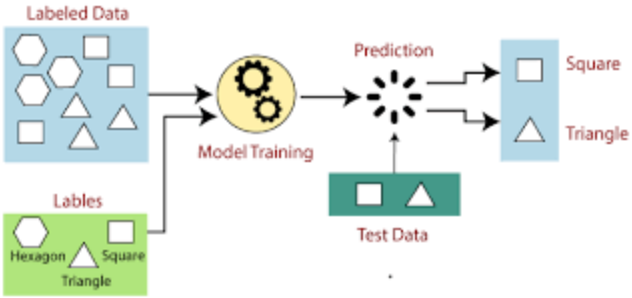
Day -16/100 of Data Science

Supervised Learning

- Supervised learning is a category of machine learning that uses labeled datasets to train algorithms to predict outcomes and recognize patterns.

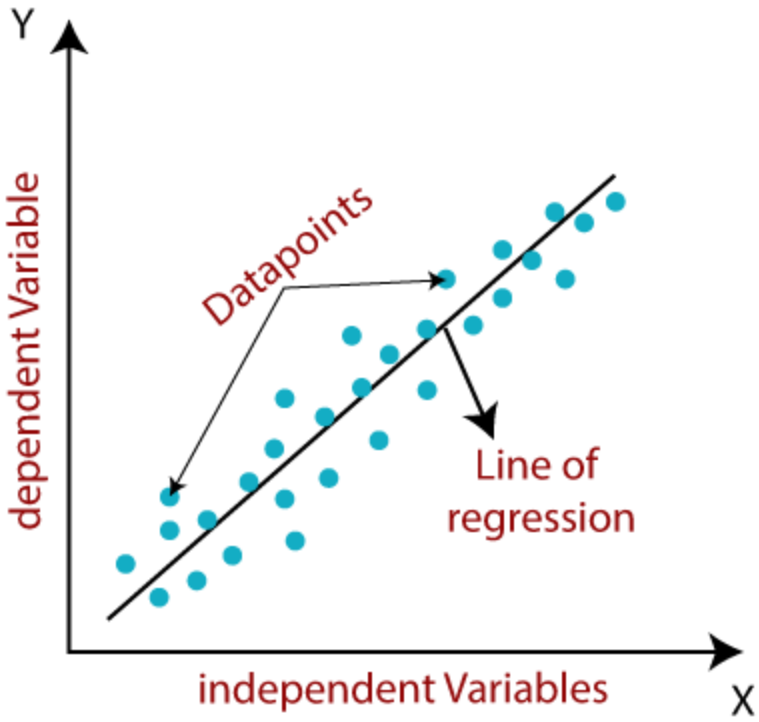


Supervised Learning Algorithms

- Linear Regression
- Logistic Regression
- Decision Trees
- Random Forest
- Support Vector Machine(SVM)
- K-Nearest Neighbors (KNN)

Linear Regression

- Linear regression is a statistical method used for modeling the relationship between a dependent variable and one or more independent variables by fitting a linear equation to the observed data.
- The basic idea is to find the best-fitting straight line (or hyperplane in the case of multiple independent variables) that minimizes the difference between the observed and predicted values of the dependent variable.



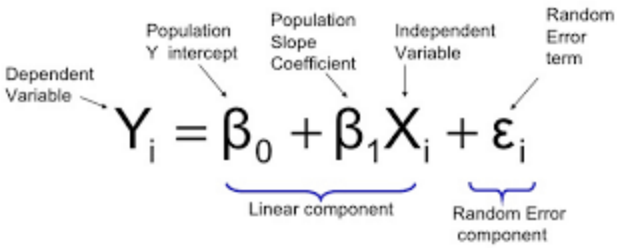
Types of Linear Regression

- Linear regression can be further divided into two types of the algorithm:

Simple Linear Regression:

- If a single independent variable is used to predict the value of a numerical dependent variable, then such a Linear Regression algorithm is called Simple Linear Regression.

