In [74]: import pandas as pd
import numpy as np

In [75]: df=pd.read\_csv(r"C:\Users\venky\Downloads\Advertising.csv")
 df

### Out[75]:

	TV	Radio	Newspaper	Sales
0	230.1	37.8	69.2	22.1
1	44.5	39.3	45.1	10.4
2	17.2	45.9	69.3	12.0
3	151.5	41.3	58.5	16.5
4	180.8	10.8	58.4	17.9
195	38.2	3.7	13.8	7.6
196	94.2	4.9	8.1	14.0
197	177.0	9.3	6.4	14.8
198	283.6	42.0	66.2	25.5
199	232.1	8.6	8.7	18.4

200 rows × 4 columns

In [76]: df.head()

Out[76]:

	TV	Radio	Newspaper	Sales
0	230.1	37.8	69.2	22.1
1	44.5	39.3	45.1	10.4
2	17.2	45.9	69.3	12.0
3	151.5	41.3	58.5	16.5
4	180.8	10.8	58.4	17.9

In [77]: df.tail()

Out[77]:

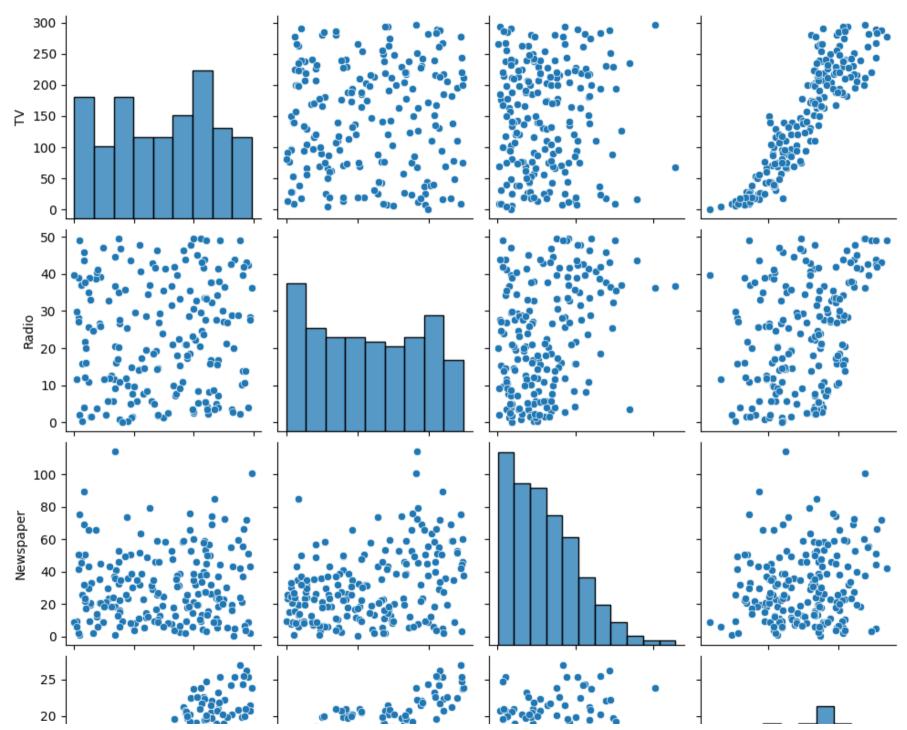
	TV	Radio	Newspaper	Sales
195	38.2	3.7	13.8	7.6
196	94.2	4.9	8.1	14.0
197	177.0	9.3	6.4	14.8
198	283.6	42.0	66.2	25.5
199	232 1	8.6	8.7	18 4

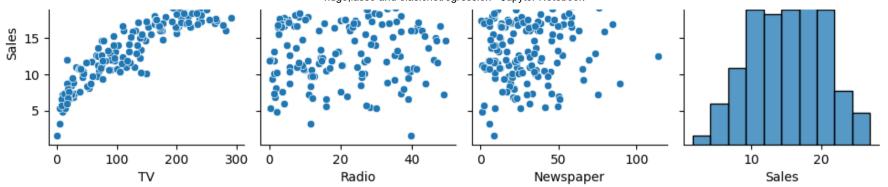
```
In [78]: df.describe()
Out[78]:
                        TV
                                Radio Newspaper
                                                      Sales
           count 200.000000
                           200.000000
                                      200.000000 200.000000
                 147.042500
                             23.264000
                                       30.554000
           mean
                                                  15.130500
                  85.854236
                             14.846809
                                       21.778621
                                                   5.283892
                   0.700000
                              0.000000
                                        0.300000
                                                   1.600000
            min
            25%
                  74.375000
                              9.975000
                                       12.750000
                                                  11.000000
            50% 149.750000
                             22.900000
                                       25.750000
                                                  16.000000
            75% 218.825000
                             36.525000
                                       45.100000
                                                  19.050000
            max 296.400000
                            49.600000 114.000000
                                                  27.000000
In [79]: df.columns
Out[79]: Index(['TV', 'Radio', 'Newspaper', 'Sales'], dtype='object')
In [80]: df.shape
Out[80]: (200, 4)
In [81]: import seaborn as sns
          import matplotlib.pyplot as plt
In [82]: from sklearn import preprocessing, svm
          from sklearn.model selection import train test split
          from sklearn.linear model import LinearRegression
          from sklearn.preprocessing import StandardScaler
In [83]: | df=df[['TV', 'Radio', 'Newspaper', 'Sales']]
```

In [84]: df.columns=['TV','Radio','Newspaper','Sales']

```
In [85]: sns.pairplot(df)
```

