Chapter_3_TL

January 27, 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
```

```
--2022-01-27 11:24:48--  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  84.2MB/s    in 3.3s

2022-01-27 11:24:51 (80.5 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
```

```python
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

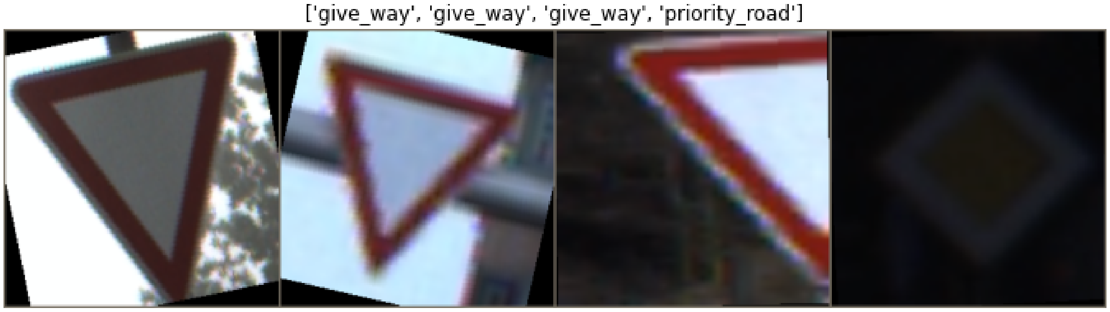
[ ]:
```
data_dir = Path('data')
# create a pytorch dataset for each of the images
image_datasets = {
                  k: ImageFolder(f"{data_dir}/{k}",transforms[k]) for k in␣
 ↪DATASETS
                  }
# make a dataloader out of the datasets
data_loaders = {
                o: DataLoader(image_datasets[o],batch_size=4,␣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

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

Visualizing the Image Transformations

[ ]:
```python
# 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', 'give_way', 'give_way', 'priority_road']



Making the model - Transfer Learning

[ ]:
```python
# 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

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
```

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
```

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
```

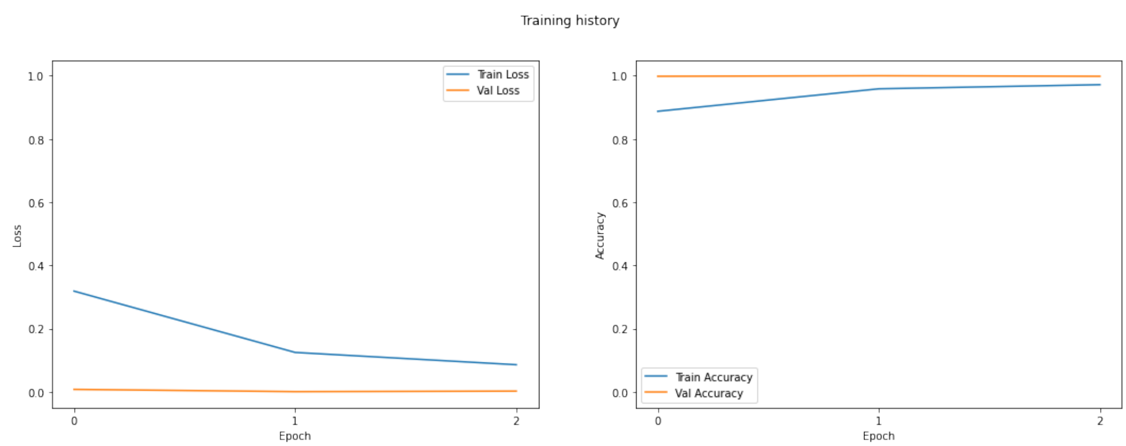
[ ]:
```
base_model, history = train_model(base_model, data_loaders, size_ds, device)
```

```
Epoch: 1/3
TRAINING: LOSS:0.3188715517628802 ACCURACY: 0.8876016260162601
VALIDATION: LOSS:0.008109279425806054 ACCURACY: 0.9983739837398374

Epoch: 2/3
TRAINING: LOSS:0.12497505745169639 ACCURACY: 0.958739837398374
VALIDATION: LOSS:0.0009808485402312986 ACCURACY: 1.0

Epoch: 3/3
TRAINING: LOSS:0.08614138082549784 ACCURACY: 0.9717479674796748
VALIDATION: LOSS:0.002622378306607988 ACCURACY: 0.9983739837398374

THE BEST ACCURACY: 1.0
```

