Segmentacja słów i lini

Ten notatnik demonstruje algorytm pozwalający na zapewnienia ramek ograniczających otaczających odręcznie zapisany tekst.

Dane wejściowe: Obraz zawierający odręczny tekst.

Dane wyjściowe: lista ramek ograniczających.

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

import cv2
import matplotlib.pyplot as plt
import matplotlib.patches as patches

import mxnet as mx
from mxnet import nd, autograd, gluon
from mxnet.image import resize_short
from mxboard import SummaryWriter
from mxnet.gluon.model_zoo.vision import resnet34_v1
from mxnet.contrib.ndarray import MultiBoxPrior, MultiBoxTarget,␣
↪MultiBoxDetection, box_nms
import numpy as np
from skimage.draw import line_aa
from skimage import transform as skimage_tf

np.seterr(all='raise')

mx.random.seed(42)

from ocr.utils.iam_dataset import IAMDataset
from ocr.utils.draw_box_on_image import draw_boxes_on_image
```

Definiowanie sieci

Do identyfikacji każdej linii używamy sieci SSD.

[4]:
```python
class SSD(gluon.Block):
    def __init__(self, num_classes, ctx, **kwargs):
        super(SSD, self).__init__(**kwargs)

        # Seven sets of anchor boxes are defined. For each set, n=2 sizes␣
↪and m=3 ratios are defined.
```

```python
        # Four anchor boxes (n + m - 1) are generated: 2 square anchor boxes␣
↪based on the n=2 sizes and 2 rectanges based on
        # the sizes and the ratios. See https://discuss.mxnet.io/t/
↪question-regarding-ssd-algorithm/1307 for more information.

        #self.anchor_sizes = [[.1, .2], [.2, .3], [.2, .4], [.4, .6], [.5, .
↪7], [.6, .8], [.7, .9]]
        #self.anchor_ratios = [[1, 3, 5], [1, 3, 5], [1, 6, 8], [1, 5, 7],␣
↪[1, 6, 8], [1, 7, 9], [1, 7, 10]]

        self.anchor_sizes = [[.1, .2], [.2, .3], [.2, .4], [.3, .4], [.3, .5],␣
↪[.4, .6]]
        self.anchor_ratios = [[1, 3, 5], [1, 3, 5], [1, 6, 8], [1, 4, 7], [1,␣
↪6, 8], [1, 5, 7]]

        self.num_anchors = len(self.anchor_sizes)
        self.num_classes = num_classes
        self.ctx = ctx
        with self.name_scope():
            self.body, self.downsamples, self.class_preds, self.box_preds =␣
↪self.get_ssd_model()
            self.downsamples.initialize(mx.init.Normal(), ctx=self.ctx)
            self.class_preds.initialize(mx.init.Normal(), ctx=self.ctx)
            self.box_preds.initialize(mx.init.Normal(), ctx=self.ctx)

    def get_body(self):
        '''
        Create the feature extraction network of the SSD based on resnet34.
        The first layer of the res-net is converted into grayscale by␣
↪averaging the weights of the 3 channels
        of the original resnet.

        Returns
        -------
        network: gluon.nn.HybridSequential
            The body network for feature extraction based on resnet

        '''
        pretrained = resnet34_v1(pretrained=True, ctx=self.ctx)
```

```
        pretrained_2 = resnet34_v1(pretrained=True, ctx=mx.cpu(0))
        first_weights = pretrained_2.features[0].weight.data().mean(axis=1).expand_dims(axis=1)
        # First weights could be replaced with individual channels.

        body = gluon.nn.HybridSequential()
        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=self.ctx)
            first_layer.weight.set_data(first_weights)
            body.add(first_layer)
            body.add(*pretrained.features[1:-3])
        return body

    def get_class_predictor(self, num_anchors_predicted):
        '''
        Creates the category prediction network (takes input from each downsampled feature)

        Parameters
        ----------

        num_anchors_predicted: int
            Given n sizes and m ratios, the number of boxes predicted is n+m-1.
            e.g., sizes=[.1, .2], ratios=[1, 3, 5] the number of anchors predicted is 4.

