COMP5318 - Machine Learning and Data Mining: Assignment 1

load data

```
In [29]: import h5py
          import numpy as np
          import os
          import pandas as pd
          import matplotlib.pyplot as plt
          import time
          print(os.listdir("./Input/train"))
          print(os.listdir("./Input/test"))
          ['images_training.h5', 'labels_training.h5']
['images_testing.h5', 'labels_testing_2000.h5']
In [30]: with h5py.File('./Input/train/images_training.h5','r') as H:
              data_train = np. copy(H['datatrain'])
          with h5py.File('./Input/train/labels_training.h5','r') as H:
              label_train = np. copy(H['labeltrain'])
          #load images testing
          with h5py. File('./Input/test/images_testing.h5', 'r') as H:
              datatest = np. copy(H['datatest'])
          #load teating table which contain 2000 samples
          with h5py.File('./Input/test/labels_testing_2000.h5','r') as H:
              labeltest = np. copy(H['labeltest'])
          # using H['datatest'], H['labeltest'] for test dataset.
          print(data_train. shape, label_train. shape)
          print (datatest. shape, labeltest. shape)
           (30000, 784) (30000,)
           (5000, 784) (2000,)
          Functions
In [31]: def output (pred data):
              #assume output is the predicted labels from classifiers
              with h5py.File('Output/predicted_labels.h5','w') as H:
                   H. create_dataset('Output', data = pred_data)
In [32]: #calculate the accuacy for the classifier
          def cal_accuacy (pred_data, lable):
              count = 0
               for i in range (lable.shape[0]):
                   if lable[i] == pred_data[i]:
                      count += 1
              accuracy = count/lable.shape[0]
```

Split both train datasets as train and validation (80%/20%)

return accuracy

```
In [33]: from sklearn.model_selection import train_test_split

#apply splits function for the datasets
split_data_train, split_data_test, split_label_train, split_label_test = train_test_split(data_train, label_train, t
#check see if get target split
print(split_data_train.shape, split_data_test.shape)
print(split_label_train.shape, split_label_test.shape)

(24000, 784) (6000, 784)
(24000,) (6000,)
```

Data pre-processing

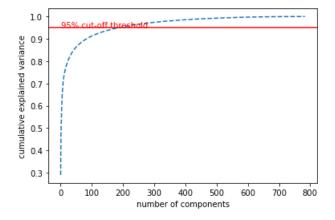
```
In [34]: #use minmac scaler normalise the data
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler(feature_range=(-1,1))
scaler.fit(split_data_train)
data_train_norm = scaler.transform(split_data_train)
data_test_norm = scaler.transform(split_data_test)
#apply scaler for datatest
data_test_norm_og = scaler.transform(datatest)
```

```
In [35]: from sklearn.decomposition import PCA

#find best components number, The redline represen 95% of explained variance
pca_find = PCA().fit(split_data_train)
plt.plot(np.cumsum(pca_find.explained_variance_ratio_), linestyle='--',)

plt.xlabel('number of components')
plt.ylabel('cumulative explained variance');
plt.axhline(y=0.95, color='r', linestyle='-')
plt.text(0.5, 0.95, '95% cut-off threshold', color = 'red', fontsize=10)
```

```
Out[35]: Text(0.5, 0.95, '95% cut-off threshold')
```



```
In [36]: # apply PCA to splited data, test from 84 (90%) to 187(95%)
pca = PCA(n_components= 84)
pca_data_train = pca. fit_transform(data_train_norm)
pca_data_test = pca. transform(data_test_norm)
#apply pca for data_test_norm_og
pca_data_test_og = pca. transform(data_test_norm_og)
```

