

# Физтех-Школа Прикладной математики и информатики (ФПМИ) МФТИ

## ▼ Путешествие по Спрингфилду.

Сегодня вам предстоит помочь телекомпании FOX в обработке их контента. Как вы знаете сериал Симпсоны идет на телеэкранах более 25 лет и за это время скопилось очень много видео материала. Персонажи менялись вместе с изменяющимися графическими технологиями и Гомер 2018 не очень похож на Гомера 1989. Нашей задачей будет научиться классифицировать персонажей проживающих в Спрингфилде. Думаю, что нет смысла представлять каждого из них в отдельности.



## ▼ Установка зависимостей

```
1 # ignore deprecation warnings
2 import warnings
3 warnings.filterwarnings(action='ignore', category=DeprecationWarning)
4
5 # standard python modules
6 import os, sys
7 import time
8
9
10 # standard ml modules
11 import random
12 import numpy as np
13 import pandas as pd
14 from matplotlib import pyplot as plt, colors
15 # work in interactive moode
```

```

16 %matplotlib inline
17
18
19 # loading files (in parallel)
20 from pathlib import Path
21 from multiprocessing.pool import ThreadPool
22
23
24 # working with images
25 import PIL
26 from PIL import Image
27 from skimage import io
28
29 # preprocessing
30 from sklearn.preprocessing import LabelEncoder
31
32
33 # torch
34 import torch
35 import torch.nn as nn
36 from torch.utils.data import Dataset, DataLoader
37 import torch.optim as optim
38 from torch.optim import lr_scheduler
39 # torchvision
40 import torchvision
41 from torchvision import transforms
42
43
44 # interactive timing
45 from tqdm import tqdm, tqdm_notebook
46
47 # saving models
48 import pickle
49 import copy

```

```

1 # we will verify that GPU is enabled for this notebook
2 # following should print: CUDA is available! Training on GPU ...
3 #
4 # if it prints otherwise, then you need to enable GPU:
5 # from Menu > Runtime > Change Runtime Type > Hardware Accelerator > GPU
6
7 train_on_gpu = torch.cuda.is_available()
8
9 if not train_on_gpu:
10     print('CUDA is not available. Training on CPU ...')
11 else:
12     print('CUDA is available! Training on GPU ...')

```

CUDA is available! Training on GPU ...

Double-click (or enter) to edit

```

1 # разные режимы датасета
2 DATA_MODES = ['train', 'val', 'test']
3 # все изображения будут масштабированы к размеру 224x224 px
4 RESCALE_SIZE = 224

```

```

5 # работаем на видеокарте
6 DEVICE = torch.device("cuda" if torch.cuda.is_available() else "cpu")

1 DEVICE

device(type='cuda')

1 from google.colab import drive
2 drive.mount('/content/gdrive/')

Mounted at /content/gdrive/

1 !unzip -q /content/gdrive/MyDrive/journey-springfield.zip -d journey-springfield

1 !nvidia-smi
2 import torch
3 torch.cuda.is_available()

```

Sun Nov 28 07:12:38 2021

+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+									
NVIDIA-SMI 495.44				Driver Version: 460.32.03				CUDA Version: 11.2	
+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+									
GPU	Name		Persistence-M	Bus-Id	Disp.A	Volatile	Uncorr. ECC		
Fan	Temp	Perf	Pwr:Usage/Cap		Memory-Usage	GPU-Util	Compute M.		
							MIG M.		
=====									
0	Tesla K80		Off	00000000:00:04.0	Off			0	
N/A	37C	P8	28W / 149W		3MiB / 11441MiB	0%	Default		
							N/A		
+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+									

+-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+									
Processes:									
GPU	GI	CI	PID	Type	Process name	GPU Memory			
	ID	ID				Usage			
=====									
No running processes found									

True

В нашем тесте будет 990 карточек, для которых вам будет необходимо предсказать класс.

```

1 # разные режимы датасета
2 DATA_MODES = ['train', 'val', 'test']
3 # все изображения будут масштабированы к размеру 224x224 px
4 RESCALE_SIZE = 224
5 # работаем на видеокарте
6 DEVICE = torch.device("cuda")

```

[https://jhui.github.io/2018/02/09/PyTorch-Data-loading-preprocess\\_torchvision/](https://jhui.github.io/2018/02/09/PyTorch-Data-loading-preprocess_torchvision/)

Ниже мы используем обертку над датасетом для удобной работы. Вам стоит понимать, что происходит с LabelEncoder и с torch.Transformation.

ToTensor конвертирует PIL Image с параметрами в диапазоне [0, 255] (как все пиксели) в FloatTensor размера (C x H x W) [0,1] , затем производится масштабирование:  $input = \frac{input - \mu}{\text{standard deviation}}$ , константы - средние и дисперсии по каналам на основе ImageNet

Стоит также отметить, что мы переопределяем метод **getitem** для удобства работы с данной структурой данных. Также используется LabelEncoder для преобразования строковых меток классов в id и обратно. В описании датасета указано, что картинки разного размера, так как брались напрямую с видео, поэтому следуем привести их к одному размер (это делает метод \_prepare\_sample)

```
1 class SimpsonsDataset(Dataset):
2     """
3     Class to work with image dataset, which
4     - loads them from the folders in parallel
5     - converts to PyTorch tensors
6     - scales the tensors to have mean = 0, standard deviation = 1
7     """
8     def __init__(self, files, mode):
9         super().__init__()
10        self.files = sorted(files) # list of files to be loaded
11        self.mode = mode           # working mode
12
13        if self.mode not in DATA_MODES:
14            print(f"{self.mode} is not correct; correct modes: {DATA_MODES}")
15            raise NameError
16
17        self.len_ = len(self.files)
18
19        self.label_encoder = LabelEncoder()
20
21        if self.mode != 'test':
22            self.labels = [path.parent.name for path in self.files]
23            self.label_encoder.fit(self.labels)
24
25            with open('label_encoder.pkl', 'wb') as le_dump_file:
26                pickle.dump(self.label_encoder, le_dump_file)
27
28
29    def __len__(self):
30        return self.len_
31
32
33    def load_sample(self, file):
34        image = Image.open(file)
35        image.load()
36        return image
37
38
39    def _prepare_sample(self, image):
40        image = image.resize((RESCALE_SIZE, RESCALE_SIZE))
41        return np.array(image)
42
43
44    def __getitem__(self, index):
45        # converts to PyTorch tensors and normalises the input
```

```

46     data_transforms = {
47         'train': transforms.Compose([
48             transforms.Resize(size=(RESCALE_SIZE, RESCALE_SIZE)),
49             transforms.RandomRotation(degrees=30),
50             transforms.RandomHorizontalFlip(),
51             transforms.ColorJitter(hue=.1, saturation=.1),
52             transforms.ToTensor(),
53             transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
54         ]),
55         'val_test': transforms.Compose([
56             transforms.Resize(size=(RESCALE_SIZE, RESCALE_SIZE)),
57             transforms.ToTensor(),
58             transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225])
59         ]),
60     }
61
62     transform = (data_transforms['train'] if self.mode == 'train' else data_transforms['val_test'])
63
64     x = self.load_sample(self.files[index]) # load image
65     x = transform(x) # apply transform defined above
66
67     if self.mode == 'test':
68         return x
69     else:
70         label = self.labels[index]
71         label_id = self.label_encoder.transform([label])
72         y = label_id.item()
73         return x, y
74

```

```

1 def imshow(inp, title=None, plt_ax=plt, default=False):
2     """Имshow для тензоров"""
3     inp = inp.numpy().transpose((1, 2, 0))
4     mean = np.array([0.485, 0.456, 0.406])
5     std = np.array([0.229, 0.224, 0.225])
6     inp = std * inp + mean
7     inp = np.clip(inp, 0, 1)
8     plt_ax.imshow(inp)
9     if title is not None:
10         plt_ax.set_title(title)
11     plt_ax.grid(False)

```

```

1 TRAIN_DIR = Path('/content/journey-springfield/train')
2 TEST_DIR = Path('/content/journey-springfield/testset')
3
4 train_val_files = sorted(list(TRAIN_DIR.rglob('*.jpg')))
5 test_files = sorted(list(TEST_DIR.rglob('*.jpg')))

```

```

1 print(len(train_val_files), 'train files')
2 train_val_files[:5]

```

20933 train files

```

[PosixPath('/content/journey-springfield/train/simpsons_dataset/abraham_grampa_simpson/pic_0000.jpg'),
 PosixPath('/content/journey-springfield/train/simpsons_dataset/abraham_grampa_simpson/pic_0001.jpg'),
 PosixPath('/content/journey-springfield/train/simpsons_dataset/abraham_grampa_simpson/pic_0002.jpg'),
 PosixPath('/content/journey-springfield/train/simpsons_dataset/abraham_grampa_simpson/pic_0003.jpg'),
 PosixPath('/content/journey-springfield/train/simpsons_dataset/abraham_grampa_simpson/pic_0004.jpg'),

```

```

1 print(len(test_files), 'test files')
2 test_files[:5]

991 test_files
[PosixPath('/content/journey-springfield/testset/testset/img0.jpg'),
 PosixPath('/content/journey-springfield/testset/testset/img1.jpg'),
 PosixPath('/content/journey-springfield/testset/testset/img10.jpg'),
 PosixPath('/content/journey-springfield/testset/testset/img100.jpg'),
 PosixPath('/content/journey-springfield/testset/testset/img101.jpg')]

1 # path.parent.name returns a folder in which the image is, which corresponds to the label in nthi
2 train_val_labels = [path.parent.name for path in train_val_files]

1 print(len(train_val_labels), 'train_val_labels')
2 train_val_labels[:5]

20933 train_val_labels
['abraham_grampa_simpson',
 'abraham_grampa_simpson',
 'abraham_grampa_simpson',
 'abraham_grampa_simpson',
 'abraham_grampa_simpson']

1 from sklearn.model_selection import train_test_split
2 train_files, val_files = train_test_split(train_val_files, test_size=0.20, stratify=train_val_labels)

1 val_dataset = SimpsonsDataset(val_files, mode='val')

```

Давайте посмотрим на наших героев внутри датасета.

```

1 fig, ax = plt.subplots(nrows=3, ncols=3, figsize=(8, 8), \
2                         sharey=True, sharex=True)
3 for fig_x in ax.flatten():
4     random_characters = int(np.random.uniform(0,1000))
5     im_val, label = val_dataset[random_characters]
6     img_label = " ".join(map(lambda x: x.capitalize(),\
7                             val_dataset.label_encoder.inverse_transform([label])[0].split('_')))
8     imshow(im_val.data.cpu(), \
9            title=img_label, plt_ax=fig_x)

```



Можете добавить ваши любимые сцены и классифицировать их. (веселые результаты можно кидать в чат)

```

1 def fit_epoch(model, train_loader, criterion, optimizer):
2     # initialize tracked variables
3     running_loss = 0.0
4     running_corrects = 0
5     processed_data = 0
6
7     for inputs, labels in train_loader:
8         inputs = inputs.to(DEVICE)
9         labels = labels.to(DEVICE)
10
11        # reset the gradient
12        optimizer.zero_grad()
13
14        # predictions (probabilities), loss, backprop
15        outputs = model(inputs)
16        loss = criterion(outputs, labels)
17        loss.backward()
18
19        # weights update
20        optimizer.step()
21
22        # predictions (classes)
23        preds = torch.argmax(outputs, 1)
24
25        # record tracked items
26        running_loss += loss.item() * inputs.size(0)
27        running_corrects += torch.sum(preds == labels.data)
28        processed_data += inputs.size(0)
29
30    # record train loss and train accuracy
31    train_loss = running_loss / processed_data
32    train_acc = running_corrects.cpu().numpy() / processed_data
33    return train_loss, train_acc

```

```

1 def eval_epoch(model, val_loader, criterion):
2     # set model model into the evaluation mode (e.g. for Dropout)
3     model.eval()
4
5     # initialize tracked variables
6     running_loss = 0.0

```

```

7     running_corrects = 0
8     processed_size = 0
9
10    for inputs, labels in val_loader:
11        inputs = inputs.to(DEVICE)
12        labels = labels.to(DEVICE)
13
14        with torch.set_grad_enabled(False):
15            outputs = model(inputs)
16            loss = criterion(outputs, labels)
17            preds = torch.argmax(outputs, 1)
18
19        # record tracked items
20        running_loss += loss.item() * inputs.size(0)
21        running_corrects += torch.sum(preds == labels.data)
22        processed_size += inputs.size(0)
23
24    # record val loss and val accuracy
25    val_loss = running_loss / processed_size
26    val_acc = running_corrects.double() / processed_size
27    return val_loss, val_acc


1 def train(train_dataset, val_dataset, model, criterion,
2           epochs, batch_size, optimizer, scheduler,
3           shuffle=True, sampler=None, patience=5):
4
5     # to record the total training time
6     since = time.time()
7
8     # note: 4 workers loading the data
9     train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=shuffle, sampler=samp
10    val_loader = DataLoader(val_dataset, batch_size=batch_size, shuffle=False, num_workers=4)
11
12    # init variables to store best model weights, best accuracy, best epoch number, epochs since
13    best_model_wts = copy.deepcopy(model.state_dict())
14    best_loss = 10
15    best_epoch = 0
16    epochs_since_best = 0
17
18    # history and log
19    history = []
20    log_template = "\nEpoch {ep:03d} train_loss: {t_loss:0.4f} \
21    val_loss {v_loss:0.4f} train_acc {t_acc:0.4f} val_acc {v_acc:0.4f}"
22
23    with tqdm(desc="epoch", total=epochs) as pbar_outer:
24
25        for epoch in range(1, epochs+1):
26            print(f"epoch {epoch}:\n")
27
28            print("Fitting on train data...")
29            # all arguments except train loader are from parameters passed to train() arguments
30            train_loss, train_acc = fit_epoch(model, train_loader, criterion, optimizer)
31            print("train loss:", train_loss)
32
33            print("Evaluating on validation data...")
34            val_loss, val_acc = eval_epoch(model, val_loader, criterion)
35            print("val loss:", val_loss)

```



```

36
37         # record history
38         history.append((train_loss, train_acc, val_loss, val_acc))
39
40         # update learning rate for the optimizer
41         scheduler.step()
42
43         # display learning status
44         pbar_outer.update(1)
45         tqdm.write(log_template.format(ep=epoch, t_loss=train_loss,\
46                                     v_loss=val_loss, t_acc=train_acc, v_acc=val_acc))
47
48         # deep copy the model if it acheives the best validation performance
49         if val_loss < best_loss:
50             best_acc = val_loss
51             best_epoch = epoch
52             best_model_wts = copy.deepcopy(model.state_dict())
53             print()
54         else:
55             epochs_since_best += 1
56
57         # early stopping
58         if epochs_since_best > patience:
59             print(f'Stopping training. The validation metric has not improved for {patience}')
60             break
61
62
63     time_elapsed = time.time() - since
64     print('Training complete in {:.0f}m {:.0f}s'.format(
65         time_elapsed // 60, time_elapsed % 60))
66     print('Best val loss: {:.4f}'.format(best_loss))
67     print('Best epoch: {}'.format(best_epoch))
68
69     # load best model weights
70     model.load_state_dict(best_model_wts)
71
72     return history

```

```

1 def predict(model, test_loader):
2     with torch.no_grad():
3         logits = []
4
5         for inputs in test_loader:
6             inputs = inputs.to(DEVICE)
7             model.eval()
8             outputs = model(inputs).cpu()
9             logits.append(outputs)
10
11     probs = nn.functional.softmax(torch.cat(logits), dim=-1).numpy()
12     return probs

```

```

1 N_CLASSES = len(np.unique(train_val_labels))

```

```

1 if val_dataset is None:
2     val_dataset = SimpsonsDataset(val_files, mode='val')
3
4 train_dataset = SimpsonsDataset(train_files, mode='train')

```

## Training only the last layer

```
1 !pip install efficientnet_pytorch
```

```
Collecting efficientnet_pytorch
```

```
  Downloading efficientnet_pytorch-0.7.1.tar.gz (21 kB)
```

```
Requirement already satisfied: torch in /usr/local/lib/python3.7/dist-packages (from efficientnet_pytorch==0.7.1)
```

```
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.7/dist-packages (from efficientnet_pytorch==0.7.1)
```

```
Building wheels for collected packages: efficientnet_pytorch
```

```
  Building wheel for efficientnet_pytorch (setup.py) ... done
```

```
  Created wheel for efficientnet_pytorch: filename=efficientnet_pytorch-0.7.1-py3-none-any.whl
```

```
  Stored in directory: /root/.cache/pip/wheels/0e/cc/b2/49e74588263573ff778da58cc99b9c6349b4966
```

```
Successfully built efficientnet_pytorch
```

```
Installing collected packages: efficientnet_pytorch
```

```
Successfully installed efficientnet_pytorch-0.7.1
```

```
1 from efficientnet_pytorch import EfficientNet
```

```
1 model_name = 'efficientnet-b2'
```

```
1 model = EfficientNet.from_pretrained(model_name)
```

```
Downloading: "https://github.com/lukemelas/EfficientNet-PyTorch/releases/download/1.0/efficientnet-b2-0.7.1-no_grad.tar.gz"
```

```
100%
```

```
35.1M/35.1M [00:00<00:00, 92.5MB/s]
```

```
Loaded pretrained weights for efficientnet-b2
```

```
1 model
```

```
      (static_padding): Identity()
    )
    (_bn2): BatchNorm2d(208, eps=0.001, momentum=0.010000000000000009, affine=True, track_running_stats=True)
    (_swish): MemoryEfficientSwish()
  )
(17): MBConvBlock(
  (_expand_conv): Conv2dStaticSamePadding(
    208, 1248, kernel_size=(1, 1), stride=(1, 1), bias=False
    (static_padding): Identity()
  )
  (_bn0): BatchNorm2d(1248, eps=0.001, momentum=0.010000000000000009, affine=True, track_running_stats=True)
  (_depthwise_conv): Conv2dStaticSamePadding(
    1248, 1248, kernel_size=(5, 5), stride=(1, 1), groups=1248, bias=False
    (static_padding): ZeroPad2d(padding=(2, 2, 2, 2), value=0.0)
  )
  (_bn1): BatchNorm2d(1248, eps=0.001, momentum=0.010000000000000009, affine=True, track_running_stats=True)
  (_se_reduce): Conv2dStaticSamePadding(
    1248, 52, kernel_size=(1, 1), stride=(1, 1)
    (static_padding): Identity()
  )
  (_se_expand): Conv2dStaticSamePadding(
    52, 1248, kernel_size=(1, 1), stride=(1, 1)
    (static_padding): Identity()
  )
  (_project_conv): Conv2dStaticSamePadding(
    1248, 208, kernel_size=(1, 1), stride=(1, 1), bias=False
    (static_padding): Identity()
  )
  (_bn2): BatchNorm2d(208, eps=0.001, momentum=0.010000000000000009, affine=True, track_running_stats=True)
```

```

        (_swish): MemoryEfficientSwish()
    )
(18): MBConvBlock(
  (_expand_conv): Conv2dStaticSamePadding(
    208, 1248, kernel_size=(1, 1), stride=(1, 1), bias=False
    (static_padding): Identity()
  )
  (_bn0): BatchNorm2d(1248, eps=0.001, momentum=0.010000000000000009, affine=True, track_running_stats=True)
  (_depthwise_conv): Conv2dStaticSamePadding(
    1248, 1248, kernel_size=(5, 5), stride=(1, 1), groups=1248, bias=False
    (static_padding): ZeroPad2d(padding=(2, 2, 2, 2), value=0.0)
  )
  (_bn1): BatchNorm2d(1248, eps=0.001, momentum=0.010000000000000009, affine=True, track_running_stats=True)
  (_se_reduce): Conv2dStaticSamePadding(
    1248, 52, kernel_size=(1, 1), stride=(1, 1)
    (static_padding): Identity()
  )
  (_se_expand): Conv2dStaticSamePadding(
    52, 1248, kernel_size=(1, 1), stride=(1, 1)
    (static_padding): Identity()
  )
  (_project_conv): Conv2dStaticSamePadding(
    1248, 208, kernel_size=(1, 1), stride=(1, 1), bias=False
    (static_padding): Identity()
  )
  (_bn2): BatchNorm2d(208, eps=0.001, momentum=0.010000000000000009, affine=True, track_running_stats=True)
  (_swish): MemoryEfficientSwish()
)

```

```

1 for param in model.parameters():
2     param.requires_grad = False
3
4 # Parameters of newly constructed modules have requires_grad=True by default
5 num_fts = model._fc.in_features
6 model._fc = nn.Linear(num_fts, N_CLASSES)
7
8 # to GPU
9 model = model.to(DEVICE)
10
11 # loss
12 criterion = nn.CrossEntropyLoss()
13
14 # learning rate optimizer
15 optimizer = torch.optim.AdamW(model.parameters())
16
17 # scheduler for the lr optimizer
18 scheduler = torch.optim.lr_scheduler.StepLR(optimizer, 3, 0.5)

1 model._fc

    Linear(in_features=1408, out_features=42, bias=True)

1 feature_extr_epochs = 3

1 history_feature_extr = train(train_dataset, val_dataset, model=model, criterion=criterion,
2                               epochs=feature_extr_epochs, batch_size=256, optimizer=optimizer, scheduler=scheduler)

```

```

cpuset_checked))
epoch: 0%|          | 0/3 [00:00<?, ?it/s]epoch 1:

Fitting on train data...
train loss: 2.816080071970822
Evaluating on validation data...
epoch: 33%|██████    | 1/3 [03:32<07:04, 212.24s/it]val loss: 2.4697439391544105

Epoch 001 train_loss: 2.8161      val_loss 2.4697 train_acc 0.3197 val_acc 0.4550

epoch 2:

Fitting on train data...
train loss: 2.0353817675655552
Evaluating on validation data...
epoch: 67%|██████████ | 2/3 [07:05<03:32, 212.87s/it]val loss: 1.7548837868444727

Epoch 002 train_loss: 2.0354      val_loss 1.7549 train_acc 0.5463 val_acc 0.6124

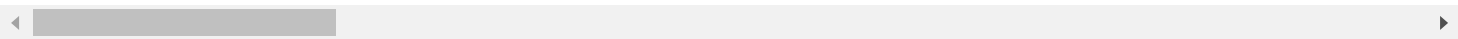
epoch 3:

Fitting on train data...
train loss: 1.5977416844631656
Evaluating on validation data...
epoch: 100%|██████████| 3/3 [10:44<00:00, 214.98s/it]val loss: 1.486225349851289

Epoch 003 train_loss: 1.5977      val_loss 1.4862 train_acc 0.6273 val_acc 0.6599

Training complete in 10m 45s
Best val loss: 10.000000
Best epoch: 3

```

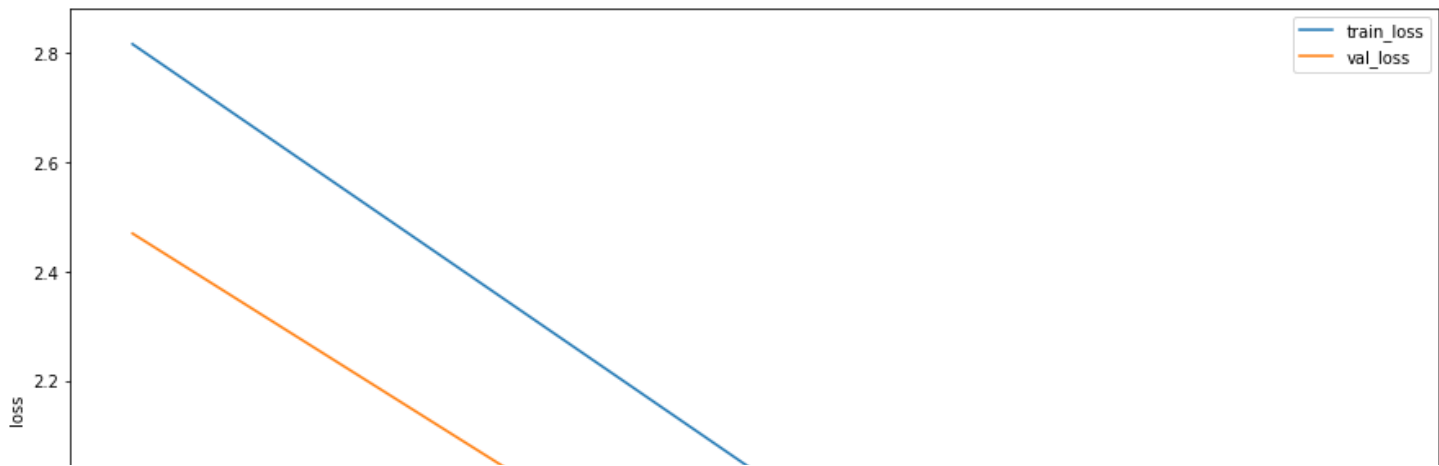


```
1 loss, acc, val_loss, val_acc = zip(*history_feature_extr)
```

```

1 plt.figure(figsize=(15, 9))
2 plt.plot(loss, label="train_loss")
3 plt.plot(val_loss, label="val_loss")
4 plt.legend(loc='best')
5 plt.xlabel("epochs")
6 plt.ylabel("loss")
7 plt.show()

```



Training all layers

```
1 for param in model.parameters():
2     param.requires_grad = True
16 |
```

```
1 finetuning_epochs = 20
```

```
1 history_fine_tune = train(train_dataset=train_dataset, val_dataset=val_dataset, model=model, crit
2                           epochs=finetuning_epochs, batch_size=16, optimizer=optimizer, scheduler
```

```
cpuset_checked))
```

```
epoch: 0%|          | 0/20 [00:00<?, ?it/s]epoch 1:
```

```
Fitting on train data...
```

```
train loss: 0.4610751473526055
```

```
Evaluating on validation data...
```

```
epoch: 5%|█          | 1/20 [07:39<2:25:36, 459.83s/it]val loss: 0.1900292584273099
```

```
Epoch 001 train_loss: 0.4611      val_loss 0.1900 train_acc 0.8803 val_acc 0.9520
```

```
epoch 2:
```

```
Fitting on train data...
```

```
train loss: 0.227955534666559
```

```
Evaluating on validation data...
```

```
epoch: 10%|██         | 2/20 [15:20<2:18:04, 460.23s/it]val loss: 0.16228132652883298
```

```
Epoch 002 train_loss: 0.2280      val_loss 0.1623 train_acc 0.9402 val_acc 0.9577
```

```
epoch 3:
```

```
Fitting on train data...
```

```
train loss: 0.19532413977905666
```

```
Evaluating on validation data...
```

```
epoch: 15%|███        | 3/20 [23:00<2:10:24, 460.27s/it]val loss: 0.1761299595274226
```

```
Epoch 003 train_loss: 0.1953      val_loss 0.1761 train_acc 0.9483 val_acc 0.9570
```

```
epoch 4:
```

```
Fitting on train data...
```

```
train loss: 0.07108287800511714
```

```
Evaluating on validation data...
```

```
epoch: 20%|████       | 4/20 [30:40<2:02:44, 460.27s/it]val loss: 0.10210113575921802
```

```
Epoch 004 train_loss: 0.0711      val_loss 0.1021 train_acc 0.9827 val_acc 0.9756
```

```
epoch 5:
```

```
Fitting on train data...
```

```
train loss: 0.05060067677520271
```

```
Evaluating on validation data...
```

```
epoch: 25%|█████      | 5/20 [38:21<1:55:05, 460.37s/it]val loss: 0.15314130060279219
```

```
Epoch 005 train_loss: 0.0506      val_loss 0.1531 train_acc 0.9870 val_acc 0.9644
```

```
epoch 6:
```

```
Fitting on train data...
```

```
train loss: 0.07118963005940708
```

```
Evaluating on validation data...
```

```
1 loss, acc, val_loss, val_acc = zip(*history_fine_tune)
```

```
epoch 006 train_loss: 0.0712      val_loss 0.1572 train_acc 0.9799 val_acc 0.9721
```

```
1 plt.figure(figsize=(15, 9))
```

```
2 plt.plot(loss, label="train_loss")
```

```
3 plt.plot(val_loss, label="val_loss")
```

```
4 plt.legend(loc='best')
```

```
5 plt.xlabel("epochs")
```

```
6 plt.ylabel("loss")
```

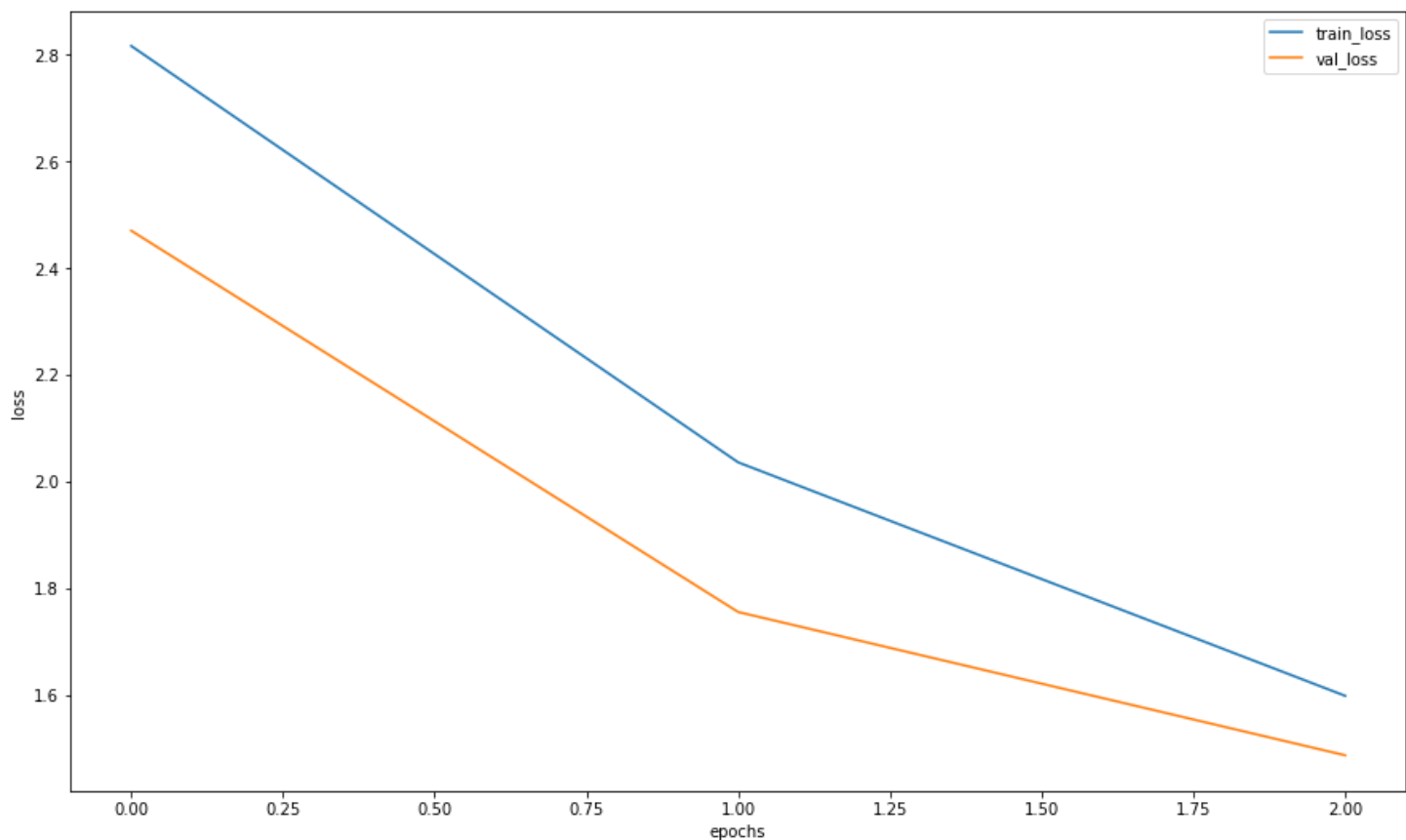
```
7
```

```
8
```

```

9 plt.savefig(f"{model_name}_{feature_extr_epochs}FeatureExtrEpochs-{finetuning_epochs}FinetuningEpochs-LearningCurve.png")
10 plt.show()

```



```

1 f"{model_name}_{feature_extr_epochs}FeatureExtrEpochs-{finetuning_epochs}FinetuningEpochs-LearningCurve.png"
   'efficientnet-b2_3FeatureExtrEpochs-20FinetuningEpochs-LearningCurve.png'

```

```

1 # save the weights of our net
2 model_weights = copy.deepcopy(model.state_dict())
3 torch.save(model_weights, f"{model_name}_{feature_extr_epochs}FeatureExtrEpochs-{finetuning_epochs}FinetuningEpochs-weights.pth")

```

```

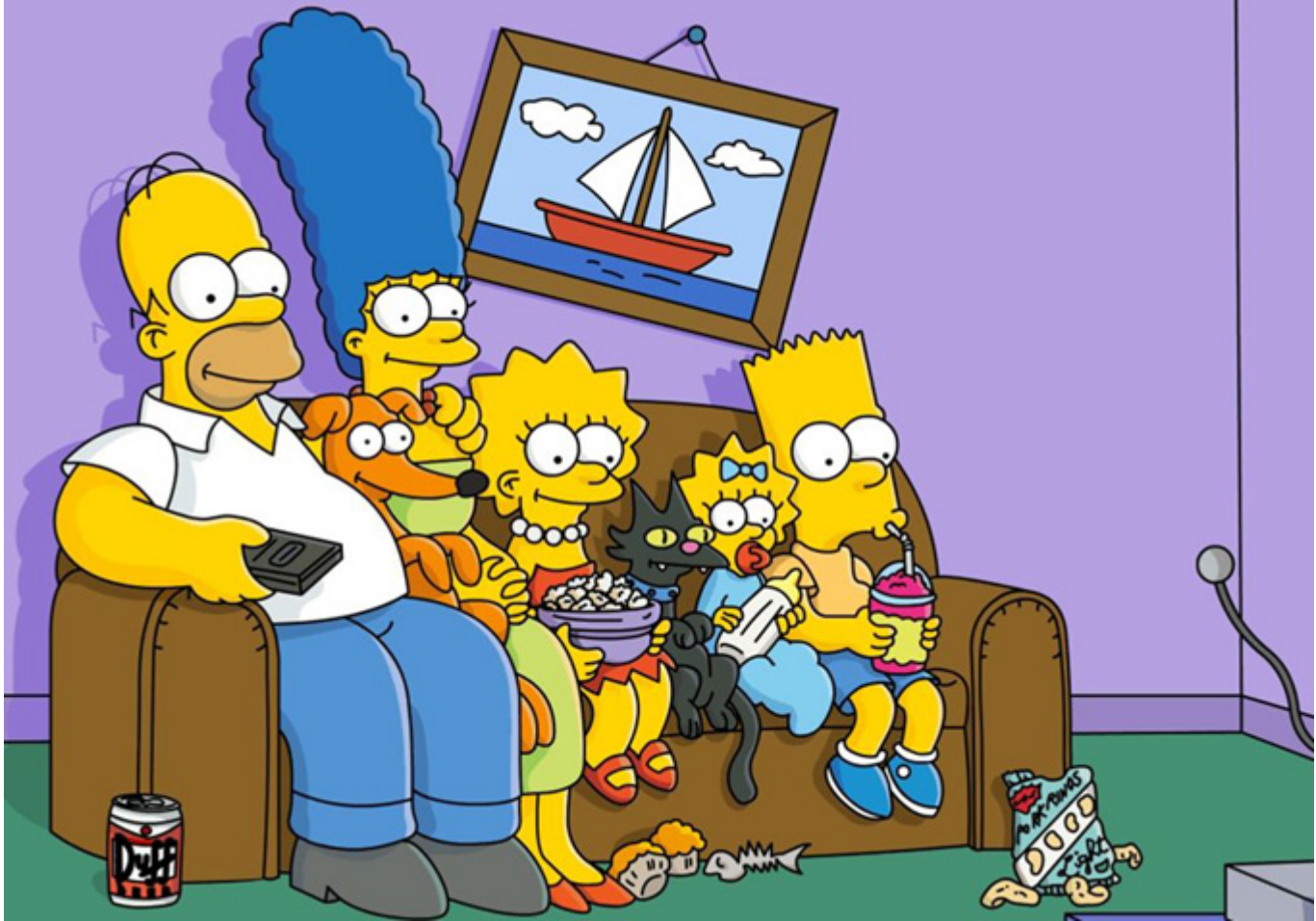
1 %ls
   efficientnet-b2_3FeatureExtrEpochs-20FinetuningEpochs-LearningCurve.png
   efficientnet-b2_3FeatureExtrEpochs-20FinetuningEpochs-weights.pth
   gdrive/
   journey-springfield/
   label_encoder.pkl
   sample_data/

```

```

1 # загружаем сохраненное состояние весов нейросети
2 model.load_state_dict(torch.load(f"{model_name}_{feature_extr_epochs}FeatureExtrEpochs-{finetuning_epochs}FinetuningEpochs-weights.pth"))
   <All keys matched successfully>

```



Хорошо бы понять, как сделать сабмит. У нас есть сеть и методы `eval` у нее, которые позволяют перевести сеть в режим предсказания. Стоит понимать, что у нашей модели на последнем слое стоит `softmax`, которые позволяет получить вектор вероятностей того, что объект относится к тому или иному классу. Давайте воспользуемся этим.

```
1 def predict_one_sample(model, inputs, device=DEVICE):
2     """Предсказание, для одной картинке"""
3     with torch.no_grad():
4         inputs = inputs.to(device)
5         model.eval()
6         logit = model(inputs).cpu()
7         probs = torch.nn.functional.softmax(logit, dim=-1).numpy()
8     return probs
```

```
1 random_characters = int(np.random.uniform(0,1000))
2 ex_img, true_label = val_dataset[random_characters]
3 probs_im = predict_one_sample(model, ex_img.unsqueeze(0))
```

```
1 idxs = list(map(int, np.random.uniform(0,1000, 20)))
2 imgs = [val_dataset[id][0].unsqueeze(0) for id in idxs]
3
4 probs_ims = predict(model, imgs)
```

```
1 actual_labels = [val_dataset[id][1] for id in idxs]
2 actual_labels
```

```
[4, 6, 0, 4, 6, 7, 4, 0, 0, 6, 4, 1, 6, 4, 6, 6, 0, 6, 6, 4]
```



```

1 y_pred = np.argmax(probs_ims, -1)
2 y_pred

array([4, 6, 0, 4, 6, 7, 4, 0, 0, 6, 4, 1, 6, 4, 6, 6, 0, 6, 6, 4])

1 label_encoder = pickle.load(open("label_encoder.pkl", 'rb'))

1 actual_class = [label_encoder.classes_[i] for i in actual_labels]
2 actual_class

['bart_simpson',
 'charles_montgomery_burns',
 'abraham_grampa_simpson',
 'bart_simpson',
 'charles_montgomery_burns',
 'chief_wiggum',
 'bart_simpson',
 'abraham_grampa_simpson',
 'abraham_grampa_simpson',
 'charles_montgomery_burns',
 'bart_simpson',
 'agnes_skinner',
 'charles_montgomery_burns',
 'bart_simpson',
 'charles_montgomery_burns',
 'charles_montgomery_burns',
 'abraham_grampa_simpson',
 'charles_montgomery_burns',
 'charles_montgomery_burns',
 'bart_simpson']

1 preds_class = [label_encoder.classes_[i] for i in y_pred]
2 preds_class

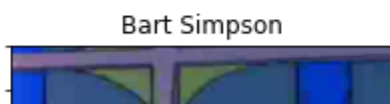
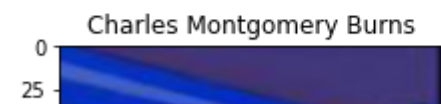
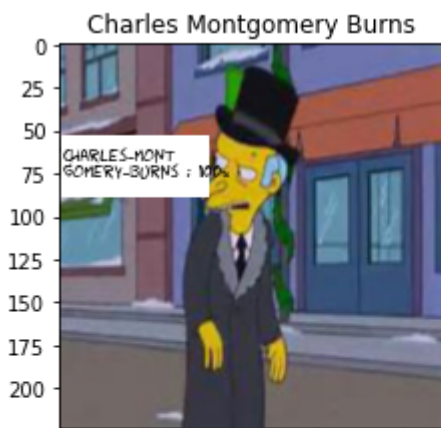
['bart_simpson',
 'charles_montgomery_burns',
 'abraham_grampa_simpson',
 'bart_simpson',
 'charles_montgomery_burns',
 'chief_wiggum',
 'bart_simpson',
 'abraham_grampa_simpson',
 'abraham_grampa_simpson',
 'charles_montgomery_burns',
 'bart_simpson',
 'agnes_skinner',
 'charles_montgomery_burns',
 'bart_simpson',
 'charles_montgomery_burns',
 'charles_montgomery_burns',
 'abraham_grampa_simpson',
 'charles_montgomery_burns',
 'charles_montgomery_burns',
 'bart_simpson']

1 from sklearn.metrics import f1_score
2
3 f1_score(actual_class, preds_class, average='weighted')

```

1.0

```
1 import matplotlib.patches as patches
2 from matplotlib.font_manager import FontProperties
3
4 fig, ax = plt.subplots(nrows=3, ncols=3,figsize=(12, 12), \
5                         sharey=True, sharex=True)
6 for fig_x in ax.flatten():
7     random_characters = int(np.random.uniform(0,1000))
8     im_val, label = val_dataset[random_characters]
9     img_label = " ".join(map(lambda x: x.capitalize(),\
10                             val_dataset.label_encoder.inverse_transform([label])[0].split('_')))
11
12
13
14     imshow(im_val.data.cpu(), \
15            title=img_label,plt_ax=fig_x)
16
17     actual_text = "Actual : {}".format(img_label)
18
19     fig_x.add_patch(patches.Rectangle((0, 53),86,35,color='white'))
20     font0 = FontProperties()
21     font = font0.copy()
22     font.set_family("fantasy")
23     prob_pred = predict_one_sample(model, im_val.unsqueeze(0))
24     predicted_proba = np.max(prob_pred)*100
25     y_pred = np.argmax(prob_pred)
26
27     predicted_label = label_encoder.classes_[y_pred]
28     predicted_label = predicted_label[:len(predicted_label)//2] + '\n' + predicted_label[len(predicted_label)//2:]
29     predicted_text = "{} : {:.0f}%".format(predicted_label,predicted_proba)
30
31     fig_x.text(1, 59, predicted_text , horizontalalignment='left', fontproperties=font,
32               verticalalignment='top',fontsize=8, color='black',fontweight='bold')
```



Попробуйте найти те классы, которые сеть не смогла распознать. Изучите данную проблему, это понадобится в дальнейшем.



Submit на Kaggle



```
1 test_dataset = SimpsonsDataset(test_files, mode="test")
2 test_loader = DataLoader(test_dataset, shuffle=False, batch_size=64, num_workers=4)
3 probs = predict(model, test_loader)
4
5
6 preds = label_encoder.inverse_transform(np.argmax(probs, axis=1))
7 test_filenames = [path.name for path in test_dataset.files]
```

```
cpuset_checked))
```

```
1 ! ls
```

```
efficientnet-b2_3FeatureExtrEpochs-20FinetuningEpochs-LearningCurve.png
efficientnet-b2_3FeatureExtrEpochs-20FinetuningEpochs-weights.pth
gdrive
journey-springfield
label_encoder.pkl
sample_data
```

```
1 import pandas as pd
2 sample_submit = pd.read_csv("/content/journey-springfield/sample_submission.csv")
3 sample_submit.head()
```

	<b>Id</b>	<b>Expected</b>
<b>0</b>	img0.jpg	bart_simpson
<b>1</b>	img1.jpg	bart_simpson
<b>2</b>	img2.jpg	bart_simpson
<b>3</b>	img3.jpg	bart_simpson
<b>4</b>	img4.jpg	bart_simpson

```
1 my_submit = pd.DataFrame({'Id': test_filenames, 'Expected': preds})
2 print(my_submit.shape)
3 my_submit.head()
```

```
(991, 2)
```

	<b>Id</b>	<b>Expected</b>
<b>0</b>	img0.jpg	nelson_muntz
<b>1</b>	img1.jpg	bart_simpson
<b>2</b>	img10.jpg	ned_flanders
<b>3</b>	img100.jpg	chief_wiggum
<b>4</b>	img101.jpg	apu_nahasapeemapetilon

```
1 my_submit.to_csv(f"{model_name}_{feature_extr_epochs}FeatureExtrEpochs-{finetuning_epochs}submission.csv")
```

```
1 f"{model_name}_{feature_extr_epochs}FeatureExtrEpochs-{finetuning_epochs}FinetuningEpochs-submission.csv"
```

```
'efficientnet-b2_3FeatureExtrEpochs-20FinetuningEpochs-submission.csv '
```

```
1 f"{model_name}_{feature_extr_epochs}FeatureExtrEpochs-{finetuning_epochs}FinetuningEpochs-weights.pth"
2 f"{model_name}_{feature_extr_epochs}FeatureExtrEpochs-{finetuning_epochs}FinetuningEpochs-LearningCurve.png"
3 f"{model_name}_{feature_extr_epochs}FeatureExtrEpochs-{finetuning_epochs}FinetuningEpochs-submission.csv"
```

```
'efficientnet-b2_3FeatureExtrEpochs-20FinetuningEpochs-submission.csv '
```

---

✓ 0s completed at 11:53 AM

