```
import torch, torchvision

from pathlib import Path
import numpy as np
import cv2
import pandas as pd
from tqdm import tqdm
import PIL.Image as Image
import seaborn as sns
from pylab import rcParams
import matplotlib.pyplot as plt
from matplotlib import rc
from matplotlib.ticker import MaxNLocator
from torch.optim import lr_scheduler
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, classification_report
from glob import glob
import shutil
from collections import defaultdict

from torch import nn, optim

import torch.nn.functional as F
import torchvision.transforms as T
from torchvision.datasets import ImageFolder
from torch.utils.data import DataLoader
from torchvision import models

%matplotlib inline
%config InlineBackend.figure_format='retina'

sns.set(style='whitegrid', palette='muted', font_scale=1.2)

HAPPY_COLORS_PALETTE = ["#01BEFE", "#FFDD00", "#FF7D00", "#FF006D",
"#ADFF02", "#8F00FF"]

sns.set_palette(sns.color_palette(HAPPY_COLORS_PALETTE))

rcParams['figure.figsize'] = 12, 8

RANDOM_SEED = 42
np.random.seed(RANDOM_SEED)
torch.manual_seed(RANDOM_SEED)

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

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/
_testing.py:19: FutureWarning: pandas.util.testing is deprecated. Use
```

```
the functions in the public API at pandas.testing instead.
  import pandas.util.testing as tm

device(type='cuda')
```

Recognizing traffic signs

German Traffic Sign Recognition Benchmark (GTSRB) contains more than 50,000 annotated images of 40+ traffic signs. Given an image, you'll have to recognize the traffic sign on it.

```
!wget
https://sid.erda.dk/public/archives/daaeac0d7ce1152aea9b61d9f1e19370/
GTSRB_Final_Training_Images.zip
!unzip -qq GTSRB_Final_Training_Images.zip

--2020-05-24 07:31:58--
https://sid.erda.dk/public/archives/daaeac0d7ce1152aea9b61d9f1e19370/
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   106MB/s    in
2.5s

2020-05-24 07:32:00 (106 MB/s) - ‘GTSRB_Final_Training_Images.zip’
saved [276294756/276294756]
```

Exploration

Let's start by getting a feel of the data. The images for each traffic sign are stored in a separate directory. How many do we have?

```
train_folders = sorted(glob('GTSRB/Final_Training/Images/*'))
len(train_folders)

43
```

We'll create 3 helper functions that use OpenCV and Torchvision to load and show images:

```
def load_image(img_path, resize=True):
  img = cv2.cvtColor(cv2.imread(img_path), cv2.COLOR_BGR2RGB)

  if resize:
    img = cv2.resize(img, (64, 64), interpolation = cv2.INTER_AREA)
```

```
    return img

def show_image(img_path):
  img = load_image(img_path)
  plt.imshow(img)
  plt.axis('off')

def show_sign_grid(image_paths):
  images = [load_image(img) for img in image_paths]
  images = torch.as_tensor(images)
  images = images.permute(0, 3, 1, 2)
  grid_img = torchvision.utils.make_grid(images, nrow=11)
  plt.figure(figsize=(24, 12))
  plt.imshow(grid_img.permute(1, 2, 0))
  plt.axis('off');
```

Let's have a look at some examples for each traffic sign:

```
sample_images = [np.random.choice(glob(f'{tf}/*ppm')) for tf in
train_folders]
show_sign_grid(sample_images)
```

And here is a single sign:

```
img_path = glob(f'{train_folders[16]}/*ppm')[1]

show_image(img_path)
```

Building a dataset

To keep things simple, we'll focus on classifying some of the most used traffic signs:

```
class_names = ['priority_road', 'give_way', 'stop', 'no_entry']

class_indices = [12, 13, 14, 17]
```

We'll copy the images files to a new directory, so it's easier to use the Torchvision's dataset helpers. Let's start with the directories for each class:

```
!rm -rf data

DATA_DIR = Path('data')

DATASETS = ['train', 'val', 'test']

for ds in DATASETS:
  for cls in class_names:
    (DATA_DIR / ds / cls).mkdir(parents=True, exist_ok=True)
```

We'll reserve 80% of the images for training, 10% for validation, and 10% test for each class. We'll copy each image to the correct dataset directory:

```
for i, cls_index in enumerate(class_indices):
  image_paths = np.array(glob(f'{train_folders[cls_index]}/*.ppm'))
  class_name = class_names[i]
  print(f'{class_name}: {len(image_paths)}')
  np.random.shuffle(image_paths)

  ds_split = np.split(
    image_paths,
    indices_or_sections=[int(.8*len(image_paths)),
int(.9*len(image_paths))]
  )

  dataset_data = zip(DATASETS, ds_split)

  for ds, images in dataset_data:
    for img_path in images:
      shutil.copy(img_path, f'{DATA_DIR}/{ds}/{class_name}/')
```

```
priority_road: 2100
give_way: 2160
stop: 780
no_entry: 1110
```

We have some class imbalance, but it is not that bad. We'll ignore it.

