aml_hw4_task3_4

April 4, 2018

```
In [167]: import scipy.io as sio
          import pandas as pd
          import numpy as np
          import matplotlib.pyplot as plt
          % matplotlib inline
          #plt.rcParams["figure.dpi"] = 300
          np.set_printoptions(precision=3, suppress=True)
```

1 Task 1

```
In [12]: data = sio.loadmat("annthyroid.mat")
```

```
In [13]: X_data = pd.DataFrame(data["X"])
         y_data = pd.DataFrame(data["y"])
```

```
In [14]: from sklearn.preprocessing import StandardScaler
         scaler = StandardScaler()
         X_sc = scaler.fit_transform(X_data)
```

```
In [15]: y_sc = np.array(y_data)
```

```
In [16]: y_sc = y_sc.reshape(7200,)
```

```
In [19]: y_sc.shape
```

```
Out[19]: (7200,)
```

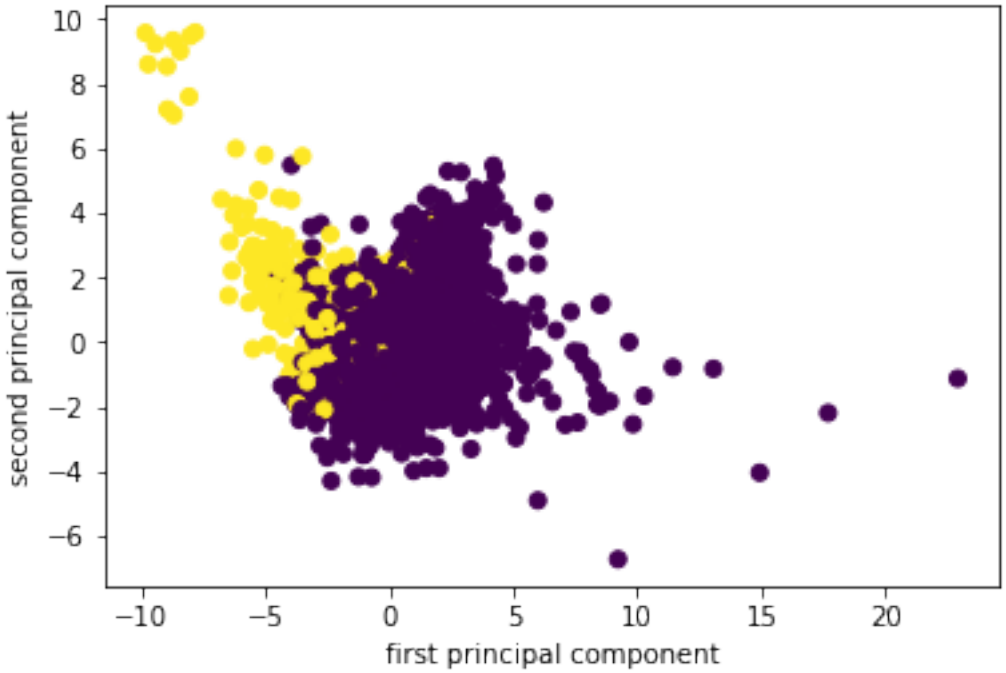
```
In [161]: from sklearn.decomposition import PCA
          import matplotlib.pyplot as plt
          %matplotlib
          #print(cancer.data.shape)
          pca = PCA(n_components=2)
          X_pca = pca.fit_transform(X_sc)
```

```
Using matplotlib backend: TkAgg
```

```
In [8]: print(X_pca.shape)
        print(y_data.shape)
```

```
(7200, 2)
(7200, 1)
```

```
In [9]: plt.scatter(X_pca[:, 0], X_pca[:, 1], c = y_sc)
        plt.xlabel("first principal component")
        plt.ylabel("second principal component")
        components = pca.components_
        #plt.imshow(components.T)
        #plt.yticks(range(len(y_data.columns)), y_data.columns)
        #plt.colorbar()
```



