Medical Expense Prediction

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Project description: This project aims at building a Machine Learning model which can predict a patient's medical expenses based on patient demographics and several characteristics.

Data: The training dataset contains information on 1,338 patients.

It includes the following features:

Age: Patient's age

Sex: Patient's sex

BMI: Patient's Body Mass Index

Children: How many children the patient has

Smoker: Whether the patient is a smoker or not

Region: Which region the patient is from (Northeast, Southeast, Soutwest, Northwest)

Data Pre - Processing

```
# Import the required libraries

# For mathemaical operations
import numpy as np
# For dataframe manipulations
import pandas as pd

# For data visualizations
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px

# Setting parameters for visualization
plt.rcParams['figure.figsize'] = (20, 10)
plt.style.use('fivethirtyeight')
```

```
# Read the data set

data = pd.read_csv('med-expense.csv')
```

```
# Total number of rows and columns

data.shape
```

```
(1338, 7)
```

So here we have total 1338 Rows and 7 Columns in the given dataset

```
# A snippet of raw dataset

data
```

	age	sex	bmi	children	smoker	region	expenses
0	19	female	27.9	0	yes	southwest	16884.92
1	18	male	33.8	1	no	southeast	1725.55
2	28	male	33.0	3	no	southeast	4449.46
3	33	male	22.7	0	no	northwest	21984.47
4	32	male	28.9	0	no	northwest	3866.86
...	...	...	...	...	...	...	...
1333	50	male	31.0	3	no	northwest	10600.55
1334	18	female	31.9	0	no	northeast	2205.98
1335	18	female	36.9	0	no	southeast	1629.83
1336	21	female	25.8	0	no	southwest	2007.95
1337	61	female	29.1	0	yes	northwest	29141.36

1338 rows × 7 columns

```
# Display all the columns with corresponding count of non null observation and along w

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   expenses  1338 non-null   float64
```

```
dtypes: float64(2), int64(2), object(3)
memory usage: 73.3+ KB
```

We observe that "age", "children", "bmi" and "expenses" are numbers, whereas "gender", "smoker" and "region" are strings (possibly categories).

None of the columns contain any missing values, which saves us a fair bit of work!

```
# Statistical measurement of variables

data.describe()
```

	age	bmi	children	expenses
count	1338.000000	1338.000000	1338.000000	1338.000000
mean	39.207025	30.665471	1.094918	13270.422414
std	14.049960	6.098382	1.205493	12110.011240
min	18.000000	16.000000	0.000000	1121.870000
25%	27.000000	26.300000	0.000000	4740.287500
50%	39.000000	30.400000	1.000000	9382.030000
75%	51.000000	34.700000	2.000000	16639.915000
max	64.000000	53.100000	5.000000	63770.430000

From the above dataset we can see that Age, BMI, Children, Expenses are only Numeric Values and also get corresponding their statistical measurement.

Here from the above information we can conclude that Age varible is symmetrically distributed as Mean = Median.

BMI is also symmetrically distributed.

But variable Expenses is positively skewed as Mean > Median.

```
# Checking for null values

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

```
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
```

```
expenses    0
```

So, here there are no null values with respect to each Column of the dataset. Hence data cleaning is not required.

```
# Checking for number of unique values

data.nunique()
```

```
age            47
sex             2
bmi           275
children        6
smoker          2
region          4
expenses     1337
dtype: int64
```

As the expenses column consists of total of 1338 values, these seems to be one duplicate value.

```
# Lets remove the duplicate value

duplicate_rows_data = data[data.duplicated()]
duplicate_rows_data
```

	age	sex	bmi	children	smoker	region	expenses
581	19	male	30.6	0	no	northwest	1639.56

```
# Identifying the duplicated row based on the expense

data[data["expenses"] == 1639.56]
```

	age	sex	bmi	children	smoker	region	expenses
195	19	male	30.6	0	no	northwest	1639.56
581	19	male	30.6	0	no	northwest	1639.56

```
# Dropping the second duplicate row

data.drop_duplicates(keep = 'first', inplace = True)
data[data.duplicated()]
```

age	sex	bmi	children	smoker	region	expenses

```
# Checking the count of dataset

data.count()
```

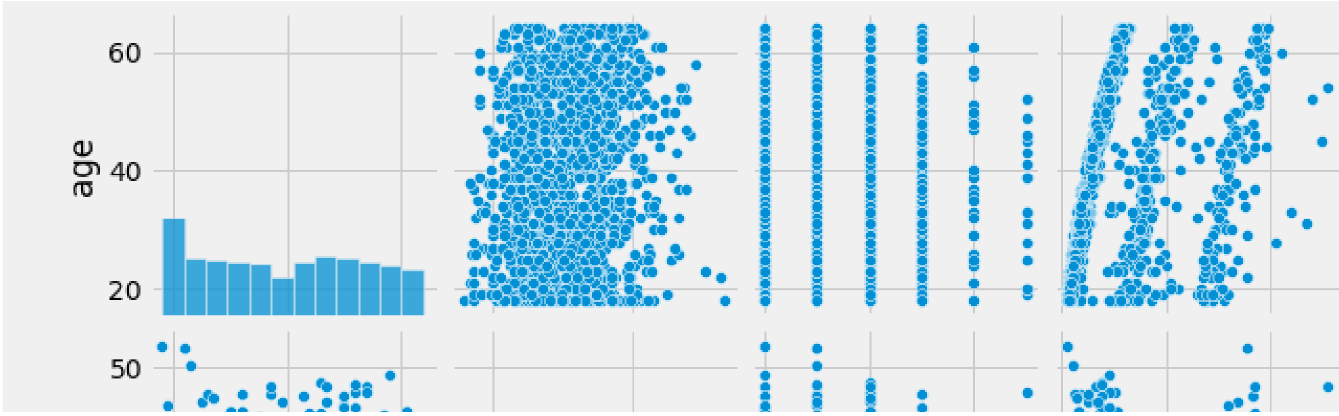
```
age         1337
sex         1337
bmi         1337
children    1337
smoker      1337
region      1337
expenses    1337
dtype: int64
```

Exploratory Data Analysis

Data Visualization

