Insurance_Data_Set_(SLR,_MLR,_PolyReg,_Lasso,_Ridge,_ElasticNet)

May 21, 2024

0.1 1. Business Ploblem Understanding

[1]:
```python
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

0.2 2. Data Understanding

0.2.1 2.1 Data Collection

[2]:
```python
df = pd.read_excel('/content/insurance.xlsx')
df.head()
```

[2]:

	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

[3]:
```python
df.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
```

1 Multiple Linear Regression

1.1 3. Data Preprocessing

1.1.1 3.1 EDA

[4]:
```
df.info()
```

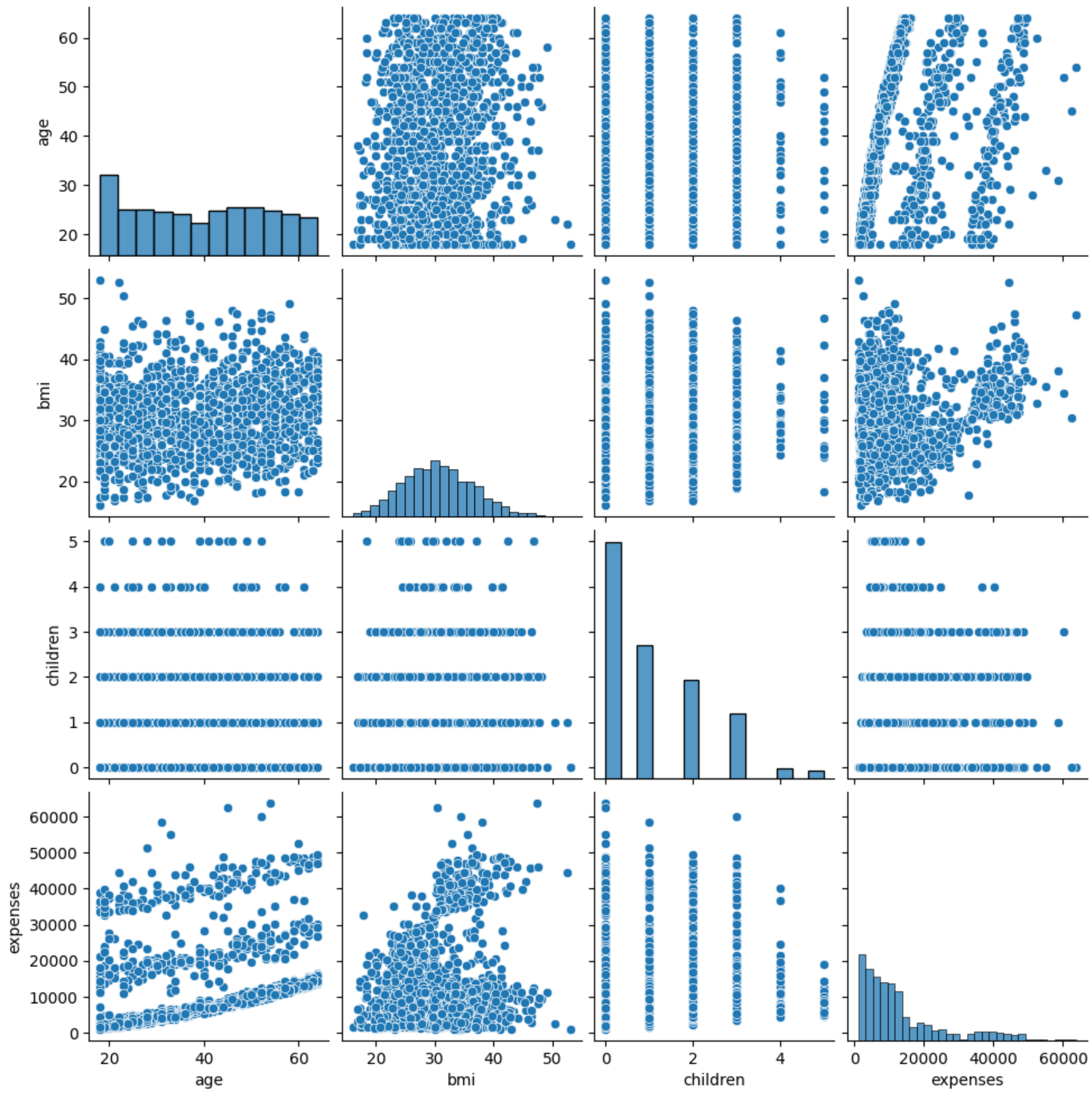
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       1338 non-null   int64
 1   sex       1338 non-null   object
 2   bmi       1338 non-null   float64
 3   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
```

[5]:
```
df.describe()
```

[5]:

	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

[6]:
```
sns.pairplot(df)
plt.show()
```

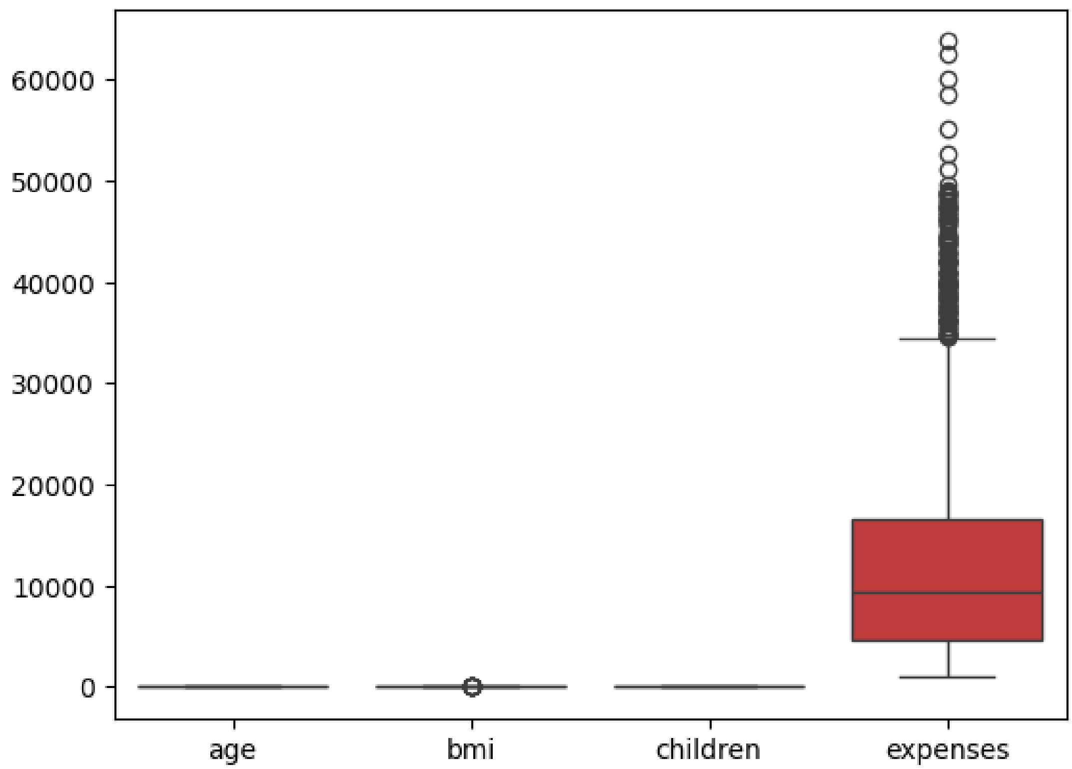



```
[7]: df.corr(numeric_only=True)
```

[7]:

	age	bmi	children	expenses
age	1.000000	0.109341	0.042469	0.299008
bmi	0.109341	1.000000	0.012645	0.198576
children	0.042469	0.012645	1.000000	0.067998
expenses	0.299008	0.198576	0.067998	1.000000

```
[8]: sns.boxplot(data=df) # Checking the Outliers
plt.show()
```



[9]:
```
df.skew(numeric_only=True)
```

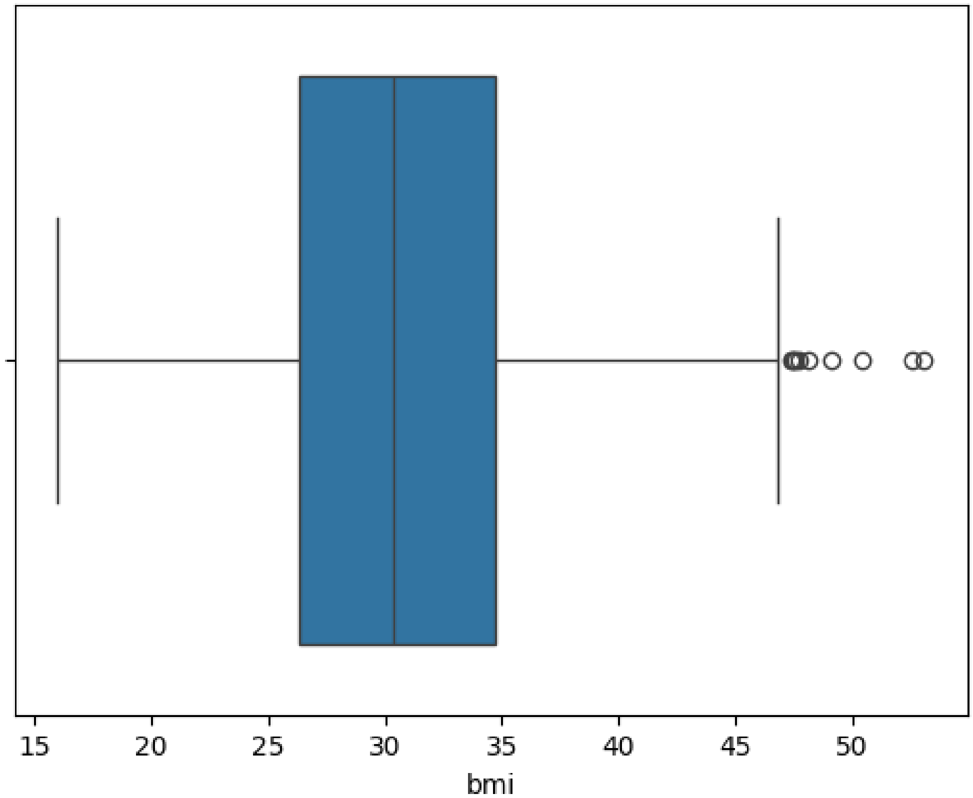
[9]:
```
age         0.055673
bmi         0.284593
children    0.938380
expenses    1.515880
dtype: float64
```

1.1.2 3.2 Data Cleaning

[10]:
```
df.isnull().sum()
```

[10]:
```
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
expenses    0
dtype: int64
```

[11]:
```
# clearing the outliers
sns.boxplot(x=df['bmi'])
plt.show()
```



[12]:
```
q1 = df['bmi'].quantile(0.25)
q3 = df['bmi'].quantile(0.75)
iqr = q3-q1
lower_limit = q1 - (iqr*1.5)
upper_limit = q3 + (iqr*1.5)
print(q1,q3,iqr,lower_limit,upper_limit)
```

```
26.3 34.7 8.400000000000002 13.699999999999998 47.300000000000004
```

[13]:
```
df[df['bmi']>47.300000000000004] # Outliers of the Variable
```

[13]:

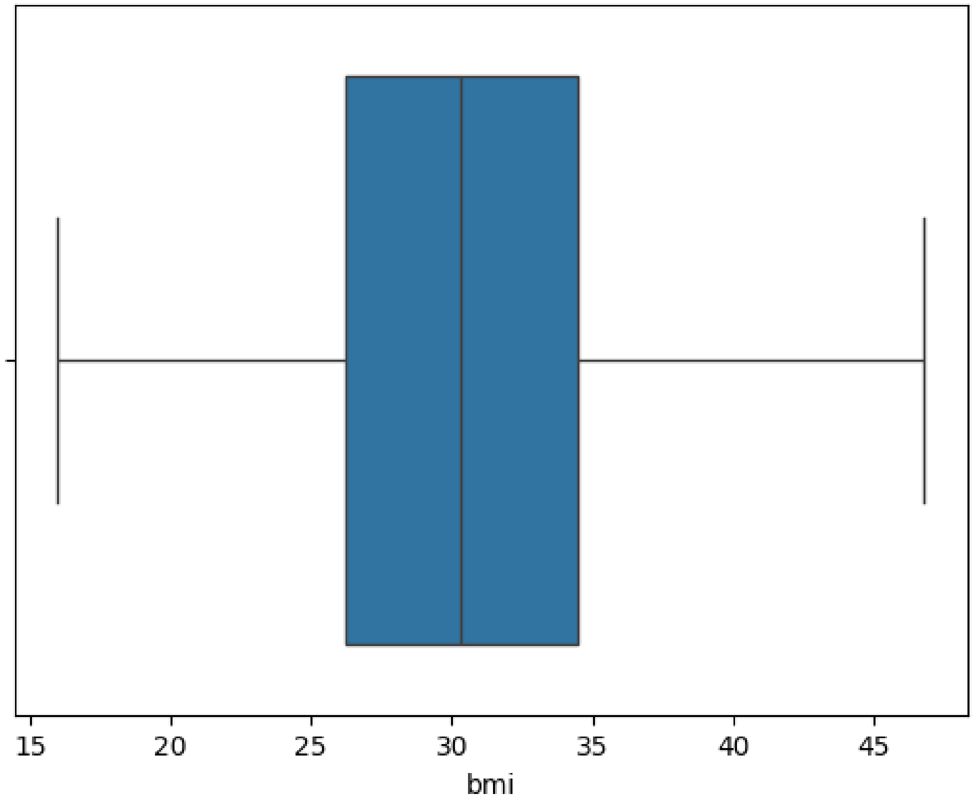
	age	sex	bmi	children	smoker	region	expenses
116	58	male	49.1	0	no	southeast	11381.33
286	46	female	48.1	2	no	northeast	9432.93
401	47	male	47.5	1	no	southeast	8083.92
543	54	female	47.4	0	yes	southeast	63770.43
847	23	male	50.4	1	no	southeast	2438.06

```
860     37  female  47.6         2    yes  southwest  46113.51
1047    22    male  52.6         1    yes  southeast  44501.40
1088    52    male  47.7         1     no  southeast   9748.91
1317    18    male  53.1         0     no  southeast   1163.46
```

```
[14]: df = df[(df['bmi']> lower_limit) & (df['bmi'] < upper_limit)] # removing the
       ↪outliers
      df
```

```
[14]:       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

      [1329 rows x 7 columns]
```

```
[15]: sns.boxplot(x=df['bmi'])
      plt.show()
```



[16]:
```
df.drop('region',axis=1,inplace=True)
```

1.1.3 3.3 Data Wrangling

[17]:
```
df['sex'].replace({'female':0,'male':1},inplace=True)
df['smoker'].replace({'no':0,'yes':1},inplace=True)
```

1.1.4 3.4 Train Test Split

[18]:
```
x = df.drop('expenses',axis=1)
y = df['expenses']
```

[19]:
```
from sklearn.model_selection import train_test_split as tts
x_train,x_test,y_train,y_test = tts(x,y, test_size = 0.2, random_state = 42)
```

[20]:
```
x_test
```

[20]:

	age	sex	bmi	children	smoker
899	19	0	22.5	0	0
115	60	1	28.6	0	0
529	18	1	25.5	0	0

```
176     38    1  27.8        2        0
63      28    0  25.9        1        0
…    …    …    …     …     …
867     57    1  43.7        1        0
558     35    0  34.1        3        1
1028    54    1  31.6        0        0
585     33    0  28.3        1        0
1222    50    1  25.3        0        0

[266 rows x 5 columns]
```

1.2 4. Modelleing and Evoluation

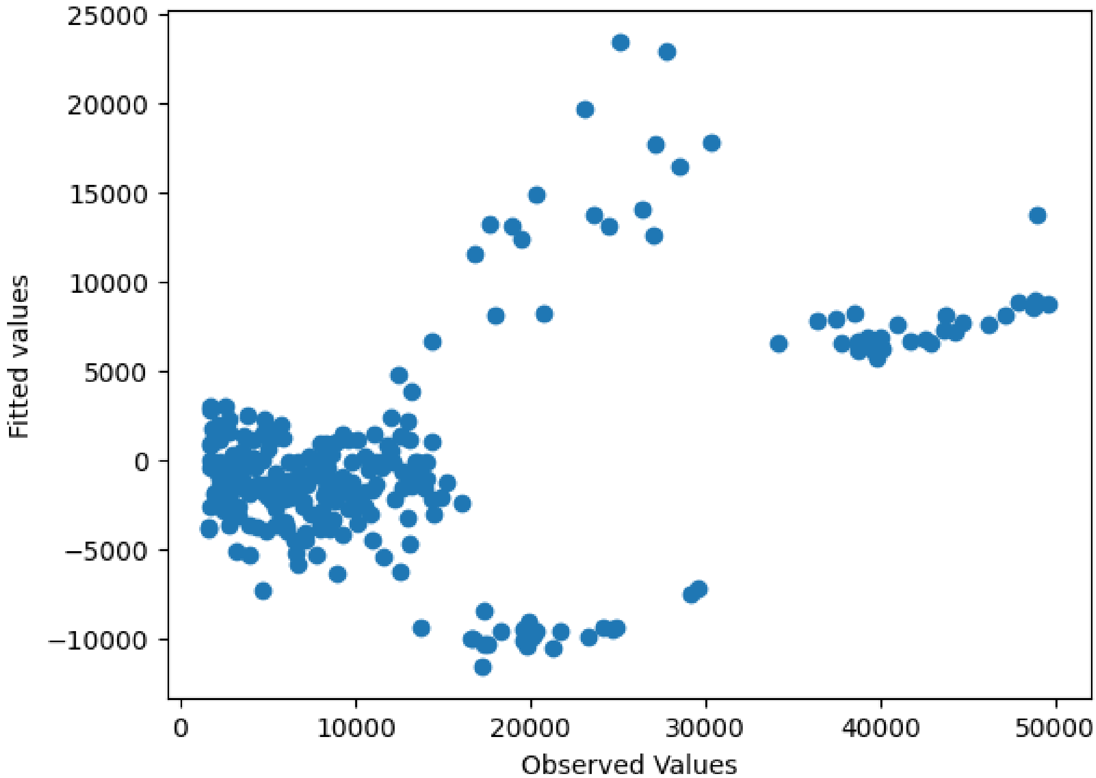
[21]:
```python
# Modeling with default paramaters
from sklearn.linear_model import LinearRegression
mlr_model = LinearRegression()
mlr_model.fit(x_train,y_train)

# Prediction
train_predictions = mlr_model.predict(x_train)
test_predictions = mlr_model.predict(x_test)

# Evaluation
from sklearn.model_selection import cross_val_score
mlr_train = mlr_model.score(x_train,y_train)
mlr_test = mlr_model.score(x_test,y_test)
mlr_cv = cross_val_score(mlr_model,x,y,cv=5).mean()

print('Train R2: ',mlr_train)
print('Test R2: ',mlr_test)
print("CV Score: ",mlr_cv)
```

```
Train R2:  0.7436049992264148
Test R2:  0.768277484877281
CV Score:  0.7458418619962311
```

1.3 Check for Assumptions

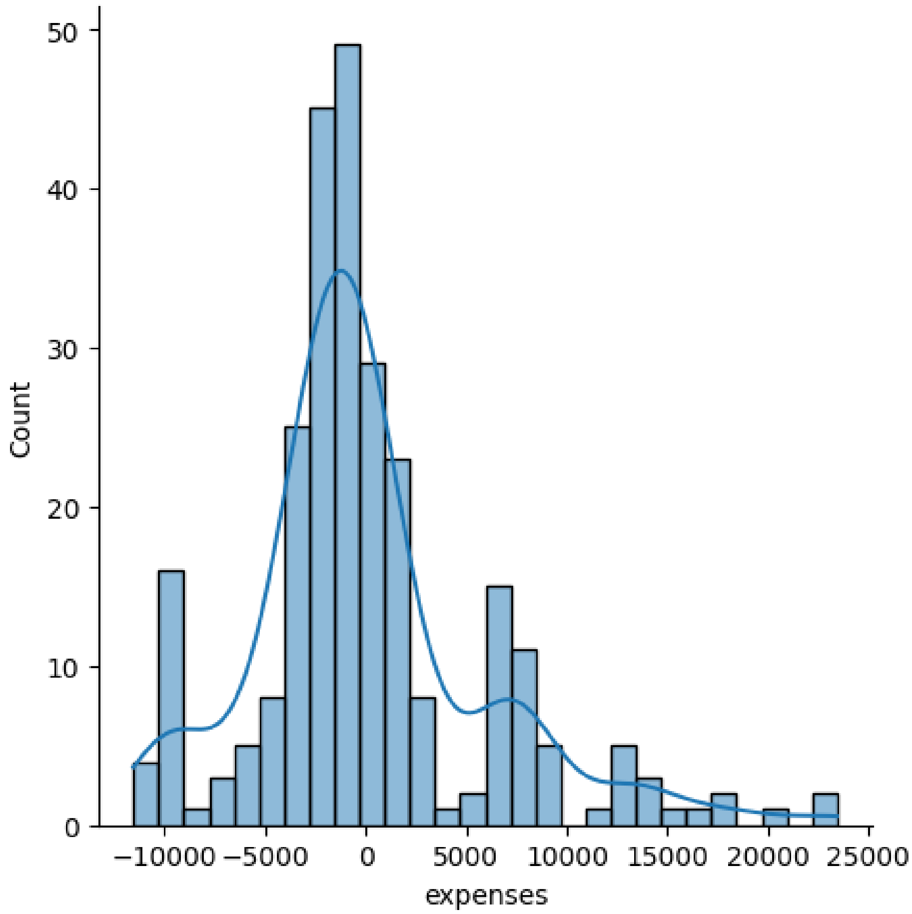
1.3.1 1.Linearity of Errors

[22]:
```python
test_res = y_test - test_predictions
plt.scatter(y_test,test_res)
plt.xlabel("Observed Values")
plt.ylabel("Fitted values")
plt.show()
```



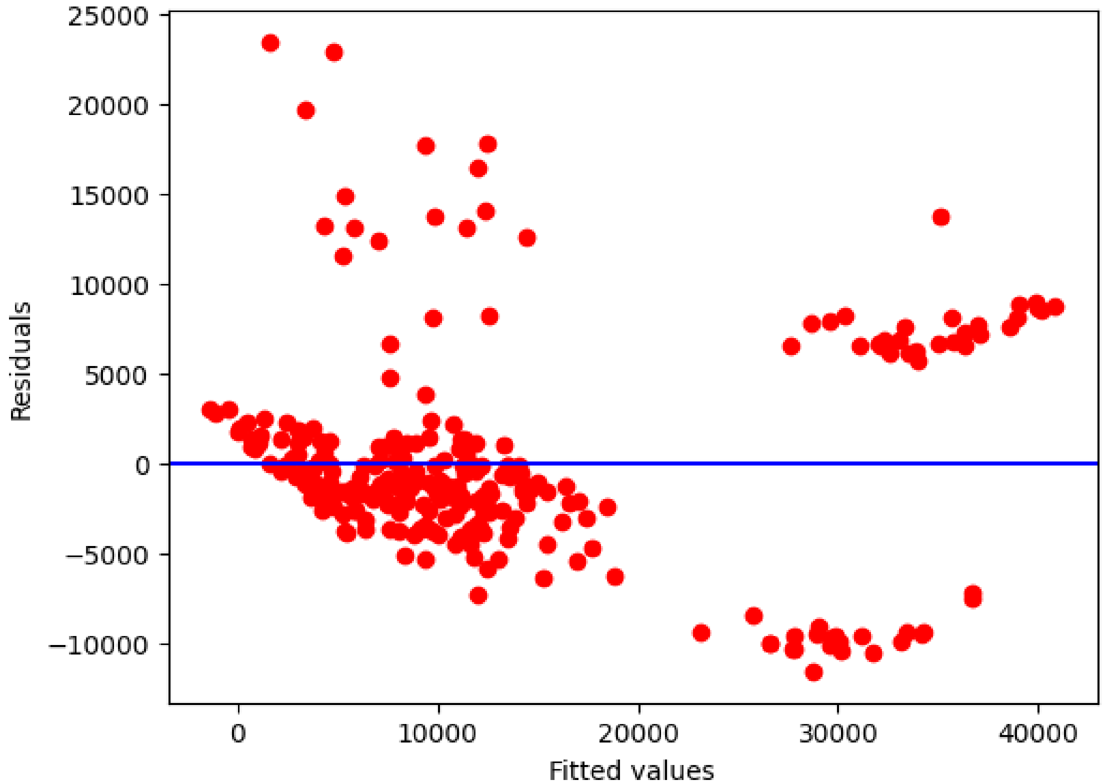
1.3.2 2.Normality of Errors

[23]:
```
sns.displot(test_res,kde=True)
plt.show()
```



1.3.3 3.Equal variance of errors (Homoscadesicity)

[24]:
```
plt.scatter(test_predictions,test_res,c="r")
plt.axhline(y=0,color='blue')
plt.xlabel("Fitted values")
plt.ylabel("Residuals")
plt.show()
```



1.3.4 4.Variables significance

[25]:
```
import statsmodels.formula.api as smf
mod=smf.ols("y~x",data=df).fit()
mod.summary()
```

[25]:

Dep. Variable:	y	**R-squared:**	0.749
Model:	OLS	**Adj. R-squared:**	0.748
Method:	Least Squares	**F-statistic:**	788.5
Date:	Sat, 04 May 2024	**Prob (F-statistic):**	0.00
Time:	15:16:32	**Log-Likelihood:**	-13450.
No. Observations:	1329	**AIC:**	2.691e+04
Df Residuals:	1323	**BIC:**	2.694e+04
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P> |t|	[0.025	0.975]
Intercept	-1.21e+04	964.025	-12.554	0.000	-1.4e+04	-1.02e+04
x[0]	257.0460	11.864	21.666	0.000	233.771	280.321
x[1]	-36.8547	332.019	-0.111	0.912	-688.195	614.486
x[2]	324.7149	28.140	11.539	0.000	269.511	379.919
x[3]	477.1451	137.039	3.482	0.001	208.307	745.983
x[4]	2.362e+04	411.630	57.377	0.000	2.28e+04	2.44e+04

Omnibus:	304.856	**Durbin-Watson:**	2.087
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	730.634
Skew:	1.236	**Prob(JB):**	2.21e-159
Kurtosis:	5.661	**Cond. No.**	299.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

2 Polynomial Regression

2.1 3. Preprocessing

[26]:
```
from sklearn.preprocessing import PolynomialFeatures
Poly_converter= PolynomialFeatures(degree=2,include_bias=False)
Poly_x = pd.DataFrame(Poly_converter.fit_transform(x))
```

2.1.1 Train Test Split

[27]:
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(Poly_x,y,test_size=0.
↪2,random_state=42)
```

2.2 4. Modelleing and Evoluation

[28]:
```
# Modeling with default paramaters
from sklearn.linear_model import LinearRegression
poly_model = LinearRegression()
poly_model.fit(x_train,y_train)

# Prediction
train_predictions = poly_model.predict(x_train)
test_predictions = poly_model.predict(x_test)

# Evaluation
print('Train R2: ',poly_model.score(x_train,y_train))
print('Test R2: ',poly_model.score(x_test,y_test))

from sklearn.model_selection import cross_val_score
print("CV Score: ",cross_val_score(poly_model,x,y,cv=5).mean())
```

```
Train R2:  0.8369153487751684
Test R2:  0.8561470786317726
CV Score:  0.7458418619962311
```

2.2.1 Ploy HyperParameter Tuning

[29]:
```python
train_r2=[]
test_r2=[]
for i in range(1,10):
    from sklearn.preprocessing import PolynomialFeatures
    Poly_converter= PolynomialFeatures(degree=i,include_bias=False)
    Poly_x = pd.DataFrame(Poly_converter.fit_transform(x))

    from sklearn.model_selection import train_test_split
    x_train,x_test,y_train,y_test = train_test_split(Poly_x,y,test_size=0.
 ↪2,random_state=42)

    from sklearn.linear_model import LinearRegression
    model = LinearRegression()
    model.fit(x_train,y_train)

    test_r2.append(model.score(x_test,y_test))
    train_r2.append(model.score(x_train,y_train))

print(pd.DataFrame([test_r2,train_r2]))
```

```
          0         1         2         3         4         5           6  \
0  0.768277  0.856147  0.853815  0.847705  0.766139  0.399658 -188.797616
1  0.743605  0.836915  0.843785  0.856941  0.870320  0.881784    0.896520

             7             8
0 -2047.899405 -18944.226103
1     0.904957      0.898268
```

2.2.2 Rebuilding Model with best HPT Parameters

[30]:
```python
final_Poly_converter= PolynomialFeatures(degree=4,include_bias=False)
Pol_x = final_Poly_converter.fit_transform(x)

x_train,x_test,y_train,y_test = train_test_split(Pol_x,y,test_size=0.
 ↪2,random_state=42)

final_model = LinearRegression()
final_model.fit(x_train,y_train)


poly_train = final_model.score(x_train,y_train)
poly_test = final_model.score(x_test,y_test)
```

```
poly_cv = cross_val_score(final_model,x,y,cv=5).mean()

print('Train R2: ',poly_train)
print('Test R2: ',poly_test)
print("CV Score: ",poly_cv)
```

```
Train R2:  0.8569408723742798
Test R2:  0.8477046103010456
CV Score:  0.7458418619962311
```

3 Lasso Regression

3.1 4. Modeling and Evaluation

[31]:
```
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_state=42)
```

[32]:
```
# Modeling with default paramaters
from sklearn.linear_model import Lasso
lasso_base = Lasso()
lasso_base.fit(x_train,y_train)

# Prediction
train_predictions = lasso_base.predict(x_train)
test_predictions = lasso_base.predict(x_test)

# Evaluation
print('Train R2: ',lasso_base.score(x_train,y_train))
print('Test R2: ',lasso_base.score(x_test,y_test))

from sklearn.model_selection import cross_val_score
print("CVS: ",cross_val_score(lasso_base,x,y,cv=5).mean() )
```

```
Train R2:  0.7436049167576863
Test R2:  0.7682845084591609
CVS:  0.7458481242772766
```

[33]:
```
# HyperParameter tuning
from sklearn.model_selection import GridSearchCV

estimator = Lasso()

#param_grid = {"alpha":[0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1,10,20,30,50,100]}
param_grid = {"alpha":list(range(1,100))}

model_hp = GridSearchCV(estimator,param_grid,cv =␣
 ↪5,scoring='neg_mean_squared_error')
```

```
model_hp.fit(x_train,y_train)
model_hp.best_params_
```

[33]:
```
{'alpha': 27}
```

[34]:
```
# Final Modeling with best HyperParameter tuning parameters
from sklearn.linear_model import Lasso
lasso_final = Lasso(alpha=27)
lasso_final.fit(x_train,y_train)

print('Intercepr: ',lasso_final.intercept_)
print('Coefficients: ',lasso_final.coef_)

# Prediction
train_predictions = lasso_final.predict(x_train)
test_predictions = lasso_final.predict(x_test)

# Evaluation

lasso_train = lasso_final.score(x_train,y_train)
lasso_test = lasso_final.score(x_test,y_test)
lasso_cv = cross_val_score(lasso_final,x,y,cv=5).mean()

print('Train R2: ',lasso_train)
print('Test R2: ',lasso_test)
print("CV Score: ",lasso_cv)
```

```
Intercepr:  -11800.259640347304
Coefficients:  [  257.25689231    -0.            313.71245413   496.51744208
 23445.34029312]
Train R2:  0.7435483160182876
Test R2:  0.7684044851038989
CV Score:  0.745964401137262
```

4 Ridge Regression

[35]:
```
# Modeling with default paramaters
from sklearn.linear_model import Ridge
ridge_base = Ridge()
ridge_base.fit(x_train,y_train)

# Prediction
train_predictions = ridge_base.predict(x_train)
test_predictions = ridge_base.predict(x_test)

# Evaluation
print('Train R2: ',ridge_base.score(x_train,y_train))
```

```
print('Test R2: ',ridge_base.score(x_test,y_test))

from sklearn.model_selection import cross_val_score
print("CV Score: ",cross_val_score(ridge_base,x,y,cv=5).mean())
```

```
Train R2:  0.7435838281857797
Test R2:  0.7682654944819229
CV Score:  0.7458250060836376
```

[36]:
```
# HyperParameter tuning
from sklearn.model_selection import GridSearchCV

estimator = Ridge()

param_grid = {"alpha":[0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1,10,20,30,50,100]}

model_hp = GridSearchCV(estimator,param_grid,cv =
 ↪5,scoring='neg_mean_squared_error')
model_hp.fit(x_train,y_train)
model_hp.best_params_
```

[36]:
```
{'alpha': 0.3}
```

[37]:
```
# Rebuildibg the final model with best HyperParameter tuning parameters

# Modeling with default paramaters
ridge_final = Ridge(alpha=0.3)
ridge_final.fit(x_train,y_train)

# Prediction
train_predictions = ridge_final.predict(x_train)
test_predictions = ridge_final.predict(x_test)

# Evaluation

ridge_train = ridge_final.score(x_train,y_train)
ridge_test = ridge_final.score(x_test,y_test)
ridge_cv = cross_val_score(ridge_final,x,y,cv=5).mean()

print('Train R2: ',ridge_train)
print('Test R2: ',ridge_test)
print("CV Score: ",ridge_cv)
```

```
Train R2:  0.7436030782325043
Test R2:  0.7682781284991226
CV Score:  0.7458412533777042
```

5 ElasticNet Regression

[38]:
```
# Modeling with default paramaters
from sklearn.linear_model import ElasticNet
ElasticNet_base = ElasticNet()
ElasticNet_base.fit(x_train,y_train)

# Prediction
train_predictions = ElasticNet_base.predict(x_train)
test_predictions = ElasticNet_base.predict(x_test)

# Evaluation
print('Train R2: ',ElasticNet_base.score(x_train,y_train))
print('Test R2: ',ElasticNet_base.score(x_test,y_test))

from sklearn.model_selection import cross_val_score
print("CV Score: ",cross_val_score(ElasticNet_base,x,y,cv=5).mean())
```

```
Train R2:  0.3823176876430222
Test R2:  0.42375809808088793
CV Score:  0.3869970168655764
```

[39]:
```
# HyperParameter tuning
from sklearn.model_selection import GridSearchCV

estimator = ElasticNet()

param_grid = {"alpha":list(range(1,100)),
              'l1_ratio':[0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1]}

model_hp = GridSearchCV(estimator,param_grid,cv =␣
 ↪5,scoring='neg_mean_squared_error')
model_hp.fit(x_train,y_train)
model_hp.best_params_
```

[39]:
```
{'alpha': 27, 'l1_ratio': 1}
```

[40]:
```
# Rebuildibg the final model with best HyperParameter tuning parameters

ElasticNet_best = ElasticNet(alpha=27,l1_ratio=1)
ElasticNet_best.fit(x_train,y_train)

# Prediction
train_predictions = ElasticNet_best.predict(x_train)
test_predictions = ElasticNet_best.predict(x_test)

# Evaluation
```

```
enr_train = ElasticNet_best.score(x_train,y_train)
enr_test = ElasticNet_best.score(x_test,y_test)
enr_cv = cross_val_score(ElasticNet_best,x,y,cv=5).mean()

print('Train R2: ',enr_train)
print('Test R2: ',enr_test)
print("CV Score: ",enr_cv)
```

```
Train R2:  0.7435483160182876
Test R2:  0.7684044851038989
CV Score:  0.745964401137262
```

[41]:
```
d1 = {'Algorithms':['Multiple Linear Regression','Polynomial Regression','Lasso␣
 ↪Regression','Ridge Regression','ElasticNet Regression'],
      'Train R2':[mlr_train,poly_train,lasso_train,ridge_train,enr_train],
      'Test R2':[mlr_test,poly_test,lasso_test,ridge_test,enr_test],
      'CV Scores':[mlr_cv,poly_cv,lasso_cv,ridge_cv,enr_cv],
      'Assumption for SLR and MLR':['No','NaN','NaN','NaN','NaN']}
all_frame = pd.DataFrame(d1)
all_frame
```

[41]:
```
                   Algorithms  Train R2   Test R2  CV Scores  \
0  Multiple Linear Regression  0.743605  0.768277   0.745842
1       Polynomial Regression  0.856941  0.847705   0.745842
2            Lasso Regression  0.743548  0.768404   0.745964
3            Ridge Regression  0.743603  0.768278   0.745841
4       ElasticNet Regression  0.743548  0.768404   0.745964

  Assumption for SLR and MLR
0                         No
1                        NaN
2                        NaN
3                        NaN
4                        NaN
```