



ELG 5142: Ubiquitous Sensing / Smart Cities Assignment 3

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1. Models and model Results:

A. SVM model:

```
ML_Model_svm = create_model('svm')
anomalies_svm = assign_model(ML_Model_svm)
```

```
results = anomalies_svm.iloc[:,:-2]
anomalies = anomalies_svm[anomalies_svm['Anomaly'] == 1].iloc[:,:-2]
results = anomalies_svm.iloc[:,:-2]
anomalies = anomalies_svm[anomalies_svm['Anomaly'] == 1].iloc[:,:-2]
anomalies.head()
for column in results.columns[1:]:
    plt.plot(anomalies_svm[column])
    plt.scatter(anomalies.index,anomalies[column],c='r',marker='o',s=60,
alpha=1)
    plt.title(" ".join(column.split('_')))
    plt.show()
```

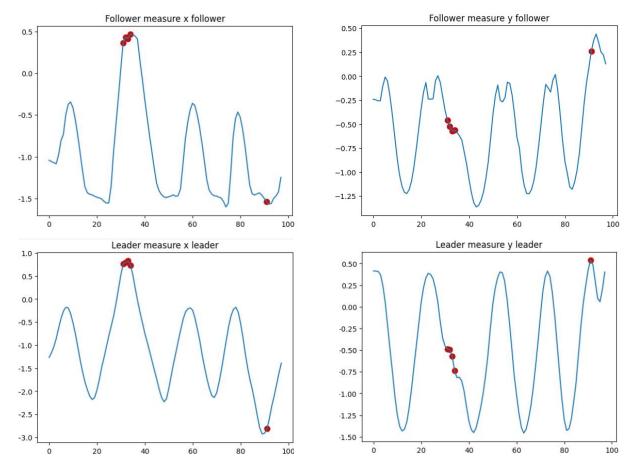


Figure 1 Plot charts of SVM

B. KNN model:

```
ML_Model_knn = create_model('knn')
anomalies_knn = assign_model(ML_Model_knn)
```

```
results = anomalies_knn.iloc[:,:-2]
anomalies = anomalies_knn[anomalies_knn['Anomaly'] == 1].iloc[:,:-2]

for column in results.columns[1:]:
    plt.plot(anomalies_knn[column])
    plt.scatter(anomalies.index,anomalies[column],c='r',marker='o',s=60,
alpha=1)
    plt.title(" ".join(column.split('_')))
    plt.show()
```

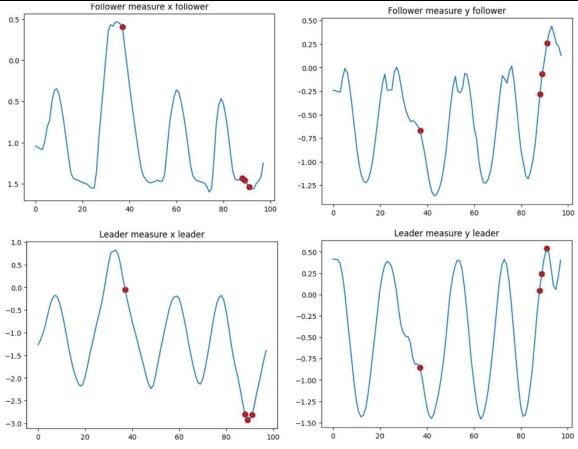


Figure 2 Plot charts of KNN

C. PCA model:

```
ML_Model_pca = create_model('pca')
anomalies_pca = assign_model(ML_Model_pca)
```

```
results = anomalies_pca.iloc[:,:-2]
anomalies = anomalies_pca[anomalies_pca['Anomaly'] == 1].iloc[:,:-2]

for column in results.columns[1:]:
    plt.plot(anomalies_pca[column])
    plt.scatter(anomalies.index,anomalies[column],c='r',marker='o',s=60,
    alpha=1)
    plt.title(" ".join(column.split('_')))
    plt.show()
```

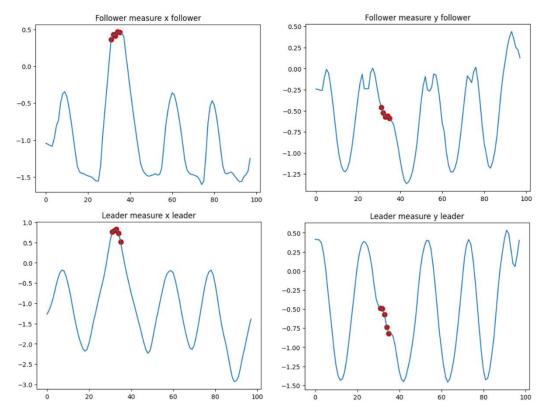
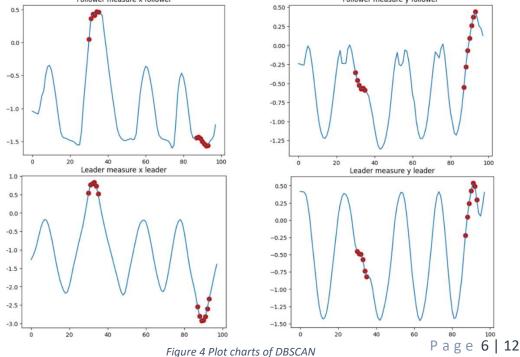


Figure 3 Plot charts of PCA

D. DBSCAN model:

To choose the values of epsilon and minpoints for DBSCAN model, a simple hyperparameter search is done to get the parameters that will make the model give the highest F1 score.

```
best pred=None
best=0
for eps in np.arange(0.1, 0.75, 0.01):
  for ms in range (2, 16):
    db = DBSCAN(eps=eps, min samples=ms)
    predLabels = db.fit predict(X)
    predLabels[predLabels != -1]=0
    predLabels[predLabels ==-1]=1
    acc=f1 score(y,predLabels)
         if (best<=acc):</pre>
      best pred=predLabels
      best=acc
df2=df2.iloc[:,:-1]
anomalies DBSC=df2.iloc[:,:-1]
anomalies DBSC['Anomaly'] = best pred
for column in results.columns[1:]:
    plt.plot(anomalies DBSC[column])
    plt.scatter(anomalies.index, anomalies[column], c='r', marker='o', s=60,
alpha=1)
    plt.title(" ".join(column.split(' ')))
    plt.show()
                    Follower measure x follower
                                                       Follower measure y follower
                                              0.25
```



2. TSNE plots:

A. SVM model:

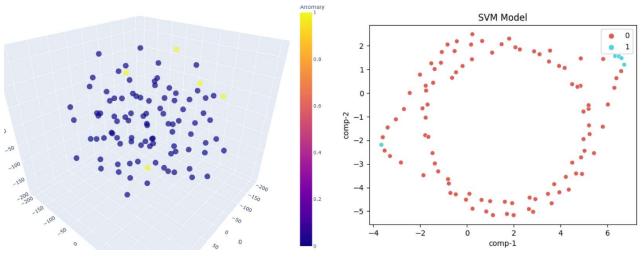
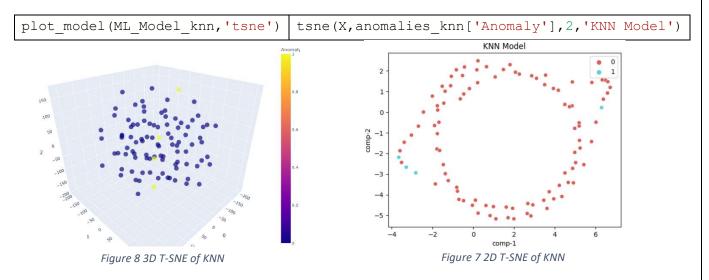


