:
```
# getting the prediction and then visualizing it
predz = get_pred_proba(base_model, 'stop-sign.jpg')
# visualize
plot_pred_proba(predz, class_names)
```



[ ]:
```python
# getting the prediction and then visualizing it
predz = get_pred_proba(base_model, 'unknown-sign.jpg')
# visualize
plot_pred_proba(predz, class_names)
```



[ ]:
```python

```