Formula

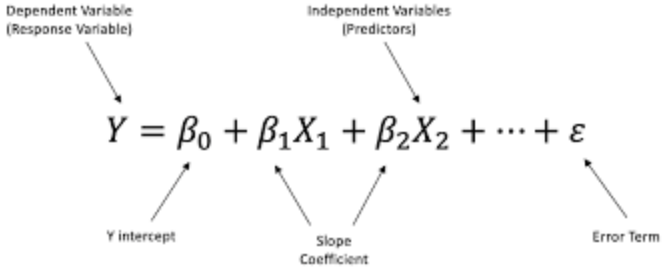


- Y = mx + c

Multiple Linear regression:

- If more than one independent variable is used to predict the value of a numerical dependent variable, then such a Linear Regression algorithm is called Multiple Linear

Regression.

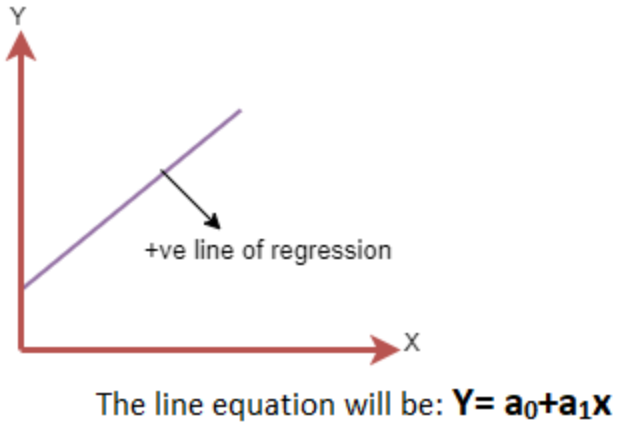


Linear Regression Line

- A linear line showing the relationship between the dependent and independent variables is called a regression line. A regression line can show two types of relationship:

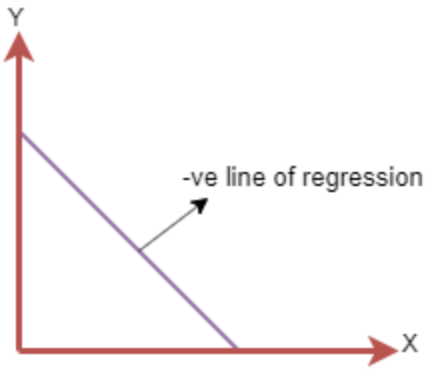
Positive Linear Relationship:

- If the dependent variable increases on the Y-axis and independent variable increases on X-axis, then such a relationship is termed as a Positive linear relationship.



Negative Linear Relationship:

- If the dependent variable decreases on the Y-axis and independent variable increases on the X-axis, then such a relationship is called a negative linear relationship.



The line of equation will be: $Y= -a_0+a_1x$

Finding the best fit line

- To find the best fit line that means the error between predicted values and actual values should be minimized.
- The best fit line will have the least error.

Mean Squared Error (MSE)

- For Linear Regression, we use the Mean Squared Error (MSE) cost function, which is the average of squared error occurred between the predicted values and actual values.
- It can be written as:

$$MSE= 1\frac{1}{N}\sum_{i=1}^{n}(y_i - (a_1x_i + a_0))^2$$

Where,

N=Total number of observation

Yi = Actual value

$(a1x_i+a_0)$= Predicted value.

Implementation of Linear Regression

In [2]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn import metrics
```

In [3]:
```
#Load dataset into jupyter notebook

# Loading the data
data = pd.read_csv(r'C:\Users\TEKS108\Vamsi Reddy\cardata.csv')
```

In [4]:
```
data.head()
```

Out[4]:

	Car_Name	Year	Selling_Price	Present_Price	Kms_Driven	Fuel_Type	Seller_Type	Transmission	Ov
0	ritz	2014	3.35	5.59	27000	Petrol	Dealer	Manual	
1	sx4	2013	4.75	9.54	43000	Diesel	Dealer	Manual	
2	ciaz	2017	7.25	9.85	6900	Petrol	Dealer	Manual	
3	wagon r	2011	2.85	4.15	5200	Petrol	Dealer	Manual	
4	swift	2014	4.60	6.87	42450	Diesel	Dealer	Manual	

In [5]:
```
data.tail()
```

Out[5]:

	Car_Name	Year	Selling_Price	Present_Price	Kms_Driven	Fuel_Type	Seller_Type	Transmission
296	city	2016	9.50	11.6	33988	Diesel	Dealer	Manual
297	brio	2015	4.00	5.9	60000	Petrol	Dealer	Manual
298	city	2009	3.35	11.0	87934	Petrol	Dealer	Manual
299	city	2017	11.50	12.5	9000	Diesel	Dealer	Manual
300	brio	2016	5.30	5.9	5464	Petrol	Dealer	Manual

In [6]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 301 entries, 0 to 300
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Car_Name       301 non-null    object 
 1   Year           301 non-null    int64  
 2   Selling_Price  301 non-null    float64
 3   Present_Price  301 non-null    float64
 4   Kms_Driven     301 non-null    int64  
 5   Fuel_Type      301 non-null    object 
 6   Seller_Type    301 non-null    object 
 7   Transmission   301 non-null    object 
 8   Owner          301 non-null    int64  
dtypes: float64(2), int64(3), object(4)
memory usage: 21.3+ KB
```

In [7]:
```
#numerical stats
data.describe()
```

Out[7]:

	Year	Selling_Price	Present_Price	Kms_Driven	Owner
count	301.000000	301.000000	301.000000	301.000000	301.000000
mean	2013.627907	4.661296	7.628472	36947.205980	0.043189
std	2.891554	5.082812	8.644115	38886.883882	0.247915
min	2003.000000	0.100000	0.320000	500.000000	0.000000
25%	2012.000000	0.900000	1.200000	15000.000000	0.000000
50%	2014.000000	3.600000	6.400000	32000.000000	0.000000
75%	2016.000000	6.000000	9.900000	48767.000000	0.000000
max	2018.000000	35.000000	92.600000	500000.000000	3.000000

In [8]:
```
#missing values
data.isna().sum()
```

Out[8]:
```
Car_Name         0
Year             0
Selling_Price    0
Present_Price    0
Kms_Driven       0
Fuel_Type        0
Seller_Type      0
Transmission     0
Owner            0
dtype: int64
```

Data Preprocessing

In [9]:
```
data['Age'] = 2024 - data['Year']
data.drop('Year',axis=1,inplace = True)
```

In [10]:
```
data.head()
```

Out[10]:

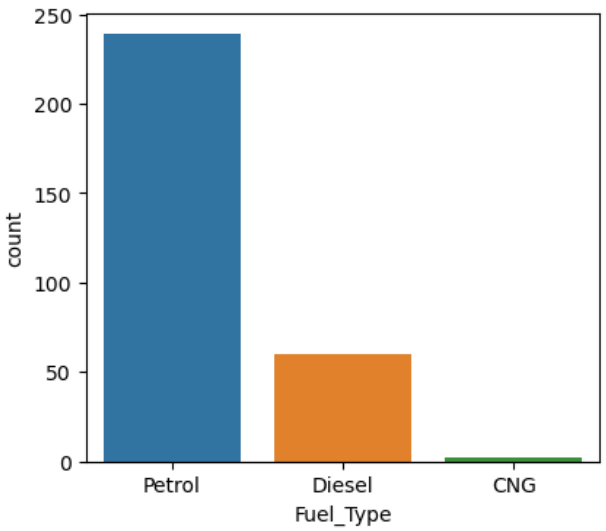
	Car_Name	Selling_Price	Present_Price	Kms_Driven	Fuel_Type	Seller_Type	Transmission	Owner
0	ritz	3.35	5.59	27000	Petrol	Dealer	Manual	0
1	sx4	4.75	9.54	43000	Diesel	Dealer	Manual	0
2	ciaz	7.25	9.85	6900	Petrol	Dealer	Manual	0
3	wagon r	2.85	4.15	5200	Petrol	Dealer	Manual	0
4	swift	4.60	6.87	42450	Diesel	Dealer	Manual	0

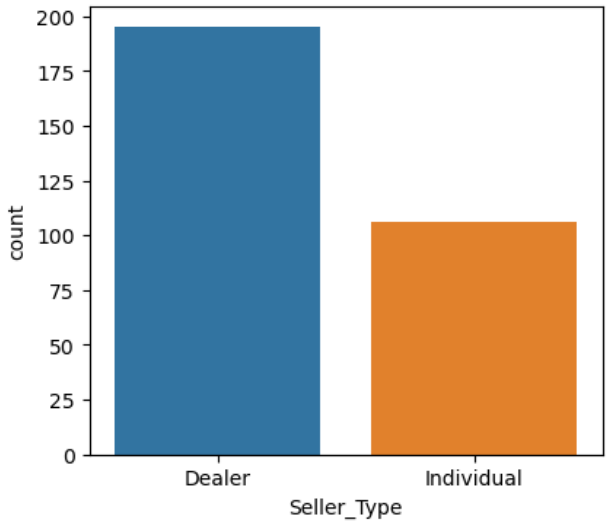
In [11]:
```
data.rename(columns = {'Selling_Price':'Selling_Price(lacs)','Present_Price':'Present_
```

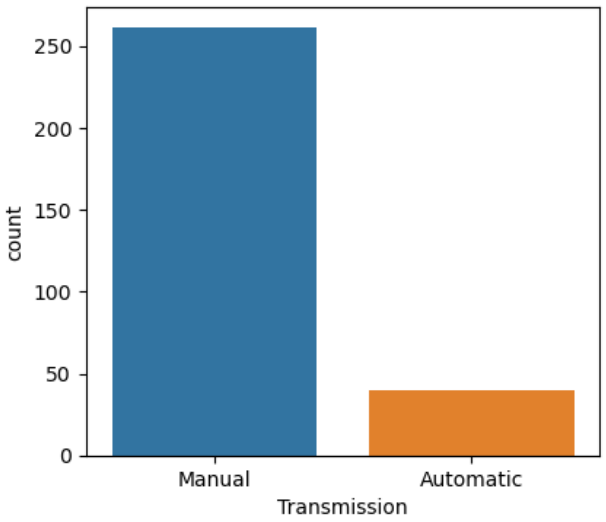
In [12]:
```
data.columns
```

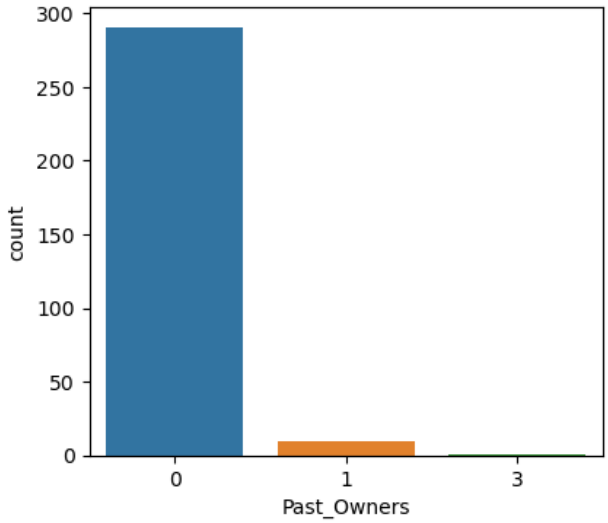
Out[12]:
```
Index(['Car_Name', 'Selling_Price(lacs)', 'Present_Price(lacs)', 'Kms_Driven',
       'Fuel_Type', 'Seller_Type', 'Transmission', 'Past_Owners', 'Age'],
      dtype='object')
```