Visualize the History

[ ]:
```python
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')
```

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

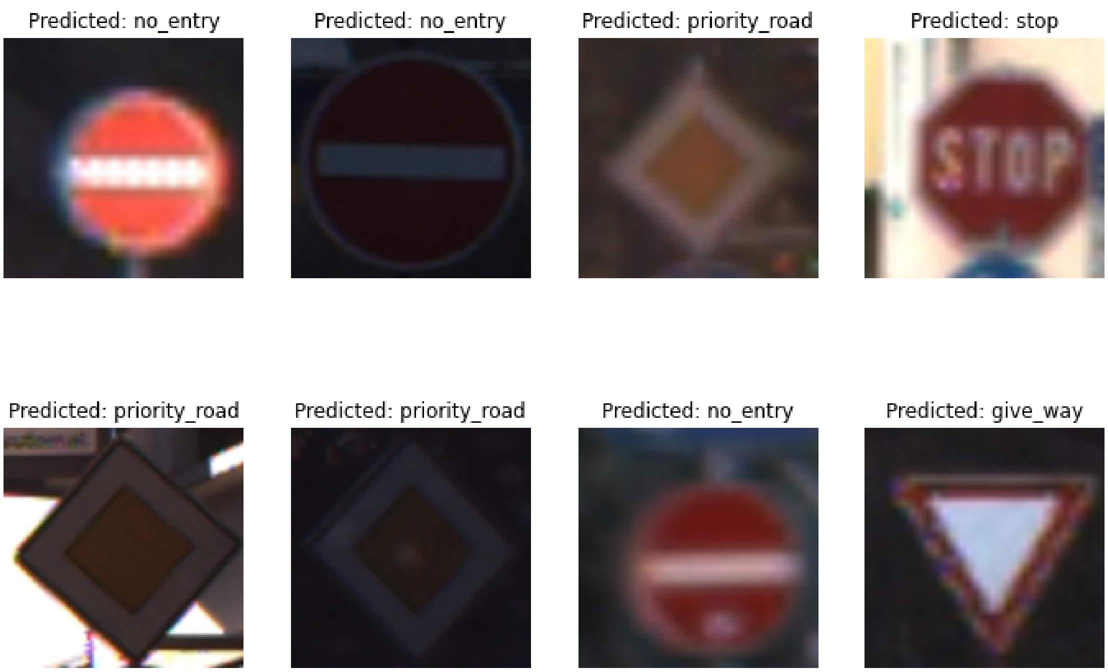


Visualize Predictions

[ ]:
```python
# we are going to show predictions on the test set now
def show_predictions(MODEL, CLASS_NAMES, N_IMAGES=6):
```

```python
    # 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'])
```