        Returns
        -------

        network: gluon.nn.HybridSequential
            The class predictor network
        '''
        return gluon.nn.Conv2D(num_anchors_predicted*(self.num_classes + 1), kernel_size=3, padding=1)

    def get_box_predictor(self, num_anchors_predicted):
```

```python
        '''
        Creates the bounding box prediction network (takes input from each␣
↪downsampled feature)

        Parameters
        ----------

        num_anchors_predicted: int
            Given n sizes and m ratios, the number of boxes predicted is␣
↪n+m-1.
            e.g., sizes=[.1, .2], ratios=[1, 3, 5] the number of anchors␣
↪predicted is 4.

        Returns
        -------

        pred: gluon.nn.HybridSequential
            The box predictor network
        '''
        pred = gluon.nn.HybridSequential()
        with pred.name_scope():
            pred.add(gluon.nn.Conv2D(channels=num_anchors_predicted*4,␣
↪kernel_size=3, padding=1))
        return pred

    def get_down_sampler(self, num_filters):
        '''
        Creates a two-stacked Conv-BatchNorm-Relu and then a pooling layer to
        downsample the image features by half.
        '''
        out = gluon.nn.HybridSequential()
        for _ in range(2):
            out.add(gluon.nn.Conv2D(num_filters, 3, strides=1, padding=1))
            out.add(gluon.nn.BatchNorm(in_channels=num_filters))
            out.add(gluon.nn.Activation('relu'))
        out.add(gluon.nn.MaxPool2D(2))
        out.hybridize()
        return out
```

```python
    def get_ssd_model(self):
        '''
        Creates the SSD model that includes the image feature, downsample,␣
↪category
        and bounding boxes prediction networks.
        '''
        body = self.get_body()
        downsamples = gluon.nn.HybridSequential()
        class_preds = gluon.nn.HybridSequential()
        box_preds = gluon.nn.HybridSequential()

        downsamples.add(self.get_down_sampler(32))
        downsamples.add(self.get_down_sampler(32))
        downsamples.add(self.get_down_sampler(32))

        for scale in range(self.num_anchors):
            num_anchors_predicted = len(self.anchor_sizes[0]) + len(self.
↪anchor_ratios[0]) - 1
            class_preds.add(self.get_class_predictor(num_anchors_predicted))
            box_preds.add(self.get_box_predictor(num_anchors_predicted))

        return body, downsamples, class_preds, box_preds

    def ssd_forward(self, x):
        '''
        Helper function of the forward pass of the sdd
        '''
        x = self.body(x)

        default_anchors = []
        predicted_boxes = []
        predicted_classes = []

        for i in range(self.num_anchors):
            default_anchors.append(MultiBoxPrior(x, sizes=self.
↪anchor_sizes[i], ratios=self.anchor_ratios[i]))
            predicted_boxes.append(self._flatten_prediction(self.
↪box_preds[i](x)))
```

```
            predicted_classes.append(self._flatten_prediction(self.
↪class_preds[i](x)))
            if i < len(self.downsamples):
                x = self.downsamples[i](x)
            elif i == 3:
                x = nd.Pooling(x, global_pool=True, pool_type='max',␣
↪kernel=(4, 4))
        return default_anchors, predicted_classes, predicted_boxes

    def forward(self, x):
        default_anchors, predicted_classes, predicted_boxes = self.
↪ssd_forward(x)
        # we want to concatenate anchors, class predictions, box predictions␣
↪from different layers
        anchors = nd.concat(*default_anchors, dim=1)
        box_preds = nd.concat(*predicted_boxes, dim=1)
        class_preds = nd.concat(*predicted_classes, dim=1)
        class_preds = nd.reshape(class_preds, shape=(0, -1, self.num_classes +␣
↪1))
        return anchors, class_preds, box_preds