```
# Visualizing using Pair Plot

sns.pairplot(data)
```

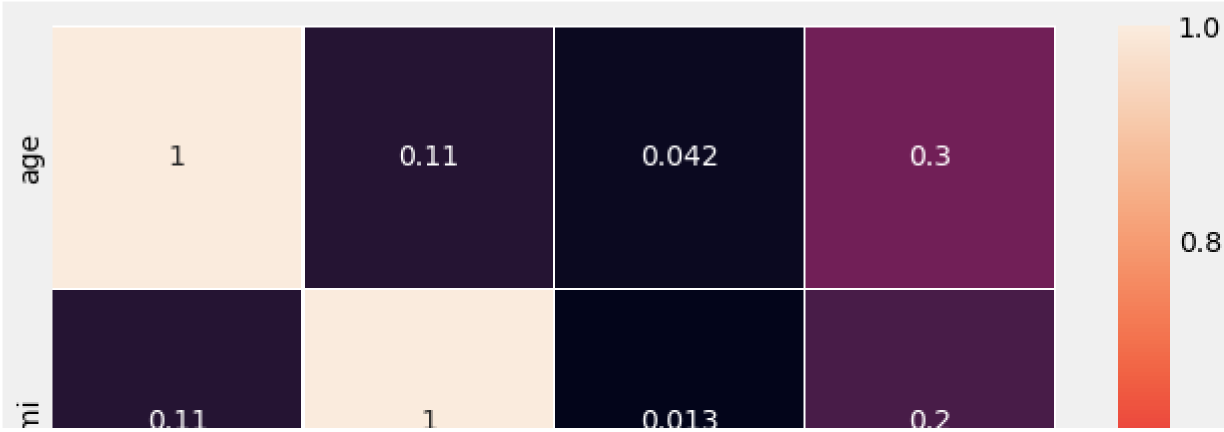
<seaborn.axisgrid.PairGrid at 0x7f8d0886d890>



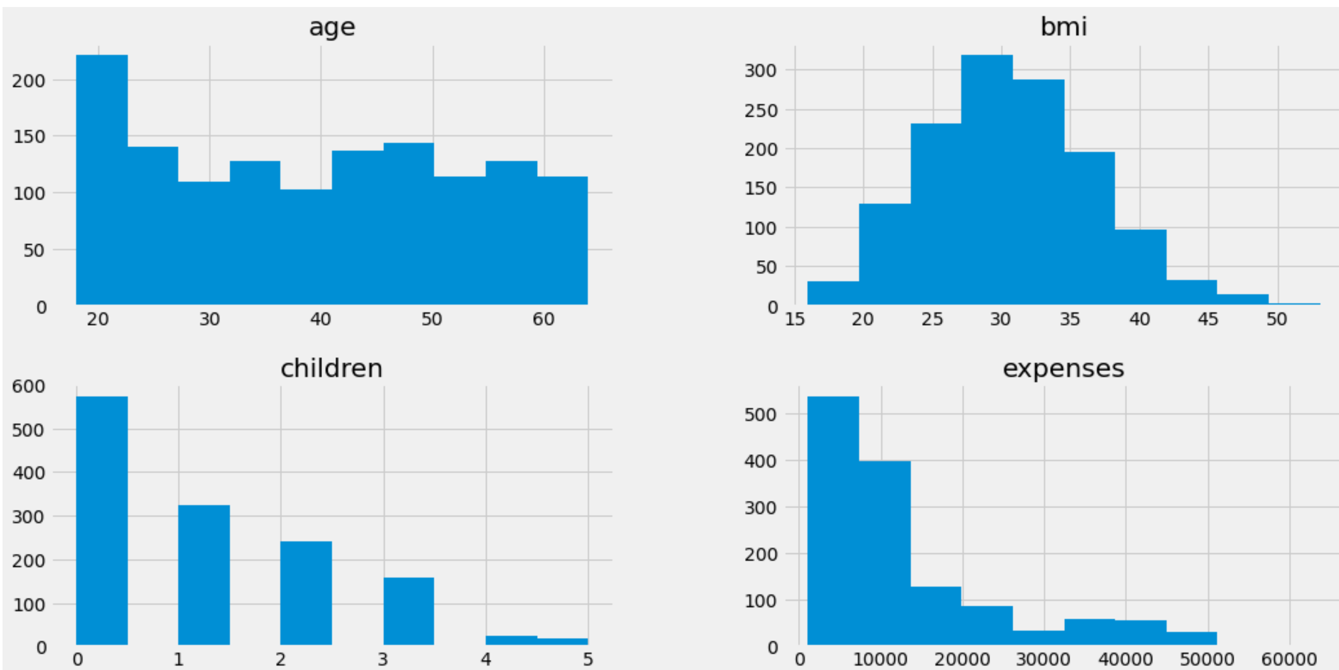

```
# Checking the correlation

data.corr()
```

	age	bmi	children	expenses
age	1.000000	0.109414	0.041536	0.298308
bmi	0.109414	1.000000	0.012641	0.198637
children	0.041536	0.012641	1.000000	0.067389
expenses	0.298308	0.198637	0.067389	1.000000


```
# Plot the Correlation Matrix with Raw Data (Linear Correlation)

plt.figure(figsize = (10,9))
sns.heatmap(data.corr(), annot = True,linewidth=0.5)
plt.show()
```

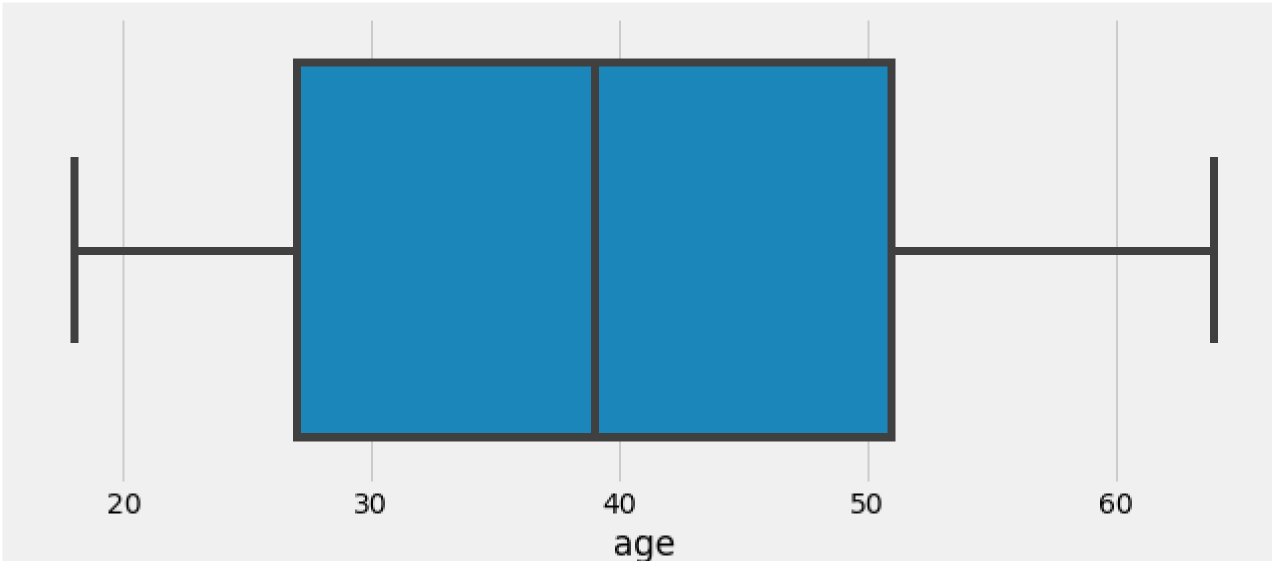



