Poszukiwanie tekstu pisanego odręcznie

Ten notatnik analizuje metody identyfikowania fragmentów pisanych odręcznie z obrazów zawierających tekst drukowany i pisany odręcznie za pomocą **DCNN**.

Jako wejście algorytm przyjmuje plik png ze zbioru danych IAM z typem danych wejściowych jako formularz oraz typem wyjściowych „bb” i formularz.

Na wyjściu otrzymujemy ramki ograniczające akapity.

[2]:
```
import multiprocessing
import time
import random
import os

import matplotlib.pyplot as plt
import matplotlib.patches as patches

import mxnet as mx
import numpy as np
from skimage.draw import line_aa
from skimage import transform as skimage_transform

from mxnet import nd, autograd, gluon
from mxnet.image import resize_short
from mxboard import SummaryWriter



from ocr.utils.iam_dataset import IAMDataset
from ocr.utils.iou_loss import IOU_loss
from ocr.utils.draw_box_on_image import draw_box_on_image

model_checkpoint_folder = "model_checkpoint"
if not os.path.isdir(model_checkpoint_folder):
    os.makedirs(model_checkpoint_folder)

ctx = mx.gpu()
mx.random.seed(42)
```

Wczytanie zbioru danych

[4]:
```
train_ds = IAMDataset("form", output_data="bb", output_parse_method="form",␣
↪train=True)
print("Number of training samples: {}".format(len(train_ds)))
```

```
test_ds = IAMDataset("form", output_data="bb", output_parse_method="form",␣
↪train=False)
print("Number of testing samples: {}".format(len(test_ds)))
```

```
Processing data:
Completed: [---------------------------------------- ]  99%Number of training␣
↪samples: 967
Number of testing samples: 232
```

Zastosowaliśmy dwie transformacje, funkcja „transform” zmienia rozmiar i normalizuje obraz. Funkcja „augment_transform” losowo przesuwa obraz i przewidywane pole ograniczające o 5%.

[5]:
```
batch_size = 32

random_y_translation, random_x_translation = (0.2, 0.2) # Randomly translate␣
↪the input image
expand_bb_scale = 0.03 # Expand the bounding box to relax the boundaries
```

[6]:
```
def transform(data, label):
    '''
    Function that converts "data"" into the input image tensor for a CNN
    Label is converted into a float tensor.
    '''
    image = mx.nd.array(data).expand_dims(axis=2)
    image = resize_short(image, int(800/3))
    image = image.transpose([2, 0, 1])/255.
    label = label[0].astype(np.float32)

    bb = label.copy()
    new_w = (1 + expand_bb_scale) * bb[2]
    new_h = (1 + expand_bb_scale) * bb[3]

    bb[0] = bb[0] - (new_w - bb[2])/2
    bb[1] = bb[1] - (new_h - bb[3])/2
    bb[2] = new_w
    bb[3] = new_h

    return image, mx.nd.array(bb)

def augment_transform(data, label):
    '''
```

```
    Function that randomly translates the input image by +-width_range and␣
↪+-height_range.
    The labels (bounding boxes) are also translated by the same amount.
    '''
    ty = random.uniform(-random_y_translation, random_y_translation)
    tx = random.uniform(-random_x_translation, random_x_translation)
    st = skimage_transform.SimilarityTransform(translation=(tx*data.shape[1],␣
↪ty*data.shape[0]))
    data = skimage_transform.warp(data, st)
    label = label.copy()
    label[0][0] = label[0][0] - tx
    label[0][1] = label[0][1] - ty
    return transform(data*255., label)
```

[7]:
```
train_data = gluon.data.DataLoader(train_ds.transform(augment_transform),␣
↪batch_size, shuffle=True, num_workers=8)
test_data = gluon.data.DataLoader(test_ds.transform(transform), batch_size,␣
↪shuffle=False, num_workers=8)
```

Tworzenie sieci

[9]:
```
class SegmentationNetwork(gluon.nn.HybridBlock):

    def __init__(self, p_dropout = 0.5, ctx=mx.cpu()):
        super(SegmentationNetwork, self).__init__()

        pretrained = gluon.model_zoo.vision.resnet34_v1(pretrained=True,␣
↪ctx=ctx)
        first_weights = pretrained.features[0].weight.data().mean(axis=1).
↪expand_dims(axis=1)

        body = gluon.nn.HybridSequential(prefix="SegmentationNetwork_")
        with body.name_scope():
            first_layer = gluon.nn.Conv2D(channels=64, kernel_size=(7, 7),␣
↪padding=(3, 3), strides=(2, 2), in_channels=1, use_bias=False)
            first_layer.initialize(mx.init.Normal(), ctx=ctx)
            first_layer.weight.set_data(first_weights)
            body.add(first_layer)
            body.add(*pretrained.features[1:6])

            output = gluon.nn.HybridSequential()
```

```python
            with output.name_scope():
                output.add(gluon.nn.Flatten())
                output.add(gluon.nn.Dense(64, activation='relu'))
                output.add(gluon.nn.Dropout(p_dropout))
                output.add(gluon.nn.Dense(64, activation='relu'))
                output.add(gluon.nn.Dropout(p_dropout))
                output.add(gluon.nn.Dense(4, activation='sigmoid'))

            output.collect_params().initialize(mx.init.Normal(), ctx=ctx)
            body.add(output)
        self.cnn = body

    def hybrid_forward(self, F, x):
        return self.cnn(x)

net = SegmentationNetwork()
net.hybridize()
net.collect_params().reset_ctx(ctx)
```

Definowanie epoki

[11]:
```python
print_every_n = 1
send_image_every_n = 20

def run_epoch(e, network, dataloader, loss_function, trainer, log_dir,
 ↪print_name, is_train):
    total_loss = nd.zeros(1, ctx)
    for i, (data, label) in enumerate(dataloader):
        data = data.as_in_context(ctx)
        label = label.as_in_context(ctx)

        with autograd.record(train_mode=is_train):
            output = network(data)
            loss_i = loss_function(output, label)
        if is_train:
            loss_i.backward()
            trainer.step(data.shape[0])

        total_loss += loss_i.mean()

        if e % send_image_every_n == 0 and e > 0 and i == 0:
```

```
            output_image = draw_box_on_image(output.asnumpy(), label.
↪asnumpy(), data.asnumpy())
    epoch_loss = float(total_loss .asscalar())/len(dataloader)

    with SummaryWriter(logdir=log_dir, verbose=False, flush_secs=5) as sw:
        sw.add_scalar('loss', {print_name: epoch_loss}, global_step=e)
        if e % send_image_every_n == 0 and e > 0:
            output_image[output_image<0] = 0
            output_image[output_image>1] = 1
            sw.add_image('bb_{}_image'.format(print_name), output_image,␣
↪global_step=e)

    return epoch_loss
```

Pre training

Sieć była początkowo szkolona w 300 epokach przy użyciu błędu średniokwadratowego (strata L2) jako funkcji straty. Zostało to wykonane, ponieważ bez rozsądnych ramek granicznych (tj. nakładających się ramek granicznych) utrata IOU nie będzie działać poprawnie.

[14]:
```
checkpoint_name = "cnn_mse.params"
best_test_loss = 10e5
```

[17]:
```
loss_function = gluon.loss.L2Loss()
epochs = 11
learning_rate = 0.00005
log_dir = "./logs/paragraph_segmentation"
```

[19]:
```
if os.path.isfile(os.path.join(model_checkpoint_folder, checkpoint_name)):
    net.load_parameters(os.path.join(model_checkpoint_folder, checkpoint_name))
```

[21]:
```
trainer = gluon.Trainer(net.collect_params(), 'adam', {'learning_rate':␣
↪learning_rate})
```

[22]:
```
for e in range(epochs):
    train_loss = run_epoch(e, net, train_data, loss_function=loss_function,␣
↪log_dir=log_dir,
                           trainer=trainer, print_name="train", is_train=True)
    test_loss = run_epoch(e, net, test_data, loss_function=loss_function,␣
↪log_dir=log_dir,
                          trainer=trainer, print_name="test", is_train=False)
    if test_loss < best_test_loss:
        print("Saving network, previous best test loss {:.6f}, current test␣
↪loss {:.6f}".format(best_test_loss, test_loss))
```

```
        net.save_parameters(os.path.join(model_checkpoint_folder,␣
↪checkpoint_name))
        best_test_loss = test_loss
    if e % print_every_n == 0 and e > 0:
        print("Epoch {0}, train_loss {1:.6f}, test_loss {2:.6f}".format(e,␣
↪train_loss, test_loss))
```

```
[09:27:18] ../src/operator/nn/./cudnn/./cudnn_algoreg-inl.h:97: Running␣
↪performance tests
to find the best convolution algorithm, this can take a while… (set the␣
↪environment
variable MXNET_CUDNN_AUTOTUNE_DEFAULT to 0 to disable)
```

```
Saving network, previous best test loss 1000000.000000, current test loss 0.
↪002516
Saving network, previous best test loss 0.002516, current test loss 0.001363
Epoch 1, train_loss 0.008476, test_loss 0.001363
Saving network, previous best test loss 0.001363, current test loss 0.001273
Epoch 2, train_loss 0.006936, test_loss 0.001273
Epoch 3, train_loss 0.006079, test_loss 0.001371
Saving network, previous best test loss 0.001273, current test loss 0.001209
Epoch 4, train_loss 0.005319, test_loss 0.001209
Saving network, previous best test loss 0.001209, current test loss 0.001129
Epoch 5, train_loss 0.004649, test_loss 0.001129
Saving network, previous best test loss 0.001129, current test loss 0.001077
Epoch 6, train_loss 0.004192, test_loss 0.001077
Saving network, previous best test loss 0.001077, current test loss 0.001073
Epoch 7, train_loss 0.003999, test_loss 0.001073
Saving network, previous best test loss 0.001073, current test loss 0.001023
Epoch 8, train_loss 0.003723, test_loss 0.001023
Epoch 9, train_loss 0.003519, test_loss 0.001060
Saving network, previous best test loss 0.001023, current test loss 0.001018
Epoch 10, train_loss 0.003356, test_loss 0.001018
```

Dopasowanie

Po przeszkoleniu sieci za pomocą średniej kwadratowej utraty błędów, utrata IOU została wykorzystana do dostrojenia sieci. Strata IOU jest bardziej drobnoziarnista, ponieważ maksymalizuje nakładanie się ramek ograniczających.

[24]:
```
if os.path.isfile(os.path.join(model_checkpoint_folder, checkpoint_name)):
    net.load_parameters(os.path.join(model_checkpoint_folder, checkpoint_name))
```

```
fine_tuning = False # I found this to consistently decrease the qualitative␣
↪results
```

[25]:
```
if fine_tuning:
    checkpoint_name = "cnn_iou.params"
    loss_function = IOU_loss()
    epochs = 150
    learning_rate = 0.00005
    log_dir = "./logs"

    best_test_loss = 10e5

    trainer = gluon.Trainer(net.collect_params(), 'adam', {'learning_rate':␣
↪learning_rate, })

    for e in range(epochs):
        train_loss = run_epoch(e, net, train_data,␣
↪loss_function=loss_function, log_dir=log_dir,
                               trainer=trainer, print_name="train",␣
↪is_train=True)
        test_loss = run_epoch(e, net, test_data, loss_function=loss_function,␣
↪log_dir=log_dir,
                              trainer=trainer, print_name="test",␣
↪is_train=False)
        if test_loss < best_test_loss:
            print("Saving network, previous best test loss {:.6f}, current␣
↪test loss {:.6f}".format(best_test_loss, test_loss))
            net.save_parameters("{}/{}".format(model_checkpoint_folder,␣
↪checkpoint_name))
            best_test_loss = test_loss
        if e % print_every_n == 0 and e > 0:
            print("Epoch {0}, train_loss {1:.6f}, test_loss {2:.6f}".
↪format(e, train_loss, test_loss))
```

Wyniki

Szkolenie i test MSE są wyświetlone w tym notatniku. Stratę i obrazy z przewidywanymi ramkami ograniczającymi pokazano poniżej.

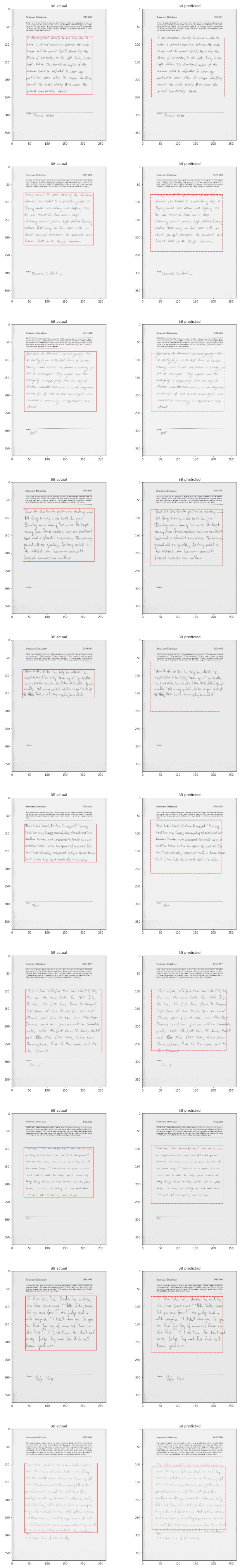
[26]:
```
figs_to_plot = 10
fig, axs = plt.subplots(figs_to_plot, 2, figsize=(15, 10 * figs_to_plot))
```

```python
for i in range(figs_to_plot):
    n = int(random.random()*len(test_ds))
    image, bb = test_ds[n]

    image, _ = transform(image, bb)
    image = image.as_in_context(ctx)
    image = image.expand_dims(axis=0)
    bb_predicted = net(image)

    (x, y, w, h) = bb[0]
    axs[i][0].imshow(image.asnumpy().squeeze(), cmap='Greys_r')
    image_h, image_w = image.shape[-2:]
    (x, y, w, h) = (x * image_w, y * image_h, w * image_w, h * image_h)
    rect = patches.Rectangle((x, y), w, h, fill=False, color="r")
    axs[i][0].add_patch(rect)
    axs[i][0].set_title("BB actual")

    axs[i][1].imshow(image.asnumpy().squeeze(), cmap='Greys_r')
    (x, y, w, h) = bb_predicted[0].asnumpy()
    image_h, image_w = image.shape[-2:]
    (x, y, w, h) = (x * image_w, y * image_h, w * image_w, h * image_h)
    rect = patches.Rectangle((x, y), w, h, fill=False, color="r", ls="--")
    axs[i][1].add_patch(rect)
    axs[i][1].set_title("BB predicted")
```


BB actual
BB predicted