jupyter EDA-Medicaim Last Checkpoint: 1 minute ago

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Code JupyterLab Python 3 (ipykernel)

[151]:
```
#lib for extraction ,maniputation,analysis
import numpy as np
import pandas as pd
# for visualtion
import matplotlib.pyplot as plt
import seaborn as sns
# for stats
import scipy.stats
from scipy.stats import shapiro, chi2, normaltest, kstest, zscore
# for vif
from statsmodels.stats.outliers_influence import variance_inflation_factor
# train test split
from sklearn.model_selection import train_test_split
# Linear regression
from sklearn.linear_model import LinearRegression, Lasso,Ridge
# regression evaluation metrics
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

[152]:
```
# importing dataset
data=pd.read_csv(r"C:\Users\deshm\OneDrive\Desktop\ML\03-LinearRegression\mediclaim.csv")
data
```

[152]:

	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

[153]:
```
#EDA for each data analysis
def eda(data):
    print("Shape:",data.shape)
    print("- "*50)
    print("Size:",data.size)
    print("- "*50)
    print("INFO:",data.info)
    print("- "*50)
    print("Describe:",data.describe())
    print("- "*50)
    print("Dtype:",data.dtypes)
    print("* "*50)
    print("Checking Null Values:",data.isnull().sum())

eda(data)
```

```
Shape: (1338, 7)
- - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - -
Size: 9366
- - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - -
INFO: <bound method DataFrame.info 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]>
- - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - -
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
- - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - -
Dtype: age          int64
sex          object
bmi         float64
```

```
children      int64
smoker       object
region       object
charges     float64
dtype: object
* * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * *
Checking Null Values: age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64
```

[154]:
```python
# Analysis for Numerical Columns
def Num_col(data, col):
    mean=data[col].mean()
    median=data[col].median()
    mode=data[col].mode()[0]
    var =data[col].var()
    std=data[col].std()
    skew=data[col].skew()
    Min=data[col].min()
    Max=data[col].max()
    Range=Max-Min
    print("Numerical Columns Analysis:")
    print(f"mean:{mean}\nmedian:{median}\nmode:{mode}\nvar:{var}\nstd:{std}\nskew:{skew}\nMIN:{Min}\nMAAX:{Max}\nRange:{Range}")
```

[155]:
```python
Num_col(data, "age")
```

```
Numerical Columns Analysis:
mean:39.20702541106129
median:39.0
mode:18
var:197.40138665754424
std:14.049960379216172
skew:0.05567251565299186
MIN:18
MAAX:64
Range:46
```

[156]:
```python
Num_col(data, "bmi")
```

```
Numerical Columns Analysis:
mean:30.66339686098655
median:30.4
mode:32.3
var:37.187883609773266
std:6.098186911679017
skew:0.2840471105987448
MIN:15.96
MAAX:53.13
Range:37.17
```

[157]:
```python
Num_col(data, "children")
```

```
Numerical Columns Analysis:
mean:1.0949177877429
median:1.0
mode:0
var:1.4532127456668944
std:1.2054927397819095
skew:0.9383804401702414
MIN:0
MAAX:5
Range:5
```

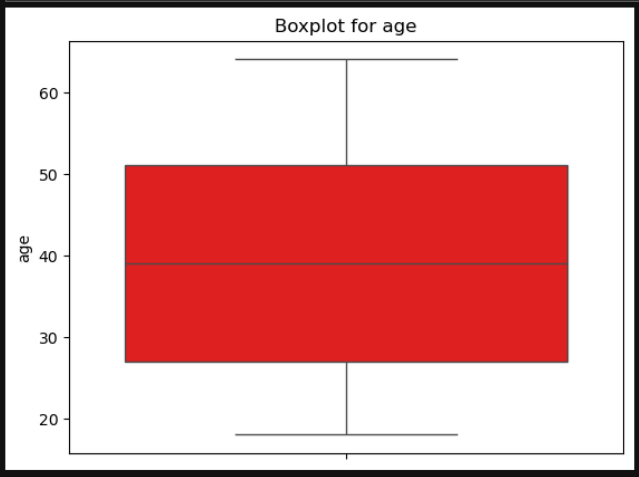
[158]:
```python
Num_col(data, "charges")
```

```
Numerical Columns Analysis:
mean:13270.422265141257
median:9382.033
mode:1639.5631
var:146652372.1528548
std:12110.011236693994
skew:1.5158796580240388
MIN:1121.8739
MAAX:63770.42801
Range:62648.554110000005
```

[159]:
```python
def Checking_and_Handling_Of_Outliers(data, col):
    sns.boxplot(data[col], color = "Red")
    plt.title(f"Boxplot for {col}")
    plt.show()

    q1 = data[col].quantile(0.25)
    q3 = data[col].quantile(0.75)

    iqr = q3 - q1

    LowerTail = q1 - 1.5*iqr
    UpperTail = q3 + 1.5*iqr

    print(f"25% Quantile q1 = {q1}\n75% Quantile q3 = {q3}\nIQR = {iqr}\n")
    print("-"*80)
    print(f"Lower Tail = {LowerTail}\nUpper Tail = {UpperTail}")
    print("-"*80)

