Machine Learning: HW3 Report

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1. Supervised learning

參考 keras example 的 layers 以創建 model, code 如下:

```
2 data = []
3 val_data = []
answers = np.zeros((4000, 10), dtype=np.int)
5 \text{ val\_answers} = \text{np.zeros}((1000, 10), \text{dtype=np.int})
7 # parsing data, answers
  for ...
10 # transform to numpy array
11 data = np.array(data)
val_data = np.array(val_data)
data = data.astype('float32')
val_data = val_data.astype('float32')
15 data /= 255
_{16} val_data /= 255
18 model = Sequential()
19 model.add(Convolution2D(32, 3, 3, border_mode='same', input_shape=data.shape[1:]))
20 model.add(Activation('relu'))
model.add(Convolution2D(32, 3, 3))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
model.add(Convolution2D(64, 3, 3, border_mode='same'))
27 model.add(Activation('relu'))
model.add(Convolution2D(64, 3, 3))
29 model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
^{31} model.add(Dropout(0.25))
33 model.add(Flatten())
^{34} model.add(Dense(512))
35 model.add(Activation('relu'))
model.add(Dropout(0.5))
37 model.add(Dense(nb_classes))
38 model.add(Activation('softmax'))
40 # Use various optimizer, in this case, rmsprop
41 model.compile(loss='categorical_crossentropy', optimizer=optimizer, metrics=['↔
```

```
accuracy'])

42

43 # train with 4/5 labeled data

44 model.fit(data, answers, batch_size=batch_size, nb_epoch=nb_epoch, shuffle=True, 

validation_data=(val_data, val_answers))

45

46 # save model to model_path

47 model.save(model_path)
```

經過各種 optimizer 測試後,此 model 以 rmsprop 為最佳, nb_epoch = 30,僅以 labeled data train就可以達到public data 0.63 (private 0.64) 的準確率。然而以這個 model 做 semi supervised training 卻會得更差的結果。

2. Semi-supervised learning(1)

將 supervised learning 後的 model 做 unlabeled data prediction 後的結果加入原本的 labeled data 作為進一步 training model 的資料,並以 predict 的屬性值線性作為 sample_weight 的參數,並加入 image preprocessing 來優化結果。code 如下:

```
1 data = []
2 training_data = []
3 \text{ answers} = []
  # parsing labeled data, unlabeled data, answers
7 # load supervised learning model from model_path
  model = load_model(model_path)
10 # predict the classes of unlabeled data
  {\tt results} = {\tt model.predict}({\tt training\_data}\,,\ {\tt verbose}{=}1)
12
13 # parsing new answers and weights
14
15 # preprocessing and data augmentation
  datagen = ImageDataGenerator(
16
       featurewise_center=False,
17
       samplewise_center=False,
18
       featurewise_std_normalization=False
19
       samplewise_std_normalization=False,
20
       zca_whitening=False,
21
       rotation\_range=0,
22
       \verb|width_shift_range| = 0.1 \,,
       height_shift_range = 0.1,
25
       horizontal_flip=True,
       vertical_flip=False)
26
27
28
  datagen.fit(data)
29
  # train the model on the batches generated by datagen.flow()
30
  model.fit_generator(datagen.flow(data, answers,
31
                        batch_size=batch_size),
32
                         samples_per_epoch=data.shape[0],
33
                        nb_epoch=nb_epoch)
34
36 # save semi-supervised model to ouput_model_path
37 model.save(output_model_path)
```

這裡的 supervised learning model 有用同樣的方式做 preprocessing,但因為單一 supervised learning 結果沒有上述的方式好,故沒有多做敘述。

這裡的 optimizer 選的是 adam, nb_epoch = 30, predict score threshold = 0.8 (不到 threshold 的 data 就不加入下一輪 training 的資料了), public data 準確率為 0.64 (private 0.65), 進步幅度其實並不大...

3. Semi-supervised learning (2)

以 autoencoder 做 semi-supervised learning, 只取前 5000 個最有可能的資料作為下一輪新的資料。code 如下:

```
n model = Sequential()
_{2} \# \dim 3072 \rightarrow encoding_{dim} ( = 512)
3 model.add(Dense(encoding_dim, activation='relu', input_shape=(3072,)))
4 # add numOfLayers ( = 5) layers
5 for i in range(numOfLayers):
      model.add(Dense(layer_dim, activation='relu'))
7 \# \dim layer_dim (= 512) -> 3072
8 model.add(Dense(3072, activation='linear'))
10 # use optimizer rmsprop
nodel.compile(loss='mse', optimizer='rmsprop', metrics=['accuracy'])
12 model.fit( data, data,
13
              batch_size=batch_size_auto,
              nb_epoch=nb_epoch_auto,
14
              verbose=1)
15
              # validation_data=(x_{test}[0:3000], x_{test}[0:3000])
16
score = model.evaluate(x_{test}[0:3000], x_{test}[0:3000])
  print('score', score)
18
19
20 # define encoder as the middle layer's data
23 # encode labeled data
data_encoded = encoder([data])[0]
25
  average_data = np.zeros((10, layer_dim), dtype=np.float)
28
29 # calculate average of each cluster of each 512 dim
  for ...
30
31
32 # encode unlabeled data
  x_test_encoded = encoder([x_test])[0]
34
35 # calculate min error of each unlabeled data of each cluster
36
  for ...
37
  # sort unlabeled data by error
38
  results = sorted (results, key = getValue)
  # pick first max_size ( = 5000) of results, linear weighted with rank
  for i in range(max_size):
42
43
45 # load supervised learning model from model_path
46 old_model = load_model(model_path)
47
48 # train the model with added data
```

這裡的 supervised model 我取 adam optimizer 與 nb_epoch = 30, 新一輪的 optimizer 與 nb_epoch 取一樣,但 private score 僅約為 0.46,可能參數與 layers 還有待調整。

4. Compare & Analyze

可能因為對 deep learning 了解不夠深,沒有設計出好的 model 來 train, 故無法作到如 supervised learning 就有 0.8 accuracy 的水準; 而 semi-supervised learning 感覺也沒有抓到核心的關鍵,加入 weighted 與 threshold 後只比試出的最佳 supervised learning 高一些些 accuracy 而已。 autoencoder 的確如老師所言不是很好做, accuracy 在 train 完後反而更糟糕了。

之後如要改進 accuracy 首要就是設計出更好的 model, 並用更好的 clustering 做 semi-supervised。