GramworkX Assignment - Pranav Rode

July 15, 2022

[1]:
```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns
import statsmodels.api as sm
import scipy.stats as stats
from sklearn.preprocessing import LabelEncoder
import copy
import warnings
warnings.filterwarnings("ignore")
```

[2]:
```
df = pd.read_csv("Expenses - Sheet1.csv")
```

[3]:
```
df.head(10)
```

[3]:

	age	sex	bmi	children	smoker	region	charges
0	19	female	28	0	yes	southwest	16885
1	18	male	34	1	no	southeast	1726
2	28	male	33	3	no	southeast	4449
3	33	male	23	0	no	northwest	21984
4	32	male	29	0	no	northwest	3867
5	31	female	26	0	no	southeast	3757
6	46	female	33	1	no	southeast	8241
7	37	female	28	3	no	northwest	7282
8	37	male	30	2	no	northeast	6406
9	60	female	26	0	no	northwest	28923

1 Exploratory Data Analysis ↓

[4]:
```
df.info()  # Summary of columns count and its dtypes
```

```
<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   int64
 3   children  1338 non-null   int64
 4   smoker    1338 non-null   object
 5   region    1338 non-null   object
 6   charges   1338 non-null   int64
dtypes: int64(4), object(3)
memory usage: 73.3+ KB
```

[5]:
```
df.isnull().sum()   # Null check
```

[5]:
```
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64
```

1.1 There are no nulls present in dataset

[6]:
```
# creating a column whether having children or not (Yes or No)
df1 = pd.DataFrame()
df1['children_status'] = df['children'].replace({0 :'No' , 1: "Yes" , 2: "Yes"␣
 ↪,3: "Yes" ,4: "Yes" ,5: "Yes" })
df = pd.concat([df,df1], axis=1)
```

[7]:
```
def uniquevals(col):
    print(f'Unique data in Column → {col} is → {df[col].unique()}')

for col in df.columns:
    uniquevals(col)
    print("-"*75)
```

```
Unique data in Column → age is → [19 18 28 33 32 31 46 37 60 25 62 23 56 27 52
30 34 59 63 55 22 26 35 24
 41 38 36 21 48 40 58 53 43 64 20 61 44 57 29 45 54 49 47 51 42 50 39]
---------------------------------------------------------------------------
Unique data in Column → sex is → ['female' 'male']
---------------------------------------------------------------------------
Unique data in Column → bmi is → [28 34 33 23 29 26 30 40 42 25 31 24 35 36 32
17 20 21 37 27 22 39 38 41
 19 49 18 16 48 46 44 43 47 45 50 53]
---------------------------------------------------------------------------
Unique data in Column → children is → [0 1 3 2 5 4]
---------------------------------------------------------------------------
Unique data in Column → smoker is → ['yes' 'no']
---------------------------------------------------------------------------
```

```
Unique data in Column → region is → ['southwest' 'southeast' 'northwest'
'northeast']
--------------------------------------------------------------------------
Unique data in Column → charges is → [16885  1726  4449 …  1630  2008 29141]
--------------------------------------------------------------------------
Unique data in Column → children_status is → ['No' 'Yes']
--------------------------------------------------------------------------
```

1.2 From above data we can see that there following types of features →

1.2.1 Continuous : age, bmi , charges

1.2.2 Ordinal : children (0,1,2,3,4,5)

1.2.3 Binary-Categorical : sex, smoker

1.2.4 Categorical/Nominal : region

[8]:
```
df.describe().T
```

[8]:
```
           count          mean           std     min     25%     50%  \
age       1338.0     39.207025     14.049960    18.0    27.0    39.0
bmi       1338.0     30.673393      6.095002    16.0    26.0    30.0
children  1338.0      1.094918      1.205493     0.0     0.0     1.0
charges   1338.0  13270.417788  12110.013559  1122.0  4740.0  9382.0

               75%      max
age          51.00     64.0
bmi          35.00     53.0
children      2.00      5.0
charges   16640.25  63770.0
```