    # Checking for Outliers
    Outliers = data[(data[col] < LowerTail) | (data[col] > UpperTail)]
    print("\nOutliers :\n",Outliers)
    print("-"*80)
```

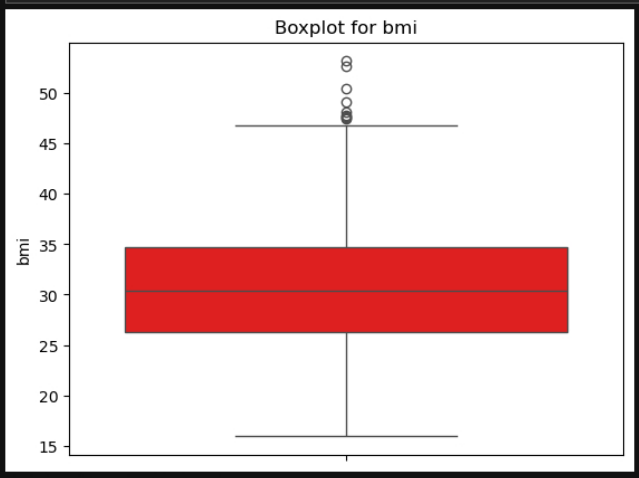
```
    #HAndling of Outliers :
    data.loc[data[col] < LowerTail, col] = LowerTail # all outliers less than lowertail, assigned by lowertail value
    data.loc[data[col] > UpperTail, col] = UpperTail # all outliers greater than uppertail, assigned by uppertail value
    print("After handling of Outliers data:\n")
    print(data.head())
```

[160]:
```
Checking_and_Handling_Of_Outliers(data, "age")
```




```
25% Quantile q1 = 27.0
75% Quantile q3 = 51.0
IQR = 24.0

--------------------------------------------------------------------------------
Lower Tail = -9.0
Upper Tail = 87.0
--------------------------------------------------------------------------------

Outliers :
 Empty DataFrame
Columns: [age, sex, bmi, children, smoker, region, charges]
Index: []
--------------------------------------------------------------------------------
After handling of Outliers 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
```

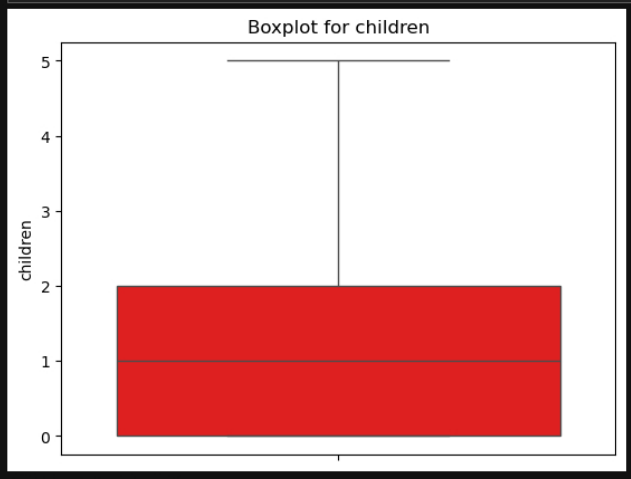
[161]:
```
Checking_and_Handling_Of_Outliers(data, "bmi")
```




```
25% Quantile q1 = 26.29625
75% Quantile q3 = 34.69375
IQR = 8.3975

--------------------------------------------------------------------------------
Lower Tail = 13.7
Upper Tail = 47.290000000000006
--------------------------------------------------------------------------------

Outliers :
      age     sex    bmi  children smoker     region      charges
116    58    male  49.06         0     no  southeast  11381.32540
286    46  female  48.07         2     no  northeast   9432.92530
401    47    male  47.52         1     no  southeast   8083.91980
543    54  female  47.41         0    yes  southeast  63770.42801
847    23    male  50.38         1     no  southeast   2438.05520
860    37  female  47.60         2    yes  southwest  46113.51100
1047   22    male  52.58         1    yes  southeast  44501.39820
1088   52    male  47.74         1     no  southeast   9748.91060
1317   18    male  53.13         0     no  southeast   1163.46270
--------------------------------------------------------------------------------
After handling of Outliers data:
```

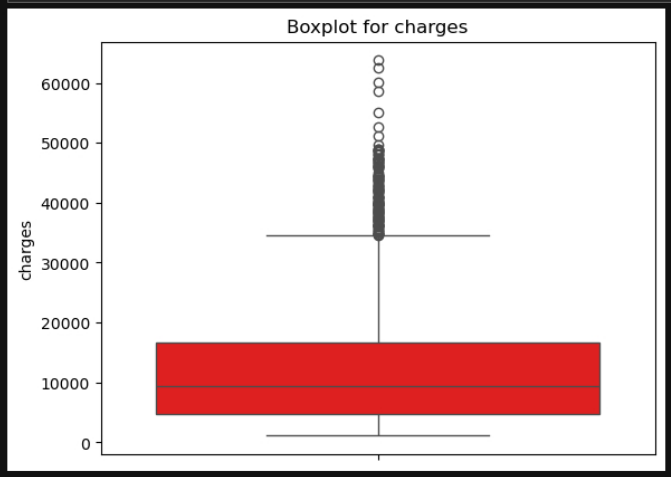
```
   age     sex     bmi  children smoker     region      charges
0   19  female  27.900         0    yes  southwest  16884.92400
1   18    male  33.770         1     no  southeast   1725.55230
2   28    male  33.000         3     no  southeast   4449.46200
3   33    male  22.705         0     no 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