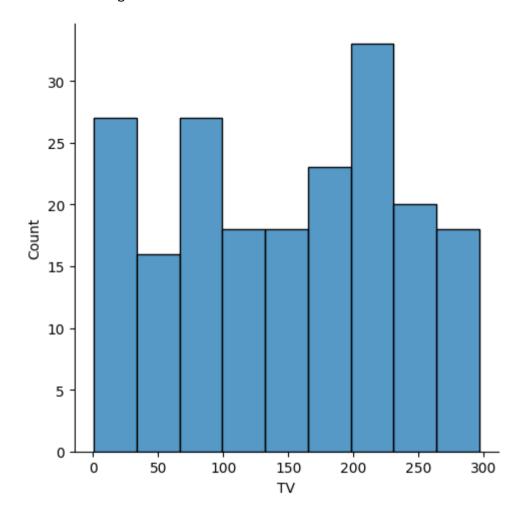
Out[85]: <seaborn.axisgrid.PairGrid at 0x27fd568aa50>





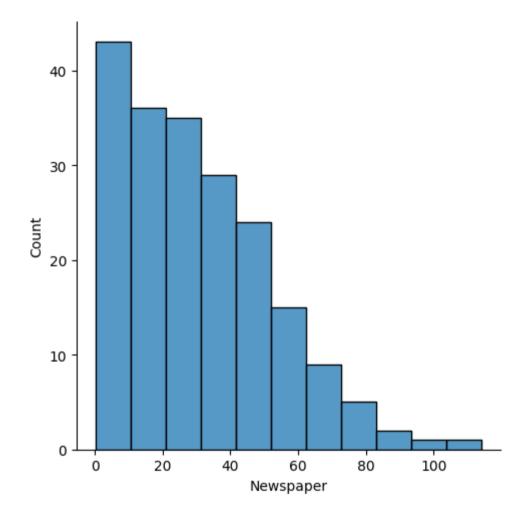
```
In [86]: sns.displot(df['TV'])
```

Out[86]: <seaborn.axisgrid.FacetGrid at 0x27fd564ba90>



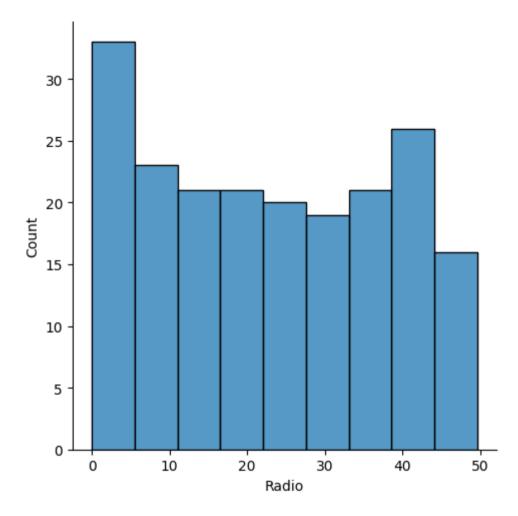
In [87]: sns.displot(df['Newspaper'])

Out[87]: <seaborn.axisgrid.FacetGrid at 0x27fd7258910>



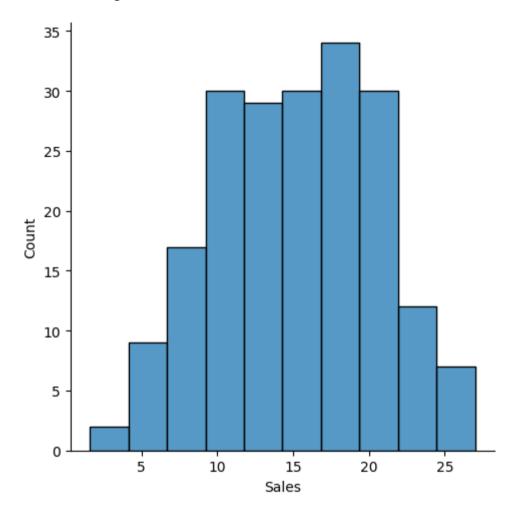
```
In [88]: sns.displot(df['Radio'])
```

Out[88]: <seaborn.axisgrid.FacetGrid at 0x27fd727db50>



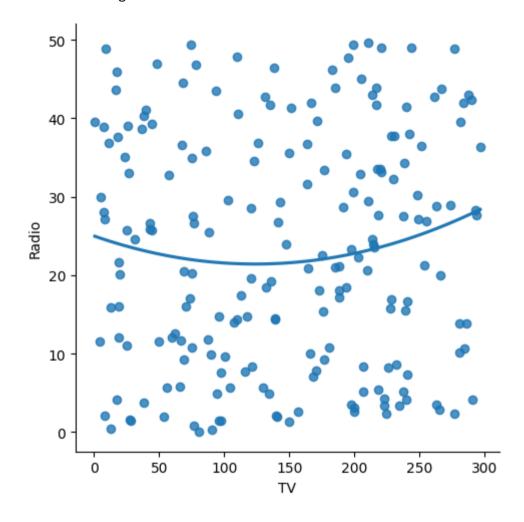
```
In [89]: sns.displot(df['Sales'])
```

Out[89]: <seaborn.axisgrid.FacetGrid at 0x27fd6d8ba90>



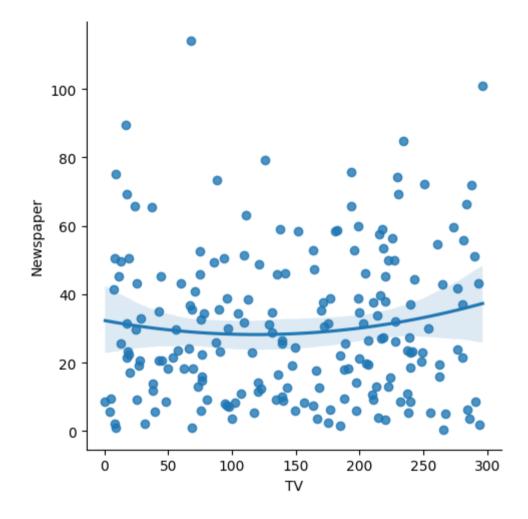
```
In [90]: sns.lmplot(x="TV",y="Radio",data=df,order=2,ci=None)
```