Classification algorithms

k-nearest neighbor classifier

```
In [37]: from sklearn.neighbors import KNeighborsClassifier
          from \ sklearn. \ model\_selection \ import \ cross\_val\_score
          #apply knn with 1 neighbours and test the splited raw data
          knn = KNeighborsClassifier(n_neighbors=1)
          #apply knn with 1 neighbours and test the PCA data
          start = time.time()
          #apply splited data_train and labl_train to train the data via knn
          knn.fit(pca_data_train, split_label_train)
          #make prediction for splicted data as reference
          knn_res_pca = knn.predict(pca_data_test)
          #make prediction for 5000 test data
          knn_res_pca_og = knn.predict(pca_data_test_og)
          end = time.time()
          #print accuacy for splited test data
          acc_knn_pca = cal_accuacy(knn_res_pca, split_label_test)
          print(f"Time taken is {format(end-start, '.3f')} seconds")
          print(f"When k = 1, knn's Accuracy result for train data is: {format(acc knn pca, '.3f')}")
          acc_knn_pca_og = cal_accuacy(knn_res_pca_og, labeltest)
          print(f"When k = 1, knn's Accuracy result for test data is: {format(acc_knn_pca_og, '.3f')}")
```

```
Time taken is 3.123 seconds When k = 1, knn's Accuracy result for train data is: 0.840 When k = 1, knn's Accuracy result for test data is: 0.828
```

```
In [38]: #find hyperparameter and use grid search with 10-fold stratified cross validation to find best performance from sklearn.model_selection import GridSearchCV k_range = list(range(1, 21, 2)) #create a parameter grid use to map the parameter names to the values param_grid = dict(n_neighbors=k_range) print(param_grid)
```

```
{'n_neighbors': [1, 3, 5, 7, 9, 11, 13, 15, 17, 19]}
```

```
In [39]: #create grid for knn
           start = time.time()
           grid_knn = GridSearchCV(knn, param_grid, cv=10, n_jobs=-1)
           grid_knn.fit(pca_data_train, split_label_train)
           #best score
           print("The best train/train prediction score is:")
           print(grid_knn.best_score_)
           #use grid search find best k calue in 2,4,6,8,10
           print("The best k value is:")
           print(grid_knn.best_params_)
           knn_res_pca = grid_knn.predict(pca_data_test)
           knn_res_pca_og = grid_knn.predict(pca_data_test_og)
           end = time.time()
           print(f"Time taken is {format(end-start, '.3f')} seconds")
           acc_knn_pca = cal_accuacy(knn_res_pca, split_label_test)
           \label{lem:print}  \text{print}(f''knn's \ best \ Accuracy \ result \ for \ train \ data \ is: \ \{format(acc\_knn\_pca, \ '.3f')\}'') 
           acc_knn_pca_og = cal_accuacy(knn_res_pca_og, labeltest)
           print(f"knn's Accuracy result for test data is: {format(acc knn pca og, '.3f')}")
```

```
The best train/train prediction score is:
0.853125
The best k value is:
{'n_neighbors': 7}
Time taken is 41.013 seconds
knn's best Accuracy result for train data is: 0.849
knn's Accuracy result for test data is: 0.842
```

Gaussian Naive bayes

```
Time taken is 0.068 seconds
naive bayes's accuracy result for train data is: 0.770
naive bayes's accuracy result for test data is: 0.757
```

```
In [41]: | #use grid search with 10-fold stratified cross validation to find best performance
          \#The var_smoothing parameter's default value is 10^-9 and \%e will apply the grid search from 0 to 10^-9
          params = {'var_smoothing': np.logspace(0,-9, num=100)}
          start = time.time()
          #the GridSearchCV will give the best value
          nb_grid = GridSearchCV(nb, param_grid=params, verbose=1, cv=10, n_jobs=-1)
          nb_grid.fit(pca_data_train, split_label_train)
          print("The best train/train prediction score is:")
          print(nb_grid.best_score_)
          print("The best var_smoothing value is:")
          print(nb_grid.best_estimator_)
          #use value find via best estimator to do new prediction
          nb_res_pca_GridS = nb_grid.predict(pca_data_test)
          nb_res_pca_GridS_og = nb_grid.predict(pca_data_test_og)
          end = time.time()
          print(f"Time taken is {format(end-start, '.3f')} seconds")
          acc nb pca GridS = cal accuacy(nb res pca GridS, split label test)
          print(f"naive bayes's best accuracy result for train data after hyperparameter tunning is: {format(acc_nb_pca_Gri
          acc_nb_pca_GridS_og = cal_accuacy(nb_res_pca_GridS_og, labeltest)
          print(f"naive bayes's best accuracy result for test data after hyperparameter tunning is: {format(acc nb pca Grid
```

```
Fitting 10 folds for each of 100 candidates, totalling 1000 fits
The best train/train prediction score is:
0.7697083333333333
The best var_smoothing value is:
GaussianNB(var_smoothing=8.111308307896872e-05)
Time taken is 9.544 seconds
naive bayes's best accuracy result for train data after hyperparameter tunning is: 0.770
naive bayes's best accuracy result for test data after hyperparameter tunning is: 0.755
```