[162]:
```
Checking_and_Handling_Of_Outliers(data, "children")
```




```
25% Quantile q1 = 0.0
75% Quantile q3 = 2.0
IQR = 2.0

--------------------------------------------------------------------------------
Lower Tail = -3.0
Upper Tail = 5.0
--------------------------------------------------------------------------------

Outliers :
 Empty DataFrame
Columns: [age, sex, bmi, children, smoker, region, charges]
Index: []
--------------------------------------------------------------------------------
After handling of Outliers 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
```

[163]:
```
Checking_and_Handling_Of_Outliers(data, "charges")
```




```
25% Quantile q1 = 4740.28715
75% Quantile q3 = 16639.912515
IQR = 11899.625365

--------------------------------------------------------------------------------
Lower Tail = -13109.1508975
Upper Tail = 34489.350562499996
--------------------------------------------------------------------------------

Outliers :
       age     sex     bmi  children smoker     region      charges
14      27    male  42.130         0    yes  southeast  39611.75770
19      30    male  35.300         0    yes  southwest  36837.46700
23      34  female  31.920         1    yes  northeast  37701.87680
29      31    male  36.300         2    yes  southwest  38711.00000
30      22    male  35.600         0    yes  southwest  35585.57600
...    ...     ...     ...       ...    ...        ...          ...
1300    45    male  30.360         0    yes  southeast  62592.87309
1301    62    male  30.875         3    yes  northwest  46718.16325
1303    43    male  27.800         0    yes  southwest  37829.72420
1313    19  female  34.700         2    yes  southwest  36397.57600
1323    42  female  40.370         2    yes  southeast  43896.37630

[139 rows x 7 columns]
```

```
[1339 rows x 7 columns]
--------------------------------------------------------------------------------
After handling of Outliers 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
```

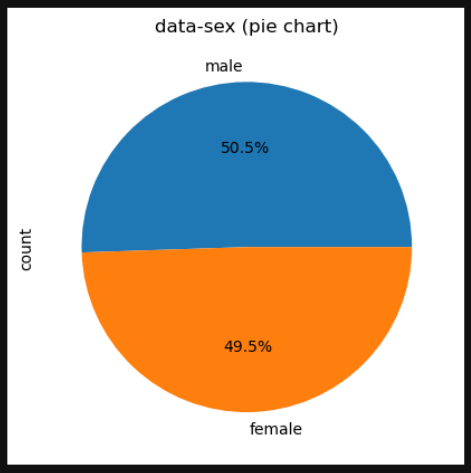
[164]:
```
# Analysis of Categorical Columns(Variable)
def Cat_col(data, col):
    unique_values = data[col].unique()  # Fixed typo: renamed to unique_values
    value_counts = data[col].value_counts()
    mode = data[col].mode()[0]  # Fixed mode access by adding parentheses

    # Enhanced string formatting for clarity
    print(f"Unique Values in '{col}':\n{unique_values}\n")
    print(f"Value Counts in '{col}':\n{value_counts}\n")
    print(f"Mode of '{col}': {mode}\n")


    data[col].value_counts().plot.pie(autopct="%1.1f%%")
    plt.title(f"data-{col} (pie chart)")
    plt.show
```

[165]:
```
data.columns
```

[165]:
```
Index(['age', 'sex', 'bmi', 'children', 'smoker', 'region', 'charges'], dtype='object')
```

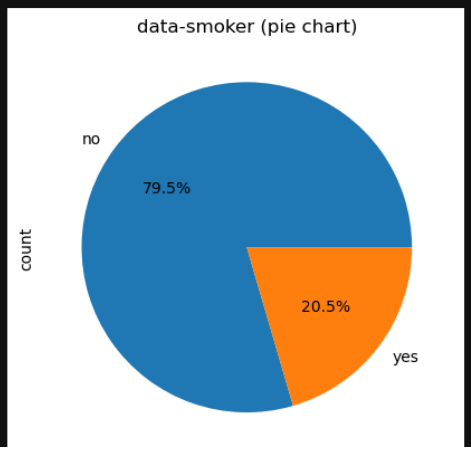
[166]:
```
Cat_col(data, "sex")
```

```
Unique Values in 'sex':
['female' 'male']

Value Counts in 'sex':
sex
male      676
female    662
Name: count, dtype: int64

Mode of 'sex': male
```



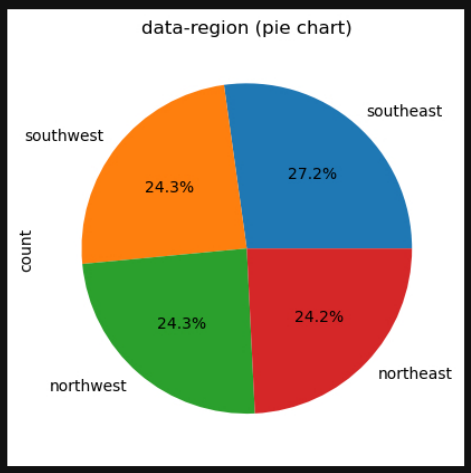
[167]:
```
Cat_col(data, "smoker")
```

```
Unique Values in 'smoker':
['yes' 'no']

Value Counts in 'smoker':
smoker
no     1064
yes     274
Name: count, dtype: int64

Mode of 'smoker': no
```