Out[90]: <seaborn.axisgrid.FacetGrid at 0x27fd6df5d50>



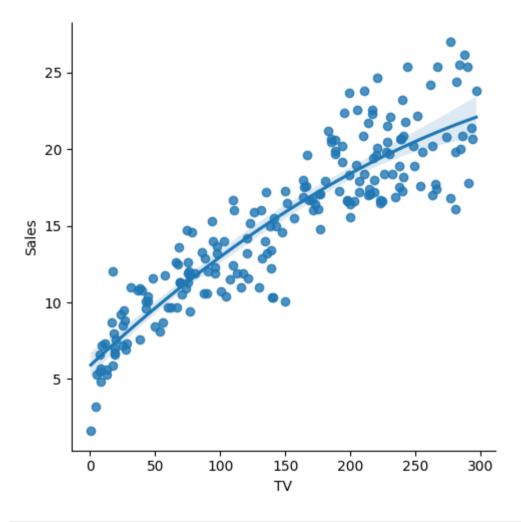
```
In [91]: sns.lmplot(x="TV",y="Newspaper",data=df,order=2)
```

Out[91]: <seaborn.axisgrid.FacetGrid at 0x27fd6d91510>



```
In [92]: sns.lmplot(x="TV",y="Sales",data=df,order=2)
```

Out[92]: <seaborn.axisgrid.FacetGrid at 0x27fd8423390>



```
In [93]: x=np.array(df['TV']).reshape(-1,1)
y=np.array(df['Radio']).reshape(-1,1)
```

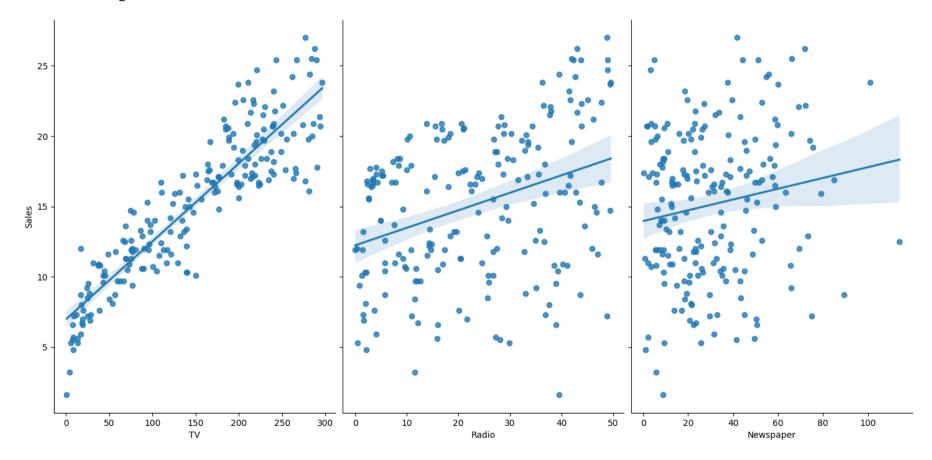
```
In [94]: df.dropna(inplace=True)
    X_train, X_test, y_train, y_test=train_test_split(x,y,test_size=0.3)
    regr=LinearRegression()
    regr.fit(X_train, y_train)
    regr.fit(X_train, y_train)
```

Out[94]: LinearRegression()

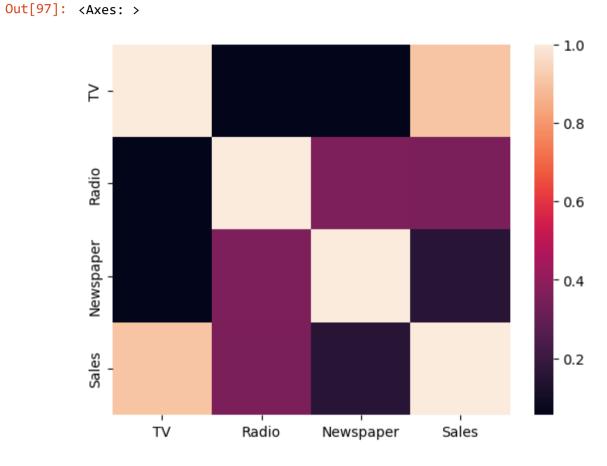
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook. On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [95]: sns.pairplot(df,x\_vars=['TV','Radio','Newspaper'],y\_vars='Sales',height=7,aspect=0.7,kind='reg')