We'll apply some image augmentation techniques to artificially increase the size of our training dataset:

```
mean_nums = [0.485, 0.456, 0.406]
std_nums = [0.229, 0.224, 0.225]

transforms = {'train': T.Compose([
  T.RandomResizedCrop(size=256),
  T.RandomRotation(degrees=15),
  T.RandomHorizontalFlip(),
  T.ToTensor(),
  T.Normalize(mean_nums, std_nums)
]), 'val': T.Compose([
  T.Resize(size=256),
  T.CenterCrop(size=224),
  T.ToTensor(),
  T.Normalize(mean_nums, std_nums)
]), 'test': T.Compose([
  T.Resize(size=256),
  T.CenterCrop(size=224),
  T.ToTensor(),
  T.Normalize(mean_nums, std_nums)
```

```
]),
}
```

We apply some random resizing, rotation, and horizontal flips. Finally, we normalize the tensors using preset values for each channel. This is a requirement of the pre-trained models in Torchvision.

We'll create a PyTorch dataset for each image dataset folder and data loaders for easier training:

```
image_datasets = {
  d: ImageFolder(f'{DATA_DIR}/{d}', transforms[d]) for d in DATASETS
}

data_loaders = {
  d: DataLoader(image_datasets[d], batch_size=4, shuffle=True,
num_workers=4)
  for d in DATASETS
}
```

We'll also store the number of examples in each dataset and class names for later:

```
dataset_sizes = {d: len(image_datasets[d]) for d in DATASETS}
class_names = image_datasets['train'].classes

dataset_sizes

{'test': 615, 'train': 4920, 'val': 615}
```

Let's have a look at some example images with applied transformations. We also need to reverse the normalization and reorder the color channels to get correct image data:

```
def imshow(inp, title=None):
  inp = inp.numpy().transpose((1, 2, 0))
  mean = np.array([mean_nums])
  std = np.array([std_nums])
  inp = std * inp + mean
  inp = np.clip(inp, 0, 1)
  plt.imshow(inp)
  if title is not None:
    plt.title(title)
  plt.axis('off')

inputs, classes = next(iter(data_loaders['train']))
out = torchvision.utils.make_grid(inputs)

imshow(out, title=[class_names[x] for x in classes])
```

['no_entry', 'stop', 'stop', 'stop']

Using a pre-trained model:

Our model will receive raw image pixels and try to classify them into one of four traffic signs. How hard can it be? Try to build a model from scratch.

Here, we'll use Transfer Learning to copy the architecture of the very popular ResNet model. On top of that, we'll use the learned weights of the model from training on the ImageNet dataset. All of this is made easy to use by Torchvision:

```
def create_model(n_classes):
  model = models.resnet34(pretrained=True)

  n_features = model.fc.in_features
  model.fc = nn.Linear(n_features, n_classes)

  return model.to(device)
```

We reuse almost everything except the change of the output layer. This is needed because the number of classes in our dataset is different than ImageNet.

Let's create an instance of our model:

```
base_model = create_model(len(class_names))
```

```
Downloading: "https://download.pytorch.org/models/resnet34-
333f7ec4.pth" to /root/.cache/torch/checkpoints/resnet34-333f7ec4.pth
```

{"model_id":"212e5b67205342b7a4f9eaf1f2c1f5b8","version_major":2,"vers
ion_minor":0}

Training

We'll write 3 helper functions to encapsulate the training and evaluation logic. Let's start with `train_epoch`:

```python
def train_epoch(
  model,
  data_loader,
  loss_fn,
  optimizer,
  device,
  scheduler,
  n_examples
):
  model = model.train()

  losses = []
  correct_predictions = 0

  for inputs, labels in data_loader:
    inputs = inputs.to(device)
    labels = labels.to(device)

    outputs = model(inputs)

    _, preds = torch.max(outputs, dim=1)
    loss = loss_fn(outputs, labels)

    correct_predictions += torch.sum(preds == labels)
    losses.append(loss.item())

    loss.backward()
    optimizer.step()
    optimizer.zero_grad()

  scheduler.step()

  return correct_predictions.double() / n_examples, np.mean(losses)
```

We start by turning our model into train mode and go over the data. After getting the predictions, we get the class with maximum probability along with the loss, so we can calculate the epoch loss and accuracy.

Note that we're also using a learning rate scheduler (more on that later).

```python
def eval_model(model, data_loader, loss_fn, device, n_examples):
  model = model.eval()

  losses = []
  correct_predictions = 0

  with torch.no_grad():
    for inputs, labels in data_loader:
      inputs = inputs.to(device)
      labels = labels.to(device)
```

```
      outputs = model(inputs)

      _, preds = torch.max(outputs, dim=1)

      loss = loss_fn(outputs, labels)

      correct_predictions += torch.sum(preds == labels)
      losses.append(loss.item())

  return correct_predictions.double() / n_examples, np.mean(losses)
```

The evaluation of the model is pretty similar, except that we don't do any gradient calculations.