[168]:
```
Cat_col(data, "region")
```

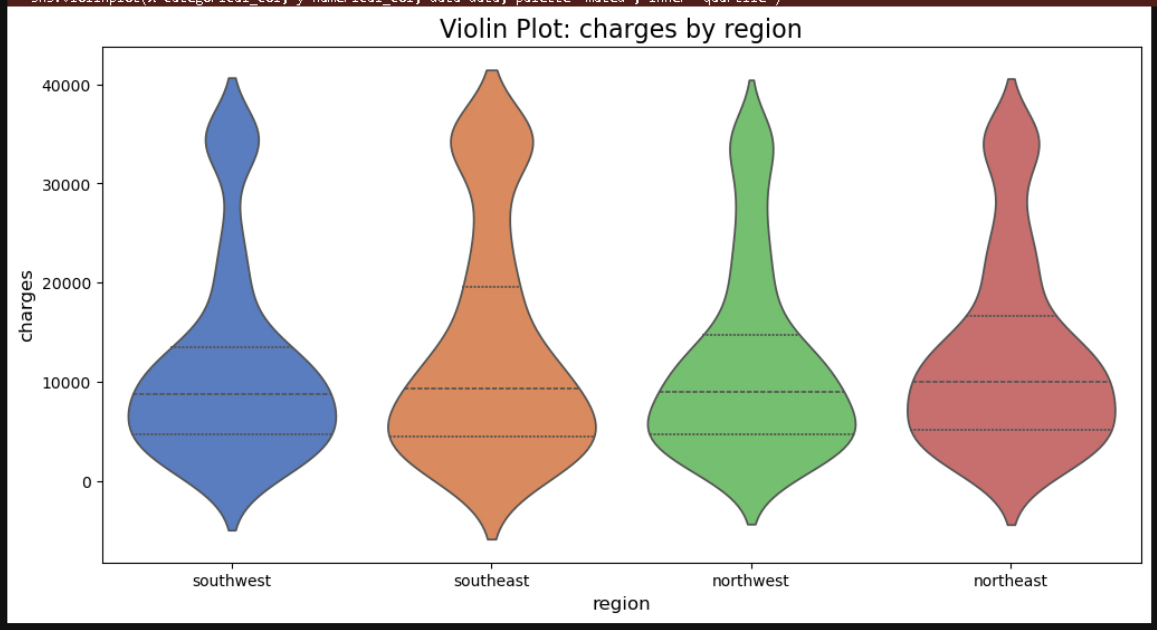
```
Unique Values in 'region':
['southwest' 'southeast' 'northwest' 'northeast']

Value Counts in 'region':
region
southeast    364
southwest    325
northwest    325
northeast    324
Name: count, dtype: int64

Mode of 'region': southeast
```



[169]:
```
# Bivariate analysis of columns
def bivariate_violin_plot(data, categorical_col, numerical_col):
    plt.figure(figsize=(12, 6))
    sns.violinplot(x=categorical_col, y=numerical_col, data=data, palette="muted", inner="quartile")
    plt.title(f'Violin Plot: {numerical_col} by {categorical_col}', fontsize=16)
    plt.xlabel(categorical_col, fontsize=12)
    plt.ylabel(numerical_col, fontsize=12)
    plt.show()
```

[170]:
```
bivariate_violin_plot(data, "region", "charges")
```

```
C:\Users\deshm\AppData\Local\Temp\ipykernel_2704\3790340880.py:4: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same e
ffect.

  sns.violinplot(x=categorical_col, y=numerical_col, data=data, palette="muted", inner="quartile")
```



[171]:
```
# Encoding

data["sex"].unique()
```

[171]:
```
array(['female', 'male'], dtype=object)
```

[172]:
```
data["sex_encoded"]=data["sex"].replace({'female':0, 'male':1})
```

```
C:\Users\deshm\AppData\Local\Temp\ipykernel_2704\3863865108.py:1: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a futu
re version. To retain the old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_si
lent_downcasting', True)`
```

```
data["sex_encoded"]=data["sex"].replace({'female':0, 'male':1})
```

[173]:
```
data["smoker"].unique()
```

[173]:
```
array(['yes', 'no'], dtype=object)
```

[174]:
```
data["smoker_encoded"]=data["smoker"].replace({'yes':0, 'no':1})
```

```
C:\Users\deshm\AppData\Local\Temp\ipykernel_2704\3939261919.py:1: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a futu
re version. To retain the old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_si
lent_downcasting', True)`
  data["smoker_encoded"]=data["smoker"].replace({'yes':0, 'no':1})
```

[175]:
```
data["region"].unique()
```

[175]:
```
array(['southwest', 'southeast', 'northwest', 'northeast'], dtype=object)
```

[176]:
```
data["region_encoded"]=data["region"].replace({'southwest':0, 'southeast':1, 'northwest':2, 'northeast':3})
```

```
C:\Users\deshm\AppData\Local\Temp\ipykernel_2704\1909166453.py:1: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a futu
re version. To retain the old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_si
lent_downcasting', True)`
  data["region_encoded"]=data["region"].replace({'southwest':0, 'southeast':1, 'northwest':2, 'northeast':3})
```

[177]:
```
data.drop(columns=["sex"],inplace=True)
data.drop(columns=["smoker"],inplace=True)
data.drop(columns=["region"],inplace=True)
```