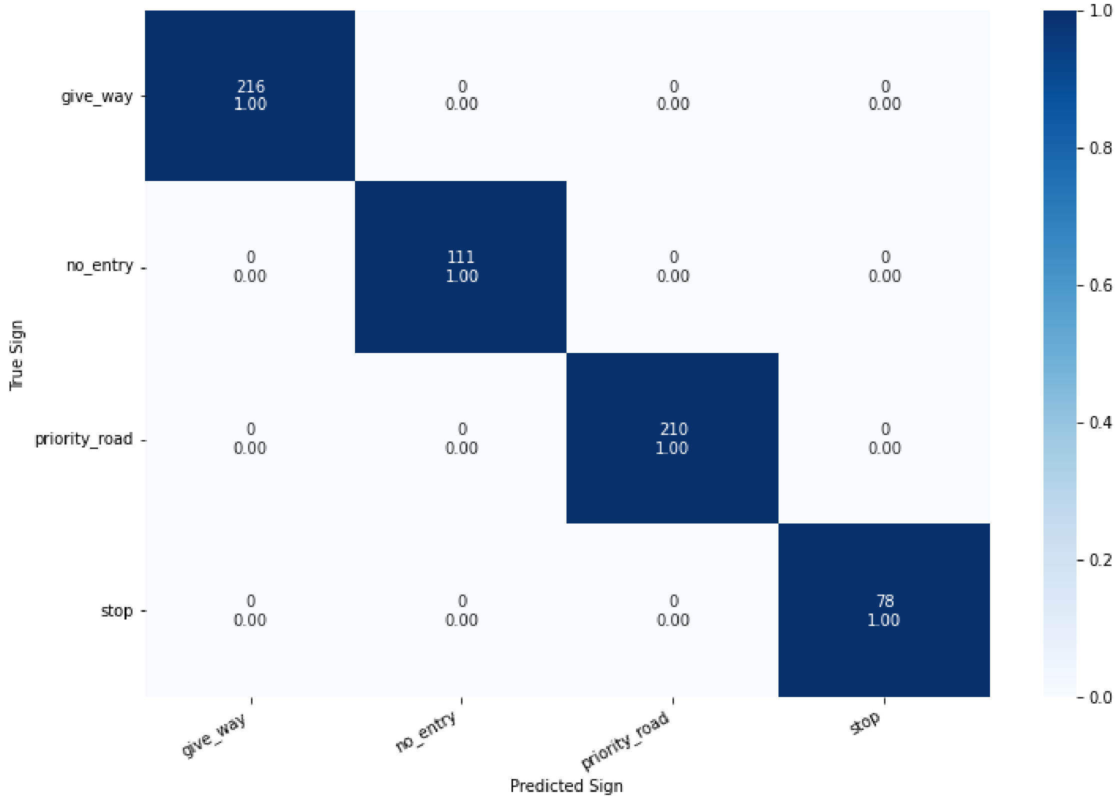
Classification Report + Matrix

[ ]:
```
# 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      1.00      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
```

[ ]:
```python
# 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')
```

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



Predict on Unseen Images

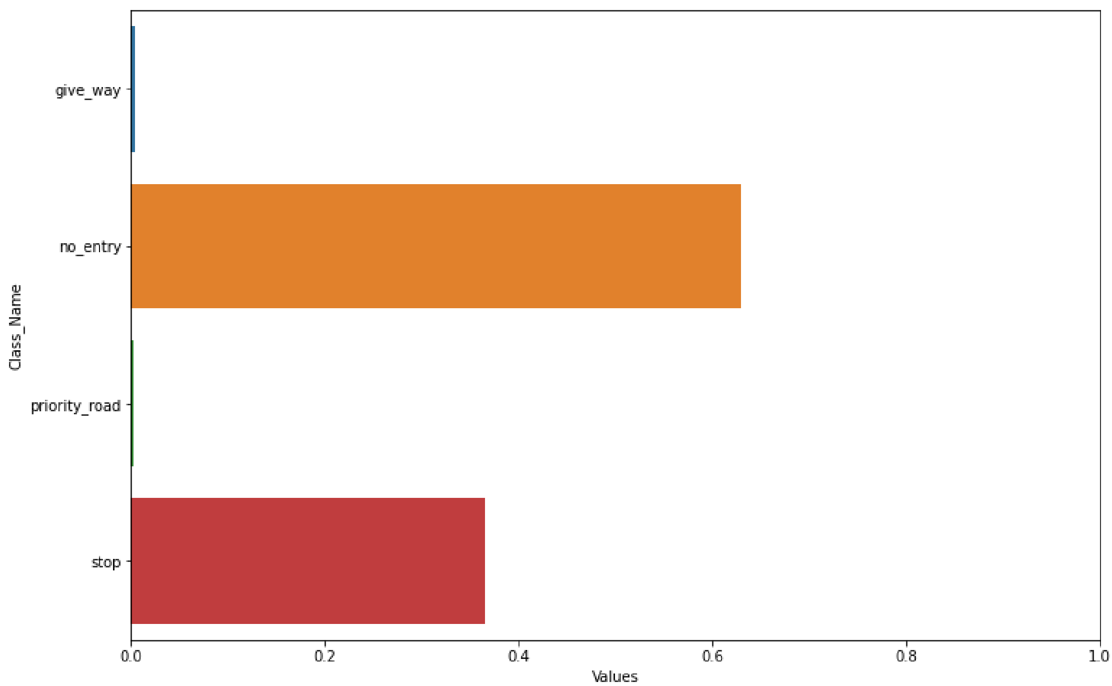
[ ]:
```python
# we need to get the probabilities for each of the classes
def get_pred_proba(MODEL, PATH):
  # reading and converting the images
  img = Image.open(PATH)
  img = img.convert('RGB')
  img = transforms['test'](img).unsqueeze(0)
  img = img.to(device)
  # predicting
  pred = MODEL(img)
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

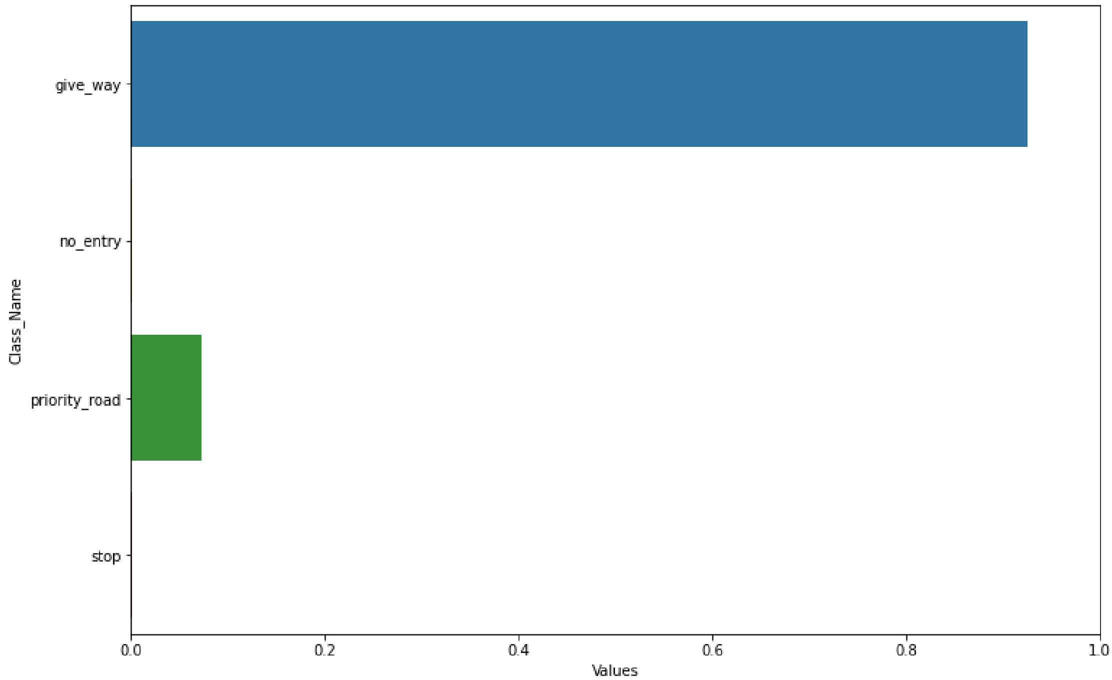
[ ]:
```
!gdown --id 19Qz3a61Ou_QSHsLeTznx8LtDBu4tbqHr
!gdown --id 1F61-iNhlJk-yKZRGcu6S9P29HxDFxF0u
```

```
Downloading…
From: https://drive.google.com/uc?id=19Qz3a61Ou_QSHsLeTznx8LtDBu4tbqHr
To: /content/stop-sign.jpg
100% 77.3k/77.3k [00:00<00:00, 28.8MB/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, 38.8MB/s]
```

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



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



Adding the Unknown class Dan Hendrycks and Kevin Gimpel demonstrate that we can measure whether a sample is misclassified by looking at the in-sample and out-of sample distributions of the softmax classification. This can cause that Neural Networks confidently predict a wrong class when the sample is not part of the training distribution. We see that different training and testing distributions affect the quality of the neural network. The paper can be found here:

https://arxiv.org/pdf/1610.02136.pdf

[ ]:
```
# First get the indices of the examples that we did not use
not_used_index = [x for x, _ in enumerate(train_folders) if x not in␣
↪class_index]
print(len(not_used_index))
```

39

[ ]:
```
def make_folders_move_unknowns():
  '''
  Helper to move the unknowns and make a folder

  '''
  # make the folder for the datasets with the label unknown
  for sets in DATASETS:
    (data_dir/sets/'unknown').mkdir(parents=True, exist_ok=True)

  # now we find the images
```

```
  for ukimg in not_used_index:
    img_path = np.array(glob(f"{train_folders[ukimg]}/*.ppm"))
    img_path = np.random.choice(img_path, 200)
  # splitting the data
  train_split = int(0.8*len(img_path)) # keeping 80% for training
  test_split = int(0.9*len(img_path))  # keeping 10 % for val + 10% testing
  ds_split = np.split(img_path, indices_or_sections=[train_split, test_split])
  # zipping
  dataset_dt = zip(DATASETS, ds_split)
  # moving the images
  for ds, imgs in dataset_dt:
    for paths in imgs:
      shutil.copy(paths, f"{data_dir}/{ds}/unknown/")

make_folders_move_unknowns()
```

[ ]:
```
# transform the dataset
x_image_dataset = {
    d: ImageFolder(f"{data_dir}/{d}", transforms[d]) for d in DATASETS
}

# dataloader
data_loaders = {

    d: DataLoader(x_image_dataset[d], batch_size=4, num_workers=2,␣
 ↪shuffle=True) for d in DATASETS
}

# getting the sizes of the datasets
dataset_sizes = {
    d: len(x_image_dataset[d]) for d in DATASETS
}

# and finally the class names
x_class_names = x_image_dataset['train'].classes

# lets look at the sizes now
dataset_sizes
```

[ ]: {'test': 648, 'train': 5086, 'val': 646}

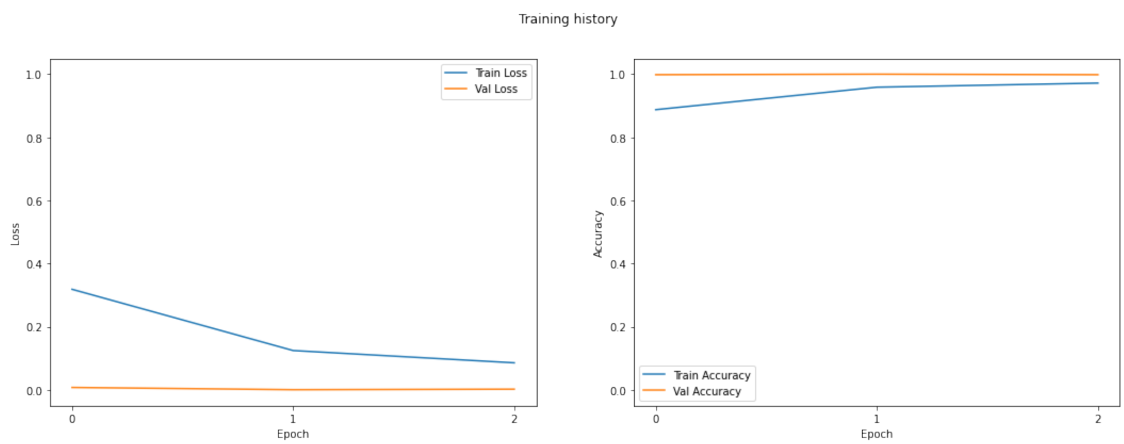
Test new model with extra class

[ ]:
```
# new model with new features
x_n_features = len(x_class_names)
x_model = make_model(x_n_features)
```

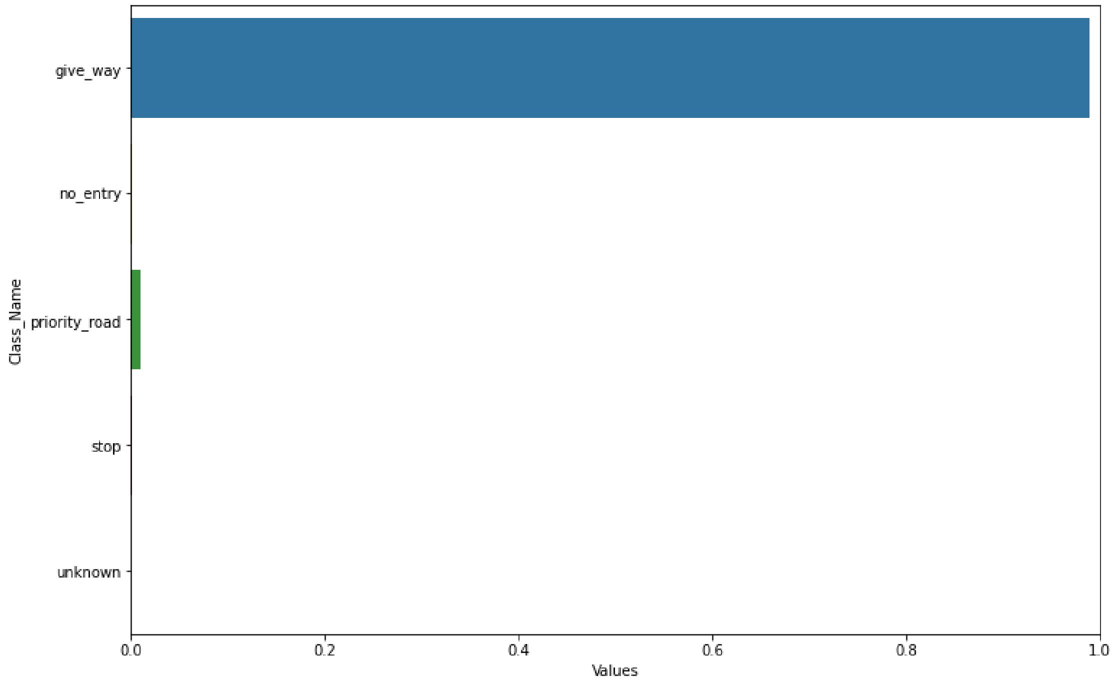
```
# training the new model

x_model, x_history = train_model(x_model, data_loaders, dataset_sizes, device)
```

```
Epoch: 1/3
TRAINING: LOSS:0.35815324049461583 ACCURACY: 0.8786865906409752
VALIDATION: LOSS:0.010733573848427361 ACCURACY: 0.9969040247678019

Epoch: 2/3
TRAINING: LOSS:0.139202132547594 ACCURACY: 0.951042076287849
VALIDATION: LOSS:0.005631997385669955 ACCURACY: 0.998452012383901

Epoch: 3/3
TRAINING: LOSS:0.08849910689006274 ACCURACY: 0.9732599292174596
VALIDATION: LOSS:0.014248965154372947 ACCURACY: 0.9969040247678019

THE BEST ACCURACY: 0.998452012383901
```

[ ]:
```
# we can plot the new training history
plot_history(x_history)
```



[ ]:
```
# getting the prediction and then visualizing it
x_predz = get_pred_proba(x_model, 'unknown-sign.jpg')
# visualize
plot_pred_proba(x_predz, x_class_names)
```

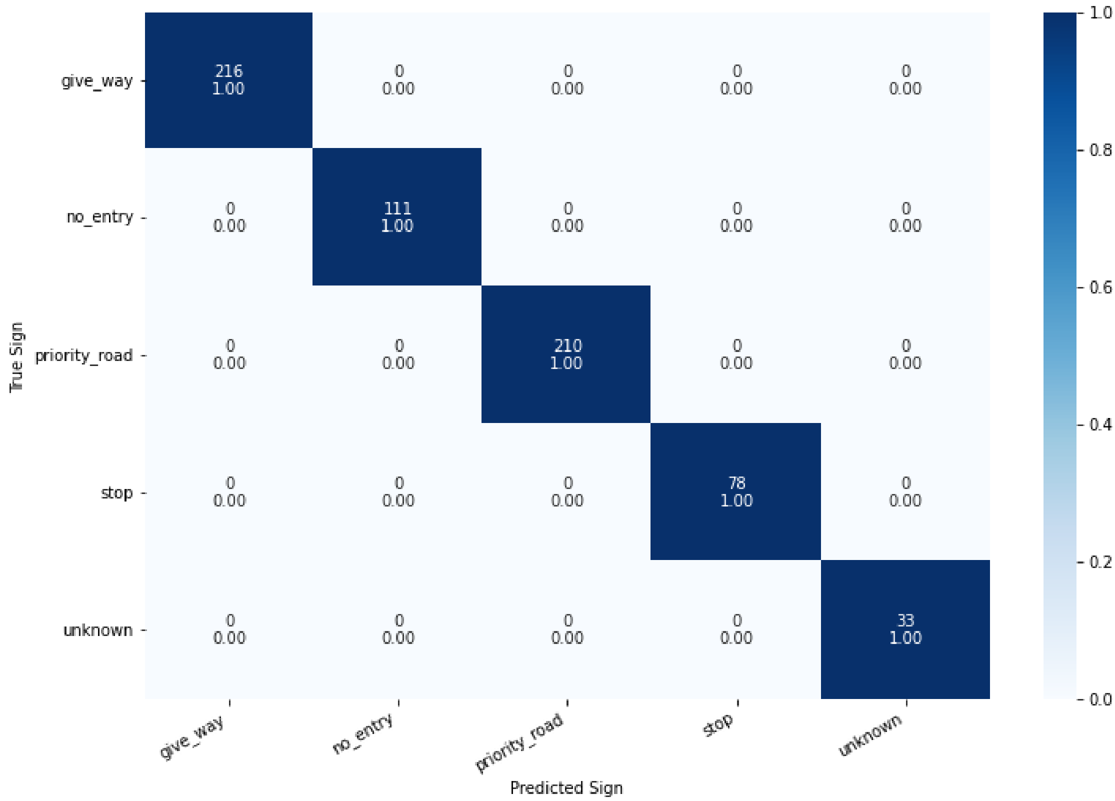


[ ]:
```
# lets look at the examples in our dataset
show_predictions(x_model, x_class_names, 8)
```

[ ]:

```python
# we can make the classification again
# get the predictions
y_pred, y_test = get_preds(x_model, data_loaders['test'])

# make the classification report
# classification report
cr = classification_report(y_test, y_pred, target_names=x_class_names)
print(cr)

# show the confusion matrix
# make the confusion matrix
cm = confusion_matrix(y_test, y_pred)
# showing it
show_cm(cm,x_class_names)
```

```
                precision    recall  f1-score   support

      give_way       1.00      1.00      1.00       216
      no_entry       1.00      1.00      1.00       111
 priority_road       1.00      1.00      1.00       210
          stop       1.00      1.00      1.00        78
       unknown       1.00      1.00      1.00        33

      accuracy                           1.00       648
     macro avg       1.00      1.00      1.00       648
  weighted avg       1.00      1.00      1.00       648
```


give_way
no_entry
priority_road
stop
unknown
True Sign
216
1.00
111
210
78
33
0
0.00
Predicted Sign
1.0
0.8
0.6
0.4
0.2
0.0