Lab2 Q2

March 20, 2020

ComS 573

Lab 2

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1 Problem 2

For this problem, I have used the following parameter combinations

```
hid_layer = [2,3]
num_epochs = [80, 100, 120]
btch_size = [128, 200]
learning_rate = [0.05, 0.1, 0.2]
momentum = [.5, 0.9, 1]
los = ['categorical_crossentropy']
scale = ['Standardize', 'Normalize']
activ = ['relu']
filters = [64, 32]
kernel_size = [(3,3), (4, 4)]
```

Also used 80% - 20% training - validation data.

```
[1]: import numpy as np
     import pandas as pd
     import sklearn.preprocessing
     import matplotlib
     import keras
     import re
     import sys
     import gc
     import time
     print('python ' +sys.version)
     print('numpy '+ np.__version__)
     print('pandas '+ pd.__version__)
     print('sklearn '+ sklearn.__version__)
     print('matplotlib '+ matplotlib.__version__)
     print('keras '+ keras.__version__)
     print('re '+ re.__version__)
```

```
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import Normalizer
from sklearn.metrics import confusion_matrix
from matplotlib import pyplot as plt
from keras import optimizers
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten
from keras.layers import Convolution2D, MaxPooling2D
from keras.utils import np utils
from keras.callbacks import EarlyStopping
from keras.callbacks import ModelCheckpoint
from keras.models import load_model
from itertools import product
Using TensorFlow backend.
python 3.7.6 (default, Jan 8 2020, 20:23:39) [MSC v.1916 64 bit (AMD64)]
numpy 1.18.1
pandas 1.0.1
sklearn 0.22.1
matplotlib 3.1.3
keras 2.3.1
re 2.2.1
```

```
path = 'D:/ISU/COMS 573 - Machine Learning/HW/Lab2/'

train_model = False

df_tr = pd.read_csv(path+'optdigits.tra',header=None)
X_tr, y_tr = df_tr.loc[:,0:63], df_tr.loc[:,64]
ccat = y_tr.unique().size

df_ts = pd.read_csv(path+'optdigits.tes',header=None)
X_ts, y_ts = df_ts.loc[:,0:63], df_ts.loc[:,64]

scaler = StandardScaler().fit(X_tr)
normalizer = Normalizer().fit(X_tr)

X_tr_std = scaler.transform(X_tr)
X_tr_norm = normalizer.transform(X_tr)

split = 0.8
size = np.shape(X_tr)
nsplit = int(np.floor(split*size[0]))
```

```
y_train1 = np_utils.to_categorical(y_tr, ccat)
y_train = y_train1[0:nsplit,:];
y_val = y_train1[nsplit:size[0],:];
y_test = np_utils.to_categorical(y_ts, ccat)
X_train_std = X_tr_std[0:nsplit,:];
X_val_std = X_tr_std[nsplit:size[0],:];
X_test_std = scaler.transform(X_ts)
X_train_std = X_train_std.reshape(-1, 8, 8, 1)
X_{val_std} = X_{val_std.reshape}(-1, 8, 8, 1)
X_test_std = X_test_std.reshape(-1, 8, 8, 1)
X_train_norm = X_tr_norm[0:nsplit,:];
X_val_norm = X_tr_norm[nsplit:size[0],:];
X_test_norm = normalizer.transform(X_ts)
X_train_norm = X_train_norm.reshape(-1, 8, 8, 1)
X_val_norm = X_val_norm.reshape(-1, 8, 8, 1)
X_test_norm = X_test_norm.reshape(-1, 8, 8, 1)
```

```
[3]: if train_model:
         hid_layer = [2,3]
         num_epochs = [80, 100, 120]
         btch_size = [128, 200]
         learning_rate = [0.05, 0.1, 0.2]
         momentum = [.5, 0.9, 1]
         los = ['categorical_crossentropy']
         scale = ['Standardize', 'Normalize']
         activ = ['relu']
         filters = [64, 32]
         kernel_size = [(3,3), (4, 4)]
         def expand_grid(dictionary):
            return pd.DataFrame([row for row in product(*dictionary.values())],
                                columns=dictionary.keys())
         dictionary = {'hidden_layers': hid_layer,
                       'filters': filters,
                       'num_epochs': num_epochs,
                       'batch_size': btch_size,
                       'learning_rate': learning_rate,
                       'momentum': momentum,
```

```
'loss_func': los,
                 'data_scaling': scale,
                 'activation_func': activ,
                 'kernel_size': kernel_size}
   prem1 = expand_grid(dictionary)
   prem1 = prem1[~((prem1['activation_func'] == 'tanh') & (prem1['loss_func']__
prem1['time'] = np.NaN
   prem1['train_loss'] = np.NaN