[178]:
```
data
```

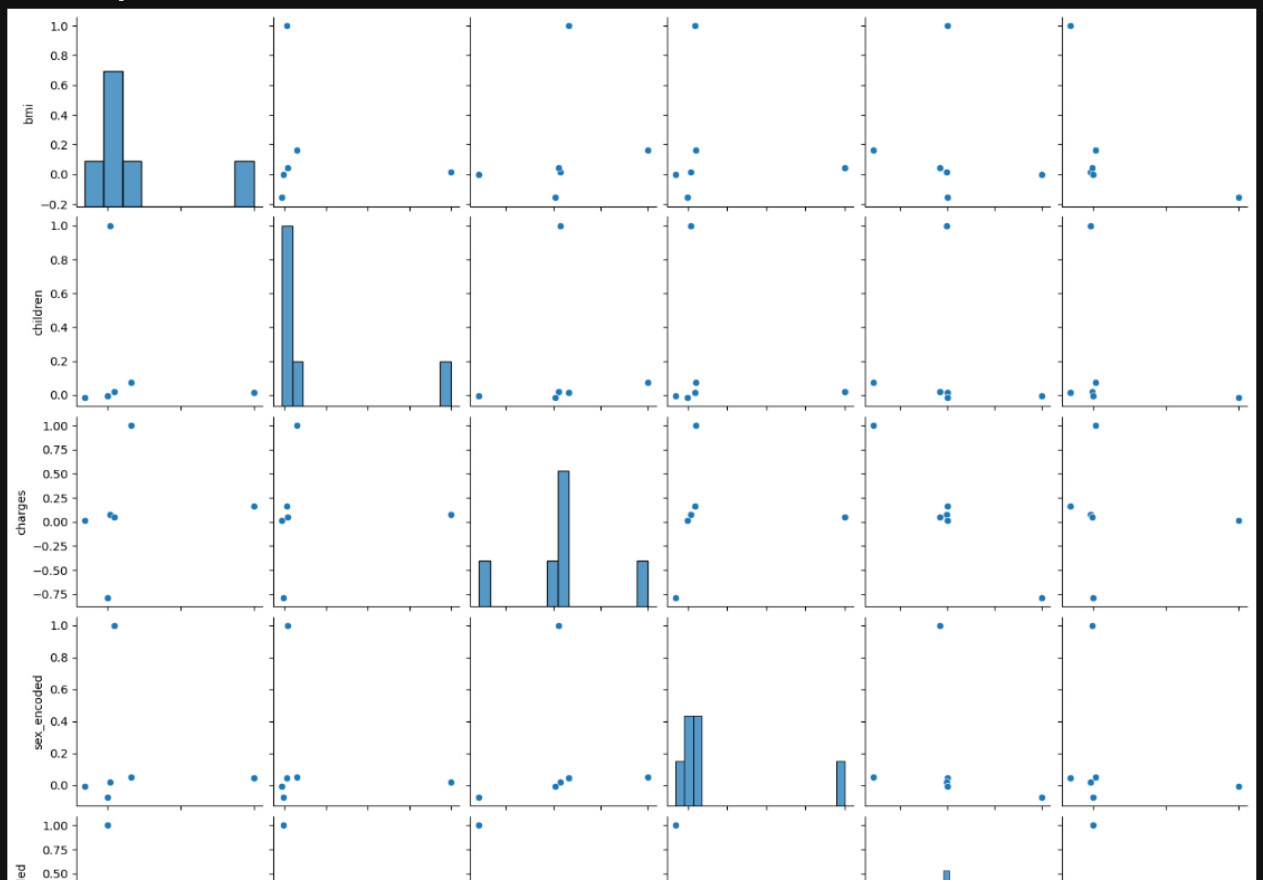
[178]:

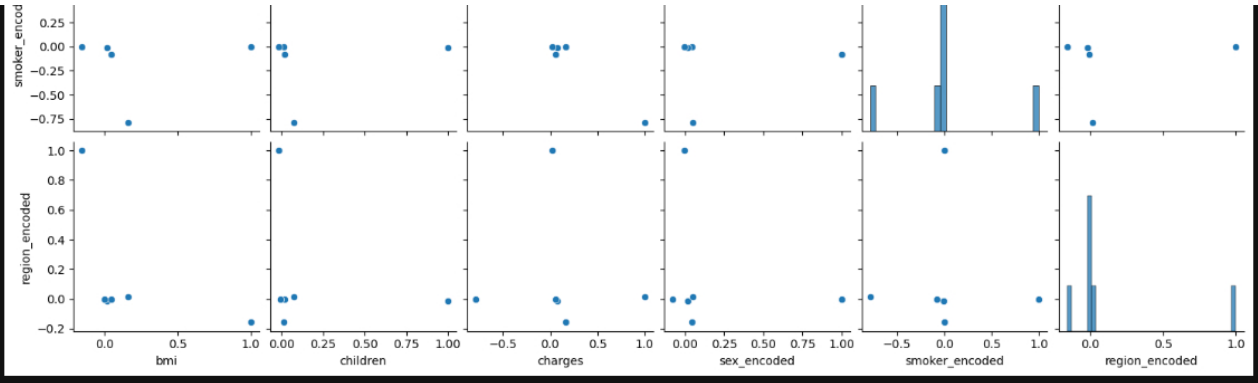
	age	bmi	children	charges	sex_encoded	smoker_encoded	region_encoded
0	19	27.900	0	16884.92400	0	0	0
1	18	33.770	1	1725.55230	1	1	1
2	28	33.000	3	4449.46200	1	1	1
3	33	22.705	0	21984.47061	1	1	2
4	32	28.880	0	3866.85520	1	1	2
...	...	...	...	...	...	...	...
1333	50	30.970	3	10600.54830	1	1	2
1334	18	31.920	0	2205.98080	0	1	3
1335	18	36.850	0	1629.83350	0	1	1
1336	21	25.800	0	2007.94500	0	1	0
1337	61	29.070	0	29141.36030	0	0	2

