Data modification

Data after modification: a small step for modification of data is done where number of features are reduced manullay as per our convinent for better performance.Concatenation of wifi_ascii number and ip_ascii is done with '00' integer in between to differentiate .

```
example
IPAddress                                192.168.1.8
ip_ascii                                         558
wifi_name                                  "B5_1201"
wifi_ascii                                       478
wifiip                                    47800558
```

Concatenation of "start time" number and "usage Time" , first 6 digits represent time

```
StartTime                                   105247
UsageTime                                        1
start_usagetime                           1052471
```

Battery , batterystauts and batterychargingsource are added

Battery is converted to tens i.e.

battery value	after conversion
34%	30
68%	70
Adapter/AC	2
USB	4
No Charging	0

Battery status :

Charging	1
Not Charging	0

Battery charging source

```
Battery                          50
BatteryChargingSource             2
BatteryStatus                     1
BBB                              53
```

To find out the little details about the behaviour of the battery, more constants are put to use. Using the constants BATTERY_STATUS_CHARGING and BATTERY_STATUS_CHARGING, we can find out if the battery is charging or not. If the battery is charging, *BStatus* is set to 1 which is otherwise 0.
To find the power source, if the battery is charging, tow more constants are used. They are BATTERY_PLUGGED_AC and BATTERY_PLUGGED_USB. So, if the device is being charged through an

adapter, *BattPowerSource* is set to 2 and if it's being charged through USB, *BattPowerSouce* is set to 4. If the battery isn't being charged, then the default value of *BattPowerSource* is 0. The end results helps us In easy break down to figure out all the 3 features .

Data Representation

Data read from json file: Data has been read from the json file and data frames created this is a small example of how the data looks under following circumstances .

	Acc_x	Acc_y	Acc_z	Battery	BatteryChargingSource
0	0.693868	0.726671	0.720240	17	0
1	0.693868	0.726671	0.720240	17	0
2	0.693868	0.726671	0.720240	17	0
3	0.693868	0.726671	0.720240	17	0
4	0.693868	0.726671	0.720240	17	0
5	0.693868	0.726671	0.720240	17	0
6	0.693868	0.726671	0.720240	17	0
7	0.223644	1.520575	3.491794	93	4
8	0.184751	1.218227	4.805725	93	4
9	0.184751	1.218227	4.805725	93	4
10	0.351918	0.965198	3.758030	93	4

	BatteryStatus	ClickEventID0
0	0	[Play video]
1	0	[Play video]
2	0	[Play video]
3	0	[Play video]
4	0	[Play video]
5	0	[Play video]
6	0	[Play video]
7	0	[1, Play Store]
8	0	NaN
9	0	[My Files]
10	0	[Internal storage, 35.42 GB / 64.00 GB]

	RKB	StartTime	TKB	TapCount	NoOfClickEvents	UTC
0	6513506	00:10:15	461335	0	1	1544208226110
1	6513506	00:10:15	461335	0	1	1544208226110
2	6513506	00:10:15	461335	0	1	1544208226110
3	6513506	00:10:15	461335	0	1	1544208226110
4	6513506	00:10:15	461335	0	1	1544208226110
5	6513506	00:10:15	461335	0	1	1544208226110
6	6513506	00:10:15	461335	0	1	1544208226110
7	1	16:52:25	0	4	1	1544181754889
8	6132948	16:52:34	446096	3	0	1544181758184
9	2	16:52:38	0	1	1	1544181759915
10	6132950	16:52:39	446098	10	3	1544181776183

	UsageTime	latitude	longitude	meanAcc_x	meanAcc_y	meanAcc_z	\
0	25	12.922172	77.492920	0.007397	-0.008721	9.811530	
1	25	12.922172	77.492920	0.007397	-0.008721	9.811530	
2	25	12.922172	77.492920	0.007397	-0.008721	9.811530	
3	25	12.922172	77.492920	0.007397	-0.008721	9.811530	
4	25	12.922172	77.492920	0.007397	-0.008721	9.811530	
5	25	12.922172	77.492920	0.007397	-0.008721	9.811530	
6	25	12.922172	77.492920	0.007397	-0.008721	9.811530	
7	0	12.920037	77.683395	0.158140	-1.075209	2.469071	
8	0	12.920037	77.683395	0.102990	-0.744553	4.849455	
9	1	12.920037	77.683395	0.102990	-0.744553	4.849455	

Data Preprocessing

Data after modification: a small step for modification of data is done where number of features are reduced manullay as per our convinent for better performance.

```
      Acc_x         Acc_y          Acc_z   Battery     BatteryChargingSource
0      0.693868   0.726671       0.720240     20.0                         0
1      0.693868   0.726671       0.720240     20.0                         0
2      0.693868   0.726671       0.720240     20.0                         0
3      0.693868   0.726671       0.720240     20.0                         0
4      0.693868   0.726671       0.720240     20.0                         0
10     0.351918   0.965198       3.758030     90.0                         4
...
796  245.345547  75.244381  186899.823606     70.0                         4
797   88.234374  26.610375   67445.676629     70.0                         4
798  184.428848  53.228362  142788.432024     70.0                         4
799  192.012064  53.236510  150274.834726     70.0                         4

     BatteryStatus                                        ClickEventID0
0                0                                          [Play video]
1                0                                          [Play video]
2                0                                          [Play video]
3                0                                          [Play video]
4                0                                          [Play video]
5                0                                          [Play video]
9                0                                            [My Files]
10               0            [Internal storage, 35.42 GB / 64.00 GB]
..             ...                                                   ...
797              0                                                    -3
798              0                                                    -3
799              0                                                    -3

[800 rows x 7 columns]
         RKB  StartTime     TKB  TapCount  TotalNoOfClickEvents  \
0    6513506     1015.0  461335         0                     1
1    6513506     1015.0  461335         0                     1
2    6513506     1015.0  461335         0                     1
10   6132950   165239.0  446098        10                     3
..       ...        ...     ...       ...                   ...
796        9   143253.0       9         4                     1
797  4113329   143303.0  288165        59                     1
798        9   143346.0       9         4                     0
799        9   143402.0       9        10                     3



                UTC  UsageTime   latitude  longitude  meanAcc_x  \
0    1544208226110         25  12.922172  77.492920   0.007397
1    1544208226110         25  12.922172  77.492920   0.007397
2    1544208226110         25  12.922172  77.492920   0.007397
3    1544208226110         25  12.922172  77.492920   0.007397

..             ...        ...        ...        ...        ...
798  1544605440041         13  12.920036  77.683361  43.622288
799  1544605454657         11  12.920036  77.683361  43.994694

          ...          meanOrien_y  meanOrien_z  package_ascii  ip_ascii  \
0         ...           -17.345741     1.221795         1876.0       653
```

1	...	-17.345741	1.221795	1876.0	653
2	...	-17.345741	1.221795	1876.0	653
3	...	-17.345741	1.221795	1876.0	653
4	...	-17.345741	1.221795	1876.0	653
5	...	-17.345741	1.221795	1876.0	653
6	...	-17.345741	1.221795	1876.0	653
7	...	-25.223969	-3.789785	2452.0	648
8	...	-25.782839	-2.346300	1351.0	648
9	...	-25.782839	-2.346300	2581.0	648
10	...	-27.219486	1.669745	1901.0	648
..	...	...	...	...	...
796	...	-56011.417969	-8164.063477	2581.0	648
797	...	-12459.999023	-1812.444214	1699.0	648
798	...	-37401.636719	-5432.669434	3015.0	648
799	...	-37427.093750	-5434.396484	1901.0	648

	Network_Provider	NetworkProvider_ascii	BBB	wifiip	UKB
0	"Xiaomi_3C74"	843.0	20.0	843.000653	6052171.0
1	"Xiaomi_3C74"	843.0	20.0	843.000653	6052171.0
2	"Xiaomi_3C74"	843.0	20.0	843.000653	6052171.0
3	"Xiaomi_3C74"	843.0	20.0	843.000653	6052171.0
4	"Xiaomi_3C74"	843.0	20.0	843.000653	6052171.0
5	"Xiaomi_3C74"	843.0	20.0	843.000653	6052171.0
6	"Xiaomi_3C74"	843.0	20.0	843.000653	6052171.0
7	-3	96.0	94.0	96.000648	1.0
8	"SYMC-MyWiFi"	898.0	94.0	898.000648	5686852.0
9	"SYMC-MyWiFi"	898.0	94.0	898.000648	2.0
10	"SYMC-MyWiFi"	898.0	94.0	898.000648	5686852.0
..	...	...	...	...	...
796	-3	96.0	75.0	96.000648	0.0
797	-3	96.0	74.0	96.000648	3825164.0
798	-3	96.0	74.0	96.000648	0.0
799	-3	96.0	74.0	96.000648	0.0

	start_usagetime
0	1015.0250
1	1015.0250
2	1015.0250
3	1015.0250
4	1015.0250
5	1015.0250
6	1015.0250
7	165225.0000
8	165234.0000
9	165238.0100
10	165239.0140
..	...
795	143217.0260
796	143253.0900
797	143303.0410
798	143346.0130
799	143402.0110

Data after conversion to numbers : Local outlier factor works with numbers only hence its essential to convent all the features to appropriate numbers :

```
start_usagetime  package_ascii  UsageTime  StartTime  DayOfTheWeek  \
0         1015.025         1876.0       25.0     1015.0           7.0
1         1015.025         1876.0       25.0     1015.0           7.0
2         1015.025         1876.0       25.0     1015.0           7.0
3         1015.025         1876.0       25.0     1015.0           7.0
4         1015.025         1876.0       25.0     1015.0           7.0
5         1015.025         1876.0       25.0     1015.0           7.0
6         1015.025         1876.0       25.0     1015.0           7.0
7       165225.000         2452.0        0.0   165225.0           6.0
8       165234.000         1351.0        0.0   165234.0           6.0
9       165238.010         2581.0        1.0   165238.0           6.0

       wifiip   BBB   latitude  longitude  TapCount     ...       Network  \
0  843.000653  20.0  12.922172  77.492920       0.0     ...           1.0
1  843.000653  20.0  12.922172  77.492920       0.0     ...           1.0
2  843.000653  20.0  12.922172  77.492920       0.0     ...           1.0
3  843.000653  20.0  12.922172  77.492920       0.0     ...           1.0
4  843.000653  20.0  12.922172  77.492920       0.0     ...           1.0
5  843.000653  20.0  12.922172  77.492920       0.0     ...           1.0
6  843.000653  20.0  12.922172  77.492920       0.0     ...           1.0
7   96.000648  94.0  12.920037  77.683395       4.0     ...           1.0
8  898.000648  94.0  12.920037  77.683395       3.0     ...           1.0
9  898.000648  94.0  12.920037  77.683395       1.0     ...           1.0

   meanAcc_x  meanAcc_y  meanAcc_z  meanGyro_x  meanGyro_y  meanGryo_z  \
0   0.007397  -0.008721   9.811530    0.991565   -0.016973    0.011061
1   0.007397  -0.008721   9.811530    0.991565   -0.016973    0.011061
2   0.007397  -0.008721   9.811530    0.991565   -0.016973    0.011061
3   0.007397  -0.008721   9.811530    0.991565   -0.016973    0.011061
4   0.007397  -0.008721   9.811530    0.991565   -0.016973    0.011061
5   0.007397  -0.008721   9.811530    0.991565   -0.016973    0.011061
6   0.007397  -0.008721   9.811530    0.991565   -0.016973    0.011061
7   0.158140  -1.075209   2.469071    1.000000    0.000000    0.000000
8   0.102990  -0.744553   4.849455    1.000000    0.000000    0.000000
9   0.102990  -0.744553   4.849455    1.000000    0.000000    0.000000

   meanOrien_x  meanOrien_y  meanOrien_z
0     1.263105   -17.345741     1.221795
1     1.263105   -17.345741     1.221795
2     1.263105   -17.345741     1.221795
3     1.263105   -17.345741     1.221795
4     1.263105   -17.345741     1.221795
5     1.263105   -17.345741     1.221795
6     1.263105   -17.345741     1.221795
7   -68.047508   -25.223969    -3.789785
8   -77.375458   -25.782839    -2.346300
9   -77.375458   -25.782839    -2.346300
```

Data segregated :

Data is now being segregated with respect to one characteristic for easy better understanding and efficient working of the algorithm

```
1506.0
50
```

	start_usagetime	UsageTime	StartTime	wifiip	BBB	latitude
2	140848.04000	4.0	140848.0	898.000659	55.0	12.920027
10	141424.07036	7036.0	141424.0	898.000659	44.0	12.920036
12	161142.00000	0.0	161142.0	898.000659	44.0	12.920036
…						
170	152834.01000	1.0	152834.0	898.000648	70.0	12.920035
172	153034.09100	91.0	153034.0	898.000648	70.0	12.920035
217	204230.02320	2320.0	204230.0	579.000650	40.0	13.027343
224	62729.03000	3.0	62729.0	579.000650	20.0	13.027338
229	114558.04113	4113.0	114558.0	898.000648	25.0	12.920037

	longitude	TapCount	UKB	Network	meanAcc_x	meanAcc_y	\
2	77.683363	5.0	1277.0	1.0	-3.000000	-3.000000	
10	77.683348	650.0	54000.0	1.0	0.018649	-0.027941	
12	77.683348	0.0	54000.0	1.0	1.646033	-2.319430	
..							
202	77.683363	10.0	288056.0	1.0	30.969275	3.572598	
206	77.622356	4.0	4059554.0	1.0	-3.000000	-3.000000	
214	77.622356	36.0	4064792.0	1.0	-2.412123	-1.355919	
217	77.622377	107.0	47278.0	1.0	-0.190471	-0.012298	
224	77.622355	9.0	15716.0	1.0	-3.000000	-3.000000	
229	77.683421	711230.0	197457.0	1.0	-1.389972	2.836159	

	meanAcc_z	meanGyro_x	meanGyro_y	meanOrien_x	meanOrien_y	\
2	-3.000000	-3.000000	-3.000000	-3.000000	-3.000000	
10	10.453092	0.795230	-0.114234	-104.496223	-24.085508	
12	884.952026	67.031052	-9.726879	-8940.844727	-2066.784912	
..						
202	5416.623535	461.266876	-68.685883	-65242.312500	-4768.722168	
206	-3.000000	-3.000000	-3.000000	-3.000000	-3.000000	
214	718.702942	63.706146	-3.076397	4665.310547	-1299.573853	
217	49.055882	4.408081	-0.205122	357.110840	-82.503586	
224	-3.000000	-3.000000	-3.000000	-3.000000	-3.000000	
229	8.608446	0.762185	-0.112540	-144.143967	-5.640756	

Feature scaling

Feature scaling can vary your results a lot while using certain algorithms and have a minimal or no effect in others. To understand this, let's look why features need to be scaled, varieties of scaling methods and when we should scale our features.

The transformation is given by:

class `sklearn.preprocessing.MinMaxScaler`(feature_range=(0, 1), copy=True)

X_std = (X - X.min(axis=0)) / (X.max(axis=0) - X.min(axis=0)) X_scaled = X_std * (max - min) + min

where min, max = feature_range.

This transformation is often used as an alternative to zero mean, unit variance scaling.we haved scaled it from 0 to 9 this example for 50 entires , some of which is illustrated below

```
[[5.41659147 1.00454804 5.4165907  6.7737557  4.83561644 8.93409781
 8.99999402 1.00005624 1.09347315 9.         1.         8.66075404
 1.         1.         8.92304205 8.85383069 9.         1.1560556
 8.8419982 ]
[5.44915833 9.         5.44915584 6.7737557  3.63013699 8.9341031
 8.99999243 1.00731128 1.19605818 9.         1.01832578 8.68338479
 1.00519997 1.01912341 8.99974755 8.85065275 8.99251198 1.15617168
 8.9959794 ]
[6.56394512 1.         6.56394654 6.7737557  3.63013699 8.9341031
 8.99999243 1.         1.19605818 9.         1.02820539 8.66593625
 1.34321647 1.35287258 8.74423733 8.57397814 8.26709572 1.14991412
 8.84116564]

 ……
[5.99767572 1.45252985 5.99767493 6.7737555  7.57534247 8.93410279
 8.99999407 1.00465672 8.04071136 9.         1.01880678 8.68489764
 1.02034874 1.03549193 8.99149485 8.83552223 8.96776704 1.1547206
 8.97591185]
[6.05986453 1.13757817 6.0598653  6.7737555  6.47945205 8.93410279
 8.99999407 1.00064114 1.30231093 9.         1.02171211 8.68811959
 1.07712339 1.0959217  8.95765089 8.7792554  8.88873639 1.15091103
 8.90456104]
[8.89263605 1.00113701 8.8926368  1.         3.19178082 8.9999914
 8.99371141 1.00004499 8.98980824 9.         1.         8.66075404
 1.         1.         8.92304205 8.85383069 9.         1.1560556
 8.8419982 ]
[9.         3.63786242 9.         1.         3.19178082 8.99999951
 8.99371355 1.00120355 1.18297895 9.         1.01705624 8.6835039
 1.02012095 1.03732785 8.99733168 8.86510611 8.97176619 1.15356721
 8.99983307]
```

Featuring Extraction :

PCA for Data Visualization

For a lot of machine learning applications it helps to be able to visualize your data. Visualizing 2 or 3 dimensional data is not that challenging. However, even the Iris dataset used in this part of the tutorial is 4 dimensional. You can use PCA to reduce that 4 dimensional data into 2 or 3 dimensions so that you can plot and hopefully understand the data better**.**

```
1506.0
50
[[-0.39091245 -0.59880565]
 [-0.53553262 -0.67791003]
 [-0.38956116 -0.42892372]
 [ 1.80910667 -0.93189361]
 [ 2.17668607 -0.7356885 ]
 [ 1.9818238  -1.05886989]
 [ 1.98182425 -1.0588727 ]
 [ 2.41818572 -0.33480851]
 [ 1.99992724 -0.7383986 ]
 [ 3.70877667  1.92837814]
 [-0.24357631  1.76721875]
 [-0.59810462  0.69472954]
 [-0.54254008  0.72577948]
 [-0.64609398 -0.21630954]
 [-0.3760541   2.10260188]
```

```
 [-0.38087724  0.12801085]
 [-0.14665919  3.88930045]
 [-0.64733916 -0.21635887]
 [-0.40256771  0.18479626]
 [-0.11136838  0.62282912]
 [-0.1102928   0.62475289]
 [-0.27905212 -0.65981529]
 [-0.27922263 -0.6595777 ]
 [-0.43607342 -0.34924367]
 [-0.04728905  2.53317384]
 [-0.41817669 -0.05462201]
 [-0.23509184 -0.57242086]
 [-0.23970603 -0.68664102]
 [-0.23699935 -0.72695564]
 [-0.28112989 -0.68872038]
 [-0.28165521 -0.68996281]
 [-0.28504527 -0.69192157]
 [-0.28603554 -0.69681711]
 [-0.53524728 -0.27074571]
 [-0.32106032 -0.62430377]
 ..
 [ 0.01835934  0.22671321]
 [-1.09440816 -0.11555654]
 [-1.07969448 -0.04235109]
 [-0.84319857 -0.64167154]
 [-0.93238208 -0.42392199]
 [-0.64833008 -0.58125121]]
```

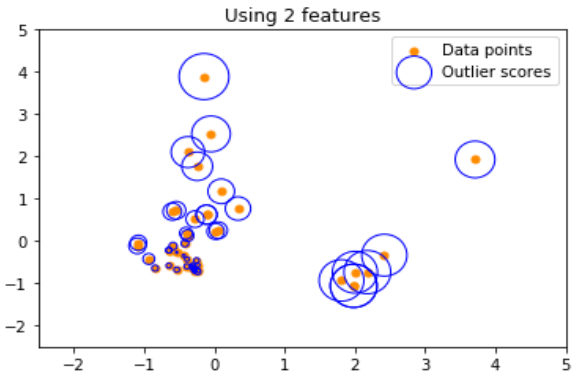
Data score :

Local outlier factor calculates a very important value known as score of each point , this score helps in differentiation outlier among the inliers , the higher the negative score value of the point more are the chances of it being an outlier .below are the scores of the points from the package “1560” with 50 entry points

```
1506.0
50
[-0.99888308 -0.99921298 -0.98817922 -3.27746669 -3.47861466 -3.48327372
 -3.48327481 -3.31947388 -3.30439962 -2.77629132 -2.05528399 -1.36506608
 -1.38598143 -1.00454219 -2.25514521 -1.14675324 -3.8210073  -1.00487158
 -1.15514457 -1.46410796 -1.46561711 -0.98763381 -0.9876221  -0.97355144
 -2.69035957 -1.03020815 -0.9826561  -0.99653548 -1.00893756 -0.99153814
 -0.99174075 -0.9920486  -0.9932756  -0.96773261 -0.9826561  -1.34265013
 -0.98406169 -0.96253383 -0.99942793 -0.98635177 -1.70530382 -1.78087875
 -1.33926742 -1.03747595 -1.31207525 -1.30115298 -1.27745589 -1.01274697
 -1.12270884 -0.9943141 ]
```

The decided as outliers are finally marked as -1 and rest of the inliers are marked as 1, below is the example
for same.

```
[ 1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1 -1  1  1  1  1  1  1  1
  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1
  1  1]
```



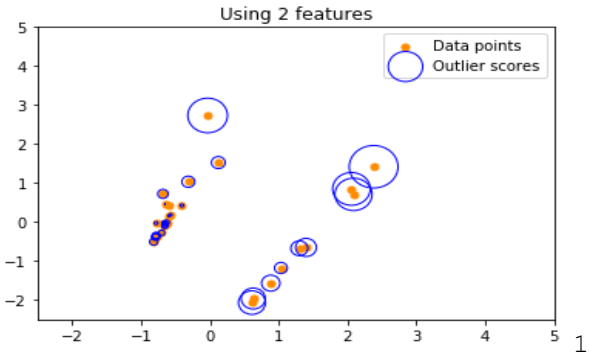
In the above example its clear we have one point that is away from the clusters formed at (2,4) which is an outlier in this case

MORE EXAMPLES

Below are some more examples :

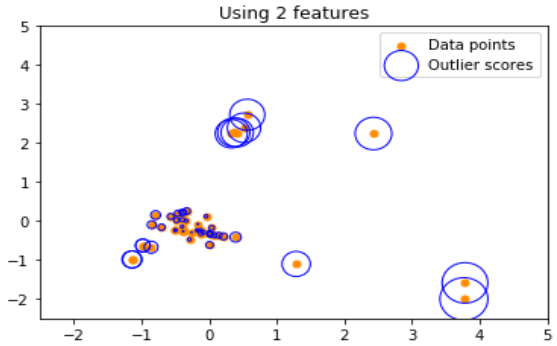
```
1676.0
30
[-0.99262362 -0.99352984 -0.99219981 -0.99299604 -0.9927245  -1.01513507
 -1.03607362 -1.22182052 -1.11173622 -1.04456439 -1.0612055  -1.08588694
 -1.39147425 -1.22740646 -0.98927265 -0.99180798 -1.25468828 -0.98715462
 -1.01565254 -0.98917631 -1.01954713 -0.98843273 -0.98715462 -0.98819037
 -1.00586043 -0.99834542 -0.99702134 -0.99695785 -0.99693728 -0.99727592]

[ 1  1  1  1  1  1  1  1  1  1  1  1 -1  1  1  1  1  1  1  1  1  1  1  1
  1  1 1 1 1 1]
```



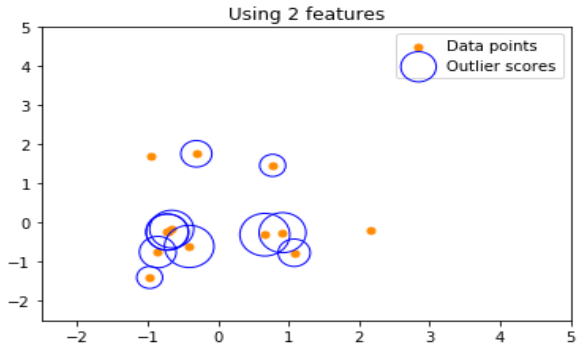

```
1437.0
48
[-4.18525931 -4.19639006 -4.13221772 -4.37477346 -4.76678212 -5.10709416
 -1.11478634 -0.98275663 -1.02906017 -1.00651811 -1.02800661 -0.94282049
 -0.96962272 -1.08005781 -3.42231994 -1.00136803 -0.9922148  -1.03354717
 -1.04442243 -0.96017617 -0.9682363  -0.97008511 -1.12824256 -1.07013565
 -1.03393289 -0.96183809 -7.41271652 -8.07582049 -1.10643655 -0.94085214
 -0.96544425 -0.9368061  -1.0817918  -1.07566655 -1.03226517 -0.94392047
 -0.96512387 -1.32489227 -1.08330646 -0.97908361 -1.18712314 -1.59694368
 -1.59691947 -1.09712881 -1.51715745 -2.1049614  -2.09669238 -1.23306459]

[ 1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1
  1  1 1-1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1]
```



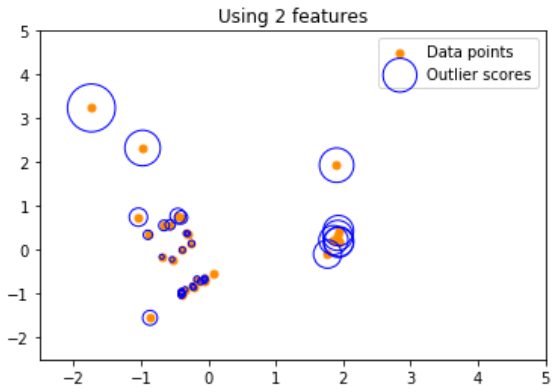

```
1467.0
13
[-1.01456096 -1.00589109 -1.00568361 -1.01086961 -0.98345281 -0.99186262
 -0.99547572 -0.98345281 -1.01394016 -0.99632194 -0.99179927 -1.00032105
 -1.00763052]

[-1  1  1  1  1  1  1  1  1  1  1  1  1]
```




```
1604.0
36
[-1.59688766 -1.61441973 -1.59207572 -1.56649541 -1.79853341 -1.6049325
 -1.52504853 -0.99282872 -1.04680351 -1.2010669  -0.9902614  -0.982243
 -1.02540672 -1.04112186 -0.98502389 -1.13502463 -0.98473675 -0.9941025
 -2.57722725 -1.08806702 -1.85707811 -0.96678827 -0.98913972 -0.98619318
 -0.98970255 -0.99063679 -0.98900619 -0.99411555 -0.99745667 -0.99101345
 -0.9910651  -1.00260642 -0.9930226  -0.9856916  -1.12092636 -0.98784328]

[ 1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1 -1  1  1  1  1  1
  1  1 1 1 1 1 1 1 1 1 1 1]
```



Roc curve :

ROC curves typically feature true positive rate on the Y axis, and false positive rate on the X axis. This means that the top left corner of the plot is the “ideal” point - a false positive rate of zero, and a true positive rate of one. This is not very realistic, but it does mean that a larger area under the curve (AUC) is usually better.

one such graph is shown which has :12 entries having

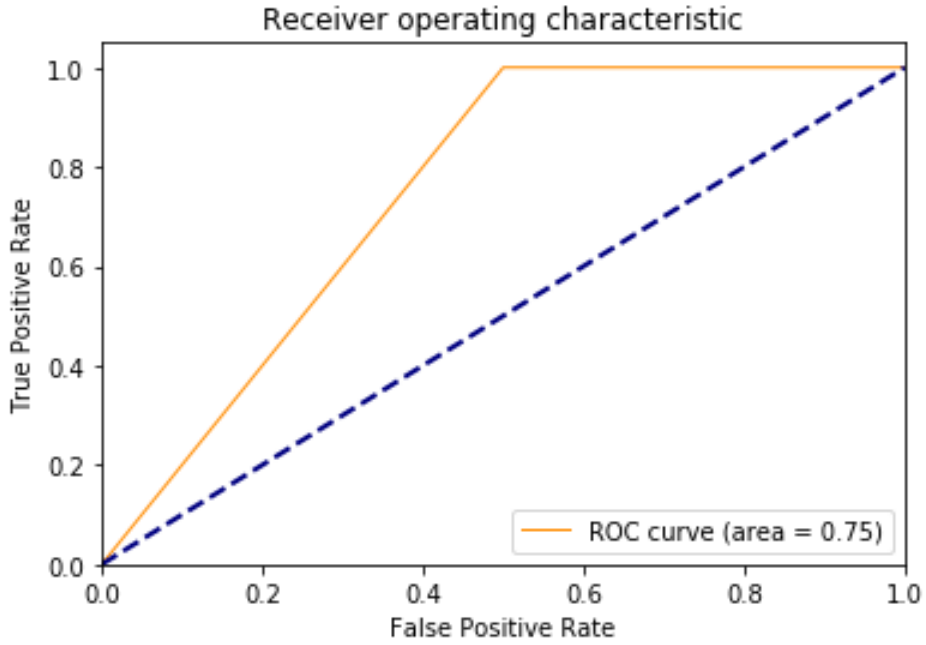
1 True positive (last entry was used by a different user)

1 True negative (last but one)

0 False positive

```
1506
```

```
[ 1  1  1  1  1  1  1  1  1  1 -1 -1]
```



Conclusion:

Once the data was retrieved from the local storage or the cloud, the algorithm was put to use, and outliers were identified. The precision and accuracy of the algorithm depended on the usage of the applications in question. Below is an statistical study of the results .

How was It done: Application was used by the owner for two days and later was used by us about few apps for sometime and then data was projected as below .

USER1 :

Analysis True Positive : 97.69%

Fasle positive : 3.68%

USER2:

Analysis True Positive : 99.43%

Fasle positive : 0.56%

True Negative: 33%

Disclaimer : Data collected and used is limited and the percentage is w.r.t only this data.