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Task 1 Data Exploration

Panda was used to import and load the training and test data from the relevant csv files. The 'iloc' method was then used to isolate the inputs and labels from the test data and training data. This method splits the data based on rows and columns. This is how the important data (all columns and rows[features] from 1 to 12) was extracted. The labels for the data were 1, 2 and 3 which corresponds to configuration of the flow of the pipe, which is homogeneous, annular and laminar respectively.

Features 1 and 2 from the training data were plotted against each other. By using the labels extracted from the training data csv file, each class was assigned to a different colour to aid in the visualization of the data.

Both datasets were normalised using the StandardScaler() method to remove the mean and divide each value to keep all the attributes in the same range. The parameter used for the normalisation of both datasets was the training set.

PCA analysis was performed on both the scaled datasets and scree plot was produced to report the variances captured by each principal component. The scree plot shows that Principal Component 1 (PC1) had the largest variance captured of more than 40%. Principal Components 2 and 3 had the second and third largest variance captured which were both slightly above 17% but below 20%. The rest of the Principal Components were below 10% decreasing more after each principal component. 2 subplots were produced which projected the first Principal Component (PC1) against second Principal Component (PC2) of the training set and the second Principal Component (PC2) against the third Principal Component (PC3) of the training set.

Lastly, the PCA spaced presented by the training set was used to project the scaled test set 'testingData'.

Task 2

The 'train_test_split' function was used to split the training set into a smaller training set and a validation set. Since a test dataset was already provided, it was not required to split the data further to produce one. From the initial training set only 25% of it was used for the validation set. The training set and validation set has 750 and 250 points, respectively as can be seen in the Appendix B.

The 'StandardScaler' function was used to normalise the smaller training set and the validation set with the smaller training set acting as the StandardScaler parameter for both.

Task 3 Non-linear Classification

A Support Vector Machine model with the Gaussian Radial Basis Kernel was utilized on the training set from the previous task. 4 combinations of the cost parameter (C) and the kernel parameter (gamma ort y) were used to find the optimal model. 2 combinations provided the most optimal model: [C=50, gamma=10] and [C=100, gamma=10]. Both these combinations gave an accuracy of 0.772. However, I chose the first combination to produce a classification report. Another SVM model was used with the combinations which gave the optimal model, to classify the test data. This produced an accuracy of 0.867.

For the feature reduction, only the first 3 principal components were used because they significantly captured more variances than the rest. The model with the reduced features gave the better classification result because it had the higher accuracy rate which is 0.913 which is 0.046 higher than the most optimal model which used the original features.

Appendix

Appendix A: Task 1

TASK 1

In [1]:
```
# a) Use Pandas to load both the training set and the test set
import pandas as pd

trnData = pd.read_csv('trndata.csv')
tstData = pd.read_csv('tstdata.csv')
```

In [2]:
```
# Isolating Inputs and Labels from Test Data and Training Data
trainInputs = trnData.iloc[:,:12]
trainLabels = trnData.iloc[:,12]
testInputs = tstData.iloc[:,:12]
testLabels = tstData.iloc[:,12]

trainInputs.head()
```

Out[2]:

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
0	0.3315	0.2156	0.6802	0.1434	0.6825	0.2720	0.6223	0.2092	0.7961	0.1530	0.5856	0.2573
1	0.0939	1.0089	0.0365	0.6944	0.0908	0.4961	0.0722	0.6521	-0.0130	0.6085	0.0631	0.6597
2	0.5184	0.2283	0.5300	0.6884	0.7456	0.6171	0.6136	0.5928	0.7678	0.6130	0.6705	0.5202
3	0.4208	0.6740	0.1651	0.7592	0.1810	0.5448	0.1707	0.7554	0.1635	0.5492	0.2598	0.6455
4	0.3130	0.6465	0.5908	0.6924	0.7664	0.6262	1.7177	0.0150	0.0851	1.9046	-0.0165	0.0221

In [3]:
```
testInputs.head()
```

Out[3]:

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
0	0.5803	0.4980	0.8809	0.8215	1.0133	0.9187	0.8508	0.8496	0.9996	0.9670	0.9111	0.7814
1	0.0026	0.6084	0.2808	0.6282	0.2995	0.7513	-0.0107	1.7503	-0.0822	2.0704	-0.0999	0.1214
2	-0.0115	1.1193	0.2201	1.3189	0.2656	1.4039	-0.0067	1.7438	0.0013	2.0020	-0.0401	1.7797
3	-0.0536	1.0370	0.0558	1.2483	0.2640	1.1456	0.0140	1.7156	0.0125	1.9889	-0.0598	0.0709
4	0.5021	0.4270	0.6450	0.8325	0.7560	0.9235	0.7289	0.7352	0.7735	0.9298	0.6013	0.8842

In [4]:
```
#b) Show one scatter plot, that is, two features of the training set against each other.
# It is your choice to show which two features you want to use.
# You need to set the labelfor the x-axis and y-axis, separately, and use different colours to distinguish the three classes

import matplotlib.pyplot as plt
import numpy as np

fig = plt.figure()

# using scatter graph to plot f2 against f3

plt.title("Graph Plots F1 against F2")
plt.xlabel("F1")
plt.ylabel("F2")

plt.scatter(trnData.iloc[:,0],trnData.iloc[:,1], c=trainLabels, edgecolor='none', alpha=0.5)
plt.show()
```

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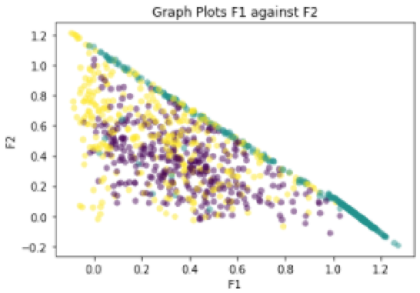


In [5]:
```
#c) Normalise the training set and the test set using StandardScaler()

from sklearn.preprocessing import StandardScaler
from sklearn import preprocessing

scaler = preprocessing.StandardScaler().fit(trainInputs)
scaled_trainData = scaler.transform(trainInputs)
scaled_testData = scaler.transform(testInputs)
```

In [6]:
```
#d)Perform a PCA analysis on the scaled training set
# Plot the scree plot to report variances captured by each principal component
import numpy as np
from sklearn.decomposition import PCA

pca = PCA()
trainingData = pca.fit_transform(scaled_trainData)

pca.explained_variance_
```

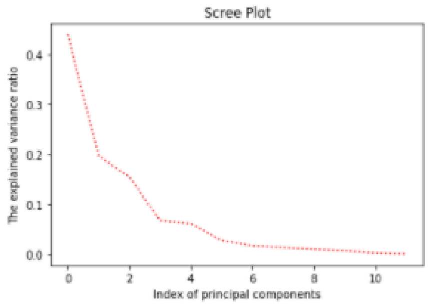
Out[6]:
```
array([5.2731389 , 2.36663461, 1.85618516, 0.80897277, 0.74169588,
       0.3417678 , 0.20270469, 0.16142449, 0.12289088, 0.09264559,
       0.03143982, 0.01251141])
```

In [7]:
```
pca.explained_variance_ratio_
```

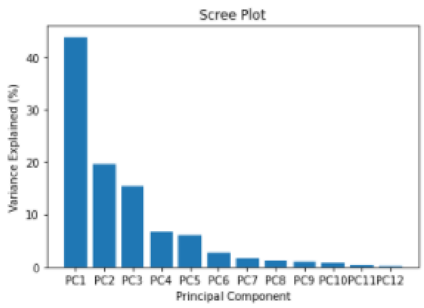
Out[7]:
```
array([0.43898881, 0.19702233, 0.15452741, 0.06734698, 0.06174618,
       0.02845217, 0.01687517, 0.01343859, 0.01023067, 0.00771275,
       0.00261736, 0.00104158])
```

In [8]:
```
#plot scree plot
fig = plt.figure()
ax = plt.gca()
plt.plot(pca.explained_variance_ratio_, color='red', linestyle='dotted')
ax.set_title("Scree Plot")
ax.set_xlabel("Index of principal components")
ax.set_ylabel("The explained variance ratio")
```

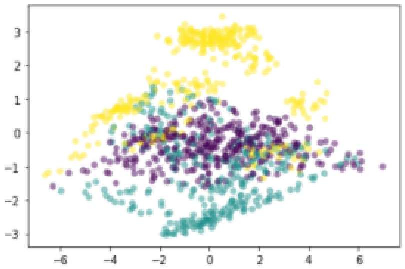
Out[8]:
```
Text(0, 0.5, 'The explained variance ratio')
```



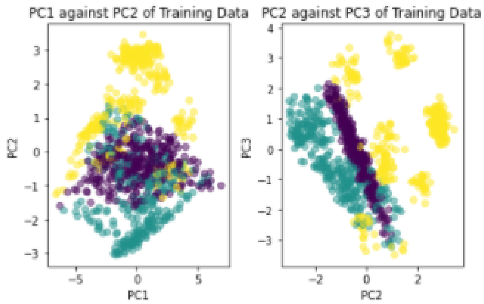
In [9]:
```
per_var = np.round(pca.explained_variance_ratio_*100, decimals = 1)
labels = ['PC' + str(n) for n in range(1, len(per_var) + 1)]

plt.bar(x=range(1,len(per_var)+1), height=per_var, tick_label=labels)
plt.ylabel('Variance Explained (%)')
plt.xlabel('Principal Component')
plt.title('Scree Plot')
plt.show()
```



In [10]:
```
plt.scatter(trainingData[:,0],trainingData[:,1], c=trainLabels, edgecolor="none", alpha=0.5)
```
Out[10]: <matplotlib.collections.PathCollection at 0x21278d5a6a0>

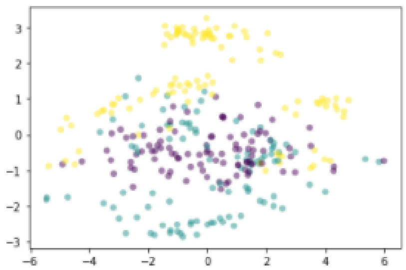


In [11]:
```
#e) Plot two subplots in one figure: one for projecting the training set in the projectionspace constructed
# using the first principal component (PC1) and the second principalcomponent (PC2);
# the other one for projecting the training set in the projection space constructed using the
# second principal component (PC2) and the third principal compo-nent (PC3).
# You need to label the data using different colours in the picture according to its class
# and set the label for thex-axis andy-axis, separately.

plt.subplot(1,2,1)
plt.title("PC1 against PC2 of Training Data")
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.scatter(trainingData[:,0],trainingData[:,1], c=trainLabels, marker="o", alpha = 0.5)

plt.subplot(1,2,2)
plt.title("PC2 against PC3 of Training Data")
plt.xlabel("PC2")
plt.ylabel("PC3")
plt.scatter(trainingData[:,1],trainingData[:,2], c=trainLabels, marker="o", alpha = 0.5)

plt.tight_layout()
plt.show()
```



In [12]:
```
#f)Obtain projections of the test set by projecting the scaled test data on the same PCA
# space produced by the training set in Task 1

testingData = pca.fit(scaled_trainData).transform(scaled_testData)
```

In [13]:
```
plt.scatter(testingData[:,0],testingData[:,1], c=testLabels,  marker="o", edgecolor="none", alpha=0.5)
```
Out[13]: <matplotlib.collections.PathCollection at 0x21278e5f400>



Appendix B: Task 2

Task 2

In [14]:
```
#a)Divide the training dataset into a smaller training set (II)
#and a validation set using the train test split tfunction and report the number of points in each set.
#Usually, we use 20%-30% of the total data points in the whole training set as the validation data.
# It is your choice on how to set the exact ratio

from sklearn.model_selection import train_test_split

SXtrain, Xvalid, Sytrain, vtest = train_test_split(trainInputs, trainLabels, test_size =0.25, random_state=42)

print('The size of the smaller training set is:', SXtrain.shape)
print('The size of the validation set is: ', Xvalid.shape)
```

```
The size of the smaller training set is: (750, 12)
The size of the validation set is:  (250, 12)
```

In [15]:
```
#b) Normalise both the training set (II) and the validation set

scaler_s = preprocessing.StandardScaler().fit(SXtrain)

scaled_trnX = scaler_s.transform(SXtrain)
scaled_valX = scaler_s.transform(Xvalid)
```

Appendix C: Task 3

TASK 3

In [16]:
```
# i) Choosing the most suitable parameters

from sklearn.svm import SVC
from sklearn import metrics

#  [C=50,γ=10]

svc1 = SVC(kernel='rbf', class_weight='balanced', C=50, gamma=10)

model1 = svc1.fit(scaled_trnX, Sytrain)

vyfit1 = model1.predict(scaled_valX)

print('Accuracy:', metrics.accuracy_score(vtest, vyfit1))
```
```
Accuracy: 0.772
```

In [17]:
```
#  [C=50,γ=20]

svc2 = SVC(kernel='rbf', class_weight='balanced', C=50, gamma=20)

model2 = svc2.fit(scaled_trnX, Sytrain)

vyfit2 = model2.predict(scaled_valX)

print('Accuracy:', metrics.accuracy_score(vtest, vyfit2))
```
```
Accuracy: 0.52
```

In [18]:
```
# [C=100,γ=10],

svc3 = SVC(kernel='rbf', class_weight='balanced', C=100, gamma=10)

model3 = svc3.fit(scaled_trnX, Sytrain)

vyfit3 = model3.predict(scaled_valX)

print('Accuracy:', metrics.accuracy_score(vtest, vyfit3))
```
```
Accuracy: 0.772
```

In [19]:
```
# [C=100,γ=20]

svc4 = SVC(kernel='rbf', class_weight='balanced', C=100, gamma=20)

model4 = svc4.fit(scaled_trnX, Sytrain)

vyfit4 = model4.predict(scaled_valX)

print('Accuracy:', metrics.accuracy_score(vtest, vyfit4))
```
```
Accuracy: 0.52
```

In [20]:
```
from sklearn.metrics import classification_report

# 2 combinations have the best accuracy [C=50,γ=10] and [C=100,γ=10]
# reported 1 combination only [c=50, γ=10]

print(classification_report(vtest, vyfit1, trainLabels))
```

```
              precision    recall  f1-score   support

           1       0.60      1.00      0.75        85
           2       1.00      0.65      0.79        78
           1       0.60      1.00      0.75        85
           2       1.00      0.65      0.79        78
           3       1.00      0.66      0.79        87
           2       1.00      0.65      0.79        78
           3       1.00      0.66      0.79        87
           3       1.00      0.66      0.79        87
           3       1.00      0.66      0.79        87
           3       1.00      0.66      0.79        87
           2       1.00      0.65      0.79        78
           2       1.00      0.65      0.79        78
           1       0.60      1.00      0.75        85
           3       1.00      0.66      0.79        87
           2       1.00      0.65      0.79        78
           1       0.60      1.00      0.75        85
           3       1.00      0.66      0.79        87
           1       0.60      1.00      0.75        85
```

In [21]:
```
scaler = preprocessing.StandardScaler().fit(trainInputs)

scaledX = scaler.transform(trainInputs)
scaledTestx = scaler.transform(testInputs)
```

In [22]:
```
svc_final = SVC(kernel='rbf', class_weight='balanced', C=50, gamma=10)

model_final = svc_final.fit(scaledX, trainLabels)
yfit_test = model_final.predict(scaledTestx)
print('Accuracy:', metrics.accuracy_score(testLabels, yfit_test))
```

```
Accuracy: 0.8666666666666667
```

In [23]:
```
# b) Advanced task - non-linear classification with features reduced using PCA
# Choosing the number of components
# i) Looking at the scree plot which you have produced in Task 1 (d),
# how many prin-cipal components (PCs) you would like to use to do feature reduction? Explain thereason

# Answer = 3 principle components because at 1-3 covers most variances. Every component after that does not cover enough

# ii) Reduce features for both the normalised training set (I)
# and the normalised test setusing the PCA result from Task 1 with the number of principal components you
# have decided to use

reduced_feature_data_train = trainingData[:,:3]
reduced_feature_data_test = testingData[:,:3]

print('The size of the reduced feature training set is:', reduced_feature_data_train.shape)
print('The size of the reduced feature test set is:', reduced_feature_data_test.shape)
```

```
The size of the reduced feature training set is: (1000, 3)
The size of the reduced feature test set is: (300, 3)
```

In [24]:
```
print('train',reduced_feature_data_train)
print('test',reduced_feature_data_test)
```

```
train [[ 1.7525665   0.24970251 -1.23222812]
 [-2.80600794  0.67677533 -1.32311273]
 [ 0.58384047 -0.82271245 -0.08518155]
 ...
 [ 1.73913261 -1.20691542  1.72647523]
 [-0.72489913 -1.88007675 -0.3545893 ]
 [-2.67630836  1.05240255 -0.64298981]]
test [[ 7.12443270e-01 -1.32568728e+00  1.72059080e+00]
 [-3.21505348e+00  8.54866223e-01 -8.57377169e-01]
 [-5.36977104e+00 -8.83424069e-01  1.94392382e+00]
 [-4.77792336e+00  4.72568582e-01  1.05097797e-01]
 [-1.57117374e-01 -1.01009095e+00  1.12396519e+00]
 [ 4.80118273e-01  2.46046661e+00  1.22738036e+00]
 [-9.93451623e-01 -6.69202743e-01  3.43355026e-01]
 [ 5.16895693e-01  5.09294231e-01 -2.23699367e+00]
 [ 1.09034164e+00 -4.13170214e-01 -2.54637449e-01]
 [ 7.80183789e-01 -6.90292164e-02 -6.23129451e-01]
 [ 7.73170755e-01  2.76963918e+00  1.08902557e+00]
 [-1.60635807e+00  1.31416804e-01 -8.80042199e-01]
 [ 2.55259283e+00 -2.07549288e+00  1.50205999e-01]
```

In [25]:
```
# iii) Do the classification using the Gaussian radial basis kernel SVM with parametervalues selected in Task 3 (a)
scaler_R = preprocessing.StandardScaler().fit(reduced_feature_data_train)
scaled_trainDataR = scaler_R.transform(reduced_feature_data_train)
scaled_testDataR = scaler_R.transform(reduced_feature_data_test)
```

In [26]:
```
svc_reduced_features = SVC(kernel='rbf', class_weight='balanced', C=50, gamma=10)

model_reduced_features = svc_reduced_features.fit(scaled_trainDataR, trainLabels)
yfit_test_R = model_reduced_features.predict(scaled_testDataR)
print('Accuracy:', metrics.accuracy_score(testLabels, yfit_test_R))
```

```
Accuracy: 0.9133333333333333
```