Computer Vision Project 5:
TinyYOLO - framework for Handwriting Recognition

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Abstract

Considered is an implementation of the tinyYOLOv3 (and tiny-YOLOv4) framework using darkflow. YOLO (you only look once) is an advanced image recognition neural network that is designed to recognize classify and draw bounding boxes around multiple objects in an image simultaneously. Here, we re-train the network to detect handwritten digits on a page. And so this involved defining 36 classes (for each letter in the alphabet and digits $0-9$.) and building a synthesized data set from EMNIST where multiple letters/digits are maintained and labeled on single images. Lastly, the tinyYOLOv3 darkflow framework was used to train the model to detect both the location and label of digits on over 400 images. Unfortunately, training the model was unsuccessful on $tinyYOLOv3$. However, worked on the pre-build library for $tiny-YOLOv4$ made by Darkflow and Roboflow.

1 GPU - Hardware Requirements

Typically, YOLO frameworks including darkflow are run on dedicated NVIDIA GPU cards, this drastically increases training and query time. Here colab was used to remotely connect to a GPU, specifically, a Tesla P100-PCIE was used to train the model (Note, colab does not guarantee the quality of available GPU's and so training speed may vary).

```
gpu_info = !nvidia-smi
gpu_info = '\n'.join(gpu_info)
if gpu_info.find('failed') >= 0:
  print('Not connected to a GPU')
else:
  print(gpu_info)
```

2 Installing Darkflow And Tensor With Compatibility

Darkflow implementation of YOLO was retrained on the synthesized data set. For this, it is critical that all libraries packages are compatible with the version of darkflow/tinyYOLO.

```
!pip install tensorflow-gpu==1.15.0
!pip install imageio

# Download and build darkflow (the tensorflow implementation of YOLO)
import os
import pathlib

if "darkflow-master" in pathlib.Path.cwd().parts:
  while "darkflow-master" in pathlib.Path.cwd().parts:
    os.chdir('..')
elif not pathlib.Path("darkflow-master").exists():
  !git clone --depth 1 https://github.com/thtrieu/darkflow.git
  # Compile darkflow
  %cd darkflow
  !python setup.py build_ext --inplace
```

```
  # Change darkflow to darkflow-master to distinguish between folder names
  %cd ../
  !mv darkflow darkflow-master
  %cd darkflow-master


# Upload yolo.weights, pre-trained weights file (for YOLO v2) from an external Google drive
weights = 'yolo'
weights_file = weights + '.weights'
if not os.path.exists('weights_file'):
  !gdown --id 0B1tW_VtY7onfTnBYYWdqSHNGSUU
  !mkdir bin
  !mv yolo.weights bin


# Imports
%cd darkflow-master
%tensorflow_version 1.15.0rc2

# For importing/exporting files, working with arrays, etc
import time
import urllib
import numpy as np
import pandas as pd
import imageio

# For actual object detection
import tensorflow as tf
from darkflow.net.build import TFNet
threshold = 0.25

# For drawing onto and plotting images
import matplotlib.pyplot as plt
import cv2
%config InlineBackend.figure_format = 'svg'
```

From here a model pipeline can be constructed by,

```
params = {
    'model': 'cfg/yolo.cfg',
    'load': 'bin/yolo.weights',
    'threshold': threshold,
    'gpu': 1.0
}

# Run the model
tfnet = TFNet(params)
```

3 Testing Darkflow Detection

The above implementation of darkflow has a pre-computed deep neural network for multiclass object detection which also automatically downloads demo images to validate if darkflow was armed correctly, (without incompatibility errors). And so this default test was run to check the model.

```
img = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
result = tfnet.return_predict(img)
for i in range(0,len(result)) :
  img = cv2.rectangle(img, (result[i]['topleft']['x'], result[i]['topleft']['y']), (result[i]['
      bottomright']['x'], result[i]['bottomright']['y']), (0, 255, 0), 7)
  img = cv2.putText(img, result[i]['label'], (result[i]['topleft']['x'], result[i]['topleft']['y']),
      cv2.FONT_HERSHEY_COMPLEX, 1, (0, 0, 0), 2)
plt.imshow(img)
```

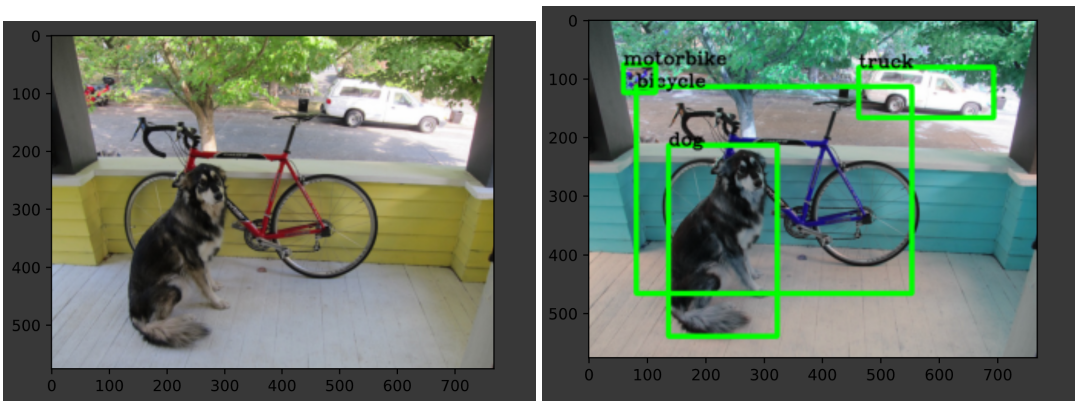


Figure 1: Darkflow - Master Demo of YOLOv3 Framework

4 Synthesizing Dataset EMNIST

EMNIST is a data set that contains 28×28 images of both digits and letters. It is an extension created by, Gregory Cohen et. al. of the original NMIST which only had digits from $0 - 9$.
The original (non-synthesized data set) is implemented by pip install,

```
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from sklearn.datasets import fetch_openml

!pip install emnist
from emnist import list_datasets
```

Also the data set needs to be warmed up,

```
list_datasets()
```

Finally, the raw training and testing images and labels (annotations) can be parsed in.

```
from emnist import extract_training_samples
from emnist import extract_test_samples

test_1, test_labels_1 = extract_test_samples('letters')
train_1, train_labels_1 = extract_training_samples('letters')

train_labels_1 = list(np.asarray(train_labels_1) + 10)
test_labels_1 = list(np.asarray(test_labels_1) + 10)

test_2, test_labels_2 = extract_test_samples('digits')
train_2, train_labels_2 = extract_training_samples('digits')

Test_images, Test_labels = np.concatenate((test_1, test_2), axis=0),np.concatenate((test_labels_1,
    test_labels_2), axis=0)
Train_images, Train_labels = np.concatenate((train_1, train_2), axis=0),np.concatenate((train_labels_1,
     train_labels_2), axis=0)

print(Test_images.shape)
print(Test_labels.shape)

print(Train_images.shape)
print(Train_labels.shape)
```

Raw images in either set are typically bounded around the letter,
Importantly, these images do not contain information about their bounding boxes and also only have a single image per image. And so are initially poor training candidates for the YOLO framework. As a result, we construct a new more compatible data set from the raw EMNIST images.
Here, a larger (200×200) black image is created, then randomly selected and randomly sized EMNIST data images are pasted/ overlayed on the blank image to make a larger image with multiple hand written digits.
Critically, by implementing this data set in this way, the original labels from EMNIST are no long compatible (because they do not contain spacial information about where each letter is located in the larger image.) And so

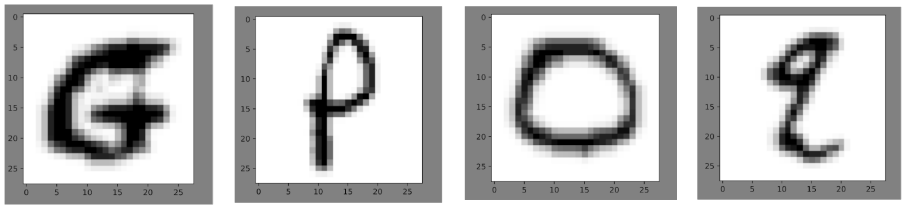


Figure 2: EMNIST Data Image Examples

new annotations/labels are parse where each image contains a non trivial set of the original labels describing both the locations of the bounding boxes around each digit and their label, $1 - 36$.

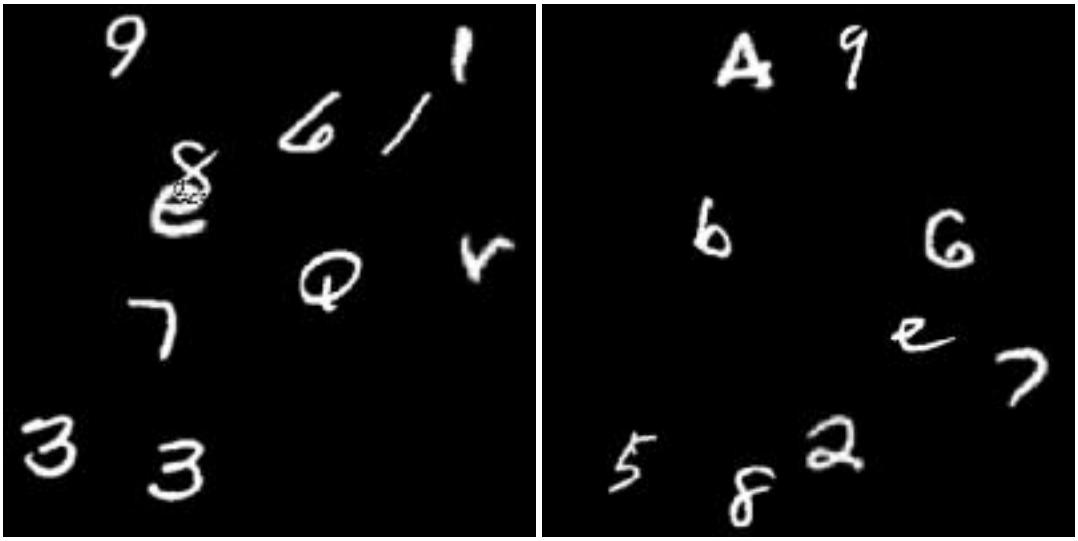


Figure 3: Synthesized Dataset Examples

Additionally, annotations needed to be in a compatible format for Darkflow automatic parsing. Which is .xml web based format. And so annotations where automatically generated to a corresponding file to each image. Each annotation contained information about each digit on the larger image, including bounding box dimensions and digit label.

```
import random
from PIL import Image
from xml.etree import ElementTree as ET

dataset_size = 1
for set_size in range(0,dataset_size) :

  #Blank Image
  temp_img = np.zeros([200,200],dtype=np.uint8)

  index = set_size
  annot = "<annotation>\n\
    <folder>VOC2007</folder>\n\
    <filename>" + str(index) + ".jpg</filename>\n\
    <source>\n\
      <database>EMNIST</database>\n\
      <annotation>EMNIST</annotation>\n\
      <image>EMNIST</image>\n\
      </source>\n\
        <owner>\n\
        <name>Gregory Cohen, Saeed Afshar, Jonathan Tapson, and Andre van Schaik</name>\n\
        </owner>\n\
          <size>\n\
            <width>200</width>\n\
            <height>200</height>\n\
            <depth>1</depth>\n\
```

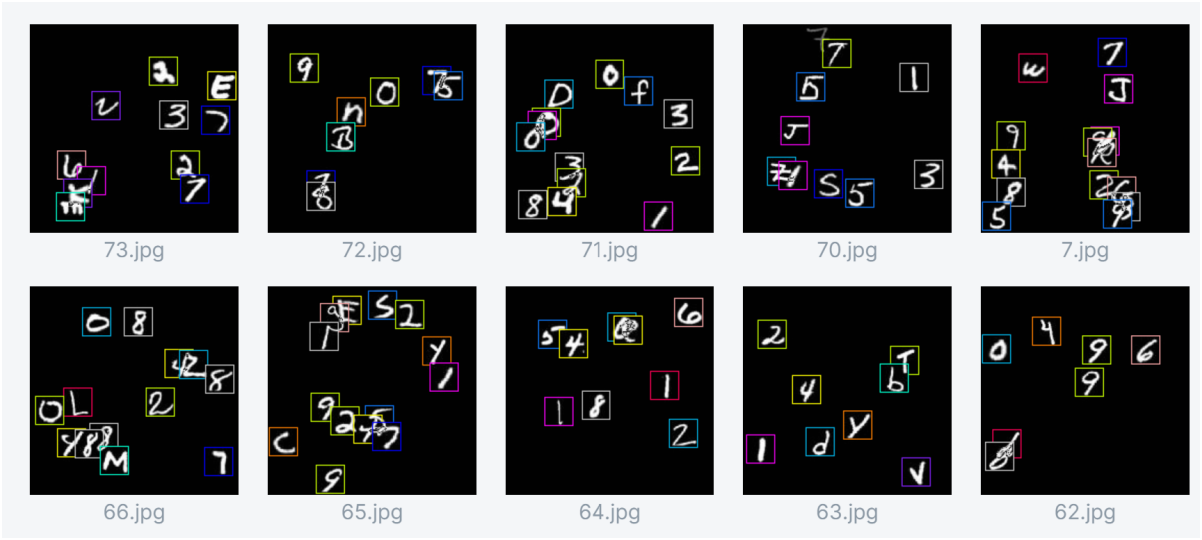


Figure 4: Synthesized Data set with bounding boxes

```
            </size>\n\
            <segmented>0</segmented>"
  stack = random.randint(7, 15)
  for i in range(0 , stack) :
    j = random.randint(0 , len(Train_images) )
    anchor = ( random.randint(0,200 - len(Train_images[j]-1)), random.randint(0,200-len(Train_images[j
        ])-1))
    temp_img[anchor[0]:anchor[0]+len(Train_images[j]),anchor[1]:anchor[1]+len(Train_images[j])] +=
        Train_images[j]
    annot += "<object>\n\
              <name>" + str(Train_labels[j]) + "</name>\n\
              <pose>Left</pose>\n\
              <truncated>0</truncated>\n\
              <difficult>0</difficult>\n\
                <bndbox>\n\
                  <xmin>" + str(anchor[0]) + "</xmin>\n\
                  <ymin>" + str(anchor[1]) + "</ymin>\n\
                  <xmax>" + str(anchor[0] + len(Train_images[j])) + "</xmax>\n\
                  <ymax>" + str(anchor[1] + len(Train_images[j])) + "</ymax>\n\
                </bndbox>\n\
              </object>\n"
  annot += "</annotation>"

  tree = ET.XML(annot)
  with open("/content/darkflow-master/test/training/annotations/" + str(index) + '.xml', "wb") as f :
    f.write(ET.tostring(tree))

  im = Image.fromarray(temp_img)
  im.save("/content/darkflow-master/test/training/images/"  + str(index) + ".jpg")
  #temp_img = temp_img.paste(img2, (0,0))
```

The dataset was generated with a subset of $40,000$ randomly selected EMNIST images to create 200 larger images containing multiple digit objects. And including bounding boxes results in,

5 Training - Original Darkflow $tiny - YOLOv3$

After the data set was initialized, Darkflow's YOLO implementation can be re-trained for the new data, with the designated number of classes.
First, ensure the colab runtime is still connected to a GPU,

```
physical_devices = tf.config.experimental.list_physical_devices('GPU')
tf.config.experimental.set_memory_growth(physical_devices[0], True)
```

Then, train the model using the file locations that store the data-set

```
with tf.device('/device:GPU:0'):
  !python flow --model cfg/tiny-yolo-voc-3c.cfg --load bin/yolo.weights --train --annotation test/
      training/annotations --dataset test/training/images
```

Unfortunately, this method was incompatible with colabs GPU and so the training time run on CPU exceeded my patience.

6 Training Roboflow Darkflow $tiny - YOLOv4$

An alternative training model was considered by uploading the synthesized dataset to Roboflow and the using the pre-built colab notebook by Darkflow that is directly compatible with Roboflow. This is mainly to test the validity of the data set and I did not write any of the code in the pre-built library. If anything was changed it was just the model parameters.
However, the code in the pre-build notebook follows the same logic as the above implementation.
Critically, this also involves switch darkflow versions to YOLOv4-tiny which is significantly faster than YOLOv3-tiny.
The model was trained for 30 minutes and these were some of the test results. **Note: that labels are numerical,** $0 - 36$**, and so letters are labeled by increasing alphabet from** 10**. So** a **is** 11**, and** z **is** 36**.**

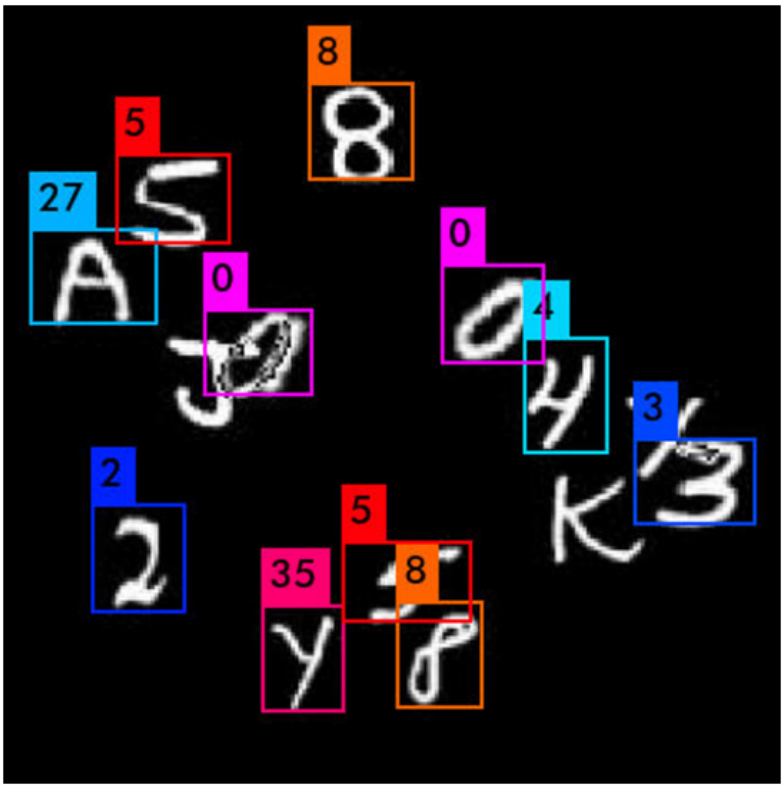
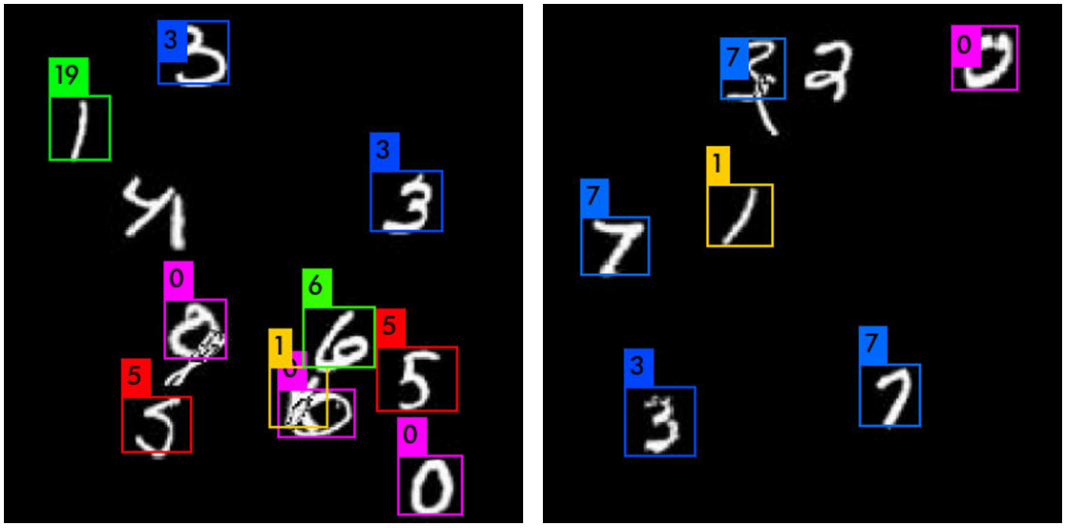


Figure 5: Test Output: tinyTOLOv4 model prediction



7 Appendix

```
gpu_info = !nvidia-smi
gpu_info = '\n'.join(gpu_info)
if gpu_info.find('failed') >= 0:
  print('Not connected to a GPU')
else:
  print(gpu_info)

from psutil import virtual_memory
ram_gb = virtual_memory().total / 1e9
print('Your runtime has {:.1f} gigabytes of available RAM\n'.format(ram_gb))

if ram_gb < 20:
  print('Not using a high-RAM runtime')
else:
  print('You are using a high-RAM runtime!')

Imports: Darkflow (YOLO) and Tensorflow

from sklearn import svm
import matplotlib.pyplot as plt
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from sklearn.datasets import fetch_openml
import numpy as np



from google.colab import drive
from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials
from google.colab import drive
drive.mount('/content/drive')

auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)

# Install required libraries
#!pip install tensorflow-gpu==1.15.0rc2
!pip install tensorflow-gpu==1.15.0
!pip install imageio
```

```
45
46  # Download and build darkflow (the tensorflow implementation of YOLO)
47  import os
48  import pathlib
49
50  if "darkflow-master" in pathlib.Path.cwd().parts:
51    while "darkflow-master" in pathlib.Path.cwd().parts:
52      os.chdir('..')
53  elif not pathlib.Path("darkflow-master").exists():
54    !git clone --depth 1 https://github.com/thtrieu/darkflow.git
55    # Compile darkflow
56    %cd darkflow
57    !python setup.py build_ext --inplace
58    # Change darkflow to darkflow-master to distinguish between folder names
59    %cd ../
60    !mv darkflow darkflow-master
61    %cd darkflow-master
62
63
64  # Upload yolo.weights, pre-trained weights file (for YOLO v2) from an external Google drive
65  weights = 'yolo'
66  weights_file = weights + '.weights'
67  if not os.path.exists('weights_file'):
68    !gdown --id 0B1tW_VtY7oniTnBYYWdqSHNGSUU
69    !mkdir bin
70    !mv yolo.weights bin
71
72
73  # Imports
74  %cd darkflow-master
75  %tensorflow_version 1.15.0rc2
76
77  # For importing/exporting files, working with arrays, etc
78  import time
79  import urllib
80  import numpy as np
81  import pandas as pd
82  import imageio
83
84  # For actual object detection
85  import tensorflow as tf
86  from darkflow.net.build import TFNet
87  threshold = 0.25
88
89  # For drawing onto and plotting images
90  import matplotlib.pyplot as plt
91  import cv2
92  %config InlineBackend.figure_format = 'svg'
93
94  Define a Model:
95
96  params = {
97      'model': 'cfg/yolo.cfg',
98      'load': 'bin/yolo.weights',
99      'threshold': threshold,
100     'gpu': 0.0
101 }
102
103 # Run the model
104 tfnet = TFNet(params)
105
106 Test a image and make a bounding box
107
108 import matplotlib.pyplot as plt
109 import matplotlib.image as mp
110 import PIL as pl
111 import cv2
112
113 image_path = '/content/darkflow-master/sample_img/sample_dog.jpg'
114 image =  mp.imread(image_path)
115 plt.imshow(image)
116
117 Query Image
```

```
118
119 img = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
120 result = tfnet.return_predict(img)
121 img.shape
122
123
124 Extract Data
125
126 tl = (result[1]['topleft']['x'], result[1]['topleft']['y'])
127 br = (result[1]['bottomright']['x'], result[1]['bottomright']['y'])
128 label = result[1]['label']
129
130 print(label)
131
132 Display Box
133
134 for i in range(0,len(result)) :
135   img = cv2.rectangle(img, (result[i]['topleft']['x'], result[i]['topleft']['y']), (result[i]['bottomright']['x'],
          result[i]['bottomright']['y']), (0, 255, 0), 7)
136   img = cv2.putText(img, result[i]['label'], (result[i]['topleft']['x'], result[i]['topleft']['y']), cv2.
          FONT_HERSHEY_COMPLEX, 1, (0, 0, 0), 2)
137 plt.imshow(img)
138
139 # EMINST Data
140
141 from sklearn import preprocessing
142 from sklearn.model_selection import train_test_split
143 from sklearn.datasets import fetch_openml
144
145 !pip install emnist
146
147 from emnist import list_datasets
148
149 list_datasets()
150
151 from emnist import extract_training_samples
152 from emnist import extract_test_samples
153
154 test_1, test_labels_1 = extract_test_samples('letters')
155 train_1, train_labels_1 = extract_training_samples('letters')
156
157 train_labels_1 = list(np.asarray(train_labels_1) + 10)
158 test_labels_1 = list(np.asarray(test_labels_1) + 10)
159
160 test_2, test_labels_2 = extract_test_samples('digits')
161 train_2, train_labels_2 = extract_training_samples('digits')
162
163 Test_images, Test_labels = np.concatenate((test_1, test_2), axis=0),np.concatenate((test_labels_1, test_labels_2),
       axis=0)
164 Train_images, Train_labels = np.concatenate((train_1, train_2), axis=0),np.concatenate((train_labels_1,
       train_labels_2), axis=0)
165
166 print(Test_images.shape)
167 print(Test_labels.shape)
168
169
170 print(Train_images.shape)
171 print(Train_labels.shape)
172
173 Train_images.shape
174
175 train_1.shape
176
177 train_2.shape
178
179 Train_images[55].shape
180
181 #Let's print first 10 letters from EMINST training samples
182 for i in range(7):
183     first_ten_letters = Train_images[i].reshape((28, 28))
184     plt.imshow(first_ten_letters, cmap = 'binary')
185     #plt.axis("off")
186     plt.show()
```

```
187
188
189
190 # Gonna Synthisize my out data set with boxes...
191
192 plt.imshow(Train_images[5])
193
194 print(Train_labels[:6])
195
196 print(len(Train_images[50]))
197
198 print(str(10))
199
200 import random
201 from PIL import Image
202 from xml.etree import ElementTree as ET
203
204 dataset_size = 80
205 for set_size in range(0,dataset_size) :
206
207   #Blank Image
208   temp_img = np.zeros([200,200],dtype=np.uint8)
209
210   index = set_size
211   annot = "<annotation>\n\
212     <folder>VOC2007</folder>\n\
213     <filename>" + str(index) + ".jpg</filename>\n\
214     <source>\n\
215       <database>EMNIST</database>\n\
216       <annotation>EMNIST</annotation>\n\
217       <image>EMNIST</image>\n\
218       </source>\n\
219         <owner>\n\
220         <name>Gregory Cohen, Saeed Afshar, Jonathan Tapson, and Andre van Schaik</name>\n\
221         </owner>\n\
222           <size>\n\
223             <width>200</width>\n\
224             <height>200</height>\n\
225             <depth>1</depth>\n\
226             </size>\n\
227             <segmented>0</segmented>"
228   stack = random.randint(7, 15)
229   for i in range(0 , stack) :
230     j = random.randint(0 , len(Train_images) )
231     anchor = ( random.randint(0,200 - len(Train_images[j]-1)), random.randint(0,200-len(Train_images[j])-1))
232     temp_img[anchor[0]:anchor[0]+len(Train_images[j]),anchor[1]:anchor[1]+len(Train_images[j])] += Train_images[j]
233     annot += "<object>\n\
234                 <name>" + str(Train_labels[j]) + "</name>\n\
235                 <pose>Left</pose>\n\
236                 <truncated>0</truncated>\n\
237                 <difficult>0</difficult>\n\
238                   <bndbox>\n\
239                     <xmin>" + str(anchor[1]) + "</xmin>\n\
240                     <ymin>" + str(anchor[0]) + "</ymin>\n\
241                     <xmax>" + str(anchor[1] + len(Train_images[j])) + "</xmax>\n\
242                     <ymax>" + str(anchor[0] + len(Train_images[j])) + "</ymax>\n\
243                   </bndbox>\n\
244                 </object>\n"
245   annot += "</annotation>"
246
247   tree = ET.XML(annot)
248   with open("/content/darkflow-master/test/training/annotations/" + str(index) + '.xml', "wb") as f :
249     f.write(ET.tostring(tree))
250
251   im = Image.fromarray(temp_img)
252   im.save("/content/darkflow-master/test/training/images/"  + str(index) + ".jpg")
253   #temp_img = temp_img.paste(img2, (0,0))
254
255 # Training
256
257 physical_devices = tf.config.experimental.list_physical_devices('GPU')
258 tf.config.experimental.set_memory_growth(physical_devices[0], True)
259
```

```
print("Num GPUs Available: ", len(tf.config.list_physical_devices('GPU')))

tf.test.gpu_device_name()

tf.config.list_physical_devices('GPU')

with tf.device('/device:GPU:0'):
  !python flow --model cfg/tiny-yolo-voc-3c.cfg --load bin/yolo.weights --train --annotation test/training/
      annotations --dataset test/training/images

!zip -r /content/darkflow-master/test/training.zip /content/darkflow-master/test/training

from google.colab import files
files.download('/content/darkflow-master/test/training.zip')



files.download("/content/darkflow-master/test/training")
```