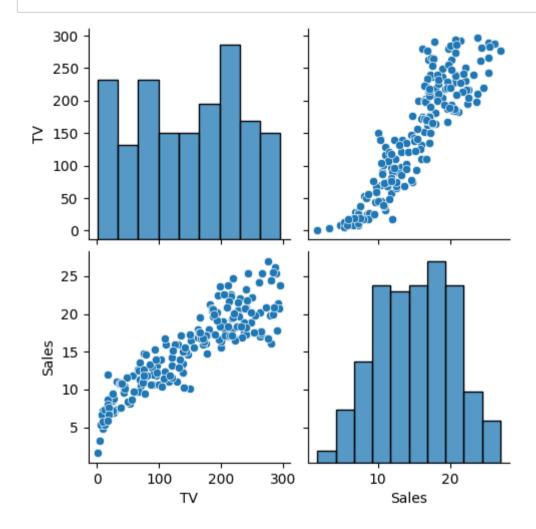
Out[95]: <seaborn.axisgrid.PairGrid at 0x27fd84212d0>



```
In [96]: hk=df[['TV','Radio','Newspaper','Sales']]
In [97]: sns.heatmap(hk.corr())
```



```
In [98]: df.drop(columns=['Radio','Newspaper'],inplace=True)
    sns.pairplot(df)
    df.Sales=np.log(df.Sales)
```



```
In [99]: features=df.columns[0:2]
          target=df.columns[-1]
          X=df[features].values
          y=df[target].values
          X train, X test, y train, y test=train test split(X,y,test size=0.3,random state=17)
          print("The dimension of X train is {}".format(X train.shape))
          print("The dimension of X test is {}".format(X test.shape))
          scaler=StandardScaler()
          X train=scaler.fit transform(X train)
          X test=scaler.transform(X test)
          The dimension of X train is (140, 2)
          The dimension of X test is (60, 2)
In [100]: from sklearn.linear model import Lasso,Ridge
In [101]: lr=LinearRegression()
          lr.fit(X train,y train)
          actual=y test
          train score lr=lr.score(X train,y train)
          test score lr=lr.score(X test,y test)
          print("\nLinear Regression Model:\n" )
          print("The train score for lr model is {}".format(train_score_lr))
          print("The train score lr model is {}".format(test score lr))
          Linear Regression Model:
          The train score for lr model is 1.0
          The train score lr model is 1.0
```

```
In [102]: ridgeReg=Ridge(alpha=10)
    ridgeReg.fit(X_train,y_train)
    train_score_ridge=ridgeReg.score(X_train,y_train)
    test_score_ridge=ridgeReg.score(X_test,y_test)
    print("\nRidge model\:\n")
    print("The train score for ridge model is {}".format(train_score_ridge))
    print("The train score for ridge model is {}".format(test_score_ridge))
```

#### Ridge model\:

The train score for ridge model is 0.990287139194161
The train score for ridge model is 0.9844266285141221

```
In [103]: plt.figure(figsize=(10,10))
    plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker='*',markersize=5,color='red',label=r'Ridge;$\alpha=
    plt.plot(features,lr.coef_,alpha=0.4,linestyle='none',marker='o',markersize=7,color='green',label='Linear Regression')
    plt.xticks(rotation=90)
    plt.legend()
    plt.show()
```





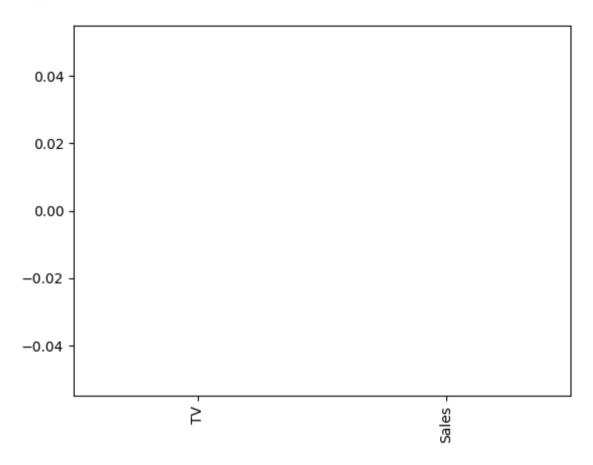
```
In [104]: lassoReg=Lasso(alpha=10)
    lassoReg.fit(X_train,y_train)
        train_score_lasso=lassoReg.score(X_train,y_train)
        test_score_lasso=lassoReg.score(X_test,y_test)
        print("\nRidge model\:\n")
        print("The train score for lasso model is {}".format(train_score_ridge))
        print("The train score for lasso model is {}".format(test_score_ridge))
```

### Ridge model\:

The train score for lasso model is 0.990287139194161
The train score for lasso model is 0.9844266285141221

```
In [105]: pd.Series(lassoReg.coef_,features).sort_values(ascending=True).plot(kind="bar")
```

Out[105]: <Axes: >



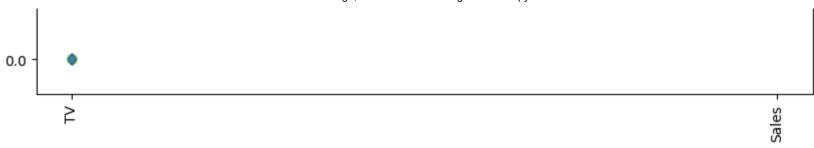
```
In [106]: from sklearn.linear_model import LassoCV
lasso_CV=LassoCV(alphas=[0.0001,0.001,0.01,1,10]).fit(X_train,y_train)
print("The train score for lasso model is{}".format(lasso_CV.score(X_train,y_train)))
print("The test score for lasso model is{}".format(lasso_CV.score(X_test,y_test)))
```

The train score for lasso model is0.9999999343798134
The test score for lasso model is0.9999999152638072

```
In [107]: plt.figure(figsize=(10,10))
    plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker='*',markersize=5,color='red',label=r'Ridge;$\alpha=
    plt.plot(features,lasso_CV.coef_,alpha=0.5,linestyle='none',marker='d',markersize=6,color='blue',label=r'lasso,$\alpha=
    plt.plot(features,lr.coef_,alpha=0.4,linestyle='none',marker='o',markersize=7,color='green',label='LinearRegression')
    plt.xticks(rotation=90)
    plt.legend()
    plt.title("comparision plot of Ridge,Lasso and LinearRegression model")
    plt.show()
```

## comparision plot of Ridge, Lasso and Linear Regression model





```
In [108]: from sklearn.linear_model import RidgeCV
    ridge_CV=RidgeCV(alphas=[0.0001,0.01,0.1,1,10]).fit(X_train,y_train)
    print("The train score for ridge model is{}".format(ridge_CV.score(X_train,y_train)))
    print("The test score for ridge model is{}".format(ridge_CV.score(X_test,y_test)))
```

The train score for ridge model is0.9999999999976281
The test score for ridge model is0.9999999999962489

[0.00417976 0. ]
2.0263839193110043
mean Squared Error on the tset set 0.5538818050142152

# **VEHICLE-SELECTION** ¶

Out[110]:

