```
"""
(Take any Dataset of your choice ,perform EDA(Exploratory Data Analysis) and apply a
suitable Classifier,Regressor or Clusterer and calculate the accuracy of the model.)

Aim - Predicting insurance charges for customers.
Problem type - Regression
Source - Kaggle (Medical Cost Personal Datasets)
Algorithms/Techniques applied - Linear Regression, Random Forest Regressor,
                                 AdaBoost Regressor, Ordinary Least Square (Statsmodel)
Data input for models - Cross-validation and Train-Test splitting
"""
```

```
# Import packages
import pandas as pd
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor, AdaBoostRegressor
from sklearn.model_selection import train_test_split, cross_val_predict
import matplotlib.pyplot as plt
from sklearn.metrics import r2_score
import statsmodels.api as sm
import seaborn as sns
```

```
# to read the dataset
data = pd.read_csv("/content/insurance.csv")
data
```

	age	sex	bmi	children	smoker	region	charges
0	19	female	27.900	0	yes	southwest	16884.92400
1	18	male	33.770	1	no	southeast	1725.55230
2	28	male	33.000	3	no	southeast	4449.46200
3	33	male	22.705	0	no	northwest	21984.47061
4	32	male	28.880	0	no	northwest	3866.85520
...	...	...	...	...	...	...	...
1333	50	male	30.970	3	no	northwest	10600.54830
1334	18	female	31.920	0	no	northeast	2205.98080
1335	18	female	36.850	0	no	southeast	1629.83350
1336	21	female	25.800	0	no	southwest	2007.94500
1337	61	female	29.070	0	yes	northwest	29141.36030

1338 rows × 7 columns

```
#View type of data and its statistical information.
# to find top 5 data from the dataset
data.head()
```

	age	sex	bmi	children	smoker	region	charges
0	19	female	27.900	0	yes	southwest	16884.92400
1	18	male	33.770	1	no	southeast	1725.55230
2	28	male	33.000	3	no	southeast	4449.46200
3	33	male	22.705	0	no	northwest	21984.47061
4	32	male	28.880	0	no	northwest	3866.85520

```
# to find last 5 data from the dataset
data.tail
```

```
<bound method NDFrame.tail of       age     sex     bmi  children smoker     region      charges
0      19  female  27.900         0    yes  southwest  16884.92400
1      18    male  33.770         1     no  southeast   1725.55230
2      28    male  33.000         3     no  southeast   4449.46200
3      33    male  22.705         0     no  northwest  21984.47061
4      32    male  28.880         0     no  northwest   3866.85520
...   ...     ...     ...       ...    ...        ...          ...
1333   50    male  30.970         3     no  northwest  10600.54830
1334   18  female  31.920         0     no  northeast   2205.98080
1335   18  female  36.850         0     no  southeast   1629.83350
1336   21  female  25.800         0     no  southwest   2007.94500
1337   61  female  29.070         0    yes  northwest  29141.36030

[1338 rows x 7 columns]>
```

```
# to find the shape of the dataset
data.shape
```

```
(1338, 7)
```

```
# View all column names and statistical description of data
data.columns
```

```
Index(['age', 'sex', 'bmi', 'children', 'smoker', 'region', 'charges'], dtype='object')
```

```
# to find the information about the dataset
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   age       1338 non-null   int64  
 1   sex       1338 non-null   object 
 2   bmi       1338 non-null   float64
 3   children  1338 non-null   int64  
 4   smoker    1338 non-null   object 
 5   region    1338 non-null   object 
 6   charges   1338 non-null   float64
dtypes: float64(2), int64(2), object(3)
memory usage: 73.3+ KB
```

```
# to describe the dataset
data.describe()
```

	age	bmi	children	charges
count	1338.000000	1338.000000	1338.000000	1338.000000
mean	39.207025	30.663397	1.094918	13270.422265
std	14.049960	6.098187	1.205493	12110.011237
min	18.000000	15.960000	0.000000	1121.873900
25%	27.000000	26.296250	0.000000	4740.287150
50%	39.000000	30.400000	1.000000	9382.033000
75%	51.000000	34.693750	2.000000	16639.912515
max	64.000000	53.130000	5.000000	63770.428010

```
# Check for missing values
data.isnull()
```

	age	sex	bmi	children	smoker	region	charges
0	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...
1333	False	False	False	False	False	False	False
1334	False	False	False	False	False	False	False
1335	False	False	False	False	False	False	False
1336	False	False	False	False	False	False	False
1337	False	False	False	False	False	False	False

1338 rows × 7 columns

```
data.isnull().sum()
```

```
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64
```

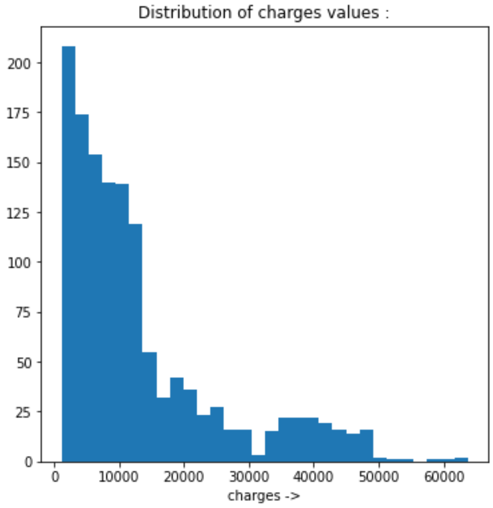
```
# Converting categorical features' string values to int
data.smoker = [1 if x == 'yes' else 0 for x in data.smoker]
```

```
data.sex = [1 if x == 'male' else 0 for x in data.sex]
```

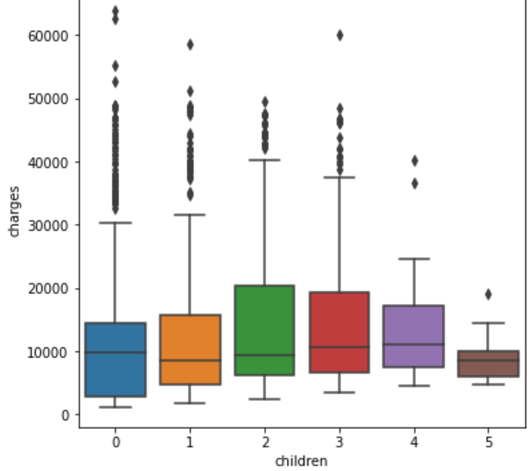
```
# Use pandas because multiple values exist for these columns.
data.region = pd.get_dummies(data.region)
data.charges = pd.to_numeric(data.charges)
data.columns.values
```

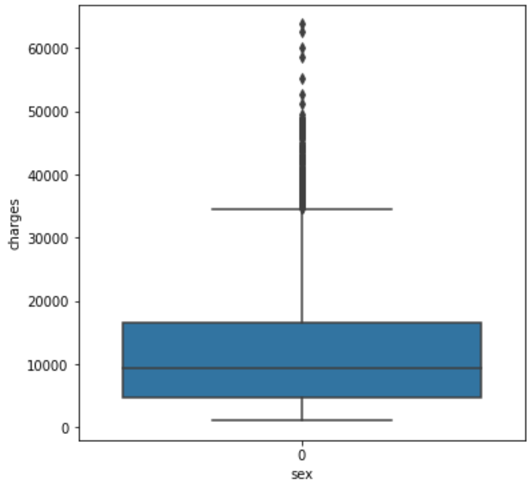
```
#------------------------------------- DATA VISUALIZATION ----------------------------------------------------
# Visualize distribution of values for target variable - 'charges'
plt.figure(figsize=(6,6))
plt.hist(data.charges, bins='auto')
plt.xlabel("charges ->")
plt.title("Distribution of charges values :")
```

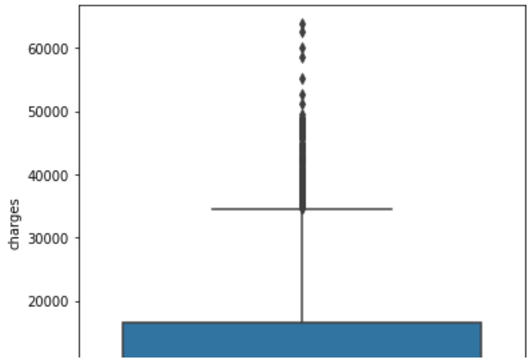
```
Text(0.5, 1.0, 'Distribution of charges values :')
```




```
# Generate Box-plots to check for outliers and relation of each feature with 'charges'
cols = ['age', 'children', 'sex', 'smoker', 'region']
for col in cols:
    plt.figure(figsize=(6,6))
    sns.boxplot(x = data[col], y = data['charges'])
```








```
# Create Correlation matrix for all features of data.
data.corr()
```

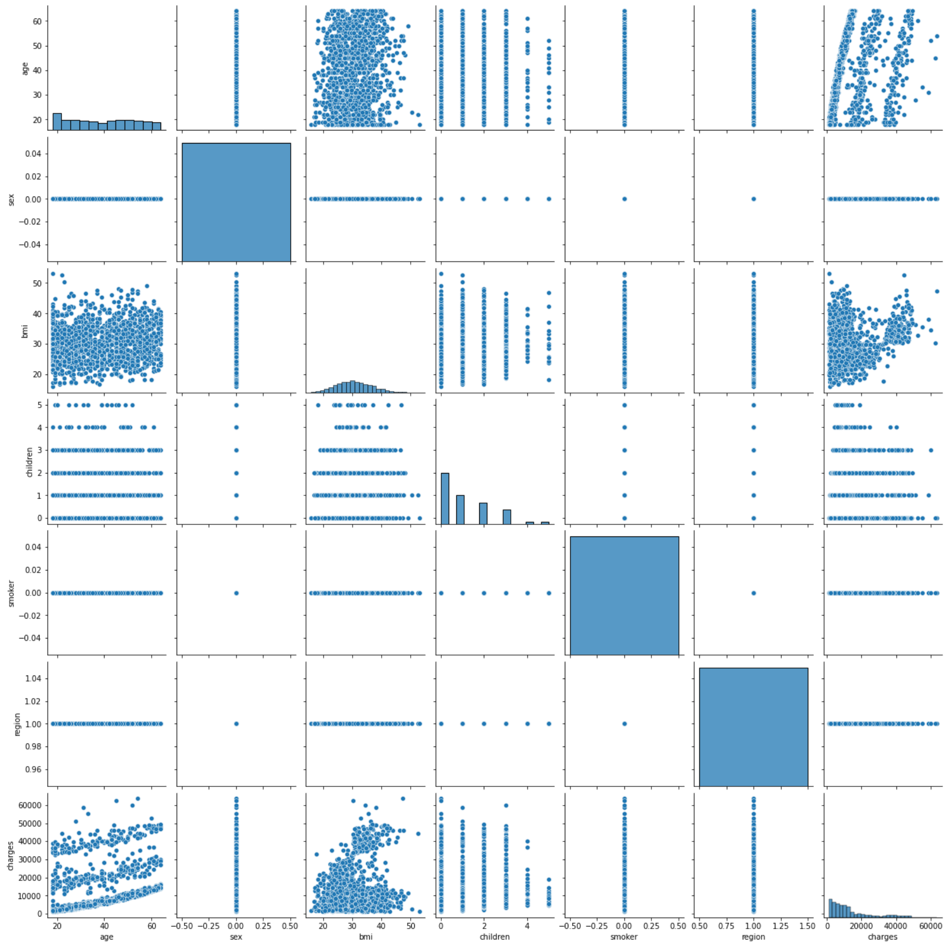
	age	sex	bmi	children	smoker	region	charges
age	1.000000	NaN	0.109272	0.042469	NaN	NaN	0.299008
sex	NaN	NaN	NaN	NaN	NaN	NaN	NaN
bmi	0.109272	NaN	1.000000	0.012759	NaN	NaN	0.198341
children	0.042469	NaN	0.012759	1.000000	NaN	NaN	0.067998
smoker	NaN	NaN	NaN	NaN	NaN	NaN	NaN
region	NaN	NaN	NaN	NaN	NaN	NaN	NaN
charges	0.299008	NaN	0.198341	0.067998	NaN	NaN	1.000000

```
# Generate heatmap to visualize strong & weak correlations.
sns.heatmap(data.corr(), square = True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fde6efde250>
```


```
# Generate predictions using all features by a Linear Regression model.
sns.pairplot(data)
```

```
<seaborn.axisgrid.PairGrid at 0x7fde6c5cb790>
```



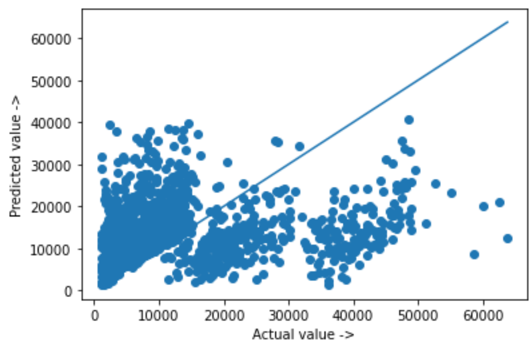

```
#-------------------------- Prepare data for predictive regression models ------------------------------------
y = data.charges.values
X = data.drop(['charges'], axis = 1)   # Drop the target
```

```
# -------------------------- PREDICTIVE MODELLING (Call the models to be used) ---------------------------------
rf_reg = RandomForestRegressor(max_features = 'auto', bootstrap = True, random_state = None)
lin_reg = LinearRegression(normalize = True)
ada_reg = AdaBoostRegressor()
```

```
# -------------------------- 1st Approach - Using Cross-validation (to avoid overfitting) -----------------------
# -------------------------- Plotting Cross-validation Predictions for each model -------------------------------
```

```
# Predict using Random Forest Regressor.
predRF = cross_val_predict(rf_reg, X, y, cv=10)
fig, ax = plt.subplots()
ax.scatter(y, predRF)
ax.plot([y.min(), y.max()], [y.min(), y.max()])
ax.set_xlabel('Actual value ->')
ax.set_ylabel('Predicted value ->')
```

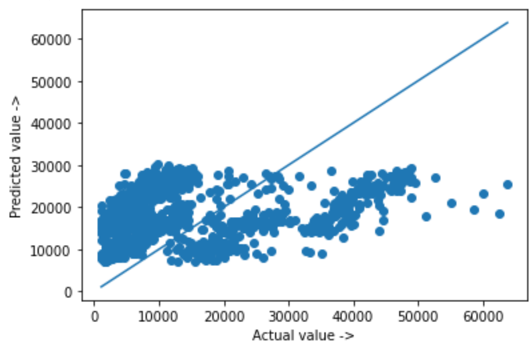
```
Text(0, 0.5, 'Predicted value ->')
```




```
# Predict using Linear Regression
predLR = cross_val_predict(lin_reg, X, y, cv=10)
fig, ax = plt.subplots()
ax.scatter(y, predLR)
ax.plot([y.min(), y.max()], [y.min(), y.max()])
ax.set_xlabel('Actual value ->')
ax.set_ylabel('Predicted value ->')
```

```
# Predict using ADABoost Regressor
predADA = cross_val_predict(ada_reg, X, y, cv=10)
fig, ax = plt.subplots()
ax.scatter(y, predADA)
ax.plot([y.min(), y.max()], [y.min(), y.max()])
ax.set_xlabel('Actual value ->')
ax.set_ylabel('Predicted value ->')
```

```
Text(0, 0.5, 'Predicted value ->')
```




```
# ----------------- 2nd Approach - Using Train-test-split ---------------------------------
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = None)
```

```
# Predict using Random Forest Regressor.
rf_reg.fit(X_train, y_train)
predtrainRF = rf_reg.predict(X_train)     # Prediction for train data
predtestRF = rf_reg.predict(X_test)       # Prediction for test data
```

```
# Compute R-squared score for both train and test data.
print("R2-score on train data:", r2_score(y_train,predtrainRF))
print("R2-score on test data:", r2_score(y_test, predtestRF))
```

```
R2-score on train data: 0.8421530759713811
R2-score on test data: 0.015220923209714687
```

```
# Predict using Linear Regression
lin_reg.fit(X_train, y_train)
predtrainL = lin_reg.predict(X_train)
predtestL = lin_reg.predict(X_test)
print("R2-score on train data:",r2_score(y_train, predtrainL))
print("R2-score on test data:",r2_score(y_test, predtestL))
```

```
# Predict using XGBoost Regressor
ada_reg.fit(X_train, y_train)
predtrainAda = ada_reg.predict(X_train)
predtestAda = ada_reg.predict(X_test)
```

```
print("R2-score on train data:",r2_score(y_train, predtrainAda))
print("R2-score on test data:",r2_score(y_test, predtestAda))
```

```
R2-score on train data: 0.0022309708434786746
R2-score on test data: 0.11948408035181801
```

```
# ------------------ Using Ordinary Least Square from Statsmodel --------------------------------
# ----------------- Allows to view full summary statistics along with p-value and F-statistics ----------------
# On Train data.
X_newtrain = sm.add_constant(X_train)
ols_train = sm.OLS(y_train, X_newtrain)
ols_train_new = ols_train.fit()
print(ols_train_new.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.112
Model:                            OLS   Adj. R-squared:                  0.109
Method:                 Least Squares   F-statistic:                     44.76
Date:                Sun, 27 Nov 2022   Prob (F-statistic):           3.04e-27
Time:                        05:45:36   Log-Likelihood:                -11481.
No. Observations:                1070   AIC:                         2.297e+04
Df Residuals:                    1066   BIC:                         2.299e+04
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
age          225.3251     24.180      9.319      0.000     177.880     272.770
sex         1.162e-12   3.98e-13      2.918      0.004    3.81e-13    1.94e-12
bmi          313.0189     55.591      5.631      0.000     203.939     422.098
children     576.8860    282.063      2.045      0.041      23.425    1130.347
smoker              0          0        nan        nan           0           0
region     -6043.4113   1930.328     -3.131      0.002   -9831.084   -2255.738
==============================================================================
Omnibus:                      276.607   Durbin-Watson:                   2.036
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              531.270
Skew:                           1.566   Prob(JB):                    4.33e-116
Kurtosis:                       4.450   Cond. No.                          inf
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is      0. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/tsatools.py:142: FutureWarning: In a future version of pandas all arguments of concat excep
  x = pd.concat(x[::order], 1)
/usr/local/lib/python3.7/dist-packages/statsmodels/regression/linear_model.py:1860: RuntimeWarning: divide by zero encountered in double_scalars
  return np.sqrt(eigvals[0]/eigvals[-1])
```

```
# On Test data.
X_newtest = sm.add_constant(X_test)
ols_test = sm.OLS(y_test, X_newtest)
ols_test_new = ols_test.fit()
print(ols_test_new.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.153
Model:                            OLS   Adj. R-squared:                  0.144
Method:                 Least Squares   F-statistic:                     15.95
Date:                Sun, 27 Nov 2022   Prob (F-statistic):           1.46e-09
Time:                        05:46:40   Log-Likelihood:                -2905.9
No. Observations:                 268   AIC:                             5820.
Df Residuals:                     264   BIC:                             5834.
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
age          295.2113     56.232      5.250      0.000     184.492     405.931
sex         3.468e-12   1.47e-12      2.358      0.019    5.72e-13    6.36e-12
bmi          394.5134    130.673      3.019      0.003     137.219     651.808
children     535.4061    631.125      0.848      0.397    -707.274    1778.086
smoker              0          0        nan        nan           0           0
region     -9976.4551   4205.032     -2.373      0.018   -1.83e+04   -1696.787
==============================================================================
Omnibus:                       52.447   Durbin-Watson:                   1.839
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               78.163
Skew:                           1.299   Prob(JB):                     1.06e-17
Kurtosis:                       3.498   Cond. No.                          inf
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is      0. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/tsatools.py:142: FutureWarning: In a future version of pandas all arguments of concat excep
  x = pd.concat(x[::order], 1)
/usr/local/lib/python3.7/dist-packages/statsmodels/regression/linear_model.py:1860: RuntimeWarning: divide by zero encountered in double_scalars
  return np.sqrt(eigvals[0]/eigvals[-1])
```