```
# Histogram per each numerical column

data.hist(figsize=(16, 8))

plt.savefig("Histogram.png")
```

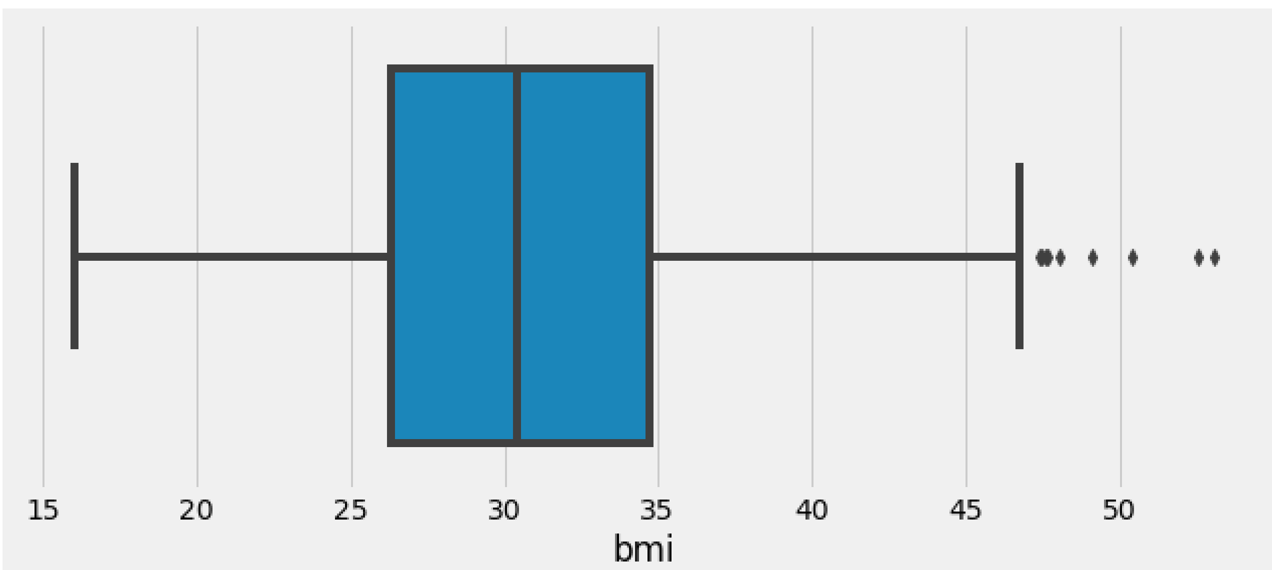



```
# Boxplot of age column

plt.figure(figsize=(10, 4))
```

```
sns.boxplot(x=data['age'])
plt.savefig("Boxplot1.png")
```

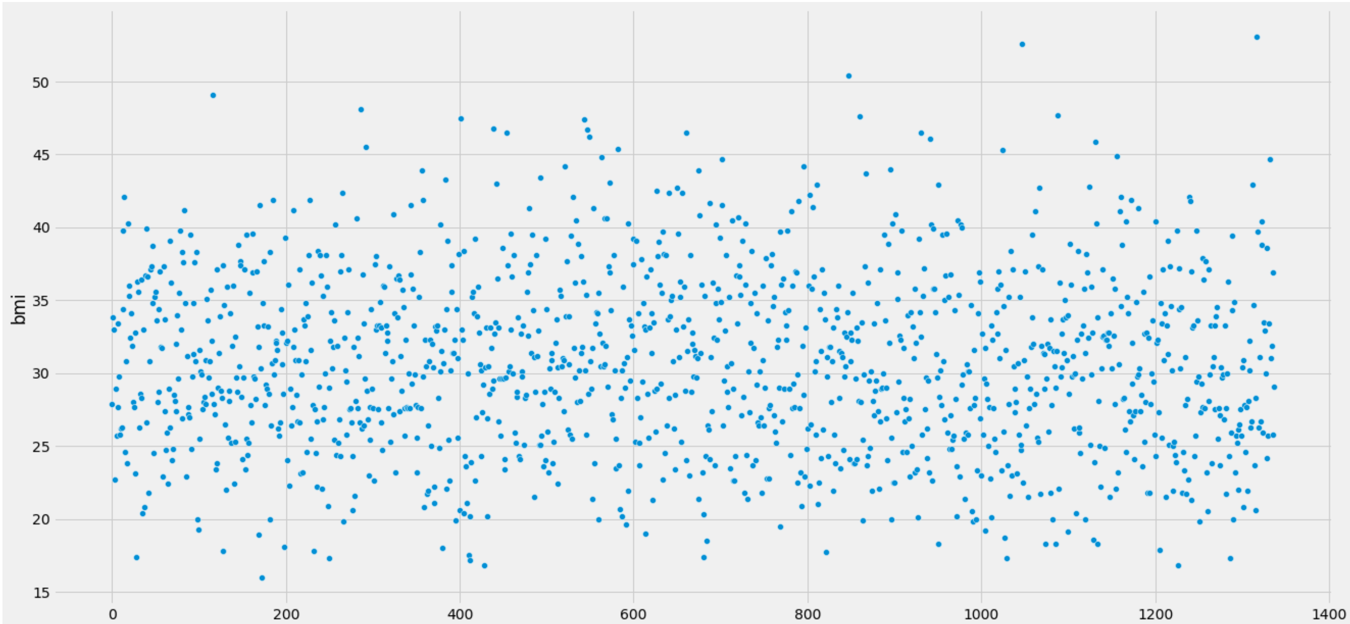



```
# Boxplot of bmi column

plt.figure(figsize=(10, 4))
sns.boxplot(x=data['bmi'])
plt.savefig("Boxplot2.png")
```

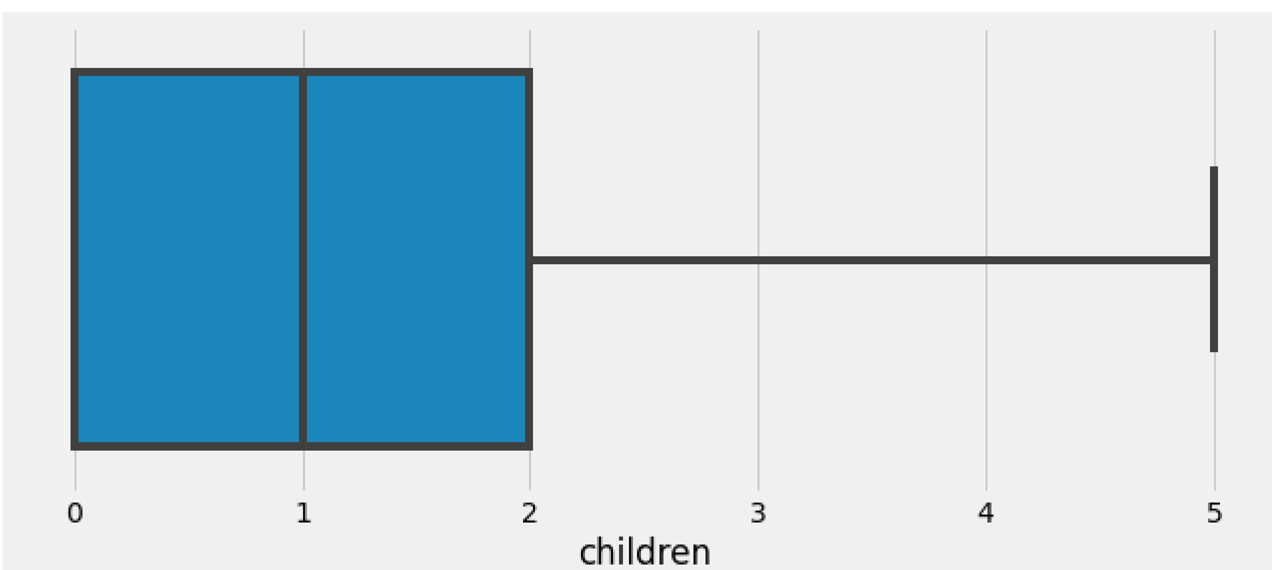



```
# Scatter plot for visualizing outliers on bmi

sns.scatterplot(data = data['bmi'])
```

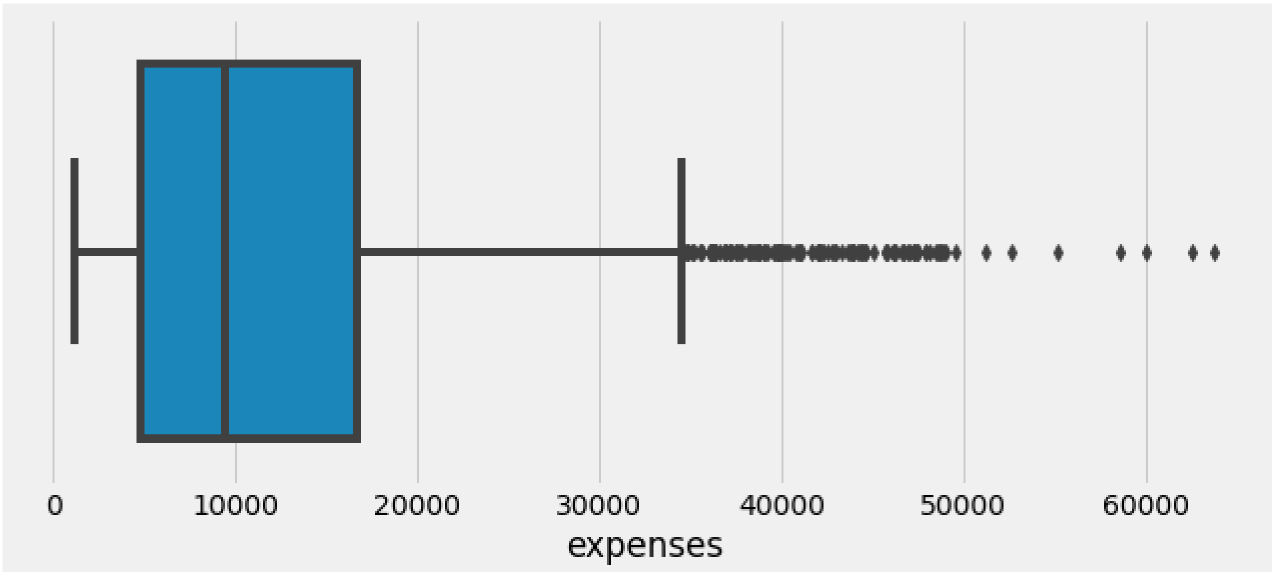
<matplotlib.axes._subplots.AxesSubplot at 0x7f8d08147550>




```
# Boxplot of children column

plt.figure(figsize=(10, 4))
sns.boxplot(x=data['children'])
plt.savefig("Boxplot3.png")
```

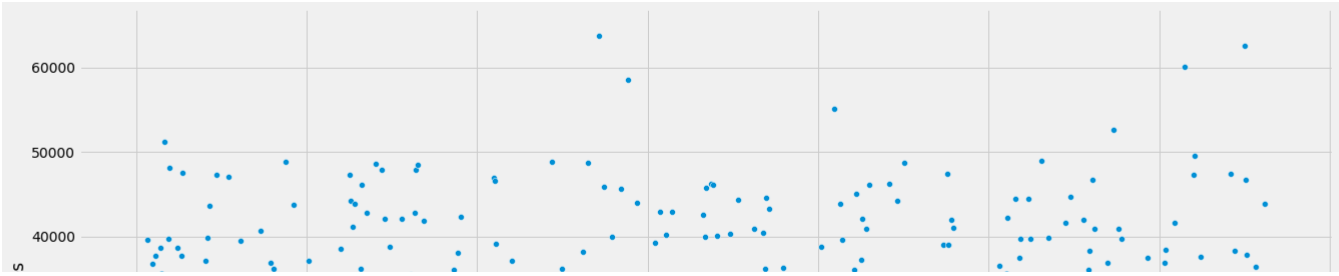


```
# Boxplot of expenses column

plt.figure(figsize=(10, 4))
sns.boxplot(x=data['expenses'])
plt.savefig("Boxplot4.png")
```



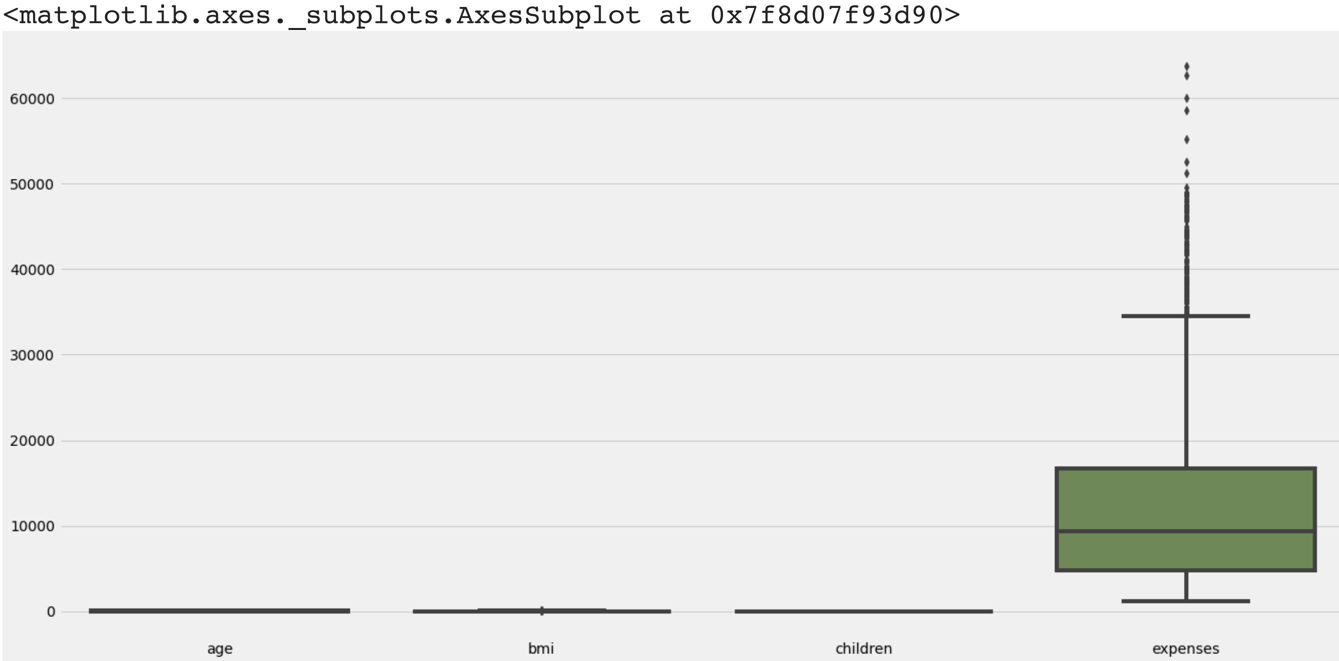

```
# Scatter plot for visualizing outliers on expenses

sns.scatterplot(data = data['expenses'])
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f8d0800cd10>




```
# Boxplot of all numerical variables

sns.boxplot(data = data)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f8d07f93d90>




```
# Statistical Measurement of dataset
```

```
data.describe()
```

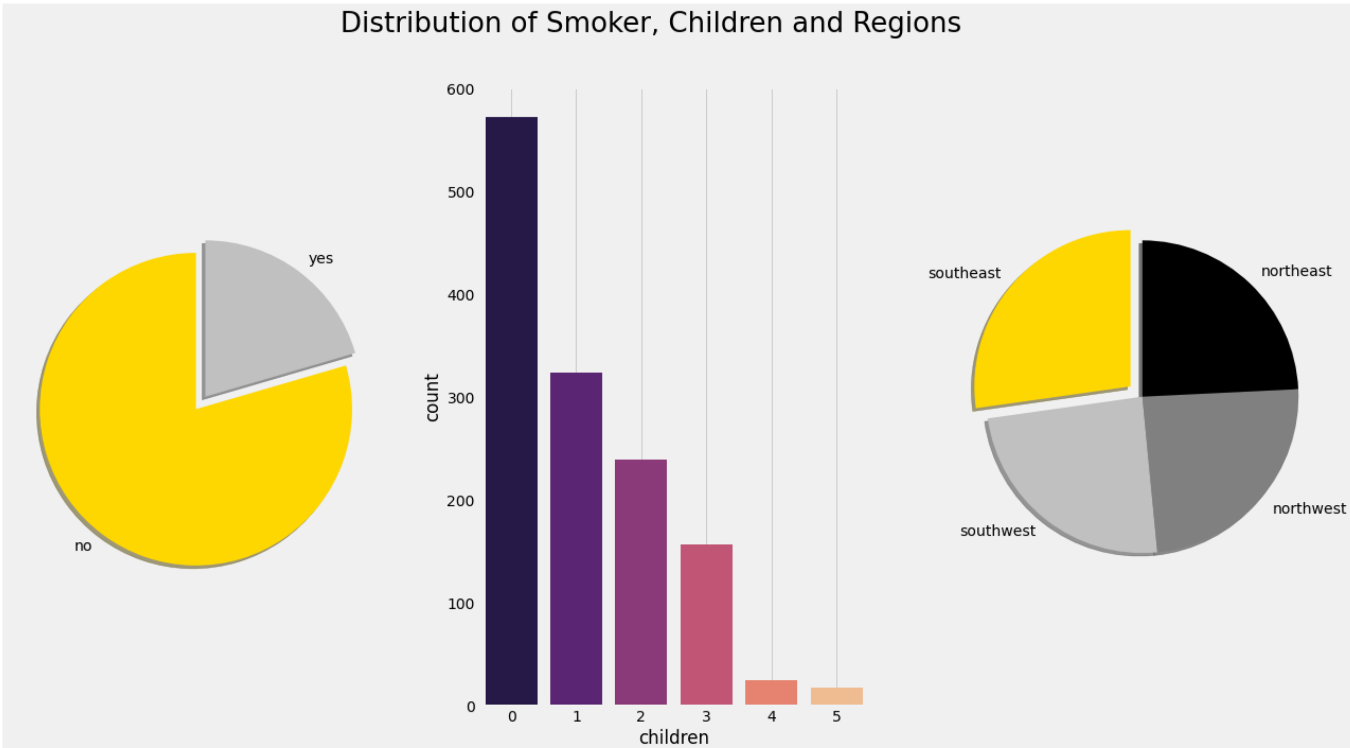
	age	bmi	children	expenses
count	1337.000000	1337.000000	1337.000000	1337.000000
mean	39.222139	30.665520	1.095737	13279.121638
std	14.044333	6.100664	1.205571	12110.359657
min	18.000000	16.000000	0.000000	1121.870000
25%	27.000000	26.300000	0.000000	4746.340000
50%	39.000000	30.400000	1.000000	9386.160000
75%	51.000000	34.700000	2.000000	16657.720000
max	64.000000	53.100000	5.000000	63770.430000

Univariate Analysis

```
# Checking distribution of smoker, children, region first

# Plot 1
plt.subplot (1, 3, 1)

plt.pie ( data['smoker'].value_counts().values,
          labels = data['smoker'].value_counts().index,
          colors = ['gold','silver'],
          startangle = 90,
          shadow = True,
          explode = [0.1, 0] )


# Plot 2
plt.subplot (1, 3, 2)

sns.countplot ( data['children'], palette = 'magma' )
plt.grid()


# Plot 3
plt.subplot (1, 3, 3)

plt.pie ( data['region'].value_counts().values,
          labels = data['region'].value_counts().index,
          colors = ['gold','silver','grey','black'],
          startangle = 90,
          shadow = True,
          explode = [0.1, 0, 0, 0] )
```

```
# Plot Out
plt.suptitle('Distribution of Smoker, Children and Regions', fontsize = 26)

plt.show()
```

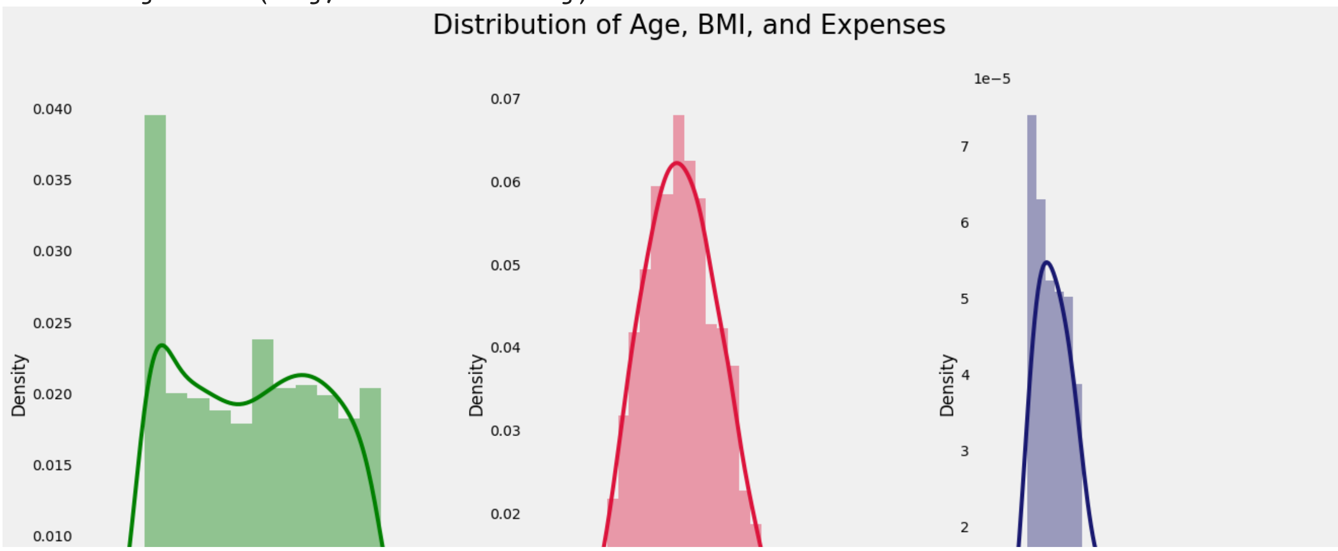
```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning:
  FutureWarning
```




```
# Checking distribution of age, bmi and expenses next

# Plot 1
plt.subplot (1, 3, 1)
```

```
sns.distplot (data['age'], color ='green')
plt.xlabel ('Age')
plt.grid()


# Plot 2
plt.subplot (1, 3, 2)

sns.distplot (data['bmi'], color = 'crimson')
plt.xlabel ('BMI')
plt.grid()


# Plot 3
plt.subplot (1, 3, 3)

sns.distplot (data['expenses'], color = 'midnightblue')
plt.xlabel ('Expenses')
plt.grid()


# Plot Out
plt.suptitle ('Distribution of Age, BMI, and Expenses', fontsize = 26)

plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarn
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarn
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarn
  warnings.warn(msg, FutureWarning)
```



Data Processing


```
# Checking for the categorical columns

data.select_dtypes('object').columns
```

```
Index(['sex', 'smoker', 'region'], dtype='object')
```

```
# Lets use One Hot Encoding to encode the above categorical columns

one_hot_encoded_data = pd.get_dummies(data, columns = ['sex', 'smoker', 'region'])
one_hot_encoded_data
```

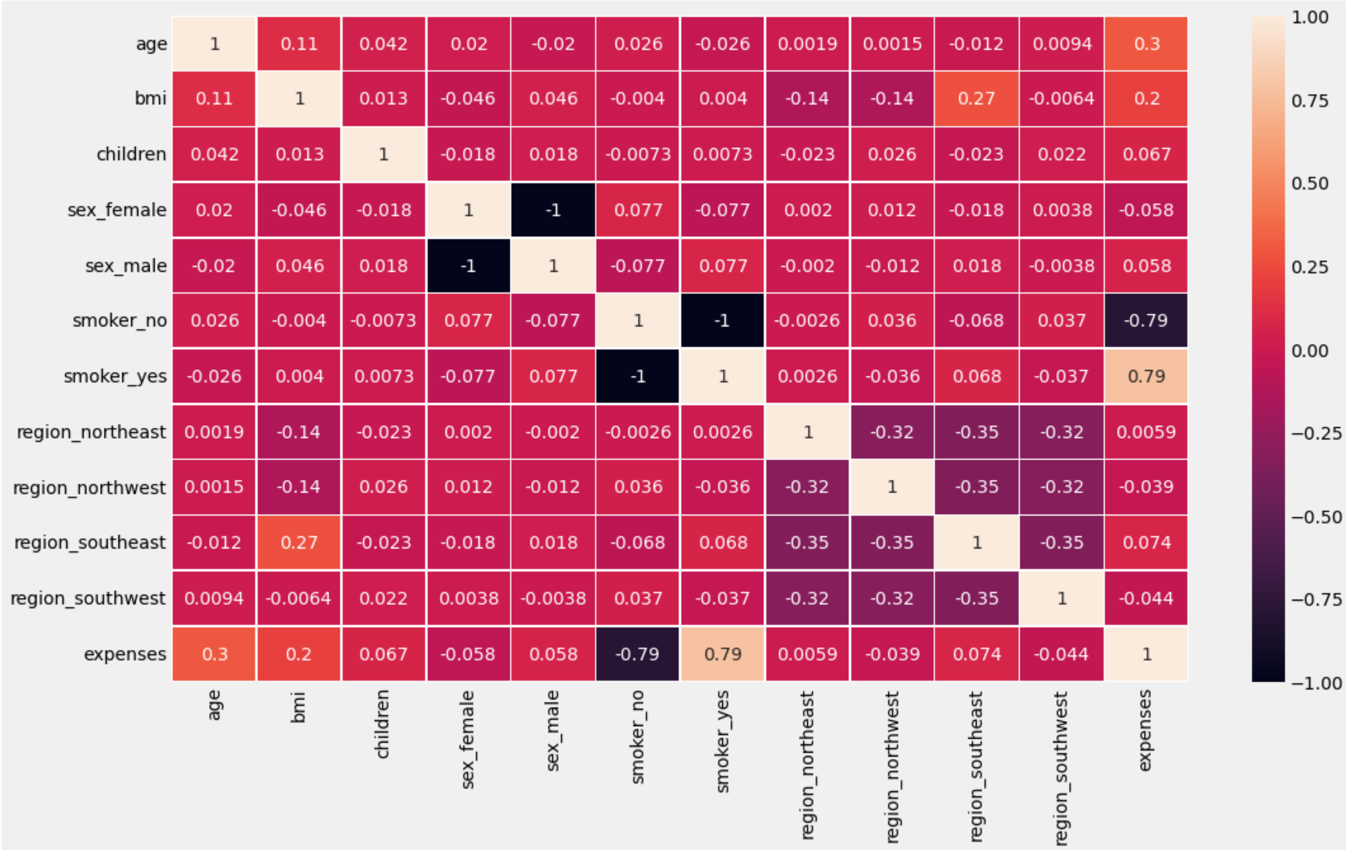
	age	bmi	children	expenses	sex_female	sex_male	smoker_no	smoker_yes
0	19	27.9	0	16884.92	1	0	0	1
1	18	33.8	1	1725.55	0	1	1	0
2	28	33.0	3	4449.46	0	1	1	0

```
# Re-ordering the data by shifting Expenses column to end

column_to_reorder = one_hot_encoded_data.pop('expenses')

one_hot_encoded_data.insert(len(one_hot_encoded_data. columns), 'expenses', column_to_

one_hot_encoded_data
```

	age	bmi	children	sex_female	sex_male	smoker_no	smoker_yes	region_nor
0	19	27.9	0	1	0	0	1	
1	18	33.8	1	0	1	1	0	
2	28	33.0	3	0	1	1	0	
3	33	22.7	0	0	1	1	0	
4	32	28.9	0	0	1	1	0	
...	...	...	...	...	...	...	...	
1333	50	31.0	3	0	1	1	0	
1334	18	31.9	0	1	0	1	0	
1335	18	36.9	0	1	0	1	0	
1336	21	25.8	0	1	0	1	0	
1337	61	29.1	0	1	0	0	1	

1337 rows × 12 columns

```
# Plot the Correlation Matrix on encoded data (Linear Correlation)

plt.figure(figsize = (16,9))
sns.heatmap(one_hot_encoded_data.corr(), annot = True,linewidth=0.5)
plt.show()
```



From the above representation we can say that,

In between Age and Sex we have very weak Correlation, age and BMI have weak coreelation, age and smoker also have weak correlation. Age and Expenses has a moderate correlation, Age and South-West region also Age and North-west region have a negative Correlation.

Sex and Expenses have a negative Correlation.

Correlation between Children and Expenses is very weak.

Correlation between Smoker and Expenses is strongly Negatively Correlated.

Correlation between South-East region and Expenses is weak.

Correlation between South-West region and Expenses is weakly negative.

Correlation between North-West region and Expenses is weakly negative.

Correlation between North-East region and Expenses is zero.

```
# Lets verify the One Hot Encoding process
```

```
print('Columns in original data frame:\n',data.columns.values)
print('\nNumber of rows and columns in the dataset:',data.shape)

print('\nColumns in data frame after One Hot Encoding:\n',one_hot_encoded_data.columns
print('\nNumber of rows and columns in the dataset:',one_hot_encoded_data.shape)
```

```
Columns in original data frame:
 ['age' 'sex' 'bmi' 'children' 'smoker' 'region' 'expenses']

Number of rows and columns in the dataset: (1337, 7)

Columns in data frame after One Hot Encoding:
 ['age' 'bmi' 'children' 'sex_female' 'sex_male' 'smoker_no' 'smoker_yes'
 'region_northeast' 'region_northwest' 'region_southeast'
 'region_southwest' 'expenses']

Number of rows and columns in the dataset: (1337, 12)
```

```
# Lets extract the encoded data to a csv file for reference

one_hot_encoded_data.to_csv("processed-insurance.csv")


# Lets form dependent and independent sets

X = one_hot_encoded_data.drop(['expenses'], axis = 1)
y = one_hot_encoded_data['expenses']


print(X.columns)
print("\n")
print(y.shape)
```

```
Index(['age', 'bmi', 'children', 'sex_female', 'sex_male', 'smoker_no',
       'smoker_yes', 'region_northeast', 'region_northwest',
       'region_southeast', 'region_southwest'],
      dtype='object')


(1337,)
```

```
# Lets perform Train - Test - Split

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_stat

print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(1069, 11)
(268, 11)
(1069,)
(268,)
```

```
# Lets perform Standardization using Standard Scaling

from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
scaler.fit(X_train)
X_train_scaled = scaler.transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

Predictive Modelling

Linear Regression Model

```
# Creating a simple Linear Regression Model

from sklearn.linear_model import LinearRegression

lin = LinearRegression()
lin.fit(X_train,y_train)

y_pred1 = lin.predict (X_test)

print("Training Score     :", lin.score(X_train,y_train))
print("Testing Score      :", lin.score(X_test,y_test))
```

```
Training Score     : 0.7488769969730097
Testing Score      : 0.7530509541914574
```

```
# Model Accuracy -- R2 // RMSE

from sklearn.metrics import r2_score, mean_squared_error


mse = mean_squared_error (y_test, y_pred1)
rmse = np.sqrt(mse)
print("RMSE Score     :", rmse)

r2_score = r2_score (y_test, y_pred1)
print("R2 Score       :", r2_score)
```

```
RMSE Score     : 6445.473682867912
R2 Score       : 0.7530509541914574
```

```
# Creating a simple Linear Regression Model with Scaled data

from sklearn.linear_model import LinearRegression

lin = LinearRegression()
lin.fit(X_train_scaled,y_train)

y_pred1_scaled = lin.predict (X_test_scaled)

print("Training Score     :", lin.score(X_train_scaled,y_train))
print("Testing Score      :", lin.score(X_test_scaled,y_test))
```

```
Training Score     : 0.7488441168659459
Testing Score      : 0.7534323358450128
```

```
# Model Accuracy for scaled data -- R2 // RMSE

from sklearn.metrics import r2_score, mean_squared_error


mse = mean_squared_error (y_test, y_pred1_scaled)
rmse = np.sqrt(mse)
print("RMSE Score     :", rmse)

r2_score = r2_score (y_test, y_pred1_scaled)
print("R2 Score       :", r2_score)
```

```
RMSE Score     : 6440.494649185112
R2 Score       : 0.7534323358450128
```

K-Nearest Neighbors Model

```
# Creating a simple KNN Model

from sklearn.neighbors import KNeighborsRegressor
knn = KNeighborsRegressor()
knn.fit(X_train,y_train)

y_pred2 = knn.predict (X_test)

print("Training Score     :", knn.score(X_train, y_train))
print("Testing Score      :", knn.score(X_test, y_test))
```

```
Training Score     : 0.4954577380856632
```

```
Testing Score      : 0.3391870610379586
```

```
# Model Accuracy -- R2 // RMSE

from sklearn.metrics import r2_score, mean_squared_error


mse = mean_squared_error (y_test, y_pred2)
rmse = np.sqrt(mse)
print("RMSE Score     :", rmse)

r2_score = r2_score (y_test, y_pred2)
print("R2 Score       :", r2_score)
```

```
RMSE Score     : 10543.636680643014
R2 Score       : 0.3391870610379586
```

```
# Creating a simple KNN Model with scaled data

from sklearn.neighbors import KNeighborsRegressor
knn = KNeighborsRegressor()
knn.fit(X_train_scaled,y_train)

y_pred2_scaled = knn.predict (X_test_scaled)

print("Training Score     :", knn.score(X_train_scaled, y_train))
print("Testing Score      :", knn.score(X_test_scaled, y_test))
```

```
Training Score     : 0.8636905165020783
Testing Score      : 0.798254768782863
```

```
# Model Accuracy for scaled data -- R2 // RMSE

from sklearn.metrics import r2_score, mean_squared_error


mse = mean_squared_error (y_test, y_pred2_scaled)
rmse = np.sqrt(mse)
print("RMSE Score     :", rmse)

r2_score = r2_score (y_test, y_pred2_scaled)
print("R2 Score       :", r2_score)
```

```
RMSE Score     : 5825.762855660883
R2 Score       : 0.798254768782863
```

Random Forest Model

```
# Creating a Random Forest Model

from sklearn.ensemble import RandomForestRegressor

rf = RandomForestRegressor()
rf.fit (X_train, y_train)

y_pred3 = rf.predict (X_test)

print("Training Score     :", rf.score(X_train, y_train))
print("Testing Score      :", rf.score(X_test, y_test))
```

```
Training Score     : 0.9762764499033985
Testing Score      : 0.837595785661922
```

```
# Model Accuracy -- R2 // RMSE

from sklearn.metrics import r2_score, mean_squared_error

mse = mean_squared_error (y_test, y_pred3)
rmse = np.sqrt(mse)
print("RMSE Score     :", rmse)

r2_score = r2_score (y_test, y_pred3)
print("R2 Score       :", r2_score)
```

```
RMSE Score     : 5226.967631772907
R2 Score       : 0.837595785661922
```

```
# Creating a Random Forest Model with scaled data

from sklearn.ensemble import RandomForestRegressor

rf = RandomForestRegressor()
rf.fit (X_train_scaled, y_train)

y_pred3_scaled = rf.predict (X_test_scaled)

print("Training Score     :", rf.score(X_train_scaled, y_train))
print("Testing Score      :", rf.score(X_test_scaled, y_test))
```

```
Training Score     : 0.9759904982575159
Testing Score      : 0.8368746225543691
```

```
# Model Accuracy for scaled data -- R2 // RMSE

from sklearn.metrics import r2_score, mean_squared_error
```

```
mse = mean_squared_error (y_test, y_pred3_scaled)
rmse = np.sqrt(mse)
print("RMSE Score     :", rmse)

r2_score = r2_score (y_test, y_pred3_scaled)
print("R2 Score       :", r2_score)
```

```
RMSE Score     : 5238.560067496894
R2 Score       : 0.8368746225543691
```

Ensemble of all three models

```
# Trying to identify a good ensemble of methods

# Ensemble by average of all three models

from sklearn.metrics import r2_score, mean_squared_error

avg_model = (y_pred1 + y_pred2 + y_pred3) / 3


mse = mean_squared_error (y_test, avg_model)
rmse = np.sqrt(mse)
print("RMSE Score     :", rmse)

r2_score = r2_score (y_test, avg_model)
print("R2 Score       :", r2_score)
```

```
RMSE Score     : 6330.466538209766
R2 Score       : 0.7617849979933369
```

```
# Ensemble by average for scaled models

from sklearn.metrics import r2_score, mean_squared_error

avg_model = (y_pred1_scaled + y_pred2_scaled + y_pred3_scaled) / 3


mse = mean_squared_error (y_test, avg_model)
rmse = np.sqrt(mse)
print("RMSE Score     :", rmse)

r2_score = r2_score (y_test, avg_model)
print("R2 Score       :", r2_score)
```

```
RMSE Score     : 5399.657692747645
R2 Score       : 0.8266874024911137
```

Weighted Average Model

```
# Creating a weighted average model

# Giving 50% weight to random forest
# 30% weight to knn
# and 20% weight to linear regression

weight_avg_model = 0.2*y_pred1_scaled + 0.3*y_pred2_scaled + 0.5*y_pred3_scaled

# Checking the Model accuracy
from sklearn.metrics import r2_score, mean_squared_error

mse = mean_squared_error(y_test, weight_avg_model)
rmse = np.sqrt(mse)
print("RMSE Score     :", rmse)

r2_score = r2_score(y_test, weight_avg_model)
print("R2 Score       :",r2_score)
```

```
RMSE Score     : 5243.92529493142
R2 Score       : 0.8365403120100317
```

Cross Validation

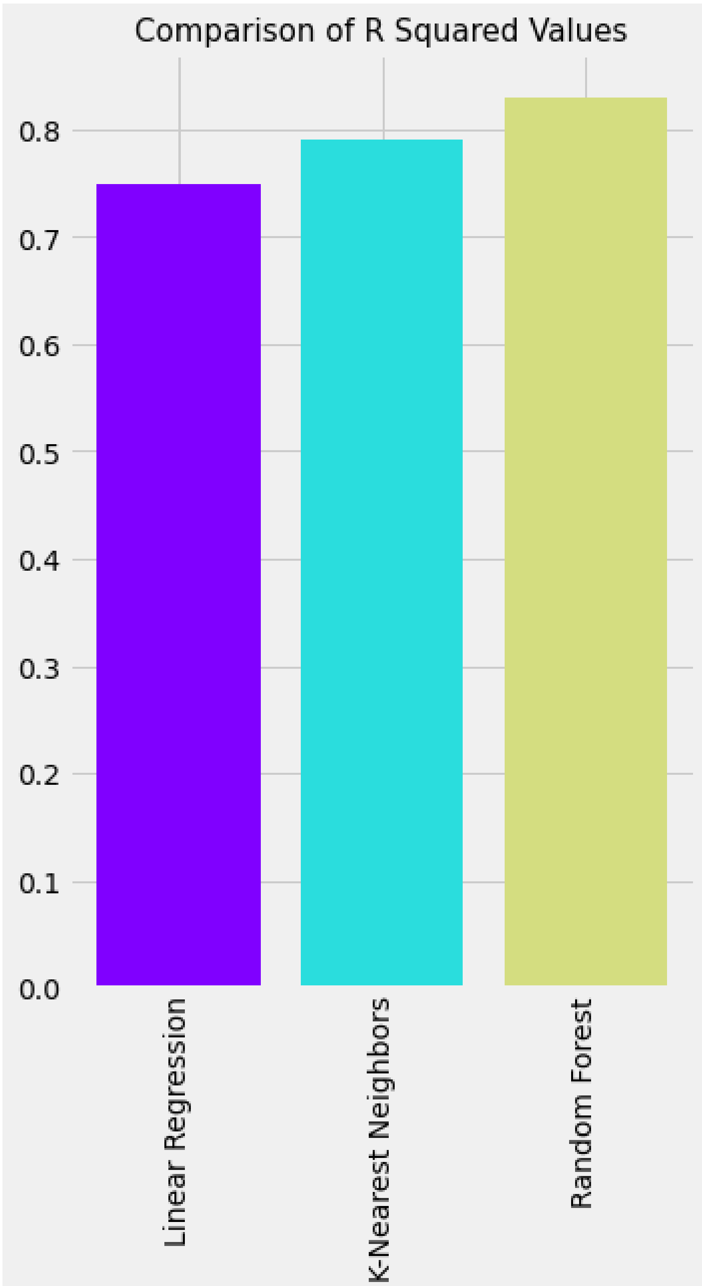
```
# 5-fold Cross validation

from sklearn.model_selection import cross_val_score
scores = cross_val_score(rf, X, y, cv= 5)
print("The 5-fold Cross Validation scores using Random Forest model   :",scores)
```

```
The 5-fold Cross Validation scores using Random Forest model   : [0.85036998 0.7
```

Comparision of all three models with scaled data

```
# Comparing R Squared Values

r2_score = np.array([0.75, 0.79, 0.83])
labels = np.array(['Linear Regression', 'K-Nearest Neighbors' , 'Random Forest'])
index = np.argsort(r2_score)
color = plt.cm.rainbow(np.linspace(0, 1, 4))

plt.style.use('fivethirtyeight')
plt.rcParams['figure.figsize'] = (5, 8)
```

```
plt.bar(range(len(index)), r2_score[index], color = color)
plt.xticks(range(0, 3), ['Linear Regression', 'K-Nearest Neighbors','Random Forest'],
plt.title('Comparison of R Squared Values', fontsize = 15)
plt.show()
```



Possible Improvements

- We can try some more predictive models and compare the results.
- We can try converting the expense column to a normal distribution using log or square root transformation.
- We can try some more predictive models on this dataset to get more accuracy.

Conclusion

We have built three models among which the Random Forest Regressor model shows the best result through which we can say 83.75% variability of expenses can well be explained by predictor variables and which yields comparatively low RMSE value so our predicted expense through this model will not vary too much from the actual expense.