Let's put everything together:

```
def train_model(model, data_loaders, dataset_sizes, device,
n_epochs=3):
  optimizer = optim.SGD(model.parameters(), lr=0.001, momentum=0.9)
  scheduler = lr_scheduler.StepLR(optimizer, step_size=7, gamma=0.1)
  loss_fn = nn.CrossEntropyLoss().to(device)

  history = defaultdict(list)
  best_accuracy = 0

  for epoch in range(n_epochs):

    print(f'Epoch {epoch + 1}/{n_epochs}')
    print('-' * 10)

    train_acc, train_loss = train_epoch(
      model,
      data_loaders['train'],
      loss_fn,
      optimizer,
      device,
      scheduler,
      dataset_sizes['train']
    )

    print(f'Train loss {train_loss} accuracy {train_acc}')

    val_acc, val_loss = eval_model(
      model,
      data_loaders['val'],
      loss_fn,
      device,
      dataset_sizes['val']
    )
```

```
    print(f'Val   loss {val_loss} accuracy {val_acc}')
    print()

    history['train_acc'].append(train_acc)
    history['train_loss'].append(train_loss)
    history['val_acc'].append(val_acc)
    history['val_loss'].append(val_loss)

    if val_acc > best_accuracy:
      torch.save(model.state_dict(), 'best_model_state.bin')
      best_accuracy = val_acc

  print(f'Best val accuracy: {best_accuracy}')

  model.load_state_dict(torch.load('best_model_state.bin'))

  return model, history
```

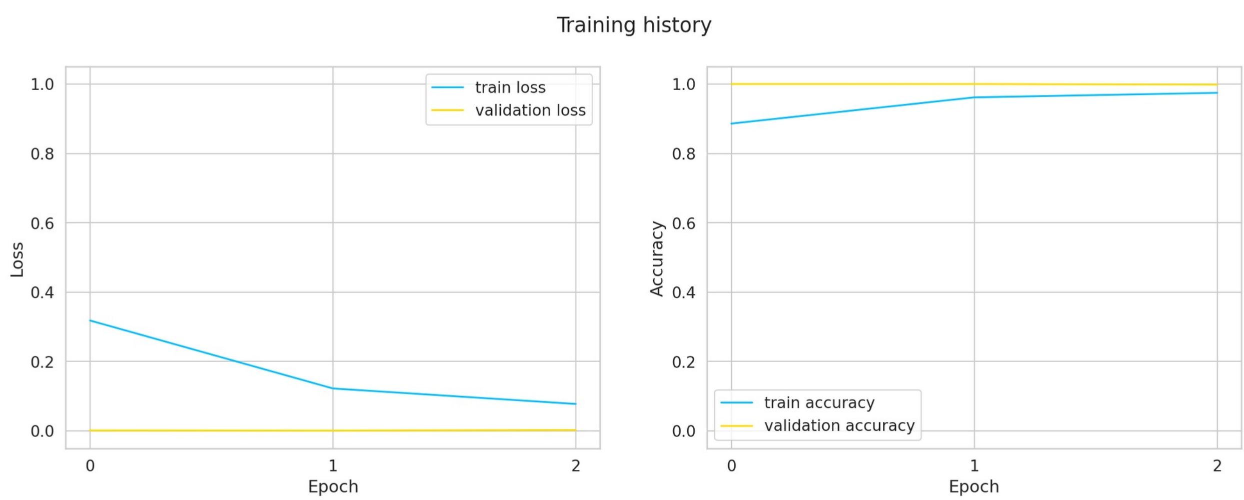
We do a lot of string formatting and recording of the training history. The hard stuff gets delegated to the previous helper functions. We also want the best model, so the weights of the most accurate model(s) get stored during the training.

Let's train our first model:

```
%%time

base_model, history = train_model(base_model, data_loaders,
dataset_sizes, device)

Epoch 1/3
----------
Train loss 0.31827690804876935 accuracy 0.8859756097560976
Val   loss 0.0012465072916699694 accuracy 1.0

Epoch 2/3
----------
Train loss 0.12230596961529275 accuracy 0.9615853658536585
Val   loss 0.0007955377752130681 accuracy 1.0

Epoch 3/3
----------
Train loss 0.07771141678094864 accuracy 0.9745934959349594
Val   loss 0.0025791768387877366 accuracy 0.9983739837398374

Best val accuracy: 1.0
CPU times: user 2min 24s, sys: 48.2 s, total: 3min 12s
Wall time: 3min 21s
```

Here's a little helper function that visualizes the training history for us:

```
def plot_training_history(history):
  fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(18, 6))

  ax1.plot(history['train_loss'], label='train loss')
  ax1.plot(history['val_loss'], label='validation loss')

  ax1.xaxis.set_major_locator(MaxNLocator(integer=True))
  ax1.set_ylim([-0.05, 1.05])
  ax1.legend()
  ax1.set_ylabel('Loss')
  ax1.set_xlabel('Epoch')

  ax2.plot(history['train_acc'], label='train accuracy')
  ax2.plot(history['val_acc'], label='validation accuracy')

  ax2.xaxis.set_major_locator(MaxNLocator(integer=True))
  ax2.set_ylim([-0.05, 1.05])
  ax2.legend()

  ax2.set_ylabel('Accuracy')
  ax2.set_xlabel('Epoch')

  fig.suptitle('Training history')

plot_training_history(history)
```



The pre-trained model is so good that we get very high accuracy and low loss after 3 epochs. Unfortunately, our validation set is too small to get some meaningful metrics from it.

Evaluation

Let's see some predictions on traffic signs from the test set:

```
def show_predictions(model, class_names, n_images=6):
  model = model.eval()
```

```
  images_handeled = 0
  plt.figure()

  with torch.no_grad():
    for i, (inputs, labels) in enumerate(data_loaders['test']):
      inputs = inputs.to(device)
      labels = labels.to(device)

      outputs = model(inputs)
      _, preds = torch.max(outputs, 1)

      for j in range(inputs.shape[0]):
        images_handeled += 1
        ax = plt.subplot(2, n_images//2, images_handeled)
        ax.set_title(f'predicted: {class_names[preds[j]]}')
        imshow(inputs.cpu().data[j])
        ax.axis('off')

        if images_handeled == n_images:
          return

show_predictions(base_model, class_names, n_images=8)
```

Very good! Even the almost not visible *priority road* sign is classified correctly. Let's dive a bit deeper.