   prem1['validation_loss'] = np.NaN
   prem1['test_loss'] = np.NaN
   prem1['train_acc'] = np.NaN
   prem1['validation_acc'] = np.NaN
   prem1['test_acc'] = np.NaN
   size_prem1 = prem1.shape
   print(prem1.head())
   11 = 0
   for j in range (0,2):
       if j == 0:
           X_train = X_train_std
           X_val = X_val_std
           X_test = X_test_std
           listind = prem1[prem1['data_scaling'] == 'Standardize'].index.
→tolist()
       else:
           X_train = X_train_norm
          X_val = X_val_norm
           X_test = X_test_norm
           listind = prem1[prem1['data_scaling'] == 'Normalize'].index.tolist()
       for i in listind:
           try:
               start = time. time()
               if prem1.iloc[i,0] == 1:
                   model = Sequential()
                   model.add(Convolution2D(filters = 64, kernel_size= prem1.
\rightarrowiloc[i,9],
                                           input_shape=(8,8,1),_
→activation='relu', padding='valid'))
                   model.add(MaxPooling2D(pool_size=(2,2), padding='valid'))
                   model.add(Dropout(0.3))
                   model.add(Flatten())
                   model.add(Dense(10, activation='softmax'))
               elif prem1.iloc[i,0] == 2:
```

```
model = Sequential()
                   model.add(Convolution2D(filters = 64, kernel_size= prem1.
\rightarrowiloc[i,9],
                                            input_shape=(8,8,1),_
→activation='relu', padding='valid'))
                   model.add(Convolution2D(filters = prem1.iloc[i,1],__
→kernel_size= prem1.iloc[i,9], padding='valid'))
                   model.add(MaxPooling2D(pool_size=(2,2), padding='valid'))
                   model.add(Dropout(0.3))
                   model.add(Flatten())
                   model.add(Dense(10, activation='softmax'))
               else:
                   model = Sequential()
                   model.add(Convolution2D(filters = 64, kernel_size= prem1.
\rightarrowiloc[i,9],
                                            input_shape=(8,8,1),_
→activation='relu', padding='valid'))
                   model.add(Convolution2D(filters = prem1.iloc[i,1],__
→kernel_size= prem1.iloc[i,9], padding='valid'))
                   model.add(Convolution2D(filters = prem1.iloc[i,1],__
→kernel_size= prem1.iloc[i,9], padding='valid'))
                   model.add(MaxPooling2D(pool size=(2,2), padding='valid'))
                   model.add(Dropout(0.3))
                   model.add(Flatten())
                   model.add(Dense(10, activation='softmax'))
               es = EarlyStopping(monitor='val_accuracy', mode='max', u
→verbose=0, patience=200)
               mc = ModelCheckpoint('best_model', monitor='val_accuracy', ___
→mode='max', verbose=0, save best only=True)
               optimizer1 = optimizers.SGD(lr=prem1.iloc[i,4], momentum=prem1.
\rightarrowiloc[i,5])
               model.compile(optimizer=optimizer1, loss=prem1.iloc[i,6],
→metrics=['accuracy'])
               fit1 = model.fit(X_train,y_train, batch_size=prem1.iloc[i,3],__
→epochs=prem1.iloc[i,2],
                                 validation_data=(X_val,y_val), callbacks=[es,_
\rightarrowmc], verbose = 0)
               fit = load_model('best_model')
               end = time.time()
               train_accuracy = fit.evaluate(X_train, y_train, verbose=0)
               val_accuracy = fit.evaluate(X_val, y_val, verbose=0)
```

```
test_accuracy = fit.evaluate(X_test, y_test, verbose=0)
                prem1.iloc[i, 10:17] = [end-start, train_accuracy[0],__
 →val_accuracy[0], test_accuracy[0],
                                       train_accuracy[1], val_accuracy[1],
→test_accuracy[1]]
                del model, es, mc, optimizer1, fit, fit1
                gc.collect()
            except:
                pass
            finally:
                11 = 11+1
                sys.stdout.write("\r Progress: %.2f%%" %round(float(ll)/
\rightarrowsize_prem1[0]*100,2))
                sys.stdout.flush()
else:
    print('skiped model fit')
```