Support Vector Machines

```
In [42]: from sklearn.svm import SVC
svm = SVC()
start = time.time()

#use PCA data
svm.fit(pca_data_train, split_label_train)
svm_res_nom = svm.predict(pca_data_test)
svm_res_nom_og = svm.predict(pca_data_test_og)
end = time.time()
print(f"Time taken is {format(end-start, '.3f')} seconds")
acc_svm_nom = cal_accuacy(svm_res_nom, split_label_test)
print(f"Support Vector Machines's accuracy result for normalised train data is: {format(acc_svm_nom, '.3f')}")
acc_svm_nom_og = cal_accuacy(svm_res_nom_og, labeltest)
print(f"Support Vector Machines's accuracy result for normalised test data is: {format(acc_svm_nom_og, '.3f')}")
```

```
Time taken is 13.704 seconds
Support Vector Machines's accuracy result for normalised train data is: 0.873
Support Vector Machines's accuracy result for normalised test data is: 0.865
```

```
In [43]: | #find hyperparameter and use grid search with 10-fold stratified cross validation to find best performance
          param_linear = {'C': [0.01, 0.1, 1, 10, 100]}
          start = time.time()
          grid_svm_linear= GridSearchCV(SVC(kernel="linear"), param_grid = param_linear, cv=10, n_jobs=-1)
          grid_svm_linear.fit(pca_data_train, split_label_train)
          print("The best train/train prediction score is:")
          print(grid_svm_linear.best_score_)
          #find the best parameters value
          print("The best parameters value is:")
          print(grid_svm_linear.best_estimator_)
          svm_res_linear = grid_svm_linear.predict(pca_data_test)
          svm_res_linear_og = grid_svm_linear.predict(pca_data_test_og)
          end = time.time()
          print(f"Time taken is {format(end-start, '.3f')} seconds")
          acc_svm_linear = cal_accuacy(svm_res_linear, split_label_test)
          print(f"Support Vector Machines's best accuracy result for train data after hyperparameter tunning is: {format(ac
          acc svm linear og = cal accuacy(svm res linear og, labeltest)
          print(f"Support Vector Machines's best accuracy result for test data after hyperparameter tunning is: {format(acc
          The best train/train prediction score is:
          0.859125
          The best parameters value is:
          SVC(C=0.01, kernel='linear')
          Time taken is 947.646 seconds
          Support Vector Machines's best accuracy result for train data after hyperparameter tunning is: 0.848
          Support Vector Machines's best accuracy result for test data after hyperparameter tunning is: 0.843
In [44]: param_rbf = {'C': [0.01, 0.1, 1, 10], 'gamma': [0.001, 0.01, 0.1]}
          start = time.time()
          grid_svm_rbf= GridSearchCV(SVC(kernel="rbf"), param_grid = param_rbf, cv=10, n_jobs=-1)
          grid_svm_rbf.fit(pca_data_train, split_label_train)
          print("The best train/train prediction score is:")
          print(grid_svm_rbf.best_score_)
          #find the best parameters value
          print("The best parameters value is:")
          print(grid_svm_rbf.best_estimator_)
          svm_res_rbf = grid_svm_rbf.predict(pca_data_test)
          svm_res_rbf_og = grid_svm_rbf.predict(pca_data_test_og)
          end = time.time()
          print(f"Time taken is {format(end-start, '.3f')} seconds")
          acc svm rbf = cal accuacy(svm res rbf, split label test)
          print(f"Support Vector Machines's best accuracy result for train data after hyperparameter tunning is: {format(ac
          acc_svm_rbf_og = cal_accuacy(svm_res_rbf_og, labeltest)
          print(f"Support Vector Machines's best accuracy result for test data after hyperparameter tunning is: {format(acc
          The best train/train prediction score is:
          0.89120833333333334
          The best parameters value is:
          SVC (C=10, gamma=0.01)
          Time taken is 908.991 seconds
          Support Vector Machines's best accuracy result for train data after hyperparameter tunning is: 0.893
```

Support Vector Machines's best accuracy result for test data after hyperparameter tunning is: 0.874

```
In [45]: param_poly = {'C': [0.01, 0.1, 1, 10], 'gamma': [0.001, 0.01, 0.1, 1]}
          start = time.time()
          grid_svm_poly= GridSearchCV(SVC(kernel="poly"), param_grid = param_poly, cv=10, n_jobs=-1)
          grid_svm_poly.fit(pca_data_train, split_label_train)
          print(grid_svm_poly.best_score_)
          #find the best parameters value
          print("The best parameters value is:")
          print(grid_svm_poly.best_estimator_)
          svm_res_poly = grid_svm_poly.predict(pca_data_test)
          svm_res_poly_og = grid_svm_poly.predict(pca_data_test_og)
          end = time.time()
          print(f"Time taken is {format(end-start, '.3f')} seconds")
          acc svm poly = cal accuacy(svm res poly, split label test)
          print(f"Support Vector Machines's best accuracy result for train data after hyperparameter tunning is: {format(ac
          acc_svm_poly_og = cal_accuacy(svm_res_poly_og, labeltest)
          print(f"Support Vector Machines's best accuracy result for test data after hyperparameter tunning is: {format(acc
          0.8885416666666666
```

The best parameters value is:
SVC(C=1, gamma=0.01, kernel='poly')
Time taken is 355.864 seconds
Support Vector Machines's best accuracy result for train data after hyperparameter tunning is: 0.890
Support Vector Machines's best accuracy result for test data after hyperparameter tunning is: 0.869

Comparing between classfiers

```
In [47]: start_nv = time.time()
    pca_nb = PCA(n_components= 84)
    pca_data_train_nb = pca_nb.fit_transform(data_train_norm)
    pca_data_test_nb_og = pca_nb.transform(data_test_norm_og)
    nb_best = GaussianNB(var_smoothing=0.0002848035868435802)
    nb_best.fit(pca_data_train_nb, split_label_train)
    nb_res_best = nb_best.predict(pca_data_test_nb_og)
    end_nv = time.time()
    acc_nb_best = cal_accuacy(nb_res_best, labeltest)
```

In [48]: start_svm = time.time()

pca_svm = PCA(n_components= 187)

pca_data_train_svm = pca_svm.fit_transform(data_train_norm)

```
pca_data_test_svm_og = pca_svm.transform(data_test_norm_og)
          svm_best = SVC(C=10, gamma=0.01, kernel="rbf")
          #use PCA data
          svm_best.fit(pca_data_train_svm, split_label_train)
          svm_res_best = svm_best.predict(pca_data_test_svm_og)
          end_svm = time.time()
          acc_svm_best = cal_accuacy(svm_res_best, labeltest)
In [50]: from sklearn.metrics import accuracy_score
          print(f''k-nearest\ neighbor\ classifier's\ Time\ taken\ is\ \{format(end\_knn-start\_knn,\ '.3f')\}\ seconds'')
          print(f"k-nearest neighbor classifier's best accuracy result for test data after hyperparameter tunning is: {form
          print(f"naive bayes's Time taken is {format(end_nv-start_nv, '.3f')} seconds")
          print(f"naive bayes's best accuracy result for test data after hyperparameter tunning is: {format(acc_nb_best, '.
          print(f"Support Vector Machines's Time taken is {format(end_svm-start_svm,'.3f')} seconds")
          print(f"Support Vector Machines's best accuracy result for test data after hyperparameter tunning is: {format(acc
          k-nearest neighbor classifier's Time taken is 2.523 seconds
          k-nearest neighbor classifier's best accuracy result for test data after hyperparameter tunning is: 0.839
          naive bayes's Time taken is 0.299 seconds
          naive bayes's best accuracy result for test data after hyperparameter tunning is: 0.754
          Support Vector Machines's Time taken is 28.272 seconds
          Support Vector Machines's best accuracy result for test data after hyperparameter tunning is: 0.879
In [51]:
          #optut the best presdicted data
          output(svm_res_best)
```

Hardware and software specifications

- 1. CPU: AMD 5900X
- 2. Ram: 16GB
- 3. GPU: RTX 3060TI