	ID	model	engine_power	age_in_days	km	previous_owners	lat	lon	price
0	1	lounge	51	882	25000	1	44.907242	8.611560	8900
1	2	pop	51	1186	32500	1	45.666359	12.241890	8800
2	3	sport	74	4658	142228	1	45.503300	11.417840	4200
3	4	lounge	51	2739	160000	1	40.633171	17.634609	6000
4	5	pop	73	3074	106880	1	41.903221	12.495650	5700
1533	1534	sport	51	3712	115280	1	45.069679	7.704920	5200
1534	1535	lounge	74	3835	112000	1	45.845692	8.666870	4600
1535	1536	pop	51	2223	60457	1	45.481541	9.413480	7500
1536	1537	lounge	51	2557	80750	1	45.000702	7.682270	5990
1537	1538	pop	51	1766	54276	1	40.323410	17.568270	7900

1538 rows × 9 columns

In [111]: df.head()

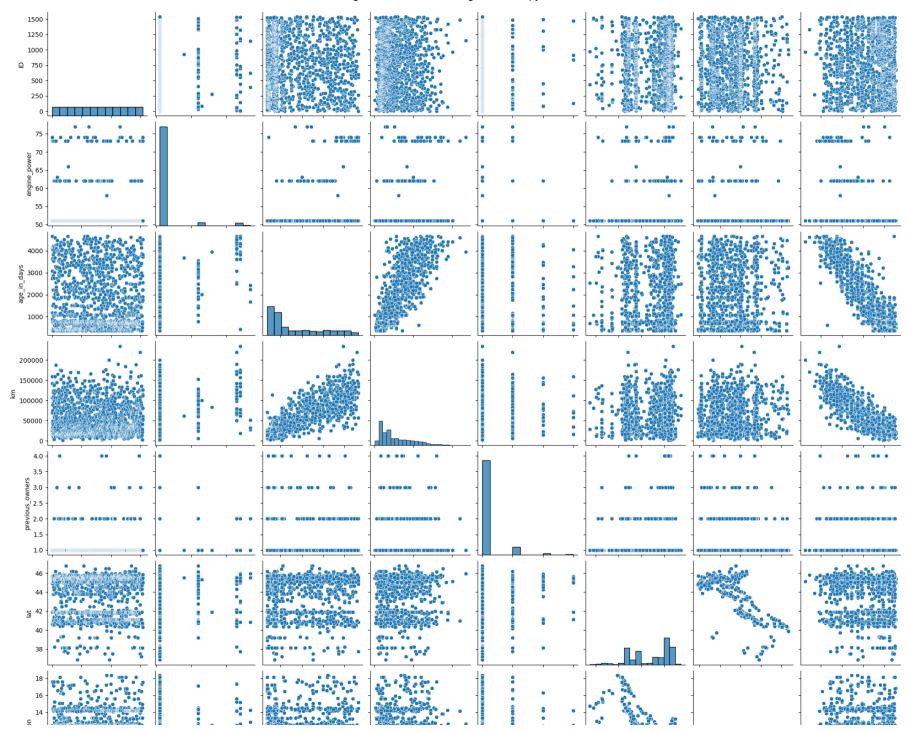
Out[111]:

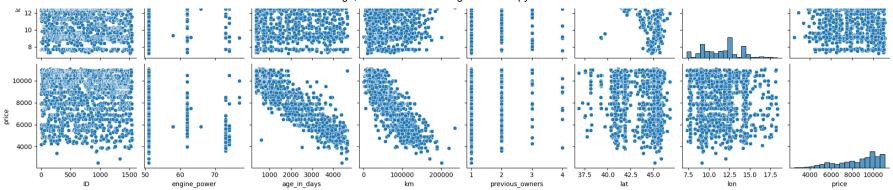
	ID	model	engine_power	age_in_days	km	previous_owners	lat	lon	price
(	0 1	lounge	51	882	25000	1	44.907242	8.611560	8900
	1 2	e pop	51	1186	32500	1	45.666359	12.241890	8800
:	2 3	sport	74	4658	142228	1	45.503300	11.417840	4200
;	3 4	lounge	51	2739	160000	1	40.633171	17.634609	6000
	4 5	рор	73	3074	106880	1	41.903221	12.495650	5700

```
In [112]: df.tail()
Out[112]:
                     ID model engine power age in days
                                                              km previous owners
                                                                                          lat
                                                                                                   Ion price
             1533 1534
                                          51
                                                     3712 115280
                                                                                1 45.069679
                                                                                               7.70492
                                                                                                        5200
                          sport
             1534 1535
                                                     3835
                                                           112000
                                                                                1 45.845692
                                                                                               8.66687
                                                                                                        4600
                        lounge
                                          74
             1535 1536
                                                     2223
                                                            60457
                                                                                1 45.481541
                                                                                               9.41348
                                                                                                       7500
                           pop
                                          51
             1536
                  1537
                                          51
                                                     2557
                                                            80750
                                                                                1 45.000702
                                                                                               7.68227
                                                                                                        5990
                        lounge
             1537 1538
                           pop
                                          51
                                                     1766
                                                            54276
                                                                                1 40.323410 17.56827
                                                                                                       7900
In [113]: df.describe()
Out[113]:
                             ID engine_power age_in_days
                                                                     km previous_owners
                                                                                                   lat
                                                                                                               lon
                                                                                                                          price
             count 1538.000000
                                  1538.000000
                                              1538.000000
                                                             1538.000000
                                                                              1538.000000
                                                                                          1538.000000 1538.000000
                                                                                                                    1538.000000
                    769.500000
                                    51.904421
                                              1650.980494
                                                                                 1.123537
                                                                                                         11.563428
                                                            53396.011704
                                                                                            43.541361
                                                                                                                    8576.003901
             mean
                    444.126671
                                     3.988023
                                              1289.522278
                                                                                                          2.328190
                                                            40046.830723
                                                                                 0.416423
                                                                                             2.133518
                                                                                                                    1939.958641
               std
                       1.000000
              min
                                    51.000000
                                               366.000000
                                                             1232.000000
                                                                                 1.000000
                                                                                            36.855839
                                                                                                          7.245400
                                                                                                                    2500.000000
              25%
                    385.250000
                                    51.000000
                                               670.000000
                                                            20006.250000
                                                                                 1.000000
                                                                                            41.802990
                                                                                                          9.505090
                                                                                                                    7122.500000
              50%
                    769.500000
                                    51.000000
                                              1035.000000
                                                            39031.000000
                                                                                 1.000000
                                                                                            44.394096
                                                                                                         11.869260
                                                                                                                    9000.000000
                                                                                                                   10000.000000
              75%
                    1153.750000
                                    51.000000
                                              2616.000000
                                                            79667.750000
                                                                                 1.000000
                                                                                            45.467960
                                                                                                         12.769040
                                              4658.000000
              max 1538.000000
                                    77.000000
                                                           235000.000000
                                                                                 4.000000
                                                                                            46.795612
                                                                                                         18.365520 11100.000000
In [114]: df.shape
Out[114]: (1538, 9)
In [115]: | df.columns
Out[115]: Index(['ID', 'model', 'engine power', 'age in days', 'km', 'previous owners',
                    'lat', 'lon', 'price'],
                   dtype='object')
```

```
In [116]: sns.pairplot(df)
```

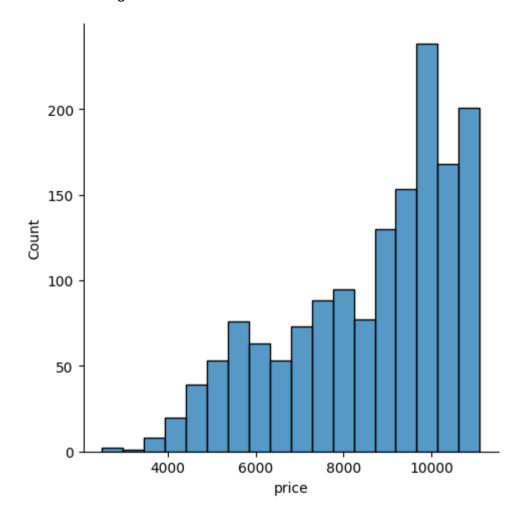
Out[116]: <seaborn.axisgrid.PairGrid at 0x27fd8f75a50>





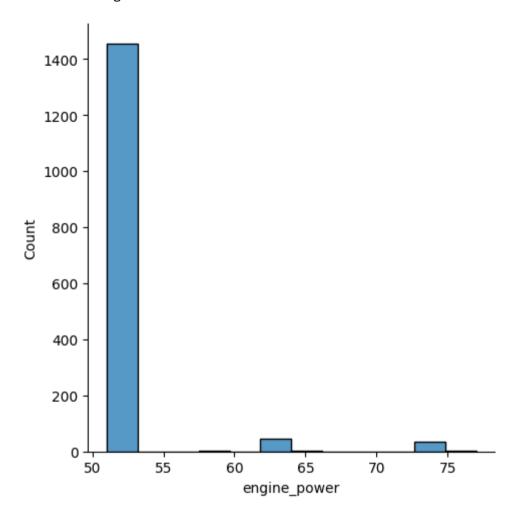
```
In [117]: sns.displot(df['price'])
```

Out[117]: <seaborn.axisgrid.FacetGrid at 0x27fdc7dba90>



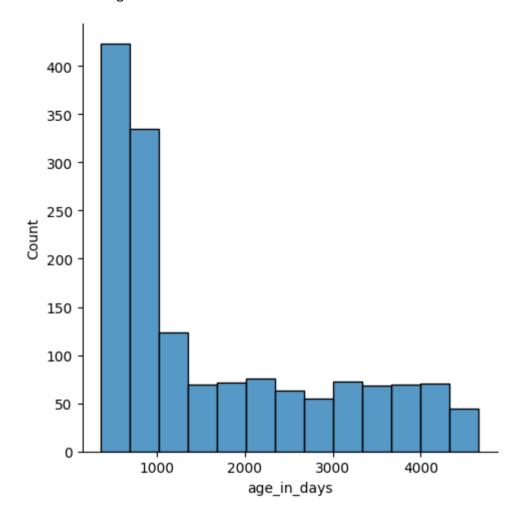
```
In [118]: sns.displot(df['engine_power'])
```

Out[118]: <seaborn.axisgrid.FacetGrid at 0x27fddb1e790>



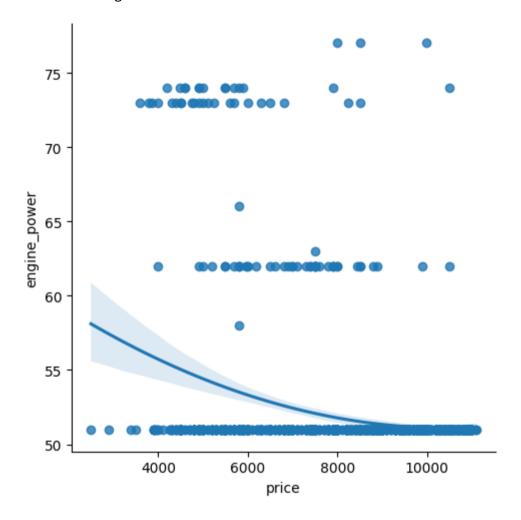
```
In [119]: sns.displot(df['age_in_days'])
```

Out[119]: <seaborn.axisgrid.FacetGrid at 0x27fdebb3a90>



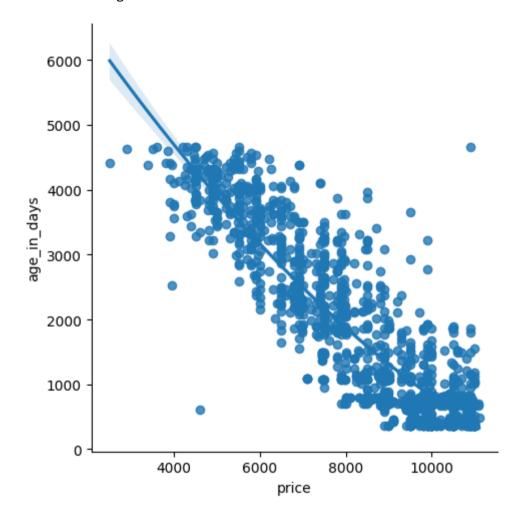
```
In [120]: sns.lmplot(x="price",y="engine_power",data=df,order=2)
```

Out[120]: <seaborn.axisgrid.FacetGrid at 0x27fddc01e50>



```
In [121]: sns.lmplot(x="price",y="age_in_days",data=df,order=2)
```

Out[121]: <seaborn.axisgrid.FacetGrid at 0x27fdec3fc10>



```
In [122]: x=np.array(df['price']).reshape(-1,1)
y=np.array(df['age_in_days']).reshape(-1,1)
```

```
In [123]: df.dropna(inplace=True)
    X_train,X_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
    regr=LinearRegression()
    regr.fit(X_train,y_train)
    regr.fit(X_train,y_train)
```

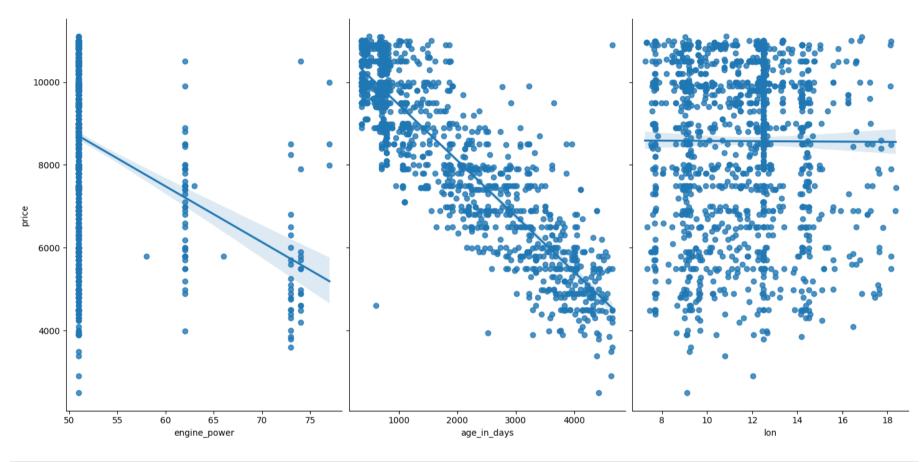
Out[123]: LinearRegression()

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook. On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

```
In [125]: df.drop(columns=["model"],inplace=True)
```

```
In [126]: sns.pairplot(df,x_vars=['engine_power','age_in_days','lon'],y_vars='price',height=7,aspect=0.7,kind='reg')
```

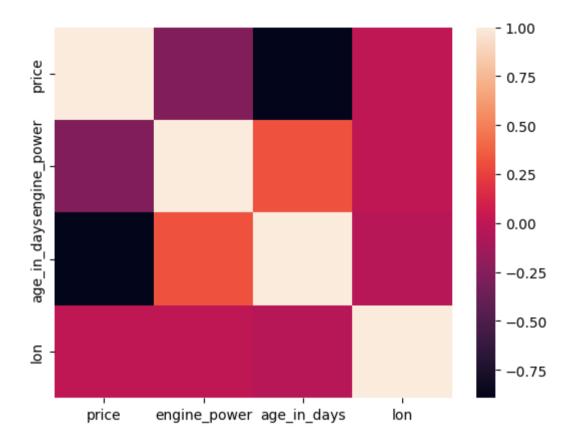
Out[126]: <seaborn.axisgrid.PairGrid at 0x27fdecc5350>



In [127]: hk=df[['price','engine\_power','age\_in\_days','lon']]

```
In [128]: sns.heatmap(hk.corr())
```

Out[128]: <Axes: >



```
In [129]: features=df.columns[0:2]
          target=df.columns[-1]
          X=df[features].values
          y=df[target].values
          X train, X test, y train, y test=train test split(X,y,test size=0.3,random state=17)
          print("The dimension of X train is {}".format(X train.shape))
          print("The dimension of X test is {}".format(X test.shape))
          scaler=StandardScaler()
          X train=scaler.fit transform(X train)
          X test=scaler.transform(X test)
          The dimension of X train is (1076, 2)
          The dimension of X test is (462, 2)
In [130]: from sklearn.linear model import Lasso,Ridge
In [131]: lr=LinearRegression()
          lr.fit(X train,y train)
          actual=y test
          train score lr=lr.score(X train,y train)
          test score lr=lr.score(X test,y test)
          print("\nLinear Regression Model:\n" )
          print("The train score for lr model is {}".format(train_score_lr))
          print("The train score lr model is {}".format(test score lr))
          Linear Regression Model:
          The train score for lr model is 0.07448634159905865
          The train score lr model is 0.07913288661070894
```

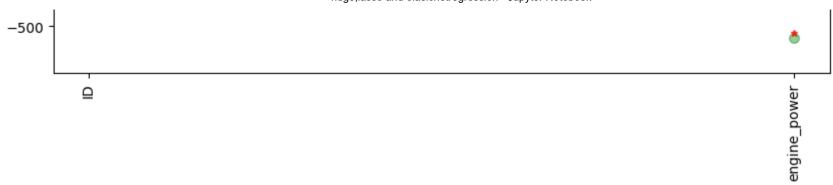
```
In [132]: ridgeReg=Ridge(alpha=10)
    ridgeReg.fit(X_train,y_train)
        train_score_ridge=ridgeReg.score(X_train,y_train)
        test_score_ridge=ridgeReg.score(X_test,y_test)
        print("\nRidge model\:\n")
        print("The train score for ridge model is {}".format(train_score_ridge))
        print("The train score for ridge model is {}".format(test_score_ridge))
```

## Ridge model\:

The train score for ridge model is 0.07448028989896427 The train score for ridge model is 0.07885996726883082

```
In [133]: plt.figure(figsize=(10,10))
    plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker='*',markersize=5,color='red',label=r'Ridge;$\alpha=
    plt.plot(features,lr.coef_,alpha=0.4,linestyle='none',marker='o',markersize=7,color='green',label='Linear Regression')
    plt.xticks(rotation=90)
    plt.legend()
    plt.show()
```



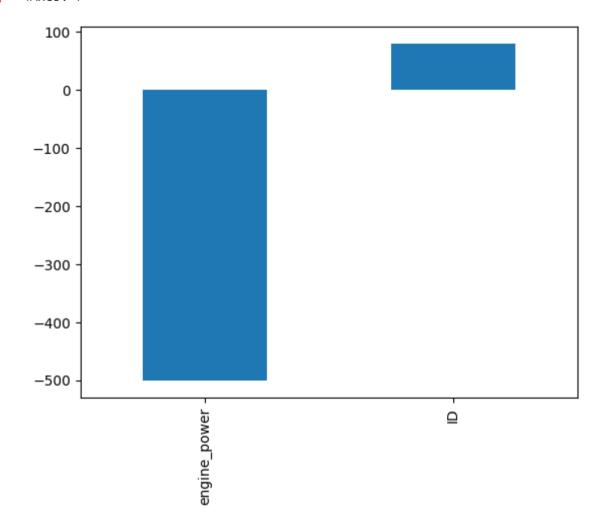


```
In [134]: lassoReg=Lasso(alpha=10)
    lassoReg.fit(X_train,y_train)
        train_score_lasso=lassoReg.score(X_train,y_train)
        test_score_lasso=lassoReg.score(X_test,y_test)
        print("\nRidge model\:\n")
        print("The train score for lasso model is {}".format(train_score_ridge))
        print("The train score for lasso model is {}".format(test_score_ridge))
```

## Ridge model\:

The train score for lasso model is 0.07448028989896427 The train score for lasso model is 0.07885996726883082 In [135]: pd.Series(lassoReg.coef\_,features).sort\_values(ascending=True).plot(kind="bar")

Out[135]: <Axes: >

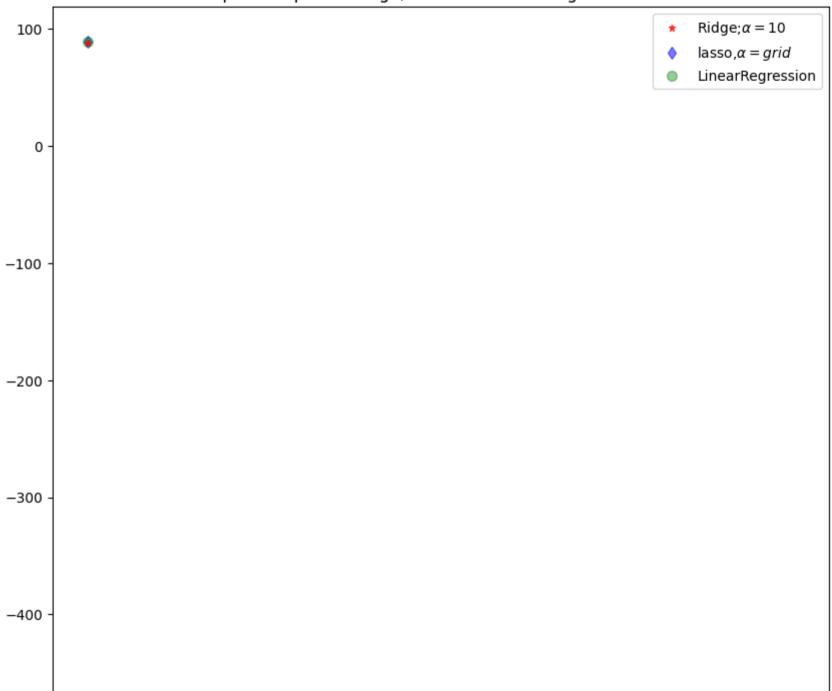


```
In [136]: from sklearn.linear_model import LassoCV
    lasso_CV=LassoCV(alphas=[0.0001,0.001,0.01,1,1,10]).fit(X_train,y_train)
    print("The train score for lasso model is{}".format(lasso_CV.score(X_train,y_train)))
    print("The test score for lasso model is{}".format(lasso_CV.score(X_test,y_test)))
```

The train score for lasso model is0.07448634159905387 The test score for lasso model is0.07913288806451946

```
In [137]: plt.figure(figsize=(10,10))
   plt.plot(features,ridgeReg.coef_,alpha=0.7,linestyle='none',marker='*',markersize=5,color='red',label=r'Ridge;$\alpha=plt.plot(features,lasso_CV.coef_,alpha=0.5,linestyle='none',marker='d',markersize=6,color='blue',label=r'lasso,$\alpha=plt.plot(features,lr.coef_,alpha=0.4,linestyle='none',marker='o',markersize=7,color='green',label='LinearRegression')
   plt.xticks(rotation=90)
   plt.legend()
   plt.title("comparision plot of Ridge,Lasso and LinearRegression model")
   plt.show()
```

## comparision plot of Ridge, Lasso and Linear Regression model





[ 8.46751882e-02 -1.30405006e+02] 15279,442735227916 mean Squared Error on the tset set 48390222.80186546

In [ ]: