

```
In [71]: import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns
```

```
In [72]: df=pd.read_csv("train_har.csv")
```

```
In [3]: df.describe()
```

Out[3]:

	tBodyAcc-mean()-X	tBodyAcc-mean()-Y	tBodyAcc-mean()-Z	tBodyAcc-std()-X	tBodyAcc-std()-Y	tBodyAcc-std()-Z	tBodyAcc-mad()-X	tBodyAcc-mad()-Y	tBodyAcc-mad()-Z	tBodyAcc-max()-X	...	fBodyBodyGyroJerkMag-skewness()	fBodyBodyGyroJerkMag-kurtosis()	angle(tBodyAccMean,gravity)
count	7352.000000	7352.000000	7352.000000	7352.000000	7352.000000	7352.000000	7352.000000	7352.000000	7352.000000	7352.000000	...	7352.000000	7352.000000	7352.000000
mean	0.274488	-0.017695	-0.109141	-0.605438	-0.510938	-0.604754	-0.630512	-0.526907	-0.606150	-0.468604	...	-0.307009	-0.625294	0.008684
std	0.070261	0.040811	0.056635	0.448734	0.502645	0.418687	0.424073	0.485942	0.414122	0.544547	...	0.321011	0.307584	0.336787
min	-1.000000	-1.000000	-1.000000	-1.000000	-0.999873	-1.000000	-1.000000	-1.000000	-1.000000	-1.000000	...	-0.995357	-0.999765	-0.976580
25%	0.262975	-0.024863	-0.120993	-0.992754	-0.978129	-0.980233	-0.993591	-0.978162	-0.980251	-0.936219	...	-0.542602	-0.845573	-0.121527
50%	0.277193	-0.017219	-0.108676	-0.946196	-0.851897	-0.859365	-0.950709	-0.857328	-0.857143	-0.881637	...	-0.343685	-0.711692	0.009509
75%	0.288461	-0.010783	-0.097794	-0.242813	-0.034231	-0.262415	-0.292680	-0.066701	-0.265671	-0.017129	...	-0.126979	-0.503878	0.150865
max	1.000000	1.000000	1.000000	1.000000	0.916238	1.000000	1.000000	0.967664	1.000000	1.000000	...	0.989538	0.956845	1.000000

8 rows × 562 columns

```
In [20]: df['subject']
```

Out[20]:

```
0      1
1      1
2      1
3      1
4      1
..
7347   30
7348   30
7349   30
7350   30
7351   30
Name: subject, Length: 7352, dtype: int64
```

```
In [4]: missing_value = ["N/a","na",np.nan]
df=pd.read_csv("train_har.csv",na_values=missing_value)
```

```
In [7]: df.isnull()
```

Out[7]:

	tBodyAcc-mean()-X	tBodyAcc-mean()-Y	tBodyAcc-mean()-Z	tBodyAcc-std()-X	tBodyAcc-std()-Y	tBodyAcc-std()-Z	tBodyAcc-mad()-X	tBodyAcc-mad()-Y	tBodyAcc-mad()-Z	tBodyAcc-max()-X	...	fBodyBodyGyroJerkMag-kurtosis()	angle(tBodyAccMean,gravity)	angle(tBodyAccJerkMean),gravityMean)	an
0	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False
...
7347	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False
7348	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False
7349	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False
7350	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False
7351	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False

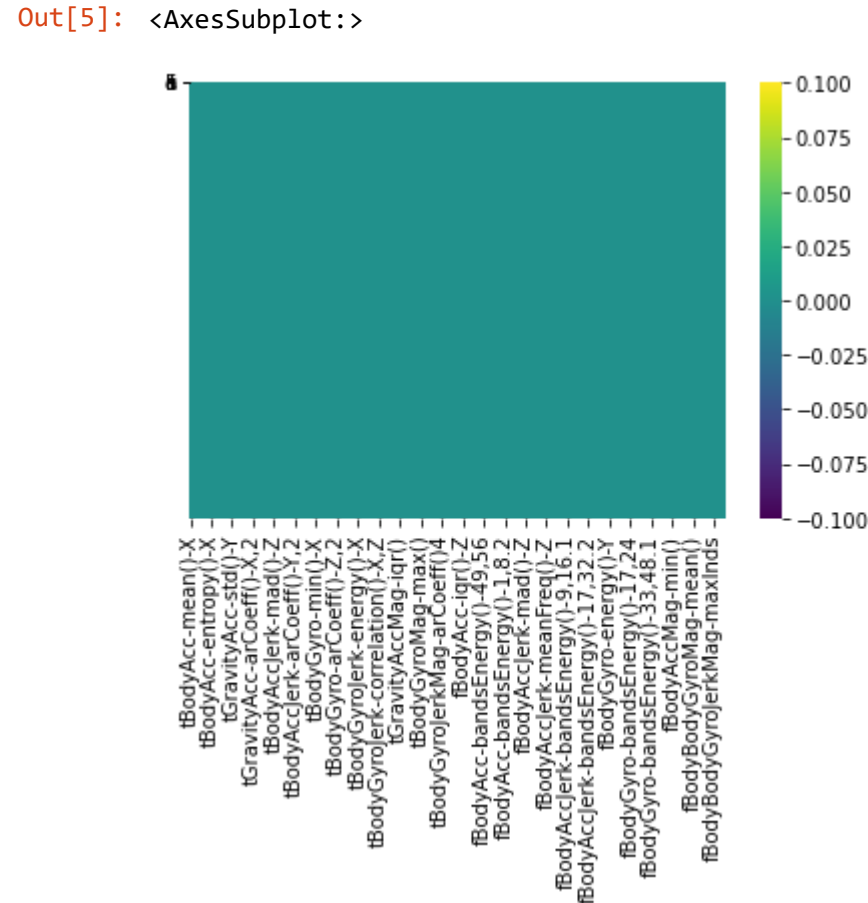
7352 rows × 563 columns

```
In [8]: df.isnull().sum()
```

Out[8]:

```
tBodyAcc-mean()-X      0
tBodyAcc-mean()-Y      0
tBodyAcc-mean()-Z      0
tBodyAcc-std()-X       0
tBodyAcc-std()-Y       0
..
angle(X,gravityMean)    0
angle(Y,gravityMean)    0
angle(Z,gravityMean)    0
subject                 0
Activity                0
Length: 563, dtype: int64
```

```
In [5]: sns.heatmap(df.isnull(),yticklabels="False",cmap='viridis')
```



No null values present in the data

```
In [ ]:
```

```
In [11]: df.head()
```

```
Out[11]:
```

	tBodyAcc-mean()-X	tBodyAcc-mean()-Y	tBodyAcc-mean()-Z	tBodyAcc-std()-X	tBodyAcc-std()-Y	tBodyAcc-std()-Z	tBodyAcc-mad()-X	tBodyAcc-mad()-Y	tBodyAcc-mad()-Z	tBodyAcc-max()-X	...	fBodyBodyGyroJerkMag-kurtosis()	angle(tBodyAccMean,gravity)	angle(tBodyAccJerkMean),gravityMean)	angle(
0	0.288585	-0.020294	-0.132905	-0.995279	-0.983111	-0.913526	-0.995112	-0.983185	-0.923527	-0.934724	...	-0.710304	-0.112754		0.030400
1	0.278419	-0.016411	-0.123520	-0.998245	-0.975300	-0.960322	-0.998807	-0.974914	-0.957686	-0.943068	...	-0.861499	0.053477		-0.007435
2	0.279653	-0.019467	-0.113462	-0.995380	-0.967187	-0.978944	-0.996520	-0.963668	-0.977469	-0.938692	...	-0.760104	-0.118559		0.177899
3	0.279174	-0.026201	-0.123283	-0.996091	-0.983403	-0.990675	-0.997099	-0.982750	-0.989302	-0.938692	...	-0.482845	-0.036788		-0.012892
4	0.276629	-0.016570	-0.115362	-0.998139	-0.980817	-0.990482	-0.998321	-0.979672	-0.990441	-0.942469	...	-0.699205	0.123320		0.122542

5 rows × 563 columns

```
In [12]: df.tail()
```

```
Out[12]:
```

	tBodyAcc-mean()-X	tBodyAcc-mean()-Y	tBodyAcc-mean()-Z	tBodyAcc-std()-X	tBodyAcc-std()-Y	tBodyAcc-std()-Z	tBodyAcc-mad()-X	tBodyAcc-mad()-Y	tBodyAcc-mad()-Z	tBodyAcc-max()-X	...	fBodyBodyGyroJerkMag-kurtosis()	angle(tBodyAccMean,gravity)	angle(tBodyAccJerkMean),gravityMean)	an
7347	0.299665	-0.057193	-0.181233	-0.195387	0.039905	0.077078	-0.282301	0.043616	0.060410	0.210795	...	-0.880324	-0.190437		0.829718
7348	0.273853	-0.007749	-0.147468	-0.235309	0.004816	0.059280	-0.322552	-0.029456	0.080585	0.117440	...	-0.680744	0.064907		0.875679
7349	0.273387	-0.017011	-0.045022	-0.218218	-0.103822	0.274533	-0.304515	-0.098913	0.332584	0.043999	...	-0.304029	0.052806		-0.266724
7350	0.289654	-0.018843	-0.158281	-0.219139	-0.111412	0.268893	-0.310487	-0.068200	0.319473	0.101702	...	-0.344314	-0.101360		0.700740
7351	0.351503	-0.012423	-0.203867	-0.269270	-0.087212	0.177404	-0.377404	-0.038678	0.229430	0.269013	...	-0.740738	-0.280088		-0.007739

5 rows × 563 columns

```
In [14]: df.shape
```

```
Out[14]: (7352, 563)
```

```
In [6]: #checking for duplicates

print('Number of duplicate entries in the dataset {}'.format(sum(df.duplicated())))
```

Number of duplicate entries in the dataset 0

```
In [ ]:
```

```
In [ ]: # Class distribution
```

```
In [16]: df['Activity'].unique()
```

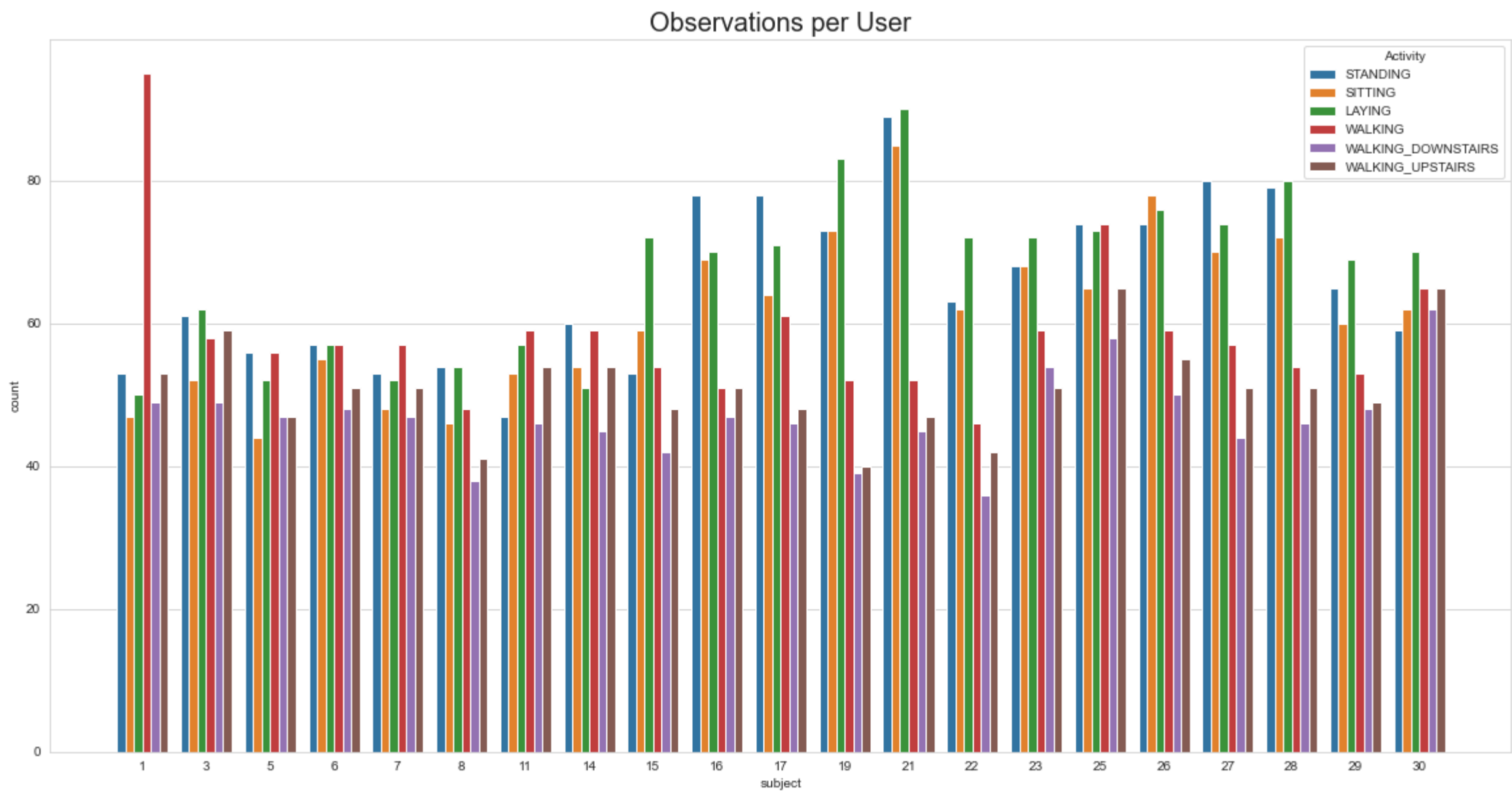
```
Out[16]: array(['STANDING', 'SITTING', 'LAYING', 'WALKING', 'WALKING_DOWNSTAIRS',
              'WALKING_UPSTAIRS'], dtype=object)
```

```
In [ ]:
```

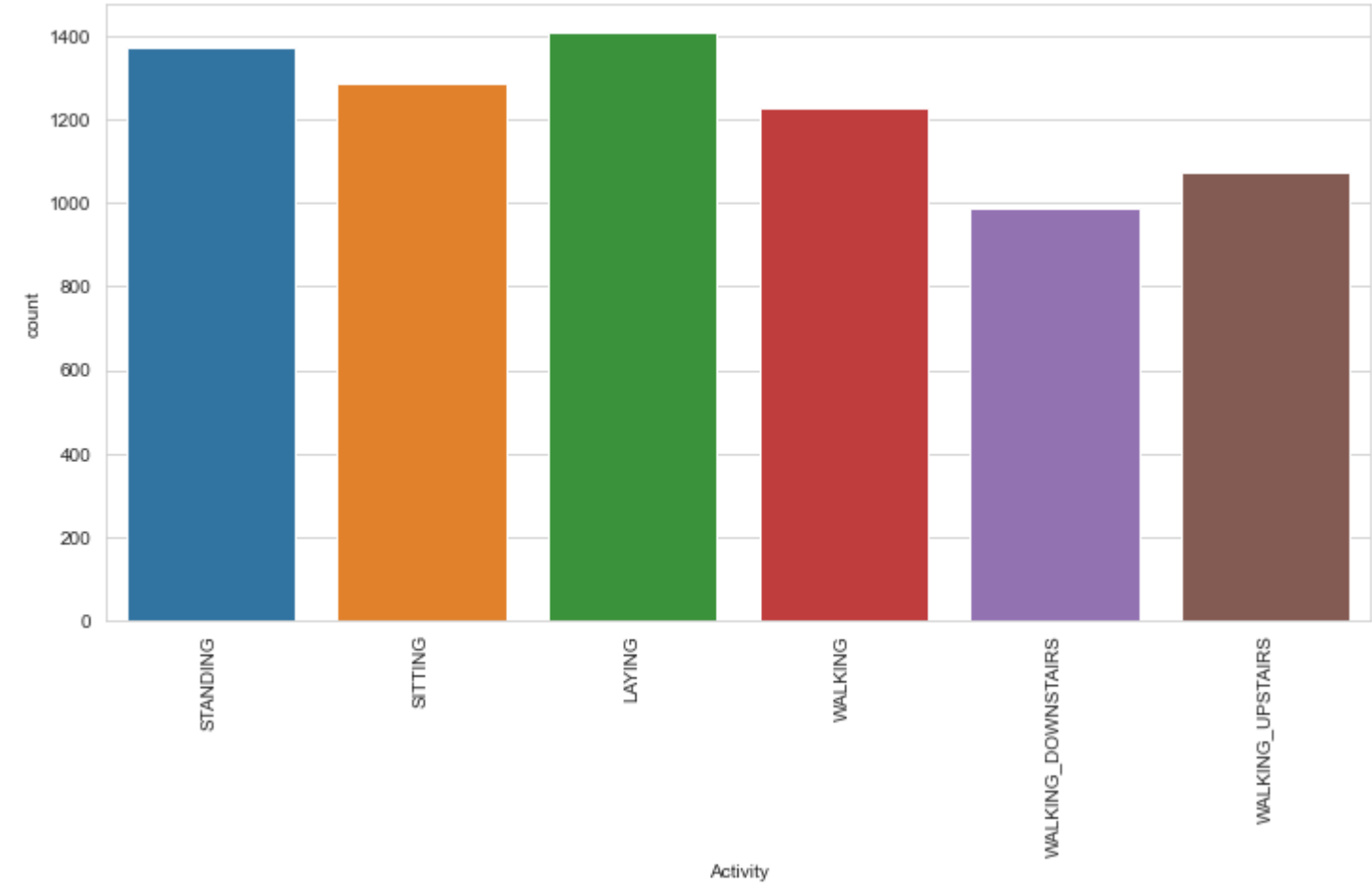
Now Visualize the class Distribution¶

```
In [4]: # Plotting data with respect to subject
sns.set_style('whitegrid')
plt.figure(figsize=(20,10))
plt.title('Observations per User', fontsize=20)
sns.countplot(x='subject', hue='Activity', data=df)
plt.plot()
```

```
Out[4]: []
```



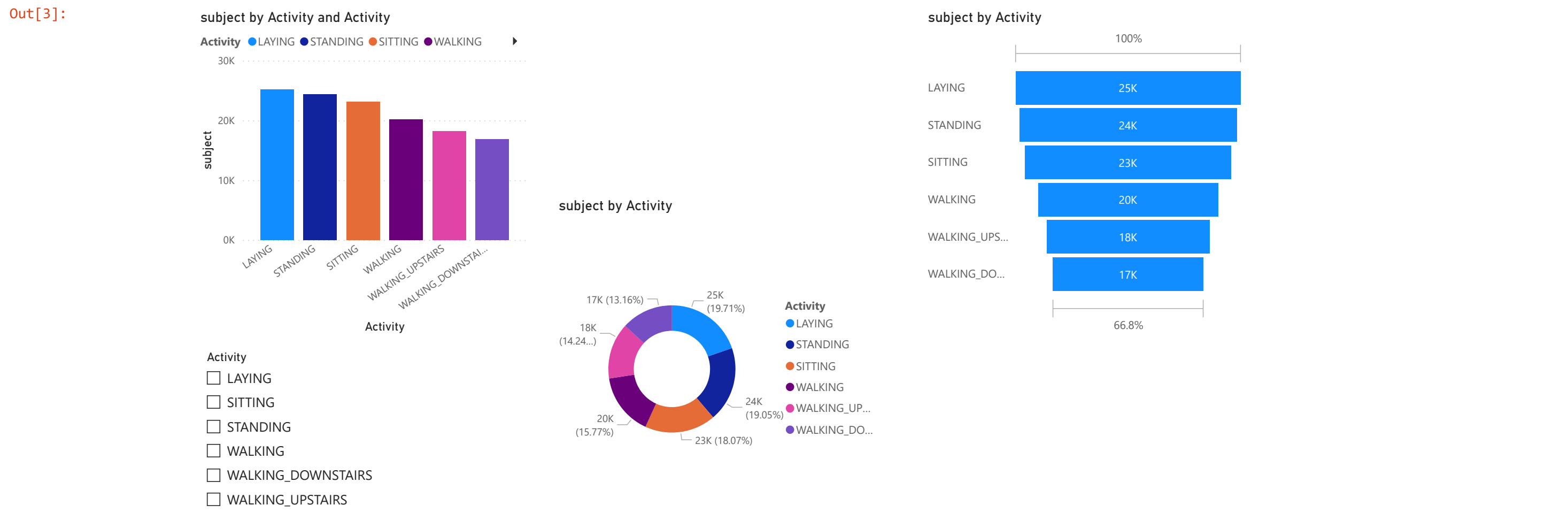
```
In [15]: plt.figure(figsize=(12,6))
axis=sns.countplot(x="Activity",data=df)
plt.xticks(x=df[ 'Activity'],rotation='vertical')
plt.show()
```



```
In [ ]:
```

Connecting Data visualization using power bi

```
In [3]: from IPython.display import IFram
powerBiEmbed = 'https://app.powerbi.com/reportEmbed?reportId=13c711a2-eb57-4fcb-9f44-63c2786d0449&autoAuth=true&ctid=6071e59a-0b4e-4894-b7ea-b4e51a072a6a&config=eyJjbHVzdGVyVXJsIjoj
IFrame(powerBiEmbed, width=1200,height=600)
```



```
In [ ]:
```

```
In [8]: df['subject'].unique()
```

```
Out[8]: array([ 1,  3,  5,  6,  7,  8, 11, 14, 15, 16, 17, 19, 21, 22, 23, 25, 26,
                27, 28, 29, 30], dtype=int64)
```

```
In [73]: X=pd.DataFrame(df.drop(['Activity','subject'],axis=1))
y= df.Activity.values.astype(object)
```

```
In [5]: X.shape , y.shape
```

```
Out[5]: ((7352, 561), (7352,))
```

```
In [6]: print(X)
```

	tBodyAcc-mean()-X	tBodyAcc-mean()-Y	tBodyAcc-mean()-Z	\	
0	0.288585	-0.020294	-0.132905		
1	0.278419	-0.016411	-0.123520		
2	0.279653	-0.019467	-0.113462		
3	0.279174	-0.026201	-0.123283		
4	0.276629	-0.016570	-0.115362		
...		
7347	0.299665	-0.057193	-0.181233		
7348	0.273853	-0.007749	-0.147468		
7349	0.273387	-0.017011	-0.045022		
7350	0.289654	-0.018843	-0.158281		
7351	0.351503	-0.012423	-0.203867		
	tBodyAcc-std()-X	tBodyAcc-std()-Y	tBodyAcc-std()-Z	tBodyAcc-mad()-X	\
0	-0.995279	-0.983111	-0.913526	-0.995112	
1	-0.998245	-0.975300	-0.960322	-0.998807	
2	-0.995380	-0.967187	-0.978944	-0.996520	
3	-0.996091	-0.983403	-0.990675	-0.997099	
4	-0.998139	-0.980817	-0.990482	-0.998321	
...	
7347	-0.195387	0.039905	0.077078	-0.282301	
7348	-0.235309	0.004816	0.059280	-0.322552	
7349	-0.218218	-0.103822	0.274533	-0.304515	
7350	-0.219139	-0.111412	0.268893	-0.310487	
7351	-0.269270	-0.087212	0.177404	-0.377404	
	tBodyAcc-mad()-Y	tBodyAcc-mad()-Z	tBodyAcc-max()-X	...	\
0	-0.983185	-0.923527	-0.934724	...	
1	-0.974914	-0.957686	-0.943068	...	
2	-0.963668	-0.977469	-0.938692	...	
3	-0.982750	-0.989302	-0.938692	...	
4	-0.979672	-0.990441	-0.942469	...	
...	
7347	0.043616	0.060410	0.210795	...	
7348	-0.029456	0.080585	0.117440	...	
7349	-0.098913	0.332584	0.043999	...	
7350	-0.068200	0.319473	0.101702	...	
7351	-0.038678	0.229430	0.269013	...	
	fBodyBodyGyroJerkMag-meanFreq()	fBodyBodyGyroJerkMag-skewness()	\		
0	-0.074323	-0.298676			
1	0.158075	-0.595051			
2	0.414503	-0.390748			
3	0.404573	-0.117290			
4	0.087753	-0.351471			
...			
7347	-0.070157	-0.588433			
7348	0.165259	-0.390738			
7349	0.195034	0.025145			
7350	0.013865	0.063907			
7351	-0.058402	-0.387052			
	fBodyBodyGyroJerkMag-kurtosis()	angle(tBodyAccMean,gravity)	\		
0	-0.710304	-0.112754			
1	-0.861499	0.053477			
2	-0.760104	-0.118559			
3	-0.482845	-0.036788			
4	-0.699205	0.123320			
...			
7347	-0.880324	-0.190437			
7348	-0.680744	0.064907			
7349	-0.304029	0.052806			
7350	-0.344314	-0.101360			
7351	-0.740738	-0.280088			
	angle(tBodyAccJerkMean,gravityMean)	angle(tBodyGyroMean,gravityMean)	\		
0	0.030400	-0.464761			
1	-0.007435	-0.732626			
2	0.177899	0.100699			
3	-0.012892	0.640011			
4	0.122542	0.693578			
...			
7347	0.829718	0.206972			
7348	0.875679	-0.879033			
7349	-0.266724	0.864404			
7350	0.700740	0.936674			
7351	-0.007739	-0.056088			
	angle(tBodyGyroJerkMean,gravityMean)	angle(X,gravityMean)	\		
0	-0.018446	-0.841247			
1	0.703511	-0.844788			
2	0.808529	-0.848933			
3	-0.485366	-0.848649			
4	-0.615971	-0.847865			
...			
7347	-0.425619	-0.791883			
7348	0.400219	-0.771840			
7349	0.701169	-0.779133			
7350	-0.589479	-0.785181			
7351	-0.616956	-0.783267			
	angle(Y,gravityMean)	angle(Z,gravityMean)			
0	0.179941	-0.058627			
1	0.180289	-0.054317			
2	0.180637	-0.049118			
3	0.181935	-0.047663			
4	0.185151	-0.043892			
...			
7347	0.238604	0.049819			
7348	0.252676	0.050053			
7349	0.249145	0.040811			
7350	0.246432	0.025339			
7351	0.246809	0.036695			

[7352 rows x 561 columns]

```
In [5]: print(y)
```

```
['STANDING' 'STANDING' 'STANDING' ... 'WALKING_UPSTAIRS'
 'WALKING_UPSTAIRS' 'WALKING_UPSTAIRS']
```

```
In [ ] :
```

Transforming Non numerical Labels into numerical labels¶¶

```
In [74]: from sklearn import preprocessing
```

```
In [75]: encoder=preprocessing.LabelEncoder()
```

```
In [76]: encoder.fit(y)
y=encoder.transform(y)
y.shape

Out[76]: (7352,)
```

```
In [10]: encoder.classes_

Out[10]: array(['LAYING', 'SITTING', 'STANDING', 'WALKING', 'WALKING_DOWNSTAIRS',
                'WALKING_UPSTAIRS'], dtype=object)
```

```
In [ ]:
```

Standard scalar

```
In [77]: from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()

In [78]: X=scaler.fit_transform(X)

In [79]: print(X)

[[ 0.20064157 -0.0636826 -0.41962845 ... -0.68721921  0.40794614
  -0.00756789]
 [ 0.05594788  0.03148567 -0.25390836 ... -0.694138    0.40911698
  0.00787517]
 [ 0.07351535 -0.04341648 -0.07629468 ... -0.702239    0.4102883
  0.02650234]
 ...
 [-0.01566765  0.0167814  1.13222107 ... -0.56584847  0.64059683
  0.34870928]
 [ 0.21586648 -0.02812252 -0.86770988 ... -0.57766781  0.63147758
  0.29327564]
 [ 1.09620157  0.12919873 -1.67268082 ... -0.57392691  0.63274259
  0.33396081]]

In [ ]:
```

Splitting the data into training and test data

```
In [80]: from sklearn.model_selection import train_test_split

X_train,X_test,y_train,y_test = train_test_split(X,y,test_size = 0.3,random_state = 100)

In [81]: print('X_train',X_train.shape)
print('X_test',X_test.shape)
print('y_train',y_train.shape)
print('y_test',y_test.shape)

X_train (5146, 561)
X_test (2206, 561)
y_train (5146,)
y_test (2206,)
```

```
In [ ]:
```

Linear Regression

```
In [82]: from sklearn.linear_model import LinearRegression

In [83]: model = LinearRegression()

In [22]: model.fit(X_train, y_train)
LinearRegression()

Out[22]: LinearRegression()

In [84]: model = LinearRegression().fit(X_train, y_train)

In [195]: r_sq = model.score(X_test, y_test)
print(f"coefficient of determination: {r_sq}")

coefficient of determination: 0.9832275611967362

In [86]: print(f"intercept: {model.intercept_}")

intercept: 2.316036200621678

In [26]: print(f"slope: {model.coef_}")

-1.18911597e-01 -2.73928515e-02  5.87718399e-02  1.22032424e+00
 1.35338848e+05  7.24847722e+04  6.46971261e+04 -5.31718117e-02
-2.01502312e-01  5.99824346e-02 -4.49157854e-02 -1.27917696e-01
-1.60950285e-01  1.03880213e-02  2.03053286e-02 -1.32510850e-02
-3.10795606e-02  2.96573821e-02  4.55298015e-02  1.70641247e-02
 7.10578386e-03 -8.50088987e-03  1.75892608e-02  4.21347142e-02
 2.34083001e-02 -2.45780467e-02 -6.27598906e-02  1.56740970e-03
 3.93235620e-02  1.45024054e-02 -8.23726047e-03  4.81237923e+00
 3.44415521e-01  5.64028059e-01  6.58542206e-01 -2.86467539e-01
 4.67453563e-01  7.17372765e-02  2.18021957e-02  7.69152468e-02
-1.40440322e-01 -3.93887578e-02 -4.10580724e-02 -6.17920701e-01
-2.60889871e+05 -2.58821418e+05 -1.07497369e+05 -1.28125236e-01

 8.02615757e-02  8.32534702e-02 -6.08944082e-03 -1.85565853e-03
 1.60532757e-02 -7.76050685e-03  5.11619031e-03 -5.93707156e-03
-2.79045095e-02  3.85463791e-02  2.84751735e-02  2.77277361e-02
-2.54211181e-03  2.25070537e-01  1.01721988e-01 -4.51394784e-02
-1.18390852e-01  3.66696798e-02 -4.61704117e-03 -2.52464832e-02
-1.29514526e-02 -5.17084968e-03 -8.23915500e-03 -1.00635010e+00
-4.71567039e-01 -4.51652863e-01  5.52382696e-01 -1.23894777e-01
 2.05604050e-02  1.51340701e-01  5.72652401e-02  5.00094516e-04

In [87]: # Making predictions using the predict() and xTest data
predictions = model.predict(X_test)

In [88]: comparison = pd.DataFrame({'Predicted Values':predictions,'Actual Values':y_test})
```



```
In [89]: print(comparison.head(10))

   Predicted Values  Actual Values
0         -0.266657             0
1          3.613355             4
2          4.276231             4
3          4.061033             4
4          3.167156             3
5          1.762185             2
6         -0.027905             0
7          3.024659             3
8          4.700019             5
9          4.735600             5

In [ ]:
```

Logistic regression

```
In [90]: from sklearn.linear_model import LogisticRegression

In [91]: logmodel=LogisticRegression()

In [92]: logmodel.fit(X_train,y_train)

C:\Users\User\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:763: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
https://scikit-learn.org/stable/modules/linear\_model.html#logistic-regression (https://scikit-learn.org/stable/modules/linear\_model.html#logistic-regression)
n_iter_i = _check_optimize_result(

Out[92]: LogisticRegression()

In [93]: predictions=logmodel.predict(X_test)

In [94]: from sklearn.metrics import classification_report

In [95]: classification_report(y_test,predictions)

Out[95]: '          precision    recall  f1-score   support\n\n         0          1.00      1.00      1.00      419\n         1          0.96      0.96      0.96      386\n         2          0.97      0.96      0.96      410\n         3          0.96      0.96      0.96      356\n         4          0.99      0.99      0.99      316\n         5          0.99      0.99      0.99      319\n\n    accuracy          0.99\n\n    macro avg       0.99\n\n    weighted avg       0.99\n\n'

In [96]: from sklearn.metrics import confusion_matrix

In [97]: confusion_matrix(y_test,predictions)

Out[97]: array([[419,  0,  0,  0,  0,  0],
                [ 0, 370, 15,  0,  0,  1],
                [ 0, 14, 396,  0,  0,  0],
                [ 0,  0,  0, 356,  0,  0],
                [ 0,  0,  0,  0, 315,  1],
                [ 0,  0,  0,  0,  1, 318]], dtype=int64)

In [98]: from sklearn.metrics import accuracy_score

In [196]: Lr=accuracy_score(y_test,predictions)

In [197]: Lr

Out[197]: 0.985494106980961

In [ ]:
```

SVM

```
In [168]: from sklearn.metrics import confusion_matrix
          from sklearn.metrics import classification_report,accuracy_score

In [169]: from sklearn import svm
          model = svm.SVC(C = 1, kernel = 'linear', gamma = 'auto')
          fit_model = model.fit(X_train,y_train)

In [170]: sv=model.score(X_test, y_test)
          print('Test set\n Accuracy: {:.2f}'.format(model.score(X_test, y_test))) #the accuracy of the model on test data is given below

Test set
Accuracy: 0.98

In [ ]:
```

Decision tree

```
In [171]: from sklearn.tree import DecisionTreeClassifier
          dtree=DecisionTreeClassifier()
          dtree.fit(X_train,y_train)

Out[171]: DecisionTreeClassifier()

In [172]: # Predicting the values of test data
          y_pred = dtree.predict(X_test)
          print("Classification report - \n", classification_report(y_test,y_pred))

Classification report -
          precision    recall  f1-score   support

         0          1.00      1.00      1.00      419
         1          0.91      0.87      0.89      386
         2          0.89      0.92      0.90      410
         3          0.95      0.94      0.95      356
         4          0.96      0.94      0.95      316
         5          0.91      0.95      0.93      319

    accuracy          0.94
    macro avg       0.94
    weighted avg       0.94
```

```
In [184]: dt=dtree.score(X_test, y_test)
print('Test set\n Accuracy: {:.2f}'.format(dtree.score(X_test, y_test))) #the accuracy of the model on test data is given below

Test set
Accuracy: 0.94

In [ ]:

In [ ]:
```

Random forest

```
In [174]: from sklearn.ensemble import RandomForestClassifier
Rn = RandomForestClassifier(n_estimators=4,criterion='entropy',random_state=0)
Rn=Rn.fit(X_train,y_train)

In [175]: rn=Rn.score(X_test, y_test)
print('Test set\n Accuracy: {:.2f}'.format(Rn.score(X_test, y_test))) #the accuracy of the model on test data is given below

Test set
Accuracy: 0.94

In [ ]:
```

Bagging Classifier Model

```
In [43]: from sklearn.ensemble import BaggingClassifier

In [44]: BC=BaggingClassifier()
BC= BC.fit(X_train , y_train)
BC

Out[44]: BaggingClassifier()

In [147]: bc=BC.score(X_test, y_test)
print('Test set\n Accuracy: {:.2f}'.format(BC.score(X_test, y_test))) #the accuracy of the model on test data is given below

Test set
Accuracy: 0.96

In [ ]:
```

XGB Classifierr Model

```
In [140]: from xgboost import XGBClassifier

In [141]: XG=XGBClassifier(verbosity = 0)
XG= XG.fit(X_train , y_train)
XG

Out[141]: XGBClassifier(base_score=0.5, booster='gbtree', callbacks=None,
                        colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
                        early_stopping_rounds=None, enable_categorical=False,
                        eval_metric=None, gamma=0, gpu_id=-1, grow_policy='depthwise',
                        importance_type=None, interaction_constraints='',
                        learning_rate=0.300000012, max_bin=256, max_cat_to_onehot=4,
                        max_delta_step=0, max_depth=6, max_leaves=0, min_child_weight=1,
                        missing=nan, monotone_constraints=(), n_estimators=100,
                        n_jobs=0, num_parallel_tree=1, objective='multi:softprob',
                        predictor='auto', random_state=0, reg_alpha=0, ...)

In [142]: xg=XG.score(X_test, y_test)
print('Test set\n Accuracy: {:.2f}'.format(XG.score(X_test, y_test))) #the accuracy of the model on test data is given below

Test set
Accuracy: 0.99

In [ ]:
```

AdaBoost Classifier Model

```
In [122]: from sklearn.ensemble import AdaBoostClassifier

In [123]: AD=AdaBoostClassifier()
AD= AD.fit(X_train , y_train)
AD

Out[123]: AdaBoostClassifier()

In [124]: ad=AD.score(X_test, y_test)
print('Test set\n Accuracy: {:.2f}'.format(AD.score(X_test, y_test))) #the accuracy of the model on test data is given below

Test set
Accuracy: 0.54

In [ ]:
```

Gradient Boosting Classifier Model

```
In [15]: from sklearn.ensemble import GradientBoostingClassifier

In [16]: GB=GradientBoostingClassifier()
GB= GB.fit(X_train , y_train)
GB

Out[16]: GradientBoostingClassifier()

In [17]: gb=GB.score(X_test, y_test)
print('Test set\n Accuracy: {:.2f}'.format(GB.score(X_test, y_test))) #the accuracy of the model on test data is given below

Test set
Accuracy: 0.98

In [ ]:
```

Comparison of Bagging and Boosting Models

```
In [207]: from prettytable import PrettyTable
```

```
In [208]: x = PrettyTable()  
print('\n')
```

```
In [209]: x.field_names = ["Model", "Accuracy"]  
x.add_row(["Linear Regression Model", round(r_sq,2)])  
x.add_row(["Logistic Regression model", round(Lr,2)])  
x.add_row(["Support Vector Machine", round(sv,2)])  
x.add_row(["Decision Tree Model", round(dt,2)])  
x.add_row(["Random Forest Classifier Model",round(rn,2)])  
x.add_row(["Bagging Classifier Model", round(bc,2)])  
x.add_row(["XGB Classifierr Model", round(xg,2)])  
x.add_row(["AdaBoost Classifier Model", round(ad,2)])  
x.add_row(["Gradient Boosting Classifier Model", round(gb,2)])
```

```
In [210]: print(x)  
print('\n')
```

+-----+ Model Accuracy +-----+	
Linear Regression Model	0.98
Logistic Regression model	0.99
Support Vector Machine	0.98
Decision Tree Model	0.94
Random Forest Classifier Model	0.94
Bagging Classifier Model	0.96
XGB Classifierr Model	0.99
AdaBoost Classifier Model	0.54
Gradient Boosting Classifier Model	0.98
+-----+	

XG Boosting and Logistic regression have given highest accuracy of 99% and while Ada Boosting had given the low accuracy of 54%

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