skiped model fit

```
[4]: if train_model:
         prem1.to_csv (path+'res_2.csv', index = False, header=True)
         prem = prem1
     else:
         prem = pd.read_csv(path+'res_2.csv',header=0)
         prem.head()
         kk1 = []
         for i in range(prem.shape[0]):
             kk1.append(tuple(map(int, prem.iloc[i,9].replace('(', '').replace(')', __
      →'').replace(' ', '').split(','))))
         prem['kernel_size'] = kk1
     top10_cce = prem[prem['loss_func'] == 'categorical_crossentropy'].
     →nlargest(10, 'test_acc')
     print('\n Best 10 hyper-parameter combination for Cross-Entropy:\n', __
     →round(top10_cce, 4))
     plt.hist(prem.iloc[:,10], density=True, alpha=0.5, label=['CNN'])
     plt.legend(loc='upper right')
     plt.title('Distribution of time to fit models')
     # plt.xlim(0, 200)
     plt.show()
     plt.hist(prem.iloc[:,16],
```

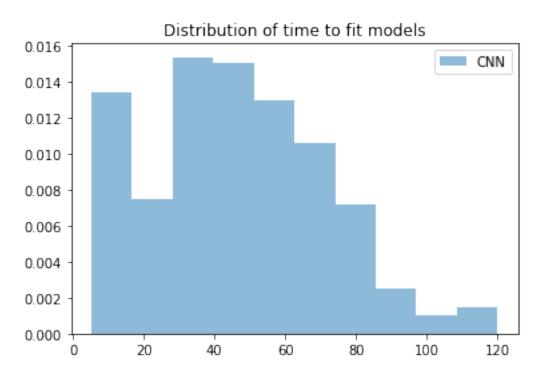
```
density=True, alpha=0.5, label=['CNN'])
plt.legend(loc='upper left')
plt.title('Distribution of test accuracy')
plt.show()
Best 10 hyper-parameter combination for Cross-Entropy:
      hidden_layers
                     filters
                               num_epochs
                                           batch_size
                                                        learning_rate
                                                                        momentum \
509
                  3
                          64
                                     100
                                                  128
                                                                 0.20
                                                                            0.5
487
                  3
                          64
                                      80
                                                  128
                                                                 0.05
                                                                            0.9
                  3
                          64
                                     120
                                                  128
                                                                 0.05
                                                                            0.9
521
                 3
579
                          32
                                     120
                                                  200
                                                                 0.10
                                                                            0.5
                 3
                          32
                                     120
                                                  200
                                                                 0.10
                                                                            0.9
580
                  3
                          32
                                                                 0.10
                                                                            0.5
547
                                      80
                                                  200
                  3
                                     100
                                                                 0.10
                                                                            0.5
556
                          32
                                                  128
332
                 2
                          64
                                     100
                                                  200
                                                                 0.10
                                                                            0.9
355
                 2
                          64
                                     120
                                                  128
                                                                 0.20
                                                                            0.5
374
                 2
                          64
                                     120
                                                  200
                                                                 0.20
                                                                            0.9
                    loss_func data_scaling activation_func kernel_size
                                                                   (3, 3)
509
     categorical_crossentropy
                                Standardize
                                                        relu
487
     categorical_crossentropy
                                Standardize
                                                        relu
                                                                   (3, 3)
                                                                   (3, 3)
521
     categorical_crossentropy
                                Standardize
                                                        relu
579
     categorical_crossentropy
                                Standardize
                                                        relu
                                                                   (3, 3)
                                                                   (3, 3)
580
     categorical_crossentropy
                                Standardize
                                                        relu
     categorical_crossentropy Standardize
                                                                   (3, 3)
547
                                                        relu
                                                                   (3, 3)
556
     categorical_crossentropy Standardize
                                                        relu
                                                                   (3, 3)
     categorical crossentropy
332
                                Standardize
                                                        relu
355
     categorical_crossentropy
                                Standardize
                                                                   (4, 4)
                                                        relu
     categorical crossentropy
                                                                   (3, 3)
374
                                Standardize
                                                        relu
         time train_loss validation_loss
                                              test_loss
                                                         train_acc \
     104.5165
                   0.0000
                                     0.0481
                                                 0.0407
                                                             1.0000
509
487
                   0.0003
                                     0.0335
                                                 0.0501
                                                             1.0000
      75.6567
521
     119.9278
                   0.0001
                                     0.0758
                                                 0.0475
                                                             1.0000
579
      85.3661
                   0.0006
                                     0.0615
                                                 0.0466
                                                             1.0000
580
      81.9683
                    0.0001
                                     0.0906
                                                 0.0623
                                                             1.0000
547
      59.1002
                    0.0020
                                     0.0466
                                                 0.0584
                                                             0.9997
556
      81.4093
                   0.0028
                                     0.0394
                                                 0.0414
                                                             0.9993
                   0.0001
                                                 0.0632
332
      71.7168
                                     0.0537
                                                             1.0000
355
      54.8639
                   0.0002
                                     0.0415
                                                 0.0633
                                                             1.0000
374
      67.5542
                   0.0000
                                     0.0308
                                                 0.0681
                                                             1.0000
     validation_acc test_acc
509
             0.9922
                        0.9900
487
             0.9948
                        0.9878
```

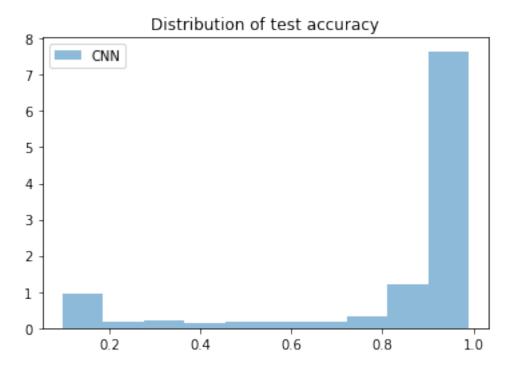
521

0.9895

0.9878

579	0.9908	0.9878
580	0.9935	0.9872
547	0.9935	0.9866
556	0.9935	0.9866
332	0.9935	0.9861
355	0.9935	0.9861
374	0.9961	0.9861





```
[5]: aaa = prem.iloc[:,10]
    print("Mean and Variance of fitted time:\n CNN: Mean = %.2f, \
    var = \%.2f\n" \%(np.mean(aaa), np.var(aaa)))
    aaa = prem.iloc[:,16]
    print("Mean and Variance of test accuracy:\n CNN: Mean = %.4f, \
    var = %.4f\n" %(np.mean(aaa), np.var(aaa)))
   Mean and Variance of fitted time:
    CNN: Mean = 46.11, var = 655.43
   Mean and Variance of test accuracy:
    CNN: Mean = 0.8302, var = 0.0736
[6]: top10 = top10_cce
    print("\n Results For CNN")
    if top10.iloc[0,7] == 'Standardize':
        X_train = X_train_std
        X_val = X_val_std
        X_{\text{test}} = X_{\text{test}}
    else:
```

```
X_train = X_train_norm
   X_val = X_val_norm
   X_test = X_test_norm
start = time. time()
if top10.iloc[0,0] == 1:
   model = Sequential()
   model.add(Convolution2D(filters = 64, kernel size= top10.iloc[0,9],
                            input_shape=(8,8,1), activation='relu', _
→padding='valid'))
   model.add(MaxPooling2D(pool_size=(2,2), padding='valid'))
   model.add(Dropout(0.3))
   model.add(Flatten())
   model.add(Dense(10, activation='softmax'))
elif top10.iloc[0,0] == 2:
   model = Sequential()
   model.add(Convolution2D(filters = 64, kernel_size= top10.iloc[0,9],
                            input_shape=(8,8,1), activation='relu',_
→padding='valid'))
   model.add(Convolution2D(filters = top10.iloc[0,1], kernel_size= top10.
→iloc[0,9], padding='valid'))
   model.add(MaxPooling2D(pool_size=(2,2), padding='valid'))
   model.add(Dropout(0.3))
   model.add(Flatten())
   model.add(Dense(10, activation='softmax'))
else:
   model = Sequential()
   model.add(Convolution2D(filters = 64, kernel_size= top10.iloc[0,9],
                            input_shape=(8,8,1), activation='relu',_
 →padding='valid'))
   model.add(Convolution2D(filters = top10.iloc[0,1], kernel_size= top10.
→iloc[0,9], padding='valid'))
   model.add(Convolution2D(filters = top10.iloc[0,1], kernel_size= top10.
→iloc[0,9], padding='valid'))
   model.add(MaxPooling2D(pool_size=(2,2), padding='valid'))
   model.add(Dropout(0.3))
   model.add(Flatten())
   model.add(Dense(10, activation='softmax'))
es = EarlyStopping(monitor='val_accuracy', mode='max', verbose=0, patience=200)
mc = ModelCheckpoint('best model', monitor='val_accuracy', mode='max', __
→verbose=0, save_best_only=True)
```

```
optimizer1 = optimizers.SGD(lr=top10.iloc[0,4], momentum=top10.iloc[0,5])
model.compile(optimizer=optimizer1, loss=top10.iloc[0,6], metrics=['accuracy'])
fit1 = model.fit(X_train,y_train, batch_size=top10.iloc[0,3], epochs=top10.
\rightarrowiloc[0,2],
                 validation_data=(X_val,y_val), callbacks=[es, mc], verbose = 0)
fit = load model('best model')
end = time.time()
train_accuracy = fit.evaluate(X_train, y_train, verbose=0)
val_accuracy = fit.evaluate(X_val, y_val, verbose=0)
test_accuracy = fit.evaluate(X_test, y_test, verbose=0)
final_res = [end-start, train_accuracy[0], val_accuracy[0], test_accuracy[0],
                      train_accuracy[1], val_accuracy[1], test_accuracy[1]]
if top10.iloc[0,7] == 'Standardize':
   X_{train11} = X_{tr_std.reshape(-1, 8, 8, 1)}
   X_test = X_test_std
   y_train11 = y_train1
else:
   X \text{ train11} = X \text{ tr norm.reshape}(-1, 8, 8, 1)
   X_test = X_test_norm
   y_train11 = y_train1
print("For hyper-parameters:\n",top10.iloc[0,:])
print("\n Time needed: %.2f" % (end-start))
scores = fit.evaluate(X_test, y_test, verbose=0)
print("\n Test Accuracy: %.2f%%" % (scores[1]*100))
A = fit.predict(X_train11)
cm = confusion_matrix(y_train11.argmax(axis=1), A.argmax(axis=1))
print("\n Train confusion matrix: \n", cm)
acc_train = np.diagonal(cm)/cm.sum(axis=1)
print("\n Class Accuracy for Training Data is:")
for i in range(10):
   print('Class %d: %.2f%%' %(i, acc_train[i]*100))
A = fit.predict(X_test)
cm = confusion_matrix(y_test.argmax(axis=1), A.argmax(axis=1))
print("\n Test confusion matrix: \n", cm)
acc_test = np.diagonal(cm)/cm.sum(axis=1)
print("\n Class Accuracy for Testing Data is:")
for i in range(10):
   print('Class %d: %.2f%%' %(i, acc_test[i]*100))
```

Results For CNN

For hyper-parameters	For	hvper-	parame	ters	:
----------------------	-----	--------	--------	------	---

<i>3</i> 1	
hidden_layers	3
filters	64
num_epochs	100
batch_size	128
learning_rate	0.2
momentum	0.5
loss_func	categorical_crossentropy
data_scaling	Standardize
activation_func	relu
kernel_size	(3, 3)
time	104.516
train_loss	3.74972e-05
validation_loss	0.0481159
test_loss	0.0407299
train_acc	1
validation_acc	0.992157
test_acc	0.989983

Name: 509, dtype: object

Time needed: 67.97

Test Accuracy: 98.55%

Train confusion matrix:

	376	3 () () () () () () () (0]
[0	389	0	0	0	0	0	0	0	0]
[0	0	380	0	0	0	0	0	0	0]
[0	0	0	388	0	0	0	0	0	1]
[0	0	0	0	386	0	1	0	0	0]
[0	0	0	0	0	376	0	0	0	0]
[0	0	0	0	0	0	377	0	0	0]
[0	0	0	1	0	0	0	386	0	0]
[0	1	0	0	0	0	0	0	378	1]
[0	0	0	0	0	0	0	0	0	382]]

Class Accuracy for Training Data is:

Class 0: 100.00% Class 1: 100.00% Class 2: 100.00% Class 3: 99.74% Class 4: 99.74% Class 5: 100.00% Class 6: 100.00% Class 7: 99.74% Class 8: 99.47% Class 9: 100.00%

```
Test confusion matrix:
ΓΓ177
               0
                                    0
                                                    01
          0
                    0
                          1
                               0
                                         0
                                              0
   0 182
              0
                        0
                              0
                                   0
                                        0
                                             0
                                                   01
                   0
         1 176
                   0
                        0
                              0
                                   0
                                        0
                                             0
                                                   0]
                                                   21
   0
         0
              0 180
                        0
                              1
                                   0
                                        0
                                             0
2
                   0 179
                              0
                                   0
                                        0
                                                  0]
              0
                                             0
Γ
   0
         0
              0
                   0
                        1 177
                                   1
                                        0
                                             0
                                                  31
0
         0
                   0
                        2
                              1 178
                                        0
                                                  0]
              0
                                             0
0
         0
              0
                   0
                        0
                              0
                                   0 177
                                             0
                                                   2]
0
                                   0
                                                   1]
   0
         1
              0
                        1
                                        0
                                          170
                   1
Γ
   0
         0
              0
                   1
                        1
                              1
                                   0
                                        0
                                             2 175]]
```

```
Class Accuracy for Testing Data is:
```

```
Class 0: 99.44%
Class 1: 100.00%
Class 2: 99.44%
Class 3: 98.36%
Class 4: 98.90%
Class 5: 97.25%
Class 6: 98.34%
Class 7: 98.88%
Class 7: 98.88%
Class 9: 97.70%
Class 9: 97.22%
```

Based on the time distribution, CNN takes longer time than fully connected feed-forward networks. However, the time distribution for CNN is less skewed than fully connected feed-forward networks.

Based on test accuracy distributions, overall accuracy for test data using CNN is higher (about 98%) than the fully connected feed-forward networks and the variance is also lower for these hyperparameter combinations.

It is found that using CNN with 3 hidden layers, 64 units, number of epochs 100, batch size 128, learning rate 0.2, momentum 0.5 and kernel size (3,3) has the highest test accuracy (about 98.00%) which is higher than the fully connected feed forward networks. Note that, this model was fitted based on only 1-fold cross validation with no repeated sample. It might be different if we use repeated k fold cross validation.

Training accuracy for all classes are almost 100%. However, test accuracy for all classes are around 98%. Class 0 and 1 have the highest test accuracy (about 100%) and class 8 has the lowest accuracy (about 97%) which is much higher than the fully connected feed forward networks. Overall classification accuracy, class accuracy, and confusion matrix for both training and testing data are given in above tables.

1.1 Important References:

- 1. https://towardsdatascience.com/building-our-first-neural-network-in-keras-bdc8abbc17f5
- 2. https://towardsdatascience.com/building-a-deep-learning-model-using-keras-1548ca149d37
- 3. https://machinelearningmastery.com/tutorial-first-neural-network-python-keras/
- $4.\ https://towardsdatascience.com/building-a-convolutional-neural-network-cnn-in-keras-329 fbbadc 5f5$
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