    def _flatten_prediction(self, pred):
        '''
        Helper function to flatten the predicted bounding boxes and␣
↪categories
        '''
        return nd.flatten(nd.transpose(pred, axes=(0, 2, 3, 1)))

    def training_targets(self, default_anchors, class_predicts, labels):
        '''
        Helper function to obtain the bounding boxes from the anchors.
        '''
        class_predicts = nd.transpose(class_predicts, axes=(0, 2, 1))
        box_target, box_mask, cls_target = MultiBoxTarget(default_anchors,␣
↪labels, class_predicts)
        return box_target, box_mask, cls_target
```

Funkcja straty

Sieć SSD został przeszkolona w celu zminimalizowania błędu klasyfikacji i wygładzonej utraty L1 między przewidywaną a rzeczywistą ramką ograniczającą. Gładka strata L1 jest zdefiniowana poniżej.

[6]:
```
class SmoothL1Loss(gluon.loss.Loss):
    '''
    A SmoothL1loss function defined in https://gluon.mxnet.io/
↪chapter08_computer-vision/object-detection.html
    '''
    def __init__(self, batch_axis=0, **kwargs):
        super(SmoothL1Loss, self).__init__(None, batch_axis, **kwargs)

    def hybrid_forward(self, F, output, label, mask):
        loss = F.smooth_l1((output - label) * mask, scalar=1.0)
        return F.mean(loss, self._batch_axis, exclude=True)
```

Transformacja i augmentacja danych

Dane są przekształcane, aby obrazy i etykiety mogły zostać wprowadzone do sieci. Dane treningowe są powiększane, dzięki czemu obrazy są losowo tłumaczone, a linie są losowo usuwane.

[8]:
```
def augment_transform(image, label):
    '''
    1) Function that randomly translates the input image by +-width_range␣
↪and +-height_range.
    The labels (bounding boxes) are also translated by the same amount.
    2) Each line can also be randomly removed for augmentation. Labels are␣
↪also reduced to correspond to this
    data and label are converted into tensors by calling the "transform"␣
↪function.
    '''
    ty = random.uniform(-random_y_translation, random_y_translation)
    tx = random.uniform(-random_x_translation, random_x_translation)

    st = skimage_tf.SimilarityTransform(translation=(tx*image.shape[1],␣
↪ty*image.shape[0]))
    image = skimage_tf.warp(image, st, cval=1.0)

    label[:, 0] = label[:, 0] - tx/2 #NOTE: Check why it has to be halfed␣
↪(found experimentally)
    label[:, 1] = label[:, 1] - ty/2

    index = np.random.uniform(0, 1.0, size=label.shape[0]) > random_remove_box
    for i, should_output_bb in enumerate(index):
        if should_output_bb == False:
```

```
            (x, y, w, h) = label[i]
            (x1, y1, x2, y2) = (x, y, x + w, y + h)
            (x1, y1, x2, y2) = (x1 * image.shape[1], y1 * image.shape[0],
                                x2 * image.shape[1], y2 * image.shape[0])
            (x1, y1, x2, y2) = (int(x1), int(y1), int(x2), int(y2))
            x1 = 0 if x1 < 0 else x1
            y1 = 0 if y1 < 0 else y1
            x2 = 0 if x2 < 0 else x2
            y2 = 0 if y2 < 0 else y2
            image_h, image_w = image.shape
            x1 = image_w-1 if x1 >= image_w else x1
            y1 = image_h-1 if y1 >= image_h else y1
            x2 = image_w-1 if x2 >= image_w else x2
            y2 = image_h-1 if y2 >= image_h else y2
            image[y1:y2, x1:x2] = image[y1, x1]

    augmented_labels = label[index, :]
    return transform(image*255., augmented_labels)

def transform(image, label):
    '''
    Function that converts resizes image into the input image tensor for a␣
↪CNN.
    The labels (bounding boxes) are expanded, converted into (x, y, x+w,␣
↪y+h), and
    zero padded to the maximum number of labels. Finally, it is converted␣
↪into a float
    tensor.
    '''
    max_label_n = 128 if detection_box == "word" else 13

    # Resize the image
    image = np.expand_dims(image, axis=2)
    image = mx.nd.array(image)
    image = resize_short(image, image_size)
    image = image.transpose([2, 0, 1])/255.

    # Expand the bounding box by expand_bb_scale
    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
    label = bb

    # Convert the predicted bounding box from (x, y, w, h to (x, y, x + w, y␣
↪+ h)
    label = label.astype(np.float32)
    label[:, 2] = label[:, 0] + label[:, 2]
    label[:, 3] = label[:, 1] + label[:, 3]

    # Zero pad the data
    label_n = label.shape[0]
    label_padded = np.zeros(shape=(max_label_n, 5))
    label_padded[:label_n, 1:] = label
    label_padded[:label_n, 0] = np.ones(shape=(1, label_n))
    label_padded = mx.nd.array(label_padded)
    return image, label_padded
```

[11]:
```
def run_epoch(e, network, dataloader, trainer, log_dir, print_name, is_train,␣
↪update_metric):
    '''
    Run one epoch to train or test the SSD network

    Parameters
    ----------

    e: int
        The epoch number

    network: nn.Gluon.HybridSequential
        The SSD network

    dataloader: gluon.data.DataLoader
        The train or testing dataloader that is wrapped around the␣
↪iam_dataset
```

```
    log_dir: Str
        The directory to store the log files for mxboard

    print_name: Str
        Name to print for associating with the data. usually this will be␣
↪"train" and "test"

    is_train: bool
        Boolean to indicate whether or not the CNN should be updated.␣
↪is_train should only be set to true for the training data

    Returns
    -------

    network: gluon.nn.HybridSequential
        The class predictor network
    '''

    total_losses = [0 for ctx_i in ctx]
    for i, (X, Y) in enumerate(dataloader):
        X = gluon.utils.split_and_load(X, ctx)
        Y = gluon.utils.split_and_load(Y, ctx)

        with autograd.record(train_mode=is_train):
            losses = []
            for x, y in zip(X, Y):
                default_anchors, class_predictions, box_predictions =␣
↪network(x)
                box_target, box_mask, cls_target = network.
↪training_targets(default_anchors, class_predictions, y)
                # losses
                loss_class = cls_loss(class_predictions, cls_target)
                loss_box = box_loss(box_predictions, box_target, box_mask)
                # sum all losses
                loss = loss_class + loss_box
                losses.append(loss)

        if is_train:
```

```
            for loss in losses:
                loss.backward()
            step_size = 0
            for x in X:
                step_size += x.shape[0]
            trainer.step(step_size)

        for index, loss in enumerate(losses):
            total_losses[index] += loss.mean().asscalar()

        if update_metric:
            cls_metric.update([cls_target], [nd.transpose(class_predictions,␣
↪(0, 2, 1))])
            box_metric.update([box_target], [box_predictions * box_mask])

        if i == 0 and e % send_image_every_n == 0 and e > 0:
            cls_probs = nd.SoftmaxActivation(nd.transpose(class_predictions,␣
↪(0, 2, 1)), mode='channel')
            output_image, number_of_bbs =␣
↪generate_output_image(box_predictions, default_anchors,
                                                                cls_probs,␣
↪box_target, box_mask,
                                                                cls_target, x,␣
↪y)
            print("Number of predicted {} BBs = {}".format(print_name,␣
↪number_of_bbs))
            with SummaryWriter(logdir=log_dir, verbose=False, flush_secs=5)␣
↪as sw:
                sw.add_image('bb_{}_image'.format(print_name), output_image,␣
↪global_step=e)



    total_loss = 0
    for loss in total_losses:
        total_loss += loss / (len(dataloader)*len(total_losses))

    with SummaryWriter(logdir=log_dir, verbose=False, flush_secs=5) as sw:
        if update_metric:
            name1, val1 = cls_metric.get()
```