1338 rows × 7 columns

[179]:
```
corr=data.iloc[:,1:8].corr()
sns.pairplot(corr)
```

[179]:
```
<seaborn.axisgrid.PairGrid at 0x25ccf8f5010>
```





[180]:
```
# Train-test split

X = data.drop(columns=['charges'])  # Replace 'target_column' with your target variable
Y = data['charges']

xtrain, xtest, ytrain, ytest = train_test_split(X, Y, test_size=0.25, random_state=42)

print(f'Shape of X_train: {xtrain.shape}')
print(f'Shape of X_test: {xtest.shape}')
print(f'Shape of y_train: {ytrain.shape}')
print(f'Shape of y_test: {ytest.shape}')
```

```
Shape of X_train: (1003, 6)
Shape of X_test: (335, 6)
Shape of y_train: (1003,)
Shape of y_test: (335,)
```

ML Model Training

[182]:
```
lin_reg = LinearRegression()
lin_reg
```

[182]:
```
LinearRegression()
```

[183]:
```
lin_reg_model = lin_reg.fit(xtrain,ytrain) # linear regression working, bfl, cost, gradient descent
lin_reg_model
```

[183]:
```
LinearRegression()
```

[184]:
```
ytrain_pred = lin_reg_model.predict(xtrain)
ytrain_pred
```

[184]:
```
array([ 3016.17380033,  5180.34750712, 12707.96514625, ...,
       11448.39181563, 31507.89919888, 11000.5053457 ])
```

[185]:
```
# Ensure consistent lengths
print("------------------------ Evaluation for Training Data ------------------------")
print("Shape of ytrain:", ytrain.shape)
print("Shape of ytrain_pred:", ytrain_pred.shape)

# Recompute predictions if necessary
if len(ytrain) != len(ytrain_pred):
    ytrain_pred = ytrain_pred[:len(ytrain)]

# Calculate MSE
mse = mean_squared_error(ytrain, ytrain_pred)
print("Mean Squared Error (MSE):", mse)
print("-" * 80)

mae = mean_absolute_error(ytrain, ytrain_pred)
print("mean absolute error (MAE) : ", mae)
print("-"*80)

rmse = np.sqrt(mse)
print("Root mean squared error (RMSE) : ", rmse)
print("-"*80)

r2score = r2_score(ytrain, ytrain_pred)
print("R2 Score : ", r2score)
print("-"*80)
```

```
------------------------ Evaluation for Training Data ------------------------
Shape of ytrain: (1003,)
Shape of ytrain_pred: (1003,)
Mean Squared Error (MSE): 26162370.951339696
--------------------------------------------------------------------------------
mean absolute error (MAE) :  3346.360391711921
--------------------------------------------------------------------------------
Root mean squared error (RMSE) :  5114.916514601162
--------------------------------------------------------------------------------
R2 Score :  0.7434776049643312
--------------------------------------------------------------------------------
```