1.2.5 Range of min to max age is from 18 to 64 years

1.2.6 Looking at the age column, data looks representative of the true age distribution of the adult population

1.2.7 Very few people have more than 2 children. 75% of the people have 2 or less children¶

1.2.8 Range of BMI is from 16 to 53

1.2.9 Range of children count is from 0 to 5

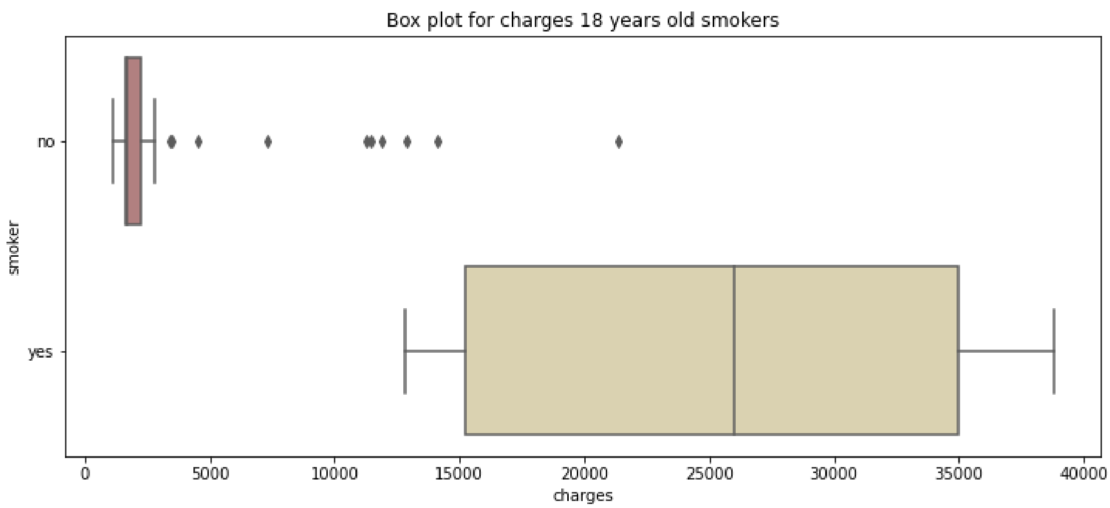
[9]:
```
print('  Sex Value Counts')
print(df.sex.value_counts())
print('**********')
print('**********')
print('  Smokers Value Counts')
print(df.smoker.value_counts())
```

```
 Sex Value Counts
male      676
female    662
Name: sex, dtype: int64
**********
**********
 Smokers Value Counts
no     1064
yes     274
Name: smoker, dtype: int64
```

1.3 Box plot for charges 18 years old smokers

[10]:
```
plt.figure(figsize=(12,5))
plt.title("Box plot for charges 18 years old smokers")
sns.boxplot(y="smoker", x="charges", data = df[(df.age == 18)] , orient="h",␣
 ↪palette = 'pink')
```

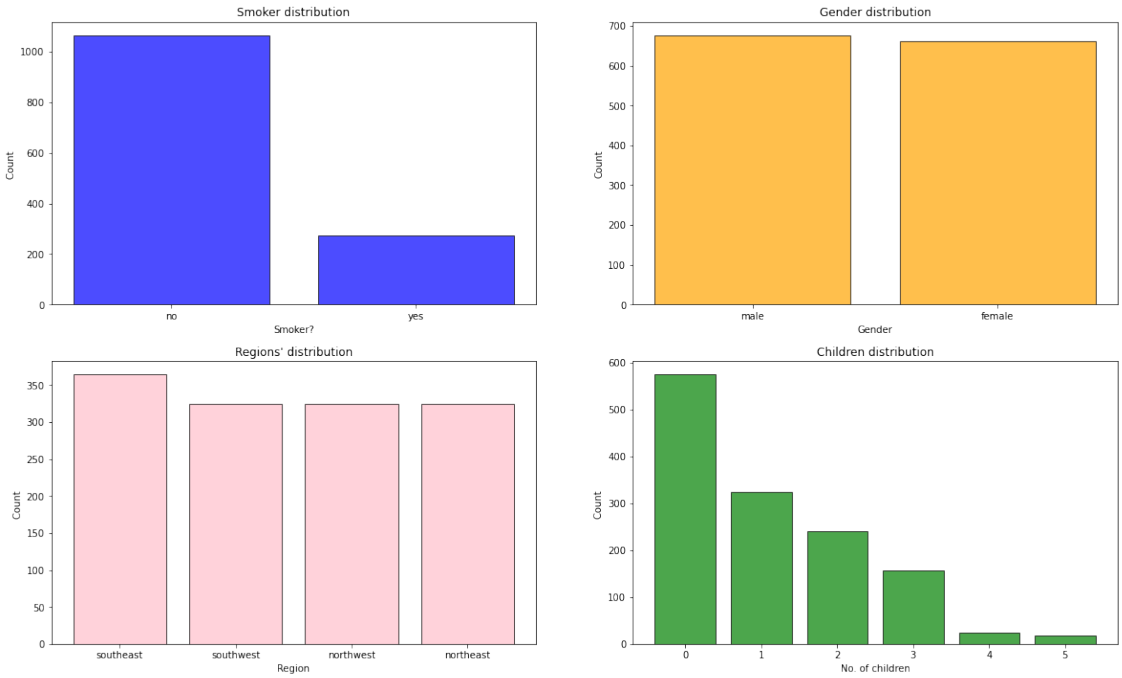
[10]:
```
<AxesSubplot:title={'center':'Box plot for charges 18 years old smokers'},
xlabel='charges', ylabel='smoker'>
```



1.4 From above as we can see, even at the age of 18 smokers spend much more on treatment than non-smokers. Among non-smokers we are seeing some " tails."

[11]:
```
plt.figure(figsize=(20,25))


x = df.smoker.value_counts().index    #Values for x-axis
```

```
y = [df['smoker'].value_counts()[i] for i in x]    # Count of each class on␣
 ↪y-axis

plt.subplot(4,2,1)
plt.bar(x,y, align='center',color = 'blue',edgecolor = 'black',alpha = 0.7) ␣
 ↪#plot a bar chart
plt.xlabel('Smoker?')
plt.ylabel('Count ')
plt.title('Smoker distribution')

x1 = df.sex.value_counts().index    #Values for x-axis
y1 = [df['sex'].value_counts()[j] for j in x1]    # Count of each class on y-axis

plt.subplot(4,2,2)
plt.bar(x1,y1, align='center',color = 'orange',edgecolor = 'black',alpha = 0.7)␣
 ↪ #plot a bar chart
plt.xlabel('Gender')
plt.ylabel('Count')
plt.title('Gender distribution')

x2 = df.region.value_counts().index    #Values for x-axis
y2 = [df['region'].value_counts()[k] for k in x2]    # Count of each class on␣
 ↪y-axis

plt.subplot(4,2,3)
plt.bar(x2,y2, align='center',color = 'pink',edgecolor = 'black',alpha = 0.7) ␣
 ↪#plot a bar chart
plt.xlabel('Region')
plt.ylabel('Count ')
plt.title("Regions' distribution")

x3 = df.children.value_counts().index    #Values for x-axis
y3 = [df['children'].value_counts()[l] for l in x3]    # Count of each class on␣
 ↪y-axis

plt.subplot(4,2,4)
plt.bar(x3,y3, align='center',color = 'green',edgecolor = 'black',alpha = 0.7) ␣
 ↪#plot a bar chart
plt.xlabel('No. of children')
plt.ylabel('Count ')
plt.title("Children distribution")

plt.show()
```



1.4.1 There are a lot more non-smokers than there are smokers in the data

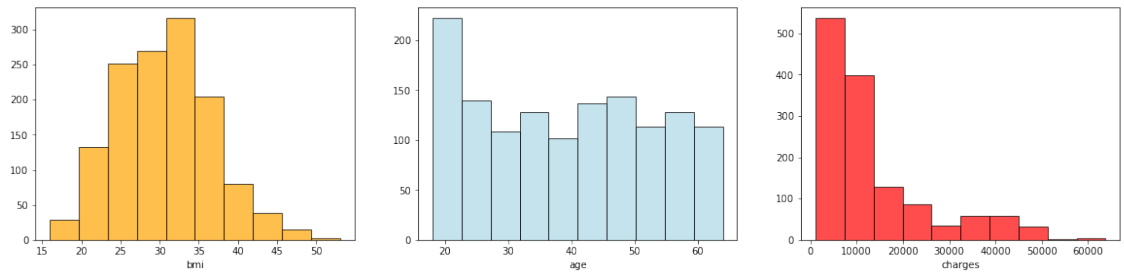
1.4.2 Instances are distributed evenly accross all regions

1.4.3 Gender is also distributed evenly

1.4.4 Most instances have less than 2 children and very few have 4 or 5 children Bi-variate distribution of every possible attribute pair

[12]:

```
#Plots to see the distribution of the continuous features individually

plt.figure(figsize= (20,15))
plt.subplot(3,3,1)
plt.hist(df.bmi, color='orange', edgecolor = 'black', alpha = 0.7)
plt.xlabel('bmi')

plt.subplot(3,3,2)
plt.hist(df.age, color='lightblue', edgecolor = 'black', alpha = 0.7)
plt.xlabel('age')

plt.subplot(3,3,3)
plt.hist(df.charges, color='red', edgecolor = 'black', alpha = 0.7)
plt.xlabel('charges')

plt.show()
```



1.4.5 bmi looks quiet normally distributed

1.4.6 Age seems be be distributed quiet uniformly¶

1.4.7 As seen in the previous step, charges are highly skewed

1.4.8 The claimed amount is higly skewed as most people would require basic medicare and only few suffer from diseases which cost more to get rid of

[13]:
```
Skewness = pd.DataFrame({'Skewness' : [stats.skew(df.bmi),stats.skew(df.
↪age),stats.skew(df.charges)]},
                        index=['bmi','age','charges'])  # Measure the skeweness␣
↪of the required columns
Skewness
```

[13]:

	Skewness
bmi	0.281822
age	0.055610
charges	1.514176

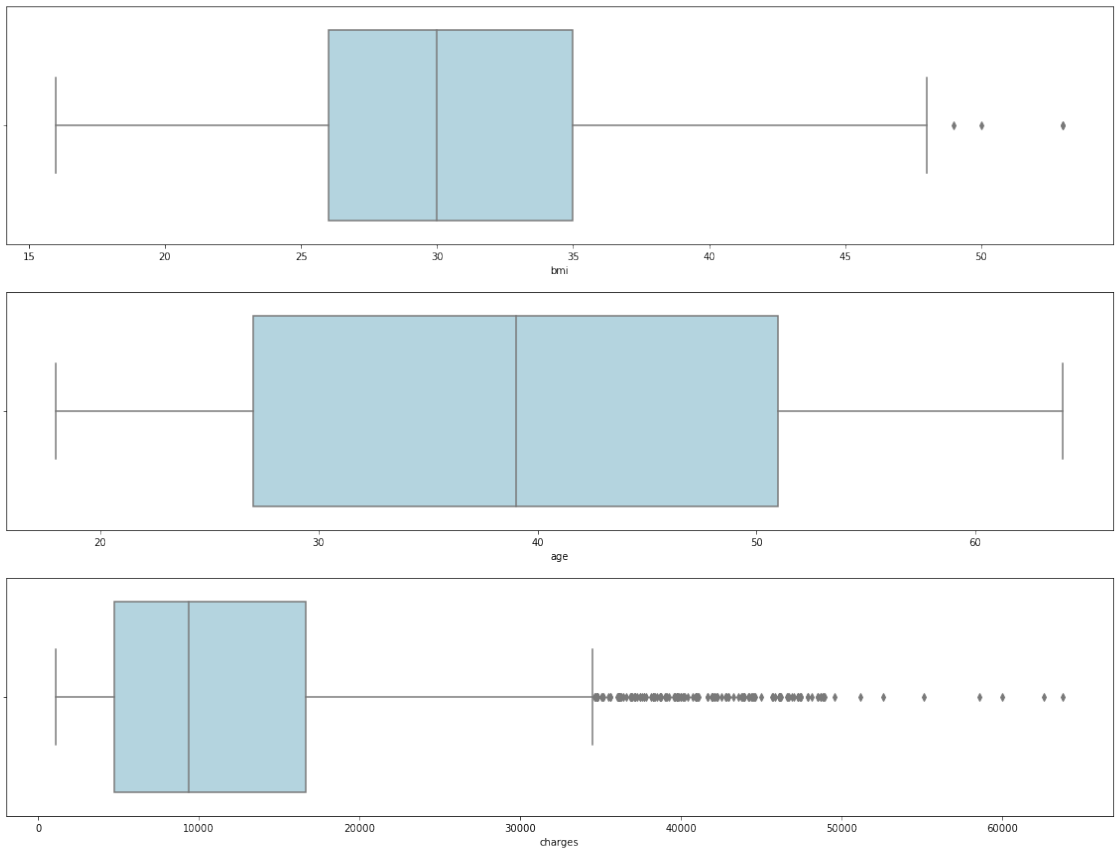
1.4.9 Skew of bmi is very less as seen in the previous step

1.4.10 age is uniformly distributed and there's hardly any skew

1.4.11 charges are highly skewed

1.5 Checking for the outliers

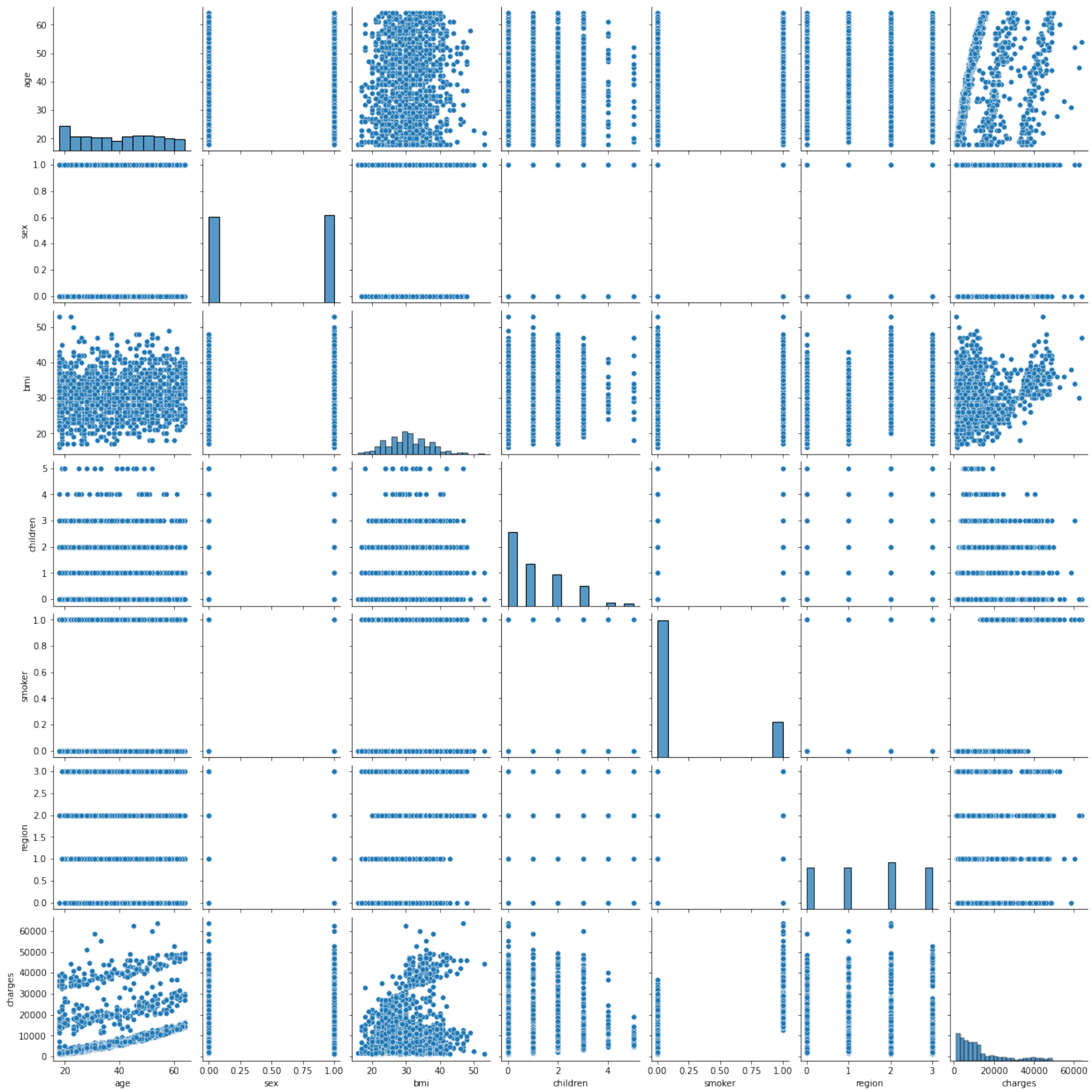
[14]:
```
plt.figure(figsize= (20,15))
plt.subplot(3,1,1)
sns.boxplot(x= df.bmi, color='lightblue')

plt.subplot(3,1,2)
sns.boxplot(x= df.age, color='lightblue')

plt.subplot(3,1,3)
sns.boxplot(x= df.charges, color='lightblue')

plt.show()
```



1.5.1 bmi has a few extreme values

1.5.2 charges as it is highly skewed, there are quiet a lot of extreme values

[15]:
```
#Label encoding the variables before doing a pairplot because pairplot ignores␣
↪strings
df_encoded = copy.deepcopy(df)
df_encoded.loc[:,['sex', 'smoker', 'region']] = df_encoded.loc[:,['sex',␣
↪'smoker', 'region']].apply(LabelEncoder().fit_transform)

sns.pairplot(df_encoded)  #pairplot
plt.show()
```



1.5.3 The only obvious correlation of 'charges' is with 'smoker'

1.5.4 Looks like smokers claimed more money than non-smokers

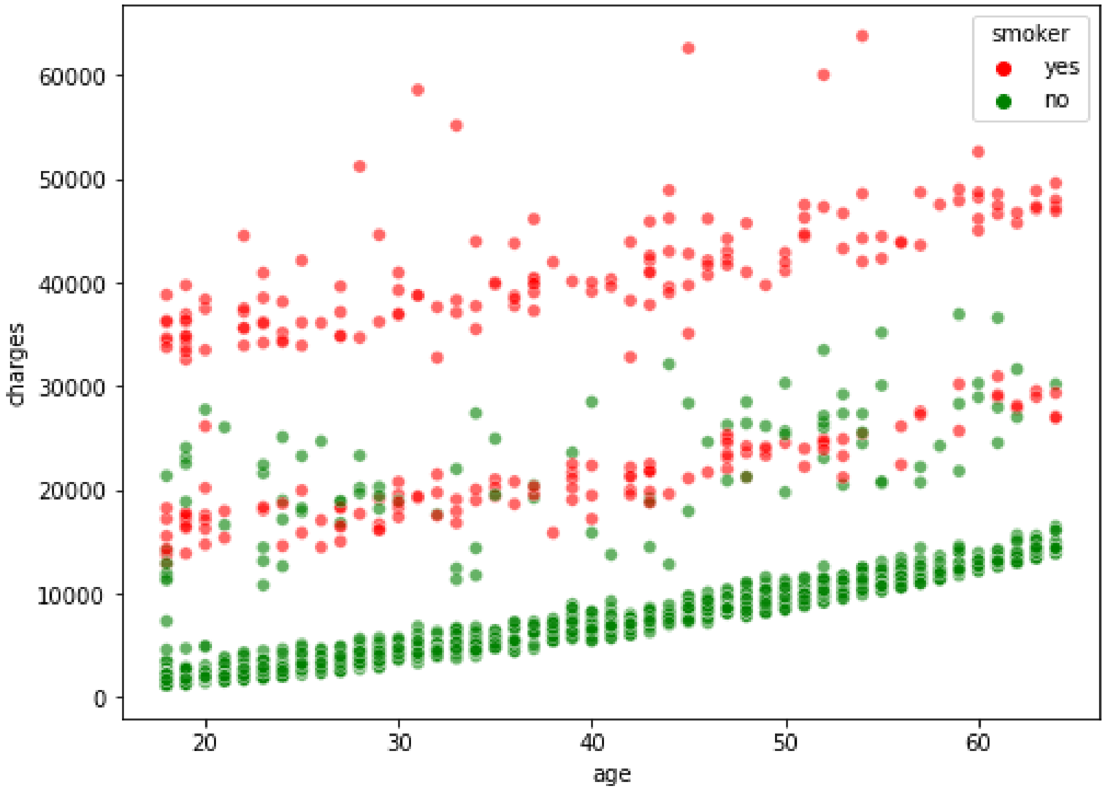
1.5.5 There's an interesting pattern between 'age' and 'charges. Could be because for the same ailment, older people are charged more than the younger ones

[16]:
```
df.smoker.value_counts()
```

[16]:
```
no     1064
yes     274
Name: smoker, dtype: int64
```

1.6 Scatter plot to look for visual evidence of dependency between attributes smoker and charges accross different ages

[17]:
```
plt.figure(figsize=(8,6))
sns.scatterplot(df.age, df.charges,hue=df.smoker,palette= ['red','green']␣
↪,alpha=0.6)
plt.show()
```

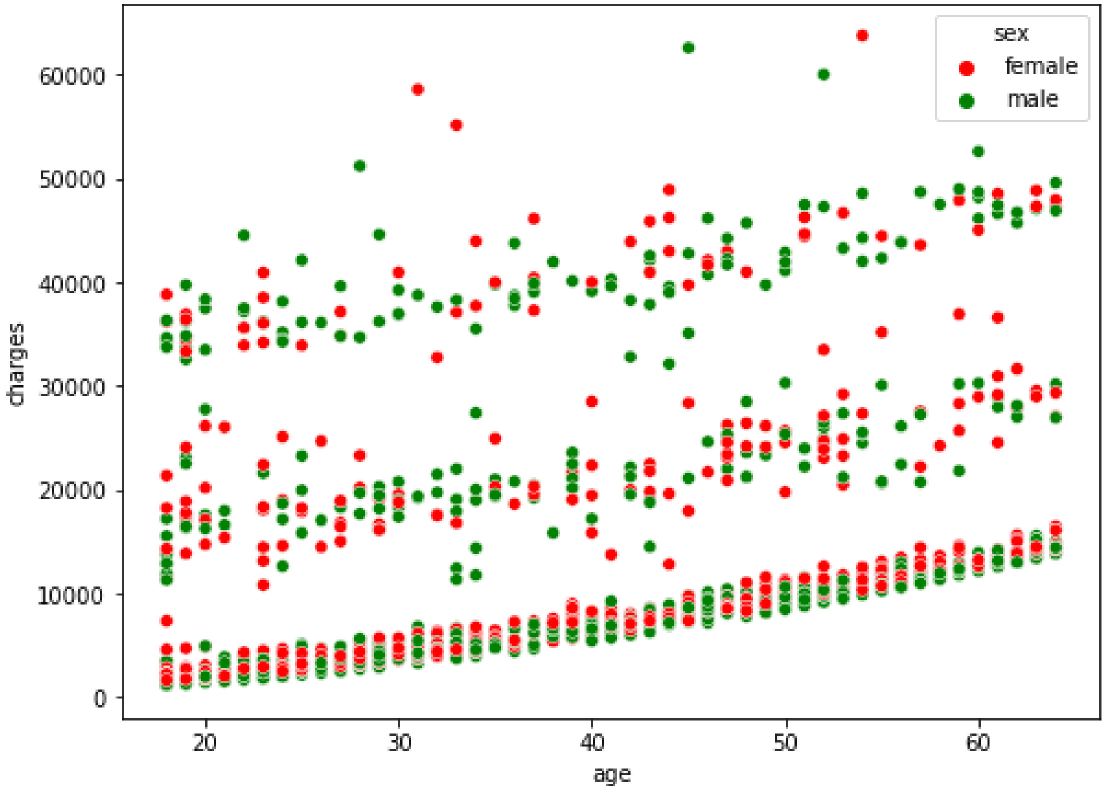


1.6.1 Visually the difference between charges of smokers and charges of non-smokers is apparent

1.6.2 Smokers seem to claim significantly more money than non-smokers

1.7 Scatter plot to look for visual evidence of dependency between attributes sex and charges accross different ages

[18]:
```
plt.figure(figsize=(8,6))
sns.scatterplot(df.age, df.charges,hue=df.sex,palette= ['red','green'] )
plt.show()
```



1.7.1 Visually, there is no apparent relation between gender and charges

1.8 Contingency table of sex and smoker attributes

[19]:
```
crosstab = pd.crosstab(df['sex'],df['smoker'])  # Contingency table of sex and␣
↪smoker attributes
crosstab
```

[19]:
```
smoker   no  yes
sex
female  547  115
male    517  159
```

1.8.1 From above proportion of smokers in males is significantly different from that of the females

1.9 Contingency table of smoker and region attributes

[20]:
```
crosstab1 = pd.crosstab(df['smoker'], df['region'])
crosstab1
```

[20]:
```
region  northeast  northwest  southeast  southwest
smoker
no            257        267        273        267
yes            67         58         91         58
```

1.9.1 From above smoking habbits of people of different regions are similar

2 Model Building

[21]:
```python
from sklearn.metrics import r2_score,mean_absolute_error , mean_squared_error
from sklearn.linear_model import LinearRegression,Ridge,Lasso, ElasticNet
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import␣
↪RandomForestRegressor,GradientBoostingRegressor,AdaBoostRegressor,ExtraTreesRegressor
from sklearn.svm import SVR
```

[22]:
```python
df2 = df.drop(columns=['children_status'])
```

[23]:
```python
df2
```

[23]:
```
      age     sex  bmi  children smoker     region  charges
0      19  female   28         0    yes  southwest    16885
1      18    male   34         1     no  southeast     1726
2      28    male   33         3     no  southeast     4449
3      33    male   23         0     no  northwest    21984
4      32    male   29         0     no  northwest     3867
…     …      …  …       …      …          …        …
1333   50    male   31         3     no  northwest    10601
1334   18  female   32         0     no  northeast     2206
1335   18  female   37         0     no  southeast     1630
1336   21  female   26         0     no  southwest     2008
1337   61  female   29         0    yes  northwest    29141

[1338 rows x 7 columns]
```

[24]:
```python
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
```

[25]:
```python
from sklearn.preprocessing import LabelEncoder
#sex
le = LabelEncoder()
le.fit(df2.sex.drop_duplicates())
df2.sex = le.transform(df2.sex)
# smoker or not
le.fit(df2.smoker.drop_duplicates())
df2.smoker = le.transform(df2.smoker)
```

```
#region
le.fit(df2.region.drop_duplicates())
df2.region = le.transform(df2.region)
```

df2[df2.select_dtypes(include=['object']).columns] = df2[df2.select_dtypes(include=['object']).columns].apply(le.fi

[26]:
```
df2.corr()['charges'].sort_values()
```

[26]:
```
region     -0.006208
sex         0.057291
children    0.067997
bmi         0.198323
age         0.299009
smoker      0.787252
charges     1.000000
Name: charges, dtype: float64
```

[27]:
```
df2
```

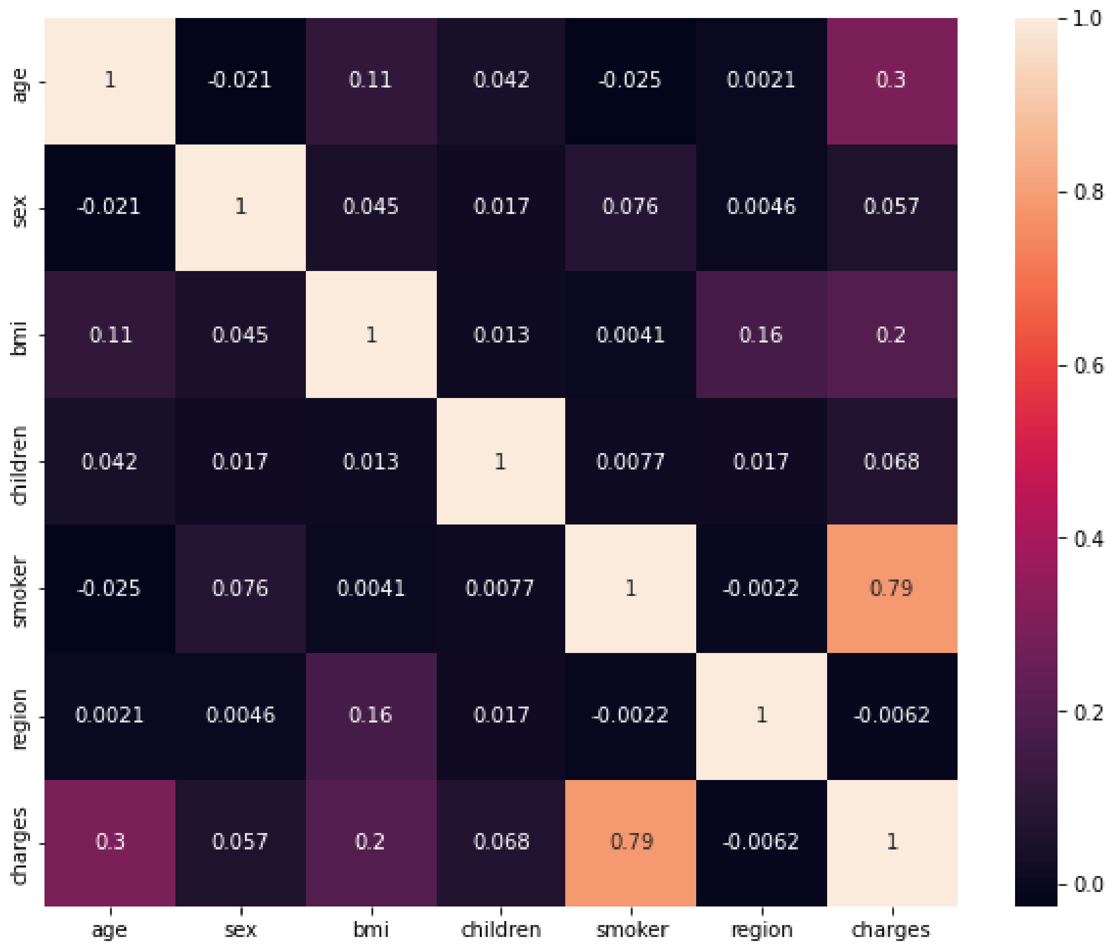
[27]:

	age	sex	bmi	children	smoker	region	charges
0	19	0	28	0	1	3	16885
1	18	1	34	1	0	2	1726
2	28	1	33	3	0	2	4449
3	33	1	23	0	0	1	21984
4	32	1	29	0	0	1	3867
…	…	…	…	…	…	…	…
1333	50	1	31	3	0	1	10601
1334	18	0	32	0	0	0	2206
1335	18	0	37	0	0	2	1630
1336	21	0	26	0	0	3	2008
1337	61	0	29	0	1	1	29141

[1338 rows x 7 columns]

[28]:
```
f, ax = plt.subplots(figsize=(10, 8))
corr = df2.corr()
sns.heatmap(corr, mask=np.zeros_like(corr, dtype=np.bool), annot=True)
```

[28]: <AxesSubplot:>



[29]:
```
X = df2.drop(columns=['charges','region'])     # independant variables
y = df2['charges']
```

[30]:
```
from sklearn.model_selection import train_test_split
X_train,X_test , y_train,y_test  = train_test_split(X , y , random_state=11)
```

[31]:
```
algos = [LinearRegression(),  Ridge(), Lasso(),ElasticNet(),
          KNeighborsRegressor(), DecisionTreeRegressor() ,␣
 ↪RandomForestRegressor(), GradientBoostingRegressor() ]

names = ['Linear Regression', 'Ridge Regression', 'Lasso␣
 ↪Regression','ElasticNet',
         'K Neighbors Regressor', 'Decision Tree Regressor',␣
 ↪'RandomForestRegressor','GradientBoostingRegressor' ]
```

[32]:
```
r2_test_list = []
r2_train_list = []
```

```python
rmse_test_list = []
rmse_train_list = []

for name in algos:

    model = name
    model.fit(X_train,y_train)

    y_pred_test = model.predict(X_test)
    y_pred_train = model.predict(X_train)

    r2_test = r2_score(y_test,y_pred_test)
    r2_train = r2_score(y_train,y_pred_train)

    rmse_test = np.sqrt(mean_squared_error(y_test,y_pred_test))
    rmse_train = np.sqrt(mean_squared_error(y_train,y_pred_train))

    r2_test_list.append(r2_test)
    r2_train_list.append(r2_train)

    rmse_test_list.append(rmse_test)
    rmse_train_list.append(rmse_train)
```

[33]:
```python
evaluation = pd.DataFrame({'Model': names,
                           'r2_test_score': r2_test_list,
                           'r2_train_score': r2_train_list,
                           'RMSE_test': rmse_test_list,
                           'RMSE_train': rmse_train_list,
                           })
```

[34]:
```python
evaluation
```

[34]:
```
                       Model  r2_test_score  r2_train_score     RMSE_test  \
0          Linear Regression       0.796048        0.734606   5342.129667
1           Ridge Regression       0.795640        0.734584   5347.479703
2           Lasso Regression       0.796045        0.734606   5342.179660
3                 ElasticNet       0.390546        0.389256   9234.668418
4      K Neighbors Regressor       0.146875        0.446786  10925.899230
5    Decision Tree Regressor       0.681290        0.990030   6678.040302
6      RandomForestRegressor       0.830470        0.967669   4870.506613
7  GradientBoostingRegressor       0.865332        0.881753   4340.941638

    RMSE_train
0  6282.391927
1  6282.657600
2  6282.392842
```

```
3   9530.359272
4   9070.393569
5   1217.661257
6   2192.744693
7   4193.486378
```

2.1 Conclusion :-

2.1.1 Here we get overall good balanced R2 score and RMSE score on both test and train data.

2.1.2 Here we get overall good R2 score and lowest RMSE score on both test and train data with Gradient boosting regressor.

```
[ ]:
```

```
[ ]:
```