We'll start by getting the predictions from our model:

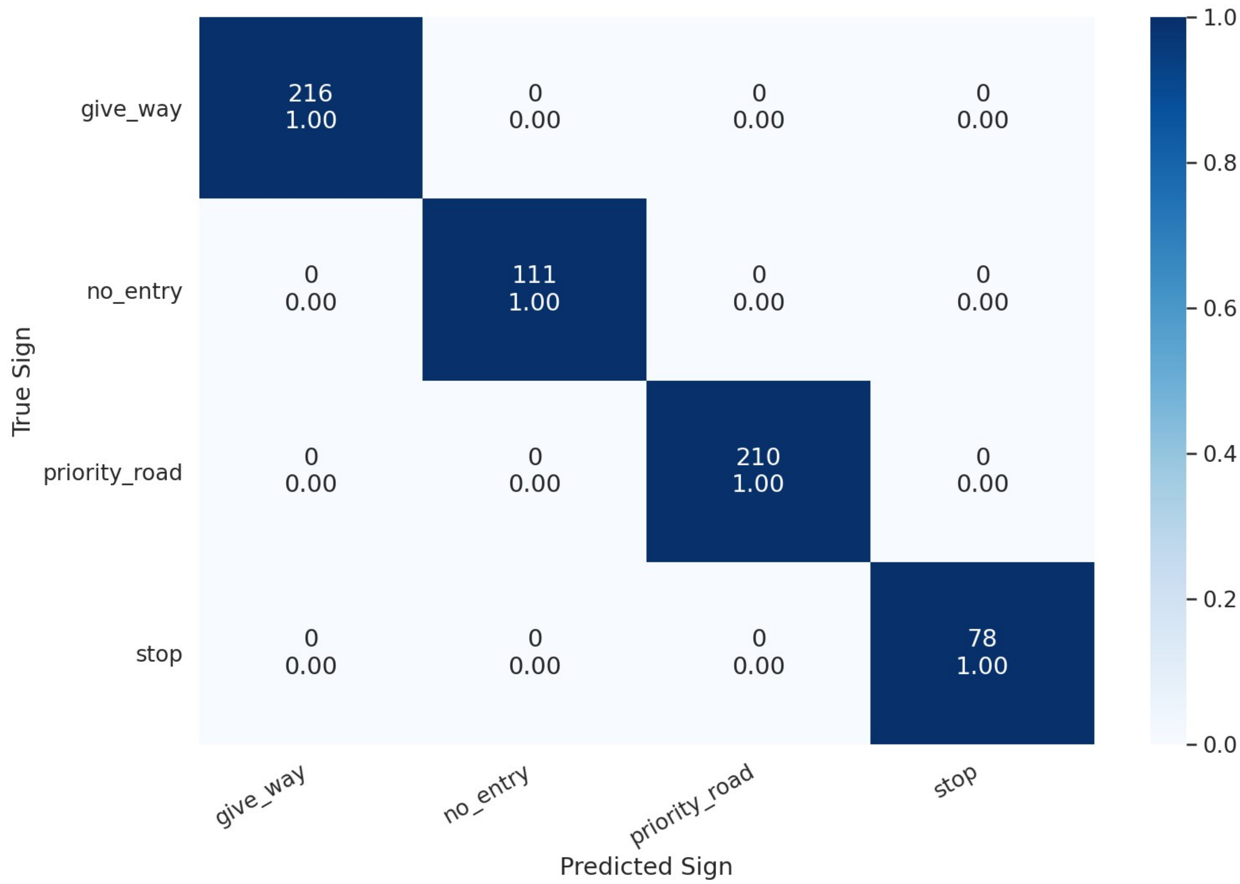
```python
def get_predictions(model, data_loader):
  model = model.eval()
  predictions = []
  real_values = []
  with torch.no_grad():
    for inputs, labels in data_loader:
      inputs = inputs.to(device)
      labels = labels.to(device)

      outputs = model(inputs)
      _, preds = torch.max(outputs, 1)
      predictions.extend(preds)
      real_values.extend(labels)
  predictions = torch.as_tensor(predictions).cpu()
  real_values = torch.as_tensor(real_values).cpu()
  return predictions, real_values

y_pred, y_test = get_predictions(base_model, data_loaders['test'])

print(classification_report(y_test, y_pred, target_names=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

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

The classification report shows us that our model is perfect, not something you see every day! Does this thing make any mistakes?

```python
def show_confusion_matrix(confusion_matrix, class_names):

  cm = confusion_matrix.copy()

  cell_counts = cm.flatten()

  cm_row_norm = cm / cm.sum(axis=1)[:, np.newaxis]

  row_percentages = ["{0:.2f}".format(value) for value in
cm_row_norm.flatten()]

  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])

  df_cm = pd.DataFrame(cm_row_norm, index=class_names,
columns=class_names)

  hmap = sns.heatmap(df_cm, annot=cell_labels, fmt="", cmap="Blues")
  hmap.yaxis.set_ticklabels(hmap.yaxis.get_ticklabels(), rotation=0,
ha='right')
  hmap.xaxis.set_ticklabels(hmap.xaxis.get_ticklabels(), rotation=30,
ha='right')
  plt.ylabel('True Sign')
  plt.xlabel('Predicted Sign');

cm = confusion_matrix(y_test, y_pred)
show_confusion_matrix(cm, class_names)
```



No, no mistakes here!

Classifying unseen images

Ok, but how good our model will be when confronted with a real-world image? Let's check it out:

```
!gdown --id 19Qz3a61Ou_QSHsLeTznx8LtDBu4tbqHr
```

```
Downloading...
From: https://drive.google.com/uc?id=19Qz3a61Ou_QSHsLeTznx8LtDBu4tbqHr
To: /content/stop-sign.jpg
   0% 0.00/77.3k [00:00<?, ?B/s] 100% 77.3k/77.3k [00:00<00:00,
27.7MB/s]
```

```
show_image('stop-sign.jpg')
```

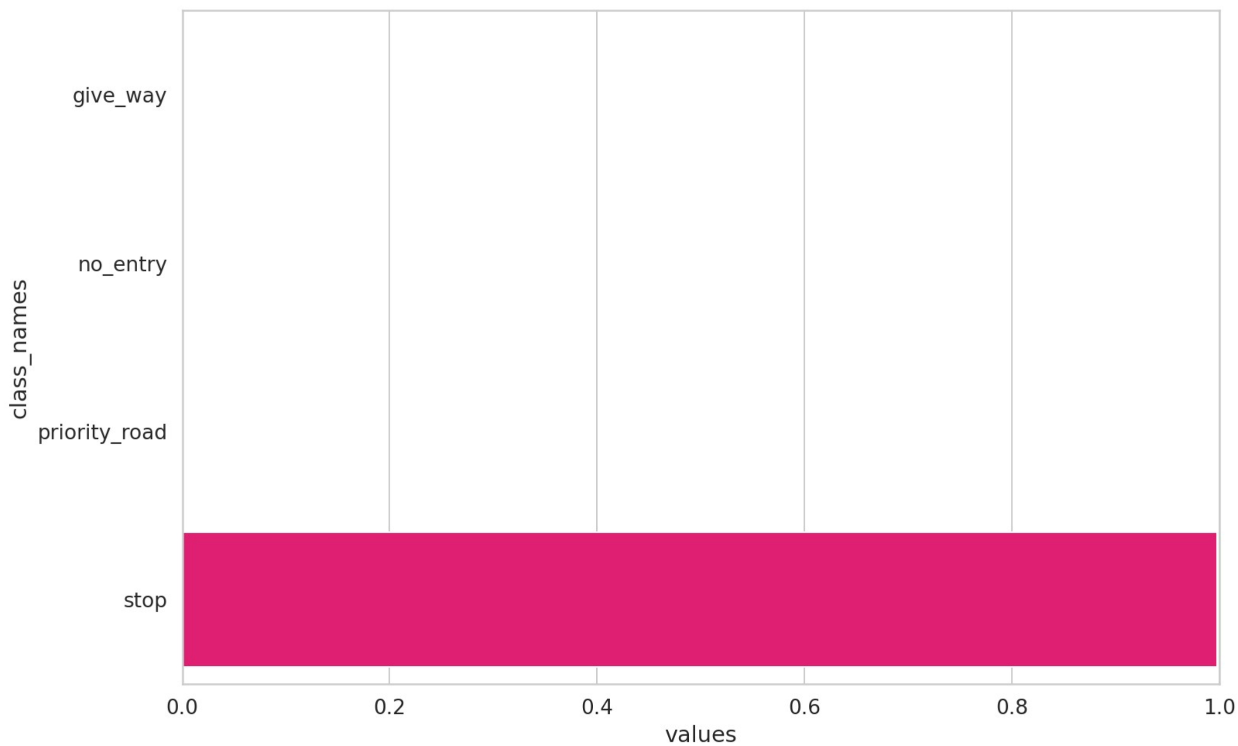
For this, we'll have a look at the confidence for each class. Let's get this from our model:

```
def predict_proba(model, image_path):
  img = Image.open(image_path)
  img = img.convert('RGB')
  img = transforms['test'](img).unsqueeze(0)

  pred = model(img.to(device))
  pred = F.softmax(pred, dim=1)
  return pred.detach().cpu().numpy().flatten()

pred = predict_proba(base_model, 'stop-sign.jpg')
pred
```

```
array([1.1296713e-03, 1.9811286e-04, 3.4486805e-04, 9.9832731e-01],
      dtype=float32)
```

This is a bit hard to understand. Let's plot it:

```
def show_prediction_confidence(prediction, class_names):
  pred_df = pd.DataFrame({
    'class_names': class_names,
    'values': prediction
  })
  sns.barplot(x='values', y='class_names', data=pred_df, orient='h')
  plt.xlim([0, 1]);

show_prediction_confidence(pred, class_names)
```



Again, our model is performing very well! Really confident in the correct traffic sign!

Classyfing unknown traffic sign

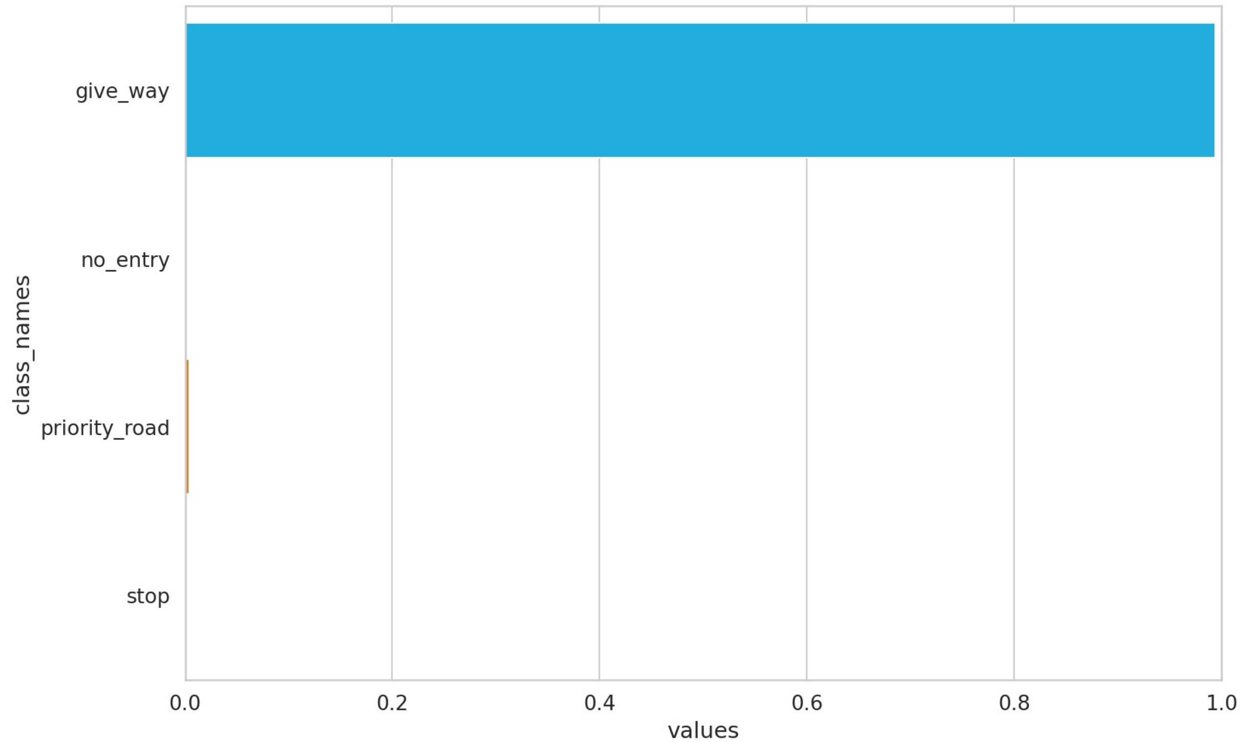
The last challenge for our model is a traffic sign that it hasn't seen before:

```
!gdown --id 1F61-iNhlJk-yKZRGcu6S9P29HxDFxF0u

Downloading...
From: https://drive.google.com/uc?id=1F61-iNhlJk-yKZRGcu6S9P29HxDFxF0u
To: /content/unknown-sign.jpg
```

```
   0% 0.00/41.4k [00:00<?, ?B/s] 100% 41.4k/41.4k [00:00<00:00, 
64.3MB/s]

show_image('unknown-sign.jpg')
```

Let's get the predictions:

```
pred = predict_proba(base_model, 'unknown-sign.jpg')
pred

array([9.9413127e-01, 1.1861280e-06, 3.9936006e-03, 1.8739274e-03],
      dtype=float32)

show_prediction_confidence(pred, class_names)
```



Our model is very certain (more than 95% confidence) that this is a *give way* sign. This is obviously wrong. How can you make your model see this?

Adding class "unknown"

While there are a variety of ways to handle this situation (one described in this paper: A Baseline for Detecting Misclassified and Out-of-Distribution Examples in Neural Networks), we'll do something simpler.

We'll get the indices of all traffic signs that weren't included in our original dataset:

```
unknown_indices = [
  i for i, f in enumerate(train_folders) \
  if i not in class_indices
]

len(unknown_indices)
```

```
39
```

We'll create a new folder for the unknown class and copy some of the images there:

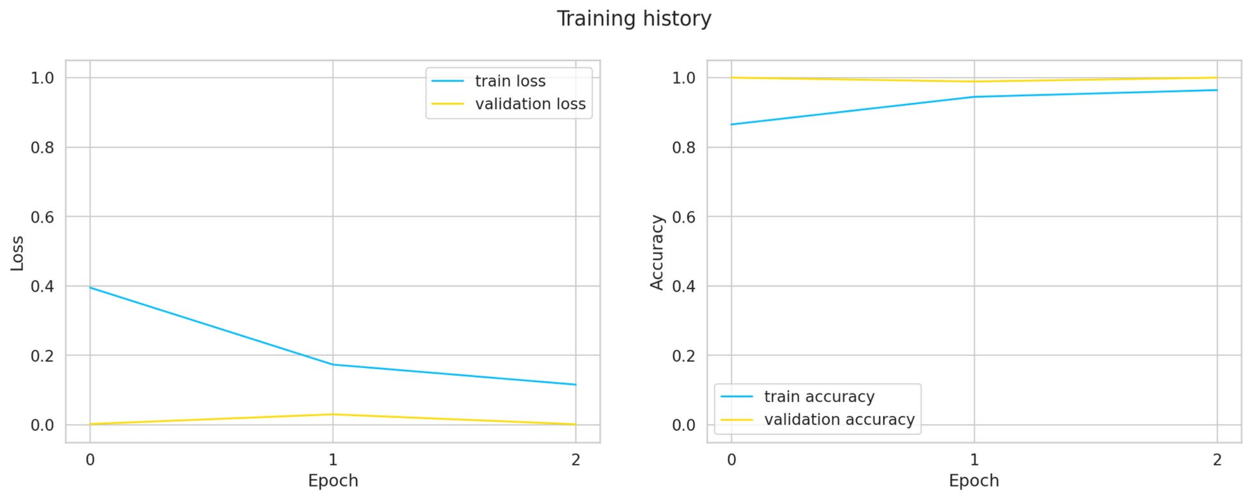
```
for ds in DATASETS:
  (DATA_DIR / ds / 'unknown').mkdir(parents=True, exist_ok=True)

for ui in unknown_indices:
  image_paths = np.array(glob(f'{train_folders[ui]}/*.ppm'))
```

```
  image_paths = np.random.choice(image_paths, 50)

  ds_split = np.split(
    image_paths,
    indices_or_sections=[int(.8*len(image_paths)),
int(.9*len(image_paths))]
  )

  dataset_data = zip(DATASETS, ds_split)

  for ds, images in dataset_data:
    for img_path in images:
      shutil.copy(img_path, f'{DATA_DIR}/{ds}/unknown/')
```

The next steps are identical to what we've already done:

```
image_datasets = {
  d: ImageFolder(f'{DATA_DIR}/{d}', transforms[d]) for d in DATASETS
}

data_loaders = {
  d: DataLoader(image_datasets[d], batch_size=4, shuffle=True,
num_workers=4)
  for d in DATASETS
}

dataset_sizes = {d: len(image_datasets[d]) for d in DATASETS}
class_names = image_datasets['train'].classes

dataset_sizes

{'test': 784, 'train': 5704, 'val': 794}

%%time

enchanced_model = create_model(len(class_names))
enchanced_model, history = train_model(enchanced_model, data_loaders,
dataset_sizes, device)

Epoch 1/3
----------
Train loss 0.39523224640235327 accuracy 0.8650070126227208
Val   loss 0.002290595416447625 accuracy 1.0

Epoch 2/3
----------
Train loss 0.173455789528505 accuracy 0.9446002805049089
Val   loss 0.030148923471944415 accuracy 0.9886649874055415

Epoch 3/3
```

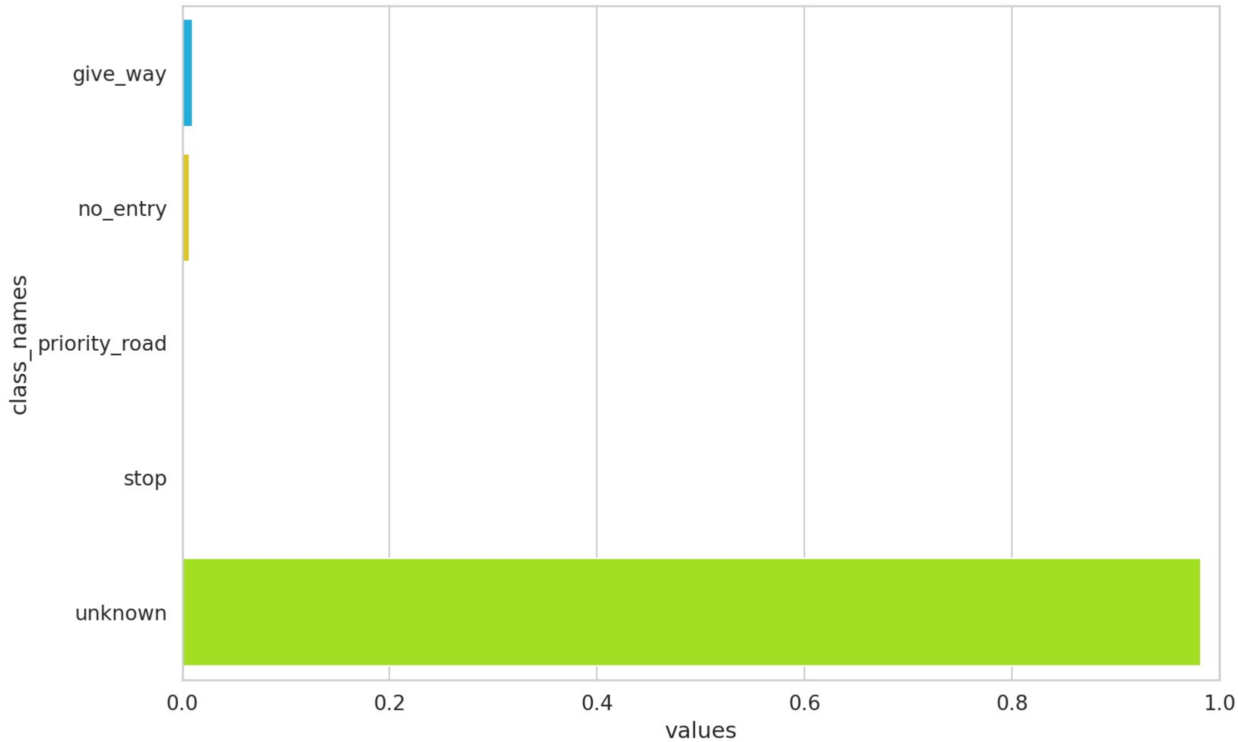
```
----------
Train loss 0.11575758963990512 accuracy 0.9640603085553997
Val   loss 0.0014996432778823317 accuracy 1.0

Best val accuracy: 1.0
CPU times: user 2min 47s, sys: 56.2 s, total: 3min 44s
Wall time: 3min 53s

plot_training_history(history)
```



Again, our model is learning very quickly. Let's have a look at the sample image again:

```
show_image('unknown-sign.jpg')
```

```
pred = predict_proba(enchanced_model, 'unknown-sign.jpg')
show_prediction_confidence(pred, class_names)
```



Great, the model doesn't give much weight to any of the known classes. It doesn't magically know that this is a two-way sign, but recognizes is as unknown.

Let's have a look at some examples of our new dataset:

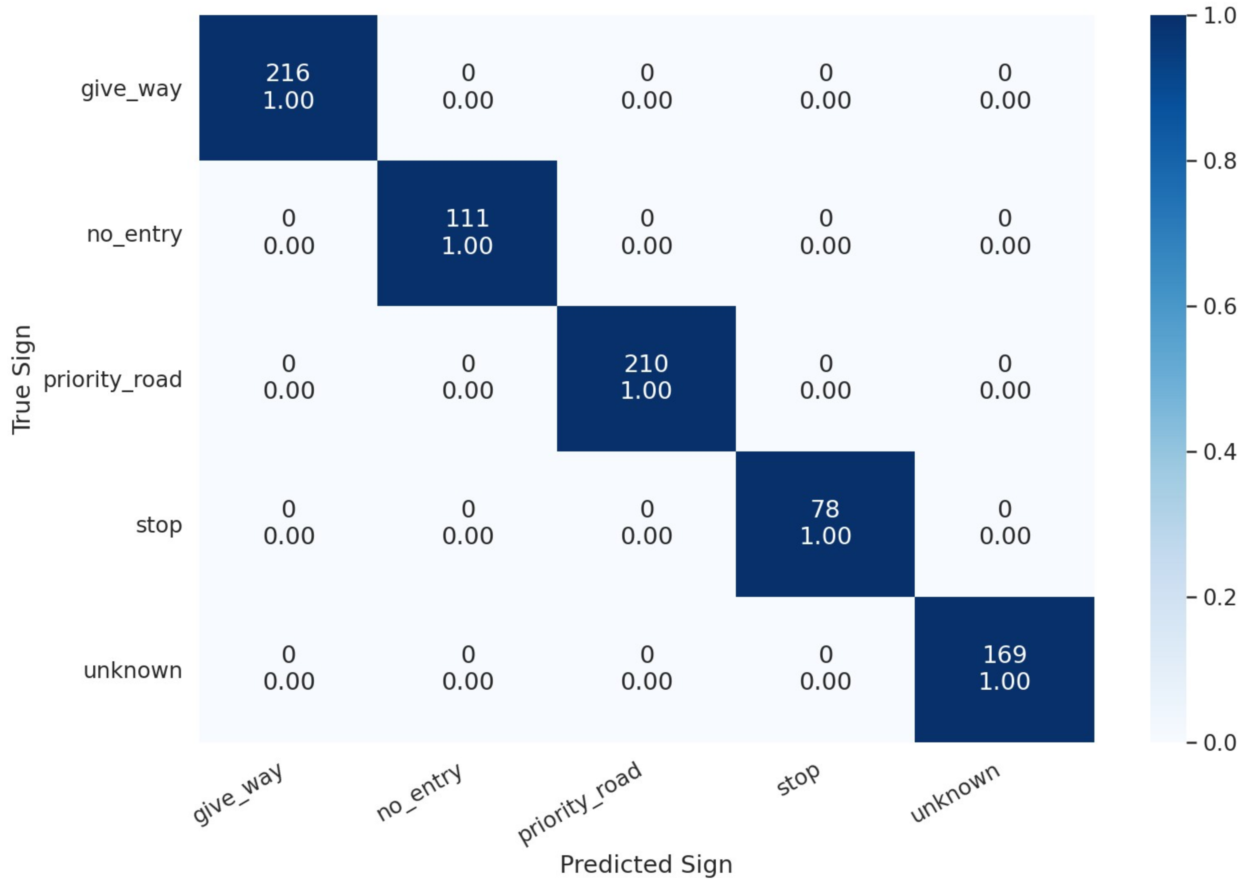
```
show_predictions(enchanced_model, class_names, n_images=8)
```

Let's get an overview of the new model's performance:

```
y_pred, y_test = get_predictions(enchanced_model,
data_loaders['test'])

print(classification_report(y_test, y_pred, target_names=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       169

    accuracy                           1.00       784
   macro avg       1.00      1.00      1.00       784
weighted avg       1.00      1.00      1.00       784
```

```
cm = confusion_matrix(y_test, y_pred)
show_confusion_matrix(cm, class_names)
```



Our model is still perfect. Go ahead, try it on more images!