[186]:
```
ytest_pred = lin_reg_model.predict(xtest)
ytest_pred
```

[186]:
```
array([ 9336.84134219,  7305.55652027, 32829.43460237,  9728.26767656,
       23557.46581852,  9532.63066135,  1692.8228067 , 15446.45811413,
        2848.20365207, 11087.73846789, 24998.88123828,  9288.50796245,
        5716.57831586, 33038.43272113, 34743.77112931, 32096.96890174,
       13684.57022334, 31260.74817834,  9269.87475494, 28006.92562062,
        4718.53566847,  9648.92588828,  2847.19105337,  6596.73755658,
       11272.02930014, 12323.04621164, 13417.12864002,  6509.36221589,
       10120.58320388,  2836.60959399,  9082.43811341, 12539.04220522,
        4686.93299424,  4818.95326244,  4758.31016028, 11794.10344382,
        2874.8468731 ,  8723.90687444, 29841.12623571, 28324.64864922,
        4495.23886739,  4703.63709011, 13052.62833026, 11464.66547311,
        8347.97068685, 11767.31874966,  5472.24321934,  4104.657937  ,
       30896.85391013,  8489.78023707, 14657.54468937,  3055.98117503,
       11214.46327831,  2478.96394981, 12539.83561298, 11979.64385661,
        5083.27089836, 28059.6482575 , 12502.46622191, 12223.18504359,
       13354.68834466,  9421.53049794, 14974.10403291,  8326.3900963 ,
       11452.78293875,  4932.99635378, 23622.77725882, 10977.00229023,
        3465.37379845,  5608.08101822,  9954.01150139, 11188.76108703,
       10536.66228178,  8949.41457436, 11005.31464239,  7004.52704208,
        7200.69135185, 10903.42598838,  6658.04213524,  9016.2867278 ,
        4022.22064191, 32520.71834864,  6569.75323139, 26709.62951322,
       27862.38966508, 30933.03798169,  7101.99659179, 12211.62949932,
        9853.85454914, 13250.80171625, 16182.50516535, 31664.32945181,
       29425.40790604,  6599.79486296, 27760.947153  ,  9098.5641489 ,
       25978.47222504,  4031.51329112, 25470.20477046,  6651.06214334,
        5954.67209627,  2590.08883126, 10422.60693844, 13825.88760868,
       11791.23602536,  4383.40177317,  9721.94592364, 28577.95589271,
        1419.07666262, 29507.89892953,  3461.94844874,  8800.25223323,
       13571.4195753 , 27759.49672384, 11136.91401409,  4063.51422384,
       12686.37108612, 28197.66454847,  8223.91826559,  4024.80555736,
        8254.65391421, 10110.46136884, 13950.9633753 ,  5516.84422954,
        4851.81987486,  9935.32679945, 10309.09624516, 10836.18082189,
       13488.51483335,  6664.71288617,  5860.54285774,  8876.35480759,
        8916.7325924 , 11532.44746323,  8070.93743258, 13953.12282207,
        8000.12709128, 27845.57918396, 30983.62371105, 27794.1710621 ,
        6591.75487787, 11915.3109435 ,  5875.94811258, 13478.02951434,
        3442.28572139, 29240.63787671,  6737.56004129,  5391.34583425,
       13383.51327857,  6938.943686  , 33758.6193611 ,  3887.58676128,
        5341.1767603 , 27605.12684035, 10560.50353343,  8099.98825933,
       13945.9807094 ,  9800.06609975, 23634.58342677, 29247.59994391,
       13836.32874118,  2822.94608458, 12877.61940056,  3259.46437644,
        5473.52026647, 10740.35398207, 34505.71484633, 32195.29748445,
       29841.7177913 ,  4286.71163422,  8143.6504353 ,  8397.322338  ,
       11065.15431875,  5537.49654412,  2869.18042222, 28621.66000451,
       22040.10140684, 15754.49383321, 24193.71818388, 10570.68010042,
       33072.72517848,  1527.24017684,  7762.55546405,  7522.33142282,
        5367.16052475,  5306.89945012,  6200.05441939,  4842.93945551,
       13431.68849089, 11043.59044813,  6475.34713299,  3255.56490361,
        2811.4258166 , 27543.31953854, 14919.52218857, 11400.91183796,
        2541.7514981 , 12247.214665  ,  2606.65431961,  8957.66051157,
        3235.43474222, 30097.43728402,  9587.55755036,  3479.29334785,
       22831.3147095 , 23568.25865914,  9614.1794375 ,  3284.63192287,
       12005.06426069,  2518.36763691, 10672.66098384, 10869.26103671,
       14601.80307094, 23780.14481502,  7500.99785778,  5730.08973536,
        6334.60339528, 12994.52867996, 11288.72796688,  8146.35623478,
        5158.72841558, 11221.30841482, 12115.71093188, 30978.03038905,
        4481.98862983, 25291.34959456,   700.27906032,  3446.97313049,
       10784.4836049 , 14198.45040041,  5053.32541998,  8024.78134016,
        4696.84617097, 27574.30903555,  8319.3156834 , 11483.33739565,
        5908.74974817,  8971.43192439, 31358.77587333,  4581.68989826,
       10434.72264793, 26901.88262948,  5796.10696856,  5102.78547631,
        2214.0430209 ,  5162.62788841,  5127.49786633,  6477.70175567,
       16484.26377745,   461.9844441 ,  2979.11366305,  9969.44471179,
        3951.04582982, 10632.63725819,  4207.28866377,  5399.10129639,
       11921.03384572,  6206.22975509,  8775.95237362,  7727.82639383,
        9105.37856848, 11013.38547821, 24485.65586146, 34105.2803857 ,
       11708.79820287,  7899.1279854 , 34900.71316165, 11540.1112273 ,
        8098.55453728,  8812.07217133,  9526.71870311, 10668.74017653,
       10676.47774352, 15750.26159333,  2231.65423443, 21248.37476425,
       11365.03359427, 28883.12538138,  6099.0553135 , 12157.7633065 ,
       10269.28887046, 16133.60375609,  9973.65170622, 10933.6309583 ,
       28031.24098256,  4108.09729653, 12622.11028552, 33896.37278921,
        5975.46029543,  5971.24153796,  3882.84513481, 11049.95365181,
       23367.02315102, 13110.06290588,  9683.01410007, 10270.25444265,
       12422.99399098,  2520.32299755,  3363.74463598, 26301.29317323,
       26190.58324457, 11929.84950227,  4320.78536005, 22611.07522761,
       12941.18415136, 26627.23467246,  4039.3067653 , 34059.42128225,
       10030.26292815,  4774.41896126,  7175.22972777,  3206.25520501,
       23161.636598  , 13443.80815371,  1856.89671964, 12244.28470488,
       11984.59859651, 13828.57277726, 30299.64226249, 13553.01889453,
       28231.20096171,  9668.76026547, 16275.83592217,  5995.64639356,
        9194.73773995,  9220.22955355, 14341.93454043,  9482.61806502,
        7631.75305592, 13438.72149538, 12532.86686952, 13654.68780122,
        7232.98262683, 22898.96629933,  8894.82096699])
```

[187]:
```
# for Testing

print("------------------------- Evaluation for Testing Data ------------------------")
mse = mean_squared_error(ytest, ytest_pred)
print("mean squared error (MSE) : ", mse)
print("-"*80)

mae = mean_absolute_error(ytest, ytest_pred)
print("mean absolute error (MAE) : ", mae)
print("-"*80)

rmse = np.sqrt(mse)
print("Root mean squared error (RMSE) : ", rmse)
print("-"*80)

r2score = r2_score(ytest, ytest_pred)
print("R2 Score : ", r2score)
print("-"*80)
```

```
------------------------- Evaluation for Testing Data ------------------------
```

```
mean squared error (MSE) :  25663562.89341267
--------------------------------------------------------------------------------
mean absolute error (MAE) :  3400.935136082026
--------------------------------------------------------------------------------
Root mean squared error (RMSE) :  5065.921721998146
--------------------------------------------------------------------------------
R2 Score :  0.7589437714409245
--------------------------------------------------------------------------------
```