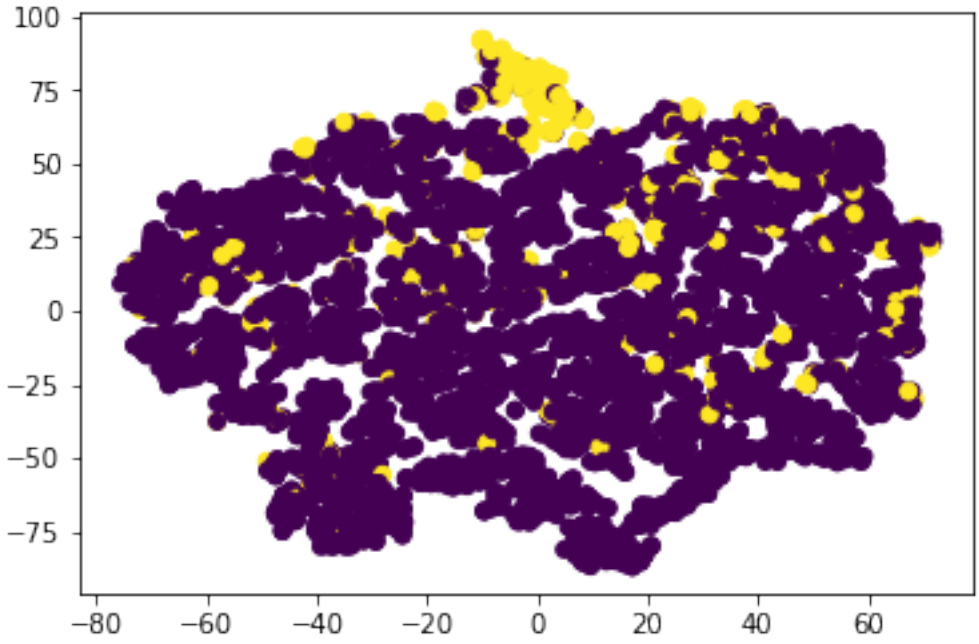

```
In [207]: from sklearn.manifold import TSNE
          #from sklearn.datasets import load_digits
          #digits = load_digits()
          #X = digits.data / 16.
          X_tsne = TSNE().fit_transform(X_sc)
          #X_pca = PCA(n_components=2).fit_transform(X_sc)

In [208]: X_tsne

Out[208]: array([[ 60.845, -18.318],
                 [-39.394, -51.906],
                 [  4.52 , -37.725],
                 ...,
```

```
                [  0.374,  30.941],
                [-59.743,  24.545],
                [ 16.716,  49.189]], dtype=float32)
```

In [ ]:

In [209]:
```
plt.scatter(X_tsne[:, 0], X_tsne[:, 1], c = y_sc)
#plt.xlabel("first principal component")
#plt.ylabel("second principal component")
```

Out[209]: <matplotlib.collections.PathCollection at 0x7f7592fc0c18>



In [27]:
```
X_sc
```

Out[27]:
```
array([[ 1.107, -0.185, -0.66 ,  0.294, -0.83 ,  0.908],
       [-1.482, -0.201,  1.33 ,  0.933,  1.843, -0.144],
       [-0.267, -0.129,  0.534, -0.207,  1.738, -0.976],
       ...,
       [-0.056, -0.178,  0.016, -0.54 , -1.616,  0.576],
       [-0.901, -0.09 ,  0.016, -0.54 , -0.463, -0.338],
       [ 1.107, -0.187,  0.016, -0.79 , -0.411, -0.643]])
```

In [ ]:

In [ ]:

2 Task 3 Outlier Detection

2.0.1 3.1

```
In [37]: #Since we can assume that we know the proportion of outliers in the data
         print("Actual proportion of outliers in the data: ", np.mean(y_sc))
```

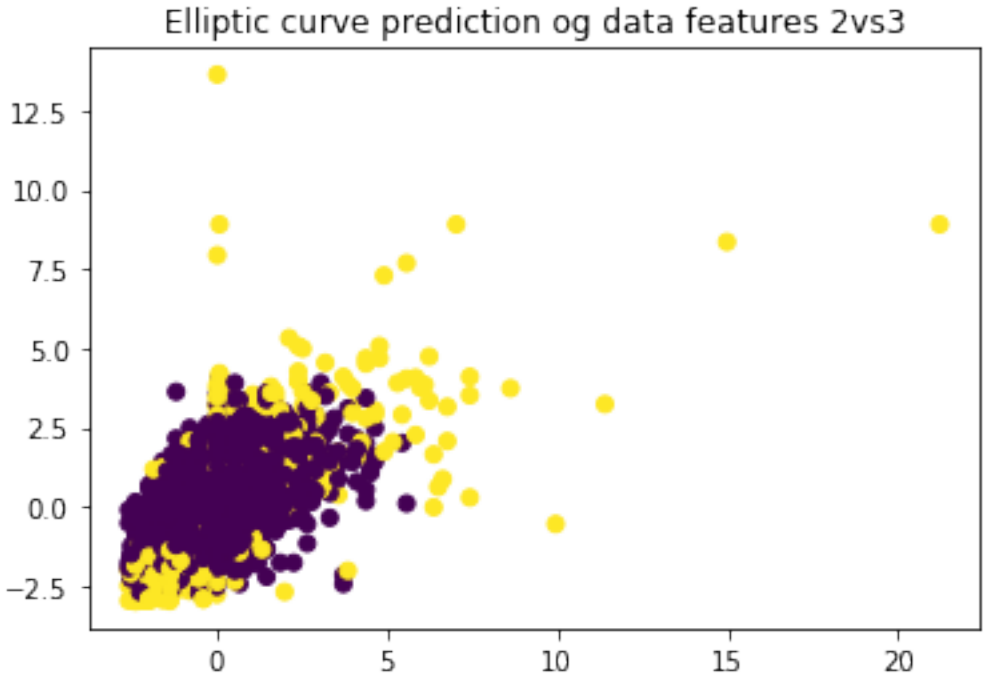
```
Actual proportion of outliers in the data:  0.07416666666666667
```

```
In [158]: from sklearn.covariance import EllipticEnvelope
          ee = EllipticEnvelope(contamination=0.07416666666666667).fit(X_sc)
          pred_ee = ee.predict(X_sc)
          print(pred_ee)
          print("Predicted proportion of outliers in the data using Elliptic Envelope: ", np.mea
```

```
[1 1 1 ... 1 1 1]
Predicted proportion of outliers in the data using Elliptic Envelope:  0.07416666666666667
```

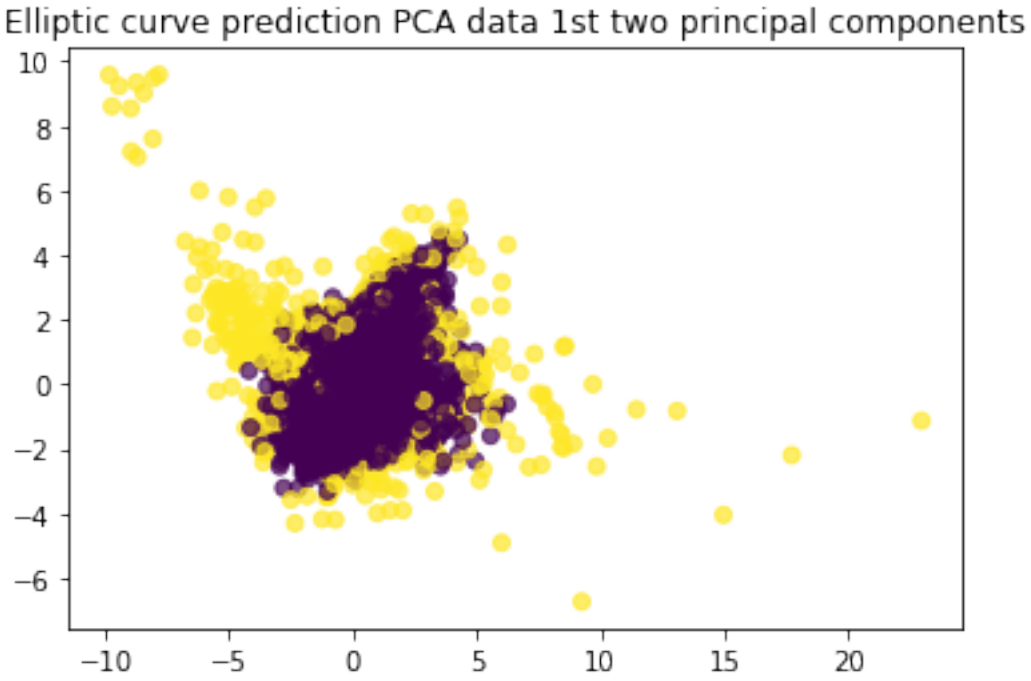
```
In [211]: plt.title("Elliptic curve prediction og data features 2vs3")
          plt.scatter(X_sc[:, 2], X_sc[:, 3], c=pred_ee)
```

```
Out[211]: <matplotlib.collections.PathCollection at 0x7f7592f5bf98>
```

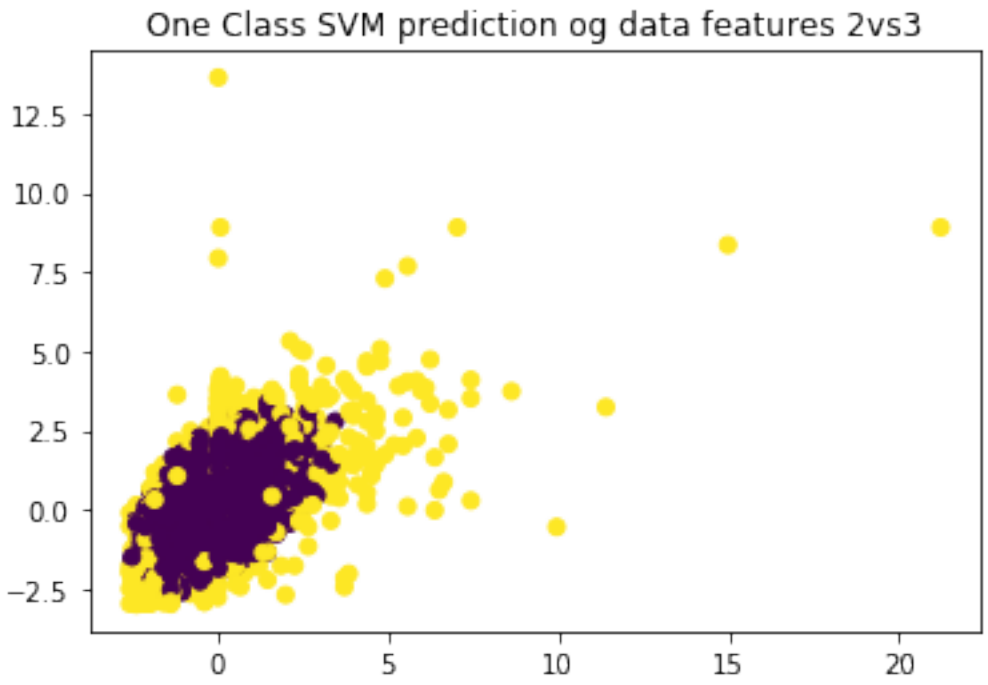



```
In [212]: plt.title("Elliptic curve prediction PCA data 1st two principal components")
          plt.scatter(X_pca[:, 0], X_pca[:, 1], c=pred_ee, alpha = 0.7)
```

```
Out[212]: <matplotlib.collections.PathCollection at 0x7f7592efaac8>
```

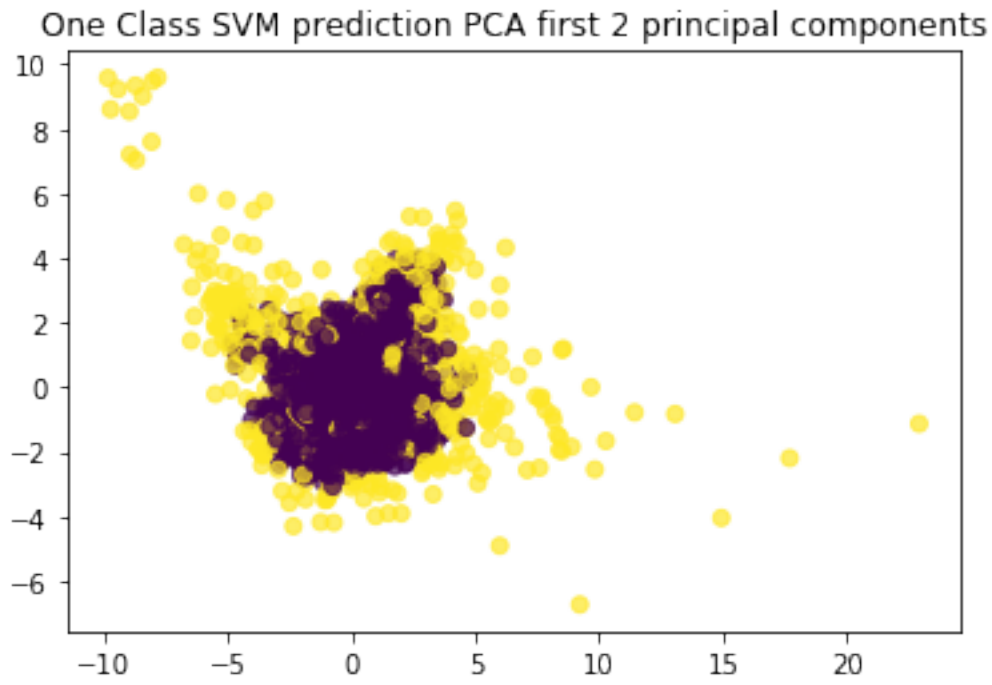



```
In [68]: from sklearn.svm import OneClassSVM
         oneclass = OneClassSVM(nu=0.07416666666666667).fit(X_sc)
         pred_oc = oneclass.predict(X_sc)

In [50]: np.mean(pred_oc == -1)

Out[50]: 0.07458333333333333

In [213]: plt.title("One Class SVM prediction og data features 2vs3")
          plt.scatter(X_sc[:, 2], X_sc[:, 3], c=pred_oc)

Out[213]: <matplotlib.collections.PathCollection at 0x7f7592efafd0>
```

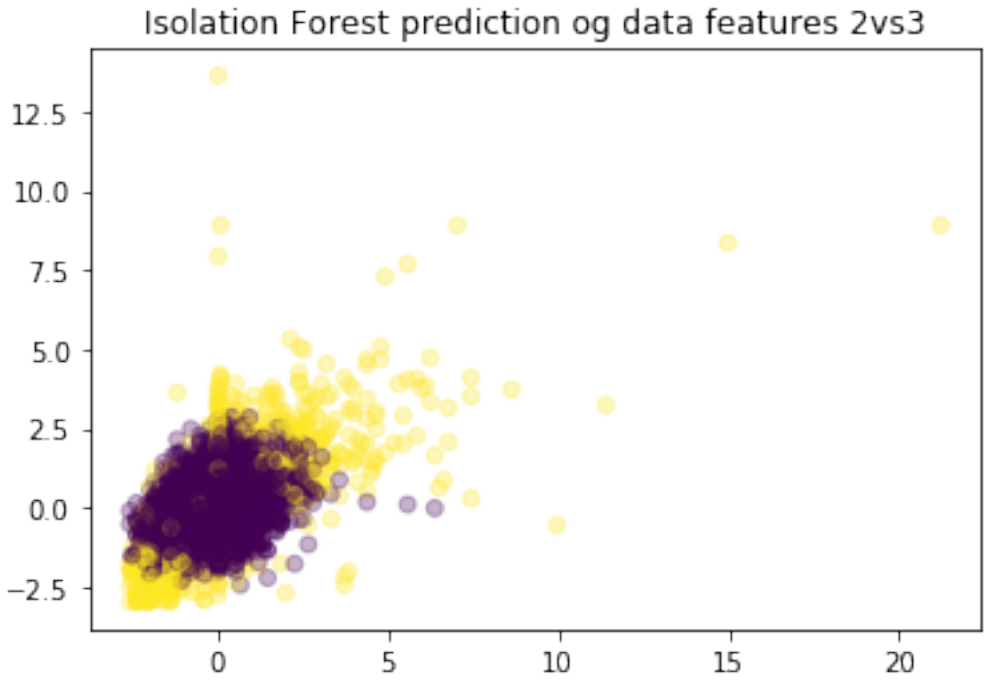



```
In [217]: plt.title("One Class SVM prediction PCA first 2 principal components")
          plt.scatter(X_pca[:, 0], X_pca[:, 1], c=pred_oc, alpha =0.7)
```

```
Out[217]: <matplotlib.collections.PathCollection at 0x7f7592e052b0>
```

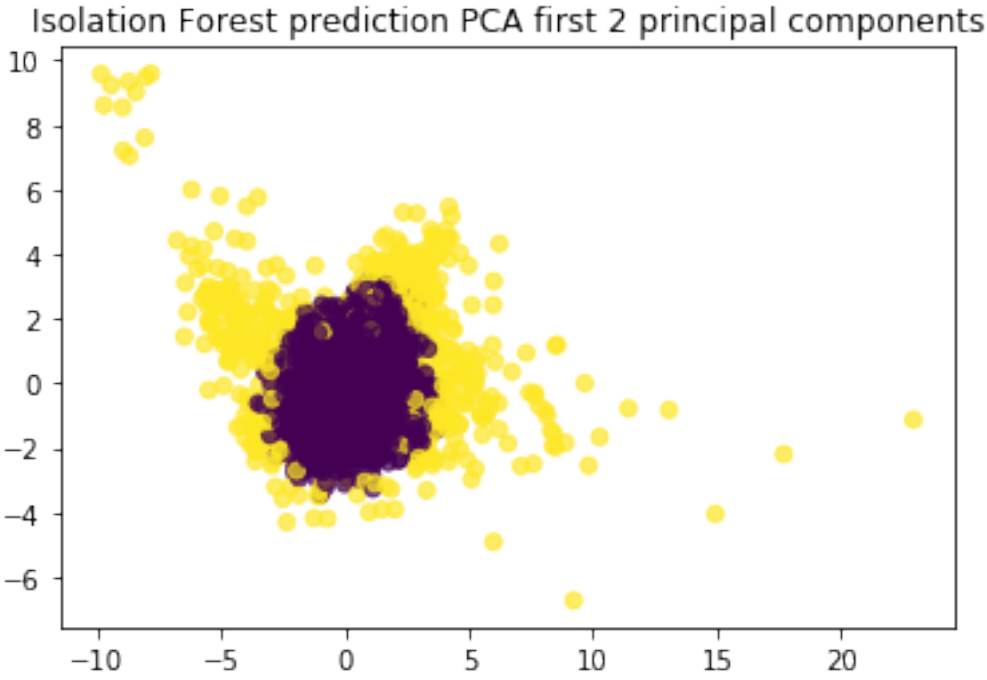


```
In [52]: from sklearn.ensemble import IsolationForest

In [110]: ifr = IsolationForest(contamination=0.07416666666666667)

In [111]: ifr.fit(X_sc)

Out[111]: IsolationForest(bootstrap=False, contamination=0.07416666666666667,
                  max_features=1.0, max_samples='auto', n_estimators=100, n_jobs=1,
                  random_state=None, verbose=0)

In [112]: pred_if = ifr.predict(X_sc)

In [113]: np.mean(pred_if == -1)

Out[113]: 0.07416666666666667

In [216]: plt.title("Isolation Forest prediction og data features 2vs3")
          plt.scatter(X_sc[:, 2], X_sc[:, 3], c=pred_if, alpha = 0.3)

Out[216]: <matplotlib.collections.PathCollection at 0x7f7592e78b38>
```




```
In [218]: plt.title("Isolation Forest prediction PCA first 2 principal components")

          plt.scatter(X_pca[:, 0], X_pca[:, 1], c=pred_if, alpha = 0.7)
```

```
Out[218]: <matplotlib.collections.PathCollection at 0x7f7592e05cc0>
```



2.0.2 Without using the ground truth we cannot really gauge how good an outlier detection algorithm works as the visualizing the predictions of all three models on X_pca leads to similar looking plots. Not much can be inferred from them

```
In [219]: ee.decision_function(X_sc)

Out[219]: array([2.553, 2.419, 1.104, ..., 2.056, 3.501, 3.143])

In [220]: oneclass.decision_function(X_sc)

Out[220]: array([[ 9.077],
                 [ 5.277],
                 [ 7.151],
                 ...,
                 [ 9.115],
                 [11.846],
                 [ 8.598]])

In [221]: ifr.decision_function(X_sc)

Out[221]: array([0.113, 0.053, 0.093, ..., 0.103, 0.137, 0.132])
```

As we can see only the Isolation Forest decision function provides output values between 0 and 1

2.0.3 3.2

```
In [65]: from sklearn.metrics import average_precision_score
```

```
In [ ]: for i in range(len(y_sc)):
            #print(y_sc[i])

        for i in range(len(y_sc)):
            if(pred_ee[i] == 1):
                pred_ee[i] = 0

            else:
                pred_ee[i] = 1
            print(pred_ee[i])

        for i in range(len(y_sc)):
            if(pred_oc[i] == 1):
                pred_oc[i] = 0

            else:
                pred_oc[i] = 1
            print(pred_oc[i])

        for i in range(len(y_sc)):
            if(pred_if[i] == 1):
                pred_if[i] = 0

            else:
                pred_if[i] = 1
            print(pred_if[i])
```

```
In [230]: average_precision_ee = average_precision_score(y_sc, pred_ee)
          average_precision_oc = average_precision_score(y_sc, pred_oc)
          average_precision_if = average_precision_score(y_sc, pred_if)


          print('Elliptic Envelope Average precision-recall score: {0:0.2f}'.format(
                average_precision_ee))

          print('One Class SVM Average precision-recall score: {0:0.2f}'.format(
                average_precision_oc))

          print('Isolation Forest Average precision-recall score: {0:0.2f}'.format(
                average_precision_if))
```

```
Elliptic Envelope Average precision-recall score: 0.25
One Class SVM Average precision-recall score: 0.11
Isolation Forest Average precision-recall score: 0.15
```

```
In [121]: average_precision_ee = average_precision_score(y_sc, pred_ee)
          average_precision_oc = average_precision_score(y_sc, pred_oc)
          average_precision_if = average_precision_score(y_sc, pred_if)


          print('Elliptic Envelope Average precision-recall score: {0:0.2f}'.format(
                average_precision_ee))

          print('One Class SVM Average precision-recall score: {0:0.2f}'.format(
                average_precision_oc))

          print('Isolation Forest Average precision-recall score: {0:0.2f}'.format(
                average_precision_if))
```

```
Elliptic Envelope Average precision-recall score: 0.25
One Class SVM Average precision-recall score: 0.11
Isolation Forest Average precision-recall score: 0.15
```

```
In [122]: from sklearn.metrics import roc_auc_score
          from sklearn.metrics import zero_one_loss
          ee_auc = roc_auc_score(y_sc, pred_ee)
          oc_auc = roc_auc_score(y_sc, pred_oc)
          if_auc = roc_auc_score(y_sc, pred_if)

          ee_loss = zero_one_loss(y_sc, pred_ee)
          oc_loss = zero_one_loss(y_sc, pred_oc)
          if_loss = zero_one_loss(y_sc, pred_if)

          print("AUC for Elliptic Envelope is ", ee_auc)
          print("AUC for One Class SVM: ", oc_auc)
          print("AUC for Isolated Forest: ", if_auc)


          print("Zero-one loss for Elliptic Envelope is ", ee_loss)
          print("Zero-one loss for One Class SVM: ", oc_loss)
          print("Zero-one loss for Isolated Forest: ", if_loss)
```

```
AUC for Elliptic Envelope is  0.7077235813468987
AUC for One Class SVM:  0.5841154340153115
AUC for Isolated Forest:  0.6288392884232243
Zero-one loss for Elliptic Envelope is  0.08027777777777778
Zero-one loss for One Class SVM:  0.11458333333333337
Zero-one loss for Isolated Forest:  0.1019444444444444
```

2.0.4 The AUC and average precision readings suggest that EllipticEnvelope is the best

The clustering approaches from task 2 yield poor results with in some cases 3 clusters giving the best results. Thus, the approaches in Task 3 which assume the additional information that you know the number of classes and their proportion gives better results

However comaparing the visualzations in Task 3 with the ground truth clustering of the PCA visualization in Task 1 we notice that even Task 3 is quite off. Therefore there is no tangible way of comparing one model from another without knowing the ground truth and just via visualization. This could be the result of the data being highly non Gaussian

3 Task 4

```
In [191]: from sklearn.model_selection import train_test_split
          X_train, X_test, y_train, y_test = train_test_split(X_sc, y_sc, stratify = y_sc)
```

Imbalanced Learning

```
In [195]: from sklearn.model_selection import cross_validate
          from sklearn.linear_model import LogisticRegression
          scores = cross_validate(LogisticRegression(),
                                  X_sc, y_sc, cv=10, scoring=('roc_auc', 'average_precision'))
          scores['test_roc_auc'].mean(), scores['test_average_precision'].mean()

Out[195]: (0.9726447870177892, 0.7637355829525652)

In [196]: from sklearn.ensemble import RandomForestClassifier
          scores = cross_validate(RandomForestClassifier(n_estimators=100),
                                  X_sc, y_sc, cv=10, scoring=('roc_auc', 'average_precision'))
          scores['test_roc_auc'].mean(), scores['test_average_precision'].mean()

Out[196]: (0.9957853471700322, 0.9321881275718397)
```

Balanced weights

```
In [197]: scores = cross_validate(LogisticRegression(class_weight='balanced'),
                                  X_sc, y_sc, cv=10, scoring=('roc_auc', 'average_precision'))
          print("Test ROC AUC for Logistic :", scores['test_roc_auc'].mean(),"| Average Precisio

Test ROC AUC for Logistic : 0.9884794372602356 | Average Precision for Logistic:  0.828698915304


In [198]: scores = cross_validate(RandomForestClassifier(n_estimators=100, class_weight='balance
                                  X_sc, y_sc, cv=10, scoring=('roc_auc', 'average_precision'))
          print("Test ROC AUC for Random Forest :", scores['test_roc_auc'].mean(),"| Average Pre

Test ROC AUC for Random Forest : 0.9957258147797312 | Average Precision for Random Forest:  0.92
```

Grid Searching C for LogReg and other pruning parameters for the trees

```
In [133]: from sklearn.model_selection import GridSearchCV

In [134]: param_grid_rf = {

              'max_depth': [80, 90, 100, 110],
              'max_features': [2, 3],

              'n_estimators': [100, 200, 300, 1000]
          }

In [135]: rf_grid = GridSearchCV(RandomForestClassifier(), param_grid=param_grid_rf, cv=3)

In [136]: rf_grid.fit(X_train,y_train)

Out[136]: GridSearchCV(cv=3, error_score='raise',
                 estimator=RandomForestClassifier(bootstrap=True, class_weight=None, criterion='
                      max_depth=None, max_features='auto', max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=1,
                      oob_score=False, random_state=None, verbose=0,
                      warm_start=False),
                 fit_params=None, iid=True, n_jobs=1,
                 param_grid={'max_depth': [80, 90, 100, 110], 'max_features': [2, 3], 'n_estimat
                 pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
                 scoring=None, verbose=0)

In [137]: rf_grid.score(X_test,y_test)

Out[137]: 0.9833333333333333

In [143]: print("AUC for RF is ", roc_auc_score(y_test, rf_grid.predict(X_test)))
          print("Avg Precision for RF : ", average_precision_score(y_test, rf_grid.predict(X_tes

AUC for RF is  0.9737045072188569
Avg Precision for RF :  0.8079279080053073


In [199]: param_grid_lr = {

              'C': [ 0.1, 1,2,5 ,10,100]
          }

In [200]: lr_grid = GridSearchCV(LogisticRegression(), param_grid=param_grid_lr, cv=10)

In [201]: lr_grid.fit(X_train,y_train)
```

```
Out[201]: GridSearchCV(cv=10, error_score='raise',
                  estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercep
                     intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
                     penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
                     verbose=0, warm_start=False),
                  fit_params=None, iid=True, n_jobs=1,
                  param_grid={'C': [0.1, 1, 2, 5, 10, 100]}, pre_dispatch='2*n_jobs',
                  refit=True, return_train_score='warn', scoring=None, verbose=0)

In [202]: lr_grid.score(X_test,y_test)

Out[202]: 0.9533333333333334

In [206]: print("AUC for LogReg is ", roc_auc_score(y_test, lr_grid.predict(X_test)))
          print("Avg Precision for LogReg : ", average_precision_score(y_test, lr_grid.predict(X

AUC for LogReg is  0.7208793965347333
Avg Precision for LogReg :  0.4249064202795546
```

3.0.1 Changing to balanced weights gives the best avg precision and recall scores. So yes. It helps

```
In [ ]:
```