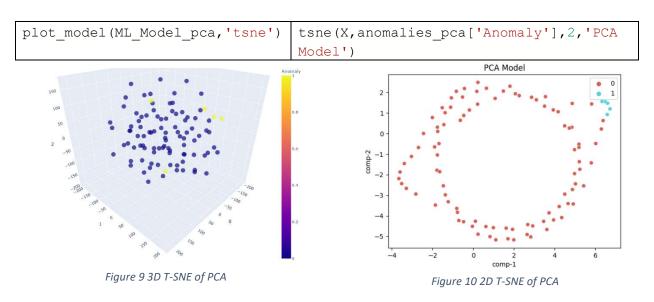
Figure 6 3D T-SNE of SVM

Figure 5 2D T-SNE of SVM

B. KNN model:



C. PCA model:



D. DBSCAN model:

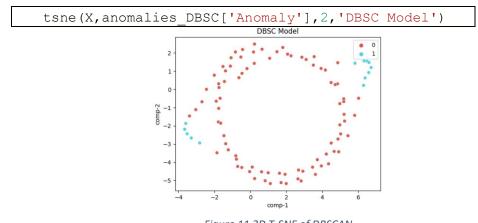


Figure 11 2D T-SNE of DBSCAN

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3. Performance evaluation results:

```
def eval(y_test,y_pred):
  acc=accuracy_score(y_test,y_pred)
 print("
               ")
  print("The Test acceracy :",acc)
 print("
               ")
  print(classification_report(y_test,y_pred))
               ")
 pr,re,fc,c=precision recall fscore support(y test, y pred, avera
ge='macro')
 pr1,re1,fc1,c=precision_recall_fscore_support(y_test, y_pred, av
erage='weighted')
 print("The macro precision on test data is :",pr)
  print("The weighted precision on test data is :",pr1)
  print("
              ")
  print("The macro recall on test data is :",re)
 print("The weighted recall on test data is :",re1)
  print("_____
  print("The macro f score on test data is :",fc)
  print("The weighted f score on test data is :",fc1)
 print("
  cm = confusion_matrix(y_test,y_pred)
  ConfusionMatrixDisplay(confusion matrix=cm).plot()
 plt.show()
```

A. SVM model:

eval(df2['labels'],anomalies svm['Anomaly']) The Test accuracy : 0.9285714285714286

	precision	recall	f1-score	support		
0.0	0.92	1.00	0.96	86		
1.0	1.00	0.42	0.59	12		
racy			0.93	98		
avg	0.96	0.71	0.77	98		
avg	0.93	0.93	0.92	98		
		0.704.50	10505055			
	1.0 racy avg avg	0.0 0.92 1.0 1.00 racy avg 0.96 avg 0.93	0.0 0.92 1.00 1.0 1.00 0.42 racy avg 0.96 0.71 avg 0.93	0.0 0.92 1.00 0.96 1.0 1.00 0.42 0.59 racy 0.96 0.71 0.77 avg 0.93 0.93 0.92	0.0 0.92 1.00 0.96 86 1.0 1.00 0.42 0.59 12 racy 0.96 0.71 0.77 98	0.0 0.92 1.00 0.96 86 1.0 1.00 0.42 0.59 12 racy 0.93 98 avg 0.96 0.71 0.77 98

The macro recall on test data is : 0.708333333333334
The weighted recall on test data is : 0.9285714285714286

The macro f_score on test data is : 0.7745645744331251
The weighted f_score on test data is : 0.9152621942631801

Figure 12 Classification Report of SVM

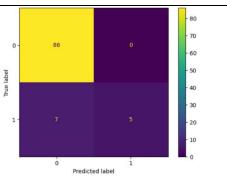


Figure 13 Confusion matrix of SVM

B. KNN model:

eval(df2['labels'], anomalies knn['Anomaly'])

		precision	recall	f1-score	support
	0.0	0.90	0.99	0.94	86
	1.0	0.75	0.25	0.38	12
accui	racy			0.90	98
macro	avg	0.83	0.62	0.66	98
weighted	avg	0.89	0.90	0.87	98
					1276595744681 885366912722535
The macro	rec	all on test	data is	: 0.6191860	0465116279
The weigh	nted	recall on te	st data i	s : 0.8979	9591836734694
The macro	o f_s	core on test	data is	: 0.65972	2222222222
		C +	4-4-	: 0 07	47165532879818

Figure 14 Classification Report of KNN

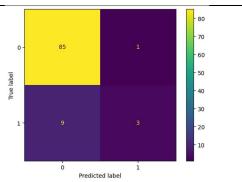


Figure 15 Confusion matrix of KNN

C. PCA model:

eval(df2['labels'], anomalies pca['Anomaly'])

	precision	recall	f1-score	support
0.0	0.92	1.00	0.96	86
1.0	1.00	0.42	0.59	12
accuracy			0.93	98
macro avg	0.96	0.71	0.77	98
weighted avg	0.93	0.93	0.92	98

The macro precision on test data is : 0.9623655913978495 The weighted precision on test data is : 0.93394777265745

The macro recall on test data is : 0.7083333333333334
The weighted recall on test data is : 0.9285714285714286

The macro f_score on test data is : 0.7745645744331251
The weighted f_score on test data is : 0.9152621942631801

Figure 17 Classification Report of PCA

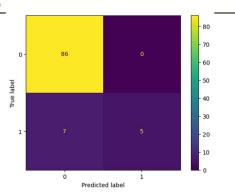
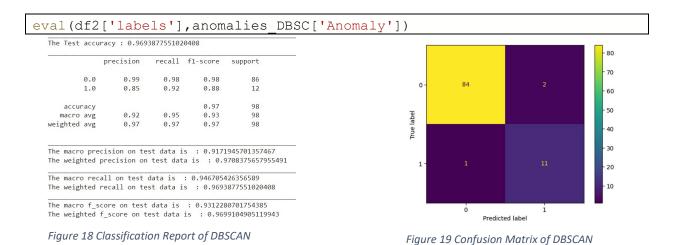


Figure 16 Confusion matrix of PCA

D. DBSCAN model:



4. Conclusive discussions:

From the plots of model results alongside with the data, it's concluded that the outlier is detected based on the values of "leader x" feature and the DBSCAN model is the best model that managed to detect the outliers in both positive and negative extreme values.

Regarding the accuracy, DBSCAN model gave the highest accuracy (96.94%) among all models. KNN model gave the lowest accuracy (89.8%) while SVM and PCA models gave the same accuracy (92.86%).

Regarding the precision for anomaly instances, SVM and PCA models gave the highest precision (100%) among all models. KNN model gave the lowest precision (75%) while DBSCAN model gave a precision of 85%.

Regarding the precision for normal instances, DBSCAN model gave the highest precision (99%) among all models. KNN model gave the lowest precision (90%) while SVM and PCA models gave the same precision (92%).

Regarding the recall for anomaly instances, DBSCAN model gave the highest recall (92%) among all models. KNN model gave the lowest recall (25%) while SVM and PCA models gave the same recall (42%).

Regarding the recall for normal instances, SVM and PCA models gave the highest recall (100%) among all models. DBSCAN model gave the lowest accuracy (98%) while KNN model gave a recall of 99%.

Regarding the F1 score for anomaly instances, DBSCAN model gave the highest score (88%) among all models. KNN model gave the lowest score (38%) while SVM and PCA models gave the same score (59%).

Regarding the F1 score for normal instances, DBSCAN model gave the highest score (98%) among all models. KNN model gave the lowest score (94%) while SVM and PCA models gave the same score (96%).

From the above comparisons, it's concluded that DBSCAN model is the best model for anomaly detection among all models and this performance is predictable as DBSCAN is a density-based clustering algorithm so it's robust to outliers.