Algorithm 2: L1- Lasso

[194]:
```
Lasso_model=Lasso()
Lasso_model
```

[194]:
```
Lasso()
```

[196]:
```
# Training the Lasso model
lasso_model = Lasso_model.fit(xtrain, ytrain)
ytrain_pred = lasso_model.predict(xtrain)

print("------------------------- Evaluation of Lasso Training Data -------------------------")
mse_train = mean_squared_error(ytrain, ytrain_pred)
print("Mean Squared Error (MSE):", mse_train)
print("-" * 80)

mae_train = mean_absolute_error(ytrain, ytrain_pred)
print("Mean Absolute Error (MAE):", mae_train)
print("-" * 80)

rmse_train = np.sqrt(mse_train)
print("Root Mean Squared Error (RMSE):", rmse_train)
print("-" * 80)

r2_train = r2_score(ytrain, ytrain_pred)
print("R2 Score:", r2_train)
print("-" * 80)
```

```
------------------------- Evaluation of Lasso Training Data -------------------------
Mean Squared Error (MSE): 26162383.23163086
--------------------------------------------------------------------------------
Mean Absolute Error (MAE): 3346.9011439298597
--------------------------------------------------------------------------------
Root Mean Squared Error (RMSE): 5114.917715040083
--------------------------------------------------------------------------------
R2 Score: 0.743477484555913
--------------------------------------------------------------------------------
```

[198]:
```
# Testing the Lasso model
ytest_pred = lasso_model.predict(xtest)

print("------------------------- Evaluation of Lasso Testing Data -------------------------")
mse_test = mean_squared_error(ytest, ytest_pred)
print("Mean Squared Error (MSE):", mse_test)
print("-" * 80)

mae_test = mean_absolute_error(ytest, ytest_pred)
print("Mean Absolute Error (MAE):", mae_test)
print("-" * 80)

rmse_test = np.sqrt(mse_test)
print("Root Mean Squared Error (RMSE):", rmse_test)
print("-" * 80)

r2_test = r2_score(ytest, ytest_pred)
print("R2 Score:", r2_test)
print("-" * 80)
```

```
------------------------- Evaluation of Lasso Testing Data -------------------------
Mean Squared Error (MSE): 25666205.392001774
--------------------------------------------------------------------------------
Mean Absolute Error (MAE): 3401.5554279432567
--------------------------------------------------------------------------------
Root Mean Squared Error (RMSE): 5066.18252651854
--------------------------------------------------------------------------------
R2 Score: 0.7589189506182465
--------------------------------------------------------------------------------
```

Algorithm 3: L2 - Ridge

[201]:
```
Ridge_model=Ridge()
Ridge_model
```

[201]:
```
Ridge()
```

[203]:
```
ridge_model=Ridge_model.fit(xtrain,ytrain)
ytrain_predict = Ridge_model.predict(xtrain)
ytrain_predict
```

[203]:
```
array([ 3044.79386716,  5204.46305323, 12733.99715313, ...,
       11472.52680989, 31410.39392572, 11024.914144  ])
```

[205]:
```
print("------------------------- Evaluation of ridge Training Data -------------------------")
mse = mean_squared_error(ytrain, ytrain_pred)
print("Mean Squared Error (MSE):", mse)
print("-" * 80)
```

```
mae = mean_absolute_error(ytrain, ytrain_pred)
print("Mean Absolute Error (MAE):", mae)
print("-" * 80)
rmse = np.sqrt(mse)
print("Root Mean Squared Error (RMSE):", rmse)
print("-" * 80)

r2score = r2_score(ytrain, ytrain_pred)
print("R2 Score:", r2score)
print("-" * 80)
```

```
------------------------- Evaluation of ridge Training Data -------------------------
Mean Squared Error (MSE): 26162383.23163086
--------------------------------------------------------------------------------
Mean Absolute Error (MAE): 3346.9011439298597
--------------------------------------------------------------------------------
Root Mean Squared Error (RMSE): 5114.917715040083
--------------------------------------------------------------------------------
R2 Score: 0.743477484555913
--------------------------------------------------------------------------------
```

[207]:
```
ytest_pred = Ridge_model.predict(xtest)
ytest_pred

print("------------------------- Ridge Evaluation for Testing Data -------------------------")
mse = mean_squared_error(ytest, ytest_pred)
print("mean squared error (MSE) : ", mse)
print("-"*80)

mae = mean_absolute_error(ytest, ytest_pred)
print("mean absolute error (MAE) : ", mae)
print("-"*80)

rmse = np.sqrt(mse)
print("Root mean squared error (RMSE) : ", rmse)
print("-"*80)

r2score = r2_score(ytest, ytest_pred)
print("R2 Score : ", r2score)
print("-"*80)
```

```
------------------------- Ridge Evaluation for Testing Data -------------------------
mean squared error (MSE) :  25690567.648712225
--------------------------------------------------------------------------------
mean absolute error (MAE) :  3412.9725338121752
--------------------------------------------------------------------------------
Root mean squared error (RMSE) :  5068.586356047634
--------------------------------------------------------------------------------
R2 Score :  0.7586901174766364
--------------------------------------------------------------------------------
```

[ ]: