## deep\_learning10

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## 0.1 Deep Learning based Text Detector in Images using OpenCV and the EAST text detector.

In text detection we only detect the bounding boxes around the text. But, in text recognition, we actually find what is written in the box.

Text Recognition engines such as Tesseract require the bounding box around the text for better performance. Thus, this detector can be used to detect the bounding boxes before doing Text Recognition.

"EAST": Efficient and Accurate Scene Text detection pipeline. The EAST pipeline is capable of predicting words and lines of text at arbitrary orientations on imagesOpenCV's EAST text detector is a deep learning model, based on a novel architecture and training pattern. It is capable of (1) running at near real-time at 13 FPS on 720p images and (2) obtains state-of-the-art text detection accuracy.

Use OpenCV's EAST detector to automatically detect text in both images and video streams. OpenCV's text detector implementation of EAST is quite robust, capable of localizing text even when it's blurred, reflective, or partially obscured.

```
[1]: # import libraries
import numpy as np
import argparse
import cv2
import easydict
from imutils.object_detection import non_max_suppression
import time
```

```
[2]: import matplotlib.pyplot as plt
plt.style.use('bmh')
%matplotlib inline
```

```
[3]: # construct the argument parser and parse the arguments
args=easydict.EasyDict({
    'image':'./Images/textimage3.jpg',
    'east_model':'./frozen_east_text_detection.pb',
    'min_confidence':0.5, #Probability threshold to determine text.
    'width':320, #Resized image width - must be multiple of 32
    'height':320 #Resized image height - must be multiple of 32
})
```

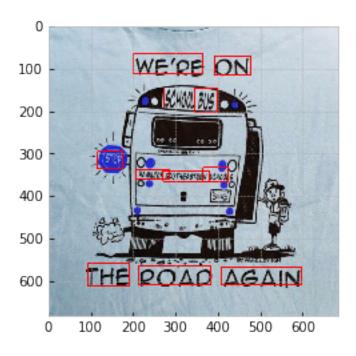
```
# load the input image and grab the image dimensions
im2=cv2.imread(args['image'])
orig=im2.copy()
(H,W)=im2.shape[:2]
# set the new width and height
(newW, newH)=(args['width'],args['height'])
rW = W / float(newW)
rH = H / float(newH)
# resize the image
im2=cv2.resize(im2,(newW,newH))
(H,W)=im2.shape[:2]
111
In order to perform text detection using OpenCV and the EAST deep learning
model, we need to extract the output feature maps of two layers
111
define the two output layer names for the EAST detector model that we are
interested, the first is the output probabilities and the second can be used
to derive the bounding box coordinates of text
output layers=[]
# The first layer is our output sigmoid activation which gives us the
→probability of a region containing text or not.
output_layers.append('feature_fusion/Conv_7/Sigmoid')
# The second layer is the output feature map that represents the "geometry" of \Box
→ the image, it is used to derive the bounding box coordinates of the text in ⊔
→ the input image
output_layers.append('feature_fusion/concat_3')
# load the pre-trained EAST text detector into memory
net=cv2.dnn.readNet(args['east_model'])
# create a 4D blob from the image
blob=cv2.dnn.blobFromImage(im2,1.0,(W,H),(123.68, 116.78, 103.94),swapRB=True,__
→crop=False)
start=time.time()
# to run the model for predicting text, set the blob as input
net.setInput(blob)
# perform a forward pass of the model to obtain the two output feature maps
(scores, geometry) = net.forward(output_layers)
end=time.time()
# show timing information on text prediction
print("[INFO] text detection took {:.6f} seconds".format(end - start))
```

```
# number of rows and columns from the scores volume
(num_rows, num_columns) = scores.shape[2:4]
#initialize our set of bounding box rectangles to store the bounding box (x, \sqcup
\rightarrow y)-coordinates for text regions
rects=[]
# Stores the probability associated with each of the bounding boxes in rects
confidences=[]
for y in range(0,num_rows):
    # extract the scores (probabilities)
    scoresData = scores[0, 0, y]
    # derive potential bounding box coordinates that surround text
    xData0 = geometry[0, 0, y]
    xData1 = geometry[0, 1, y]
    xData2 = geometry[0, 2, y]
    xData3 = geometry[0, 3, y]
    anglesData = geometry[0, 4, y]
    # loop over the number of columns
    for x in range(0, num_columns):
        # if our score does not have sufficient probability, ignore it
        if scoresData[x] < args["min confidence"]:</pre>
             continue
        The EAST text detector naturally reduces volume size as the image_
 \hookrightarrow passes
        through the network, our volume size is actually 4x smaller than our,
 \hookrightarrow input
        image so we multiply by four to bring the coordinates back into respect,
 \hookrightarrow of
        our original image.
        # compute the offset factor as our resulting feature maps will be 4x_{f L}
→ smaller than the input image
        (offsetX, offsetY) = (x * 4.0, y * 4.0)
        # extract the rotation angle for the prediction and then compute the \Box
\rightarrowsin and cosine
        angle = anglesData[x]
        cos = np.cos(angle)
        sin = np.sin(angle)
        # use the geometry volume to derive the width and height of the
\rightarrow bounding box
        h = xData0[x] + xData2[x]
        w = xData1[x] + xData3[x]
        # compute both the starting and ending (x, y)-coordinates for the textu
 → prediction bounding box
```

```
endX = int(offsetX + (cos * xData1[x]) + (sin * xData2[x]))
        endY = int(offsetY - (sin * xData1[x]) + (cos * xData2[x]))
        startX = int(endX - w)
        startY = int(endY - h)
        # add the bounding box coordinates and probability score to our
 \rightarrowrespective lists
        rects.append((startX, startY, endX, endY))
        confidences.append(scoresData[x])
# apply non-maxima suppression to suppress weak, overlapping bounding boxes
boxes = non_max_suppression(np.array(rects), probs=confidences)
# loop over the bounding boxes
for (startX, startY, endX, endY) in boxes:
    # scale the bounding box coordinates based on the respective ratios
    startX=int(startX*rW)
    startY=int(startY*rH)
    endX = int(endX *rW)
    endY = int(endY *rH)
    # draw the bounding box on the image
    cv2.rectangle(orig, (startX, startY), (endX, endY), (255, 0, 0), 2)
plt.grid('False')
plt.imshow(orig)
```

[INFO] text detection took 0.422292 seconds

## [3]: <matplotlib.image.AxesImage at 0xc04c759588>



## 0.2 Deep Learning based Text Detector in Videos using OpenCV and the EAST text detector.

```
[]: import numpy as np
     import cv2
     import argparse
     import time
     import imutils
     from imutils.video import VideoStream # to access a webcam
     from imutils.video import FPS # to benchmark our frames per second
     from imutils.object_detection import non_max_suppression
     import easydict
     # construct the argument parser and parse the arguments
     args=easydict.EasyDict({
         'video':None,
                                        #path to our input video
         'east_model':'./frozen_east_text_detection.pb',
                                                                    #EAST scene
      \rightarrow text detector model
         \verb|'min_confidence': 0.5|, \qquad \textit{\#Probability threshold to determine text}
         'width':320,
'height':320
                                   #Resized image width
         'height':320
                                   #Resized image height
     })
     # resize the frame dimenisons
     (W,H)=(None,None)
     (newW,newH)=(args['width'],args['height'])
     (rW,rH)=(None, None)
     , , ,
     In order to perform text detection using OpenCV and the EAST deep learning
     model, we need to extract the output feature maps of two layers
     111
     output layers=[]
     # The first layer is our output sigmoid activation which gives us the
     →probability of a region containing text or not.
     output_layers.append('feature_fusion/Conv_7/Sigmoid')
     # The second layer is the output feature map that represents the "geometry" of L
     → the image, it is used to derive the bounding box coordinates of the text in
     → the input image
     output_layers.append('feature_fusion/concat_3')
     # load the pre-trained EAST text detector into memory
     net=cv2.dnn.readNet(args['east_model'])
```

```
cap = cv2.VideoCapture(args['video'] if args['video'] else 0)
if cap.isOpened()==False:
    print("can't open")
# start the FPS throughput estimator
fps=FPS().start()
# loop over frames from the video stream
while True:
    # grab the current frame
    ret,frame=cap.read()
    if not ret:
        cv2.waitKey()
        break
    frame=imutils.resize(frame, width=1000)
    orig=frame.copy()
    (H,W)=frame.shape[:2]
    rW=W/float(newW)
    rH=H/float(newH)
    frame=cv2.resize(frame,(newW,newH))
    # create a 4D blob from the image
    blob=cv2.dnn.blobFromImage(frame, 1.0, (newW, newH), (123.68, 116.78, 103.
→94),swapRB=True, crop=False)
    # to run the model for predicting text, set the blob as input
    net.setInput(blob)
    # perform a forward pass of the model to obtain the two output feature maps
    (scores, geometry) = net.forward(output_layers)
    # number of rows and columns from the scores volume
    (num_rows,num_columns)=scores.shape[2:4]
    #initialize our set of bounding box rectangles to store the bounding box_
 \rightarrow (x, y)-coordinates for text regions
    rects=[]
    # Stores the probability associated with each of the bounding boxes in rects
    confidences=[]
    for y in range(0,num rows):
        # extract the scores (probabilities)
        scoresData = scores[0, 0, y]
        # derive potential bounding box coordinates that surround text
        xData0 = geometry[0, 0, y]
        xData1 = geometry[0, 1, y]
        xData2 = geometry[0, 2, y]
        xData3 = geometry[0, 3, y]
        anglesData = geometry[0, 4, y]
        # loop over the number of columns
        for x in range(0, num_columns):
            # if our score does not have sufficient probability, ignore it
            if scoresData[x] < args["min_confidence"]:</pre>
                continue
```

```
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           The EAST text detector naturally reduces volume size as the image.
\hookrightarrow passes
           through the network, our volume size is actually 4x smaller than
\hookrightarrow our input
           image so we multiply by four to bring the coordinates back into\Box
\hookrightarrow respect of
           our original image.
           # compute the offset factor as our resulting feature maps will be_
\rightarrow4x smaller than the input image
           (offsetX, offsetY) = (x * 4.0, y * 4.0)
           # extract the rotation angle for the prediction and then compute_
\rightarrow the sin and cosine
           angle = anglesData[x]
           cos = np.cos(angle)
           sin = np.sin(angle)
           # use the geometry volume to derive the width and height of the
\rightarrow bounding box
           h = xData0[x] + xData2[x]
           w = xData1[x] + xData3[x]
           # compute both the starting and ending (x, y)-coordinates for the
→ text prediction bounding box
           endX = int(offsetX + (cos * xData1[x]) + (sin * xData2[x]))
           endY = int(offsetY - (sin * xData1[x]) + (cos * xData2[x]))
           startX = int(endX - w)
           startY = int(endY - h)
           # add the bounding box coordinates and probability score to our
→respective lists
           rects.append((startX, startY, endX, endY))
           confidences.append(scoresData[x])
   # apply non-maxima suppression to suppress weak, overlapping bounding boxes
   boxes=non_max_suppression(np.array(rects),probs=confidences)
   # loop over the bounding boxes
   for (startX,startY,endX,endY) in boxes:
       # scale the bounding box coordinates based on the respective ratios
       startX=int(startX*rW)
       startY=int(startY*rH)
       endX=int(endX*rW)
       endY=int(endY*rH)
       # draw the bounding box on the frame
       cv2.rectangle(orig,(startX,startY),(endX,endY),(0,255,255),2)
```