```
            name2, val2 = box_metric.get()
            sw.add_scalar(name1, {"test": val1}, global_step=e)
            sw.add_scalar(name2, {"test": val2}, global_step=e)
        sw.add_scalar('loss', {print_name: total_loss}, global_step=e)

    return total_loss
```

Definowanie domyślny parametrów

[13]:
```
detection_box = "word" #"word" or "line"
```

[14]:
```
gpu_count = 4
expand_bb_scale = 0.05
min_c = 0.01
overlap_thres = 0.1 if detection_box == "line" else 0.001
topk = 150 if detection_box == "line" else 200

epochs = 20
learning_rate = 0.00005
batch_size = 32
image_size = 350

random_x_translation, random_y_translation = (0.03, 0.03) if detection_box ==␣
 ↪"line" else (0.005, 0.005)
random_remove_box = 0.1



log_dir = "./logs/line_word_segmentation"
checkpoint_dir, checkpoint_name = "model_checkpoint", "ssd_"+detection_box+".
 ↪params"

print_every_n = 5
send_image_every_n = 20
save_every_n = 50
```

Pętla treningowa

[23]:
```
ctx = [mx.gpu(0)]

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

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

train_data = gluon.data.DataLoader(train_ds.transform(augment_transform),␣
↪batch_size, shuffle=True, last_batch="rollover", num_workers=8)
test_data = gluon.data.DataLoader(test_ds.transform(transform), batch_size,␣
↪shuffle=False, last_batch="keep", num_workers=8)
```

```
Number of training samples: 967
Number of testing samples: 232
```

[24]:
```
net = SSD(num_classes=2, ctx=ctx)
net.hybridize()
```

[25]:
```
cls_loss = gluon.loss.SoftmaxCrossEntropyLoss()
box_loss = SmoothL1Loss()
cls_loss.hybridize()
box_loss.hybridize()

best_test_loss = 10e5
```

[26]:
```
if os.path.isfile(os.path.join(checkpoint_dir, checkpoint_name)):
    net.load_parameters(os.path.join(checkpoint_dir, checkpoint_name), ctx=ctx)
    print("Parameters loaded")
```

[27]:
```
trainer = gluon.Trainer(net.collect_params(), 'adam', {'learning_rate':␣
↪learning_rate})
for e in range(epochs):
    cls_metric = mx.metric.Accuracy()
    box_metric = mx.metric.MAE()
    train_loss = run_epoch(e, net, train_data, trainer, log_dir,␣
↪print_name="train", is_train=True, update_metric=False)
    test_loss = run_epoch(e, net, test_data, trainer, log_dir,␣
↪print_name="test", is_train=False, update_metric=True)
    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(checkpoint_dir, checkpoint_name))
        best_test_loss = test_loss
```

```
    if e % print_every_n == 0:
        name1, val1 = cls_metric.get()
        name2, val2 = box_metric.get()
        print("Epoch {0}, train_loss {1:.6f}, test_loss {2:.6f}, test {3}={4:.
↪6f}, {5}={6:.6f}".format(e, train_loss, test_loss, name1, val1, name2,␣
↪val2))
```

```
[09:56:18] ../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.
↪746653
Epoch 0, train_loss 0.858615, test_loss 0.746653, test accuracy=0.949080, mae=0.
↪029872
Saving network, previous best test loss 0.746653, current test loss 0.353118
Saving network, previous best test loss 0.353118, current test loss 0.190814
Saving network, previous best test loss 0.190814, current test loss 0.139893
Saving network, previous best test loss 0.139893, current test loss 0.114793
Saving network, previous best test loss 0.114793, current test loss 0.100580
Epoch 5, train_loss 0.096800, test_loss 0.100580, test accuracy=0.986375, mae=0.
↪022396
Saving network, previous best test loss 0.100580, current test loss 0.091744
Saving network, previous best test loss 0.091744, current test loss 0.084517
Saving network, previous best test loss 0.084517, current test loss 0.080071
Saving network, previous best test loss 0.080071, current test loss 0.075976
Saving network, previous best test loss 0.075976, current test loss 0.072644
Epoch 10, train_loss 0.064722, test_loss 0.072644, test accuracy=0.986552,␣
↪mae=0.019780
Saving network, previous best test loss 0.072644, current test loss 0.069390
Saving network, previous best test loss 0.069390, current test loss 0.067201
Saving network, previous best test loss 0.067201, current test loss 0.065241
Saving network, previous best test loss 0.065241, current test loss 0.063827
Saving network, previous best test loss 0.063827, current test loss 0.062032
Epoch 15, train_loss 0.053825, test_loss 0.062032, test accuracy=0.987415,␣
↪mae=0.017978
Saving network, previous best test loss 0.062032, current test loss 0.060555
Saving network, previous best test loss 0.060555, current test loss 0.059710
```

```
Saving network, previous best test loss 0.059710, current test loss 0.058479
Saving network, previous best test loss 0.058479, current test loss 0.057002
```

[28]:
```python
if os.path.isfile(os.path.join(checkpoint_dir, checkpoint_name)):
    net.load_parameters(os.path.join(checkpoint_dir, checkpoint_name), ctx=ctx)
```

Wyniki

Funkcja pomocnicza do przewidywania pola ograniczającego

[30]:
```python
def predict_bounding_boxes(net, image, bb):
    '''
    Given the outputs of the dataset (image and bounding box) and the␣
↪network,
    the predicted bounding boxes are provided.

    Parameters
    ----------
    net: SSD
    The trained SSD network.

    image: np.array
    A grayscale image of the handwriting passages.

    bb: [(x1, y1, x2, y2)]
    A tuple that contains the bounding box.

    Returns
    -------
    predicted_bb: [(x, y, w, h)]
    The predicted bounding boxes.

    actual_bb: [(x, y, w, h)]
    The actual bounding bounding boxes.
    '''
    image, bb = transform(image, bb)

    image = image.as_in_context(ctx[0])
    image = image.expand_dims(axis=0)

    bb = bb.as_in_context(ctx[0])
    bb = bb.expand_dims(axis=0)
```

```
    default_anchors, class_predictions, box_predictions = net(image)
    box_target, box_mask, cls_target = net.training_targets(default_anchors,␣
↪class_predictions, bb)
    cls_probs = nd.SoftmaxActivation(nd.transpose(class_predictions, (0, 2,␣
↪1)), mode='channel')

    predicted_bb = MultiBoxDetection(*[cls_probs, box_predictions,␣
↪default_anchors], force_suppress=True, clip=False)
    predicted_bb = box_nms(predicted_bb, overlap_thresh=overlap_thres,␣
↪valid_thresh=min_c, topk=topk)
    predicted_bb = predicted_bb.asnumpy()
    predicted_bb = predicted_bb[0, predicted_bb[0, :, 0] != -1]
    predicted_bb = predicted_bb[:, 2:]
    predicted_bb[:, 2] = predicted_bb[:, 2] - predicted_bb[:, 0]
    predicted_bb[:, 3] = predicted_bb[:, 3] - predicted_bb[:, 1]

    labeled_bb = bb[:, :, 1:].asnumpy()
    labeled_bb[:, :, 2] = labeled_bb[:, :, 2] - labeled_bb[:, :, 0]
    labeled_bb[:, :, 3] = labeled_bb[:, :, 3] - labeled_bb[:, :, 1]
    labeled_bb = labeled_bb[0]
    return predicted_bb, labeled_bb
```

Analiza ilościowa

Średnia IOU została obliczona dla zestawu testowego.

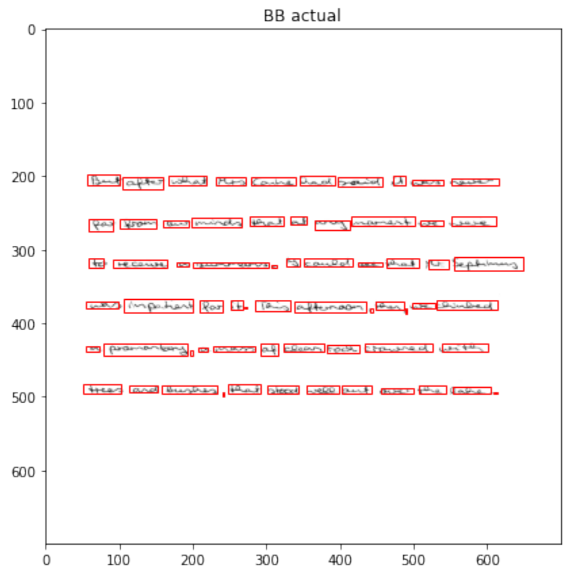
[31]:
```
def get_iou(box1, box2):
    '''
    Calculate the IOU between two bounding boxes (x, y, w, h)
    '''
    # source: https://www.pyimagesearch.com/2016/11/07/
↪intersection-over-union-iou-for-object-detection/
    x1 = max(box1[0], box2[0])
    y1 = max(box1[1], box2[1])
    x2 = min(box1[2], box2[2])
    y2 = min(box1[3], box2[3])

    inter_area = max(0, x2 - x1 + 1) * max(0, y2 - y1 + 1)

    box1_area = (box1[2] - box1[0] + 1) * (box1[3] - box1[1] + 1)
    box2_area = (box2[2] - box2[0] + 1) * (box2[3] - box2[1] + 1)
```

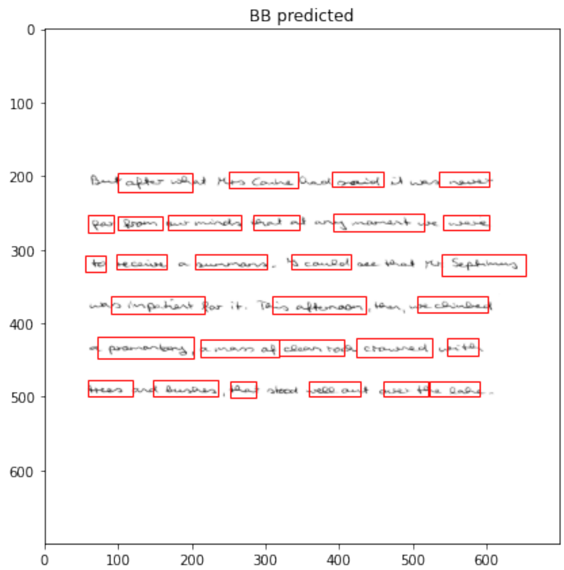
```python
    iou = inter_area / float(box1_area + box2_area - inter_area)
    return iou

def calculate_iou(dataset):
    '''
    Iterate through the dataset and calculate the mean IOU between the␣
 ↪actual and
    predicted bounding boxes.
    '''
    ious = []
    for i in range(len(dataset)):
        iou_i = 0.0
        count_i = 0
        image, bb = dataset[i]
        predicted_bb, actual_bb = predict_bounding_boxes(net, image, bb)
        # A naive 1-1 bouding box matching algorithm was used. This algorithm
        # doesn't account for insertions or deletes and may result in lower␣
 ↪IOU values.
        for predicted_bb_i, actual_bb_i in zip(predicted_bb, actual_bb):
            iou = get_iou(predicted_bb_i, actual_bb_i)
            iou_i += iou
            count_i += 1
        ious.append(iou_i/count_i)
    return np.mean(ious)

train_iou = calculate_iou(train_ds)
test_iou = calculate_iou(test_ds)
print("Train iou {} test iou {}".format(train_iou, test_iou))
```

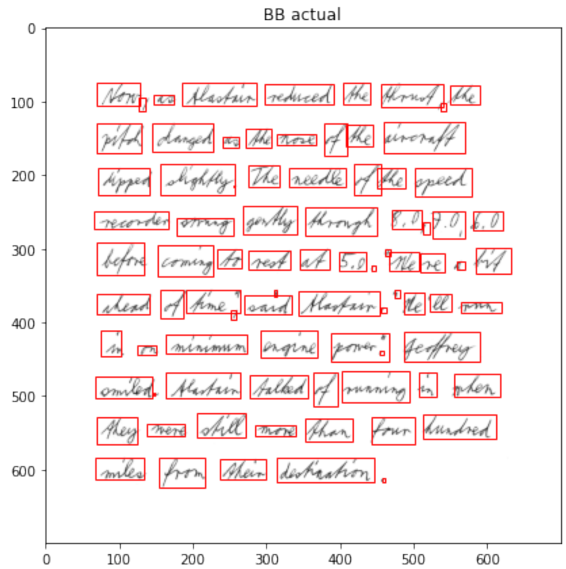
```
[10:04:15] ../src/operator/nn/./cudnn/./cudnn_algoreg-inl.h:97: Running␣
 ↪performance tests
to find the best convolution algorithm, this can take a while… (set the␣
 ↪environment
variable MXNET_CUDNN_AUTOTUNE_DEFAULT to 0 to disable)

Train iou 0.44020686944027226 test iou 0.44010712224485027
```

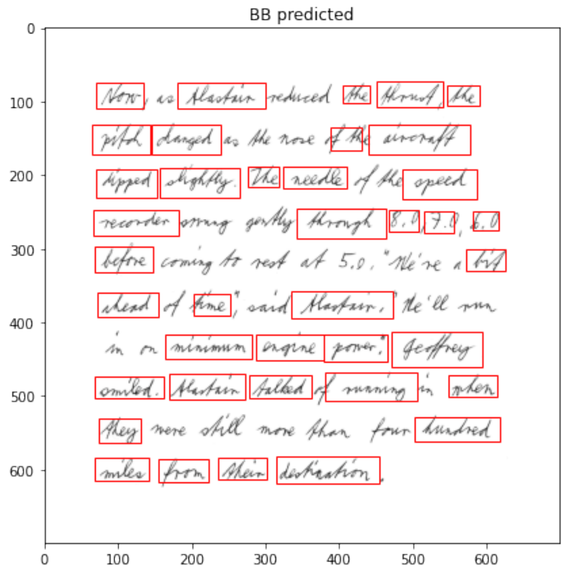
Wizualizacja przewidzianych ramek i rzeczywistego tekstu.

[32]:
```
figs_to_plot = 2
fig, axs = plt.subplots(figs_to_plot, 2, figsize=(15, 10 * figs_to_plot))
ds = test_ds
for i in range(figs_to_plot):
    n = int(random.random()*len(ds))
    image, bb = ds[n]
    predicted_bb, actual_bb = predict_bounding_boxes(net, image, bb)

    for j in range(actual_bb.shape[0]):
        (x, y, w, h) = actual_bb[j]
        axs[i][0].imshow(image, 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")

    for j in range(predicted_bb.shape[0]):
        axs[i][1].imshow(image, cmap='Greys_r')
        (x, y, w, h) = predicted_bb[j]
        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][1].add_patch(rect)
        axs[i][1].set_title("BB predicted")
```


BB actual


BB predicted


BB actual


BB predicted