In [13]:
```
cat_cols = ['Fuel_Type','Seller_Type','Transmission','Past_Owners']
i=0
while i < 4:
    fig = plt.figure(figsize=[10,4])
    #ax1 = fig.add_subplot(121)
    #ax2 = fig.add_subplot(122)

    #ax1.title.set_text(cat_cols[i])
    plt.subplot(1,2,1)
    sns.countplot(x=cat_cols[i], data=data)
    i += 1

    #ax2.title.set_text(cat_cols[i])
    plt.subplot(1,2,2)
    sns.countplot(x=cat_cols[i], data=data)
    i += 1

    plt.show()
```



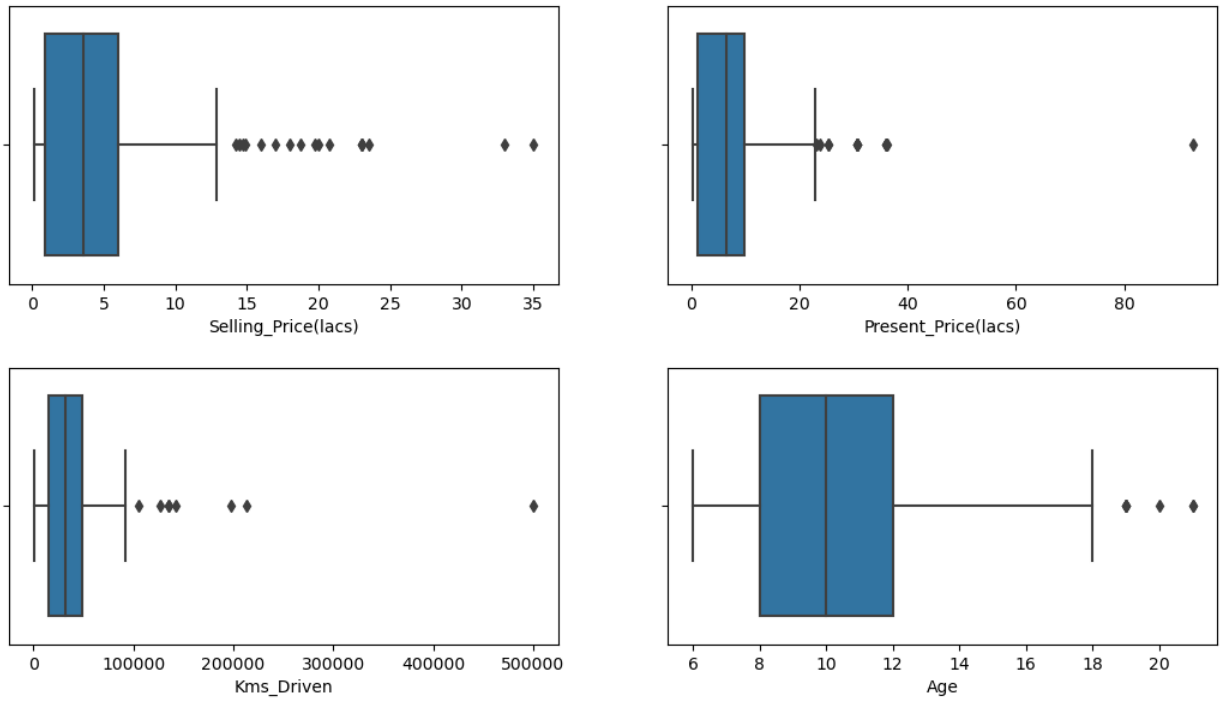






In [14]:
```
num_cols = ['Selling_Price(lacs)','Present_Price(lacs)','Kms_Driven','Age']
i=0
while i < 4:
    fig = plt.figure(figsize=[13,3])

    plt.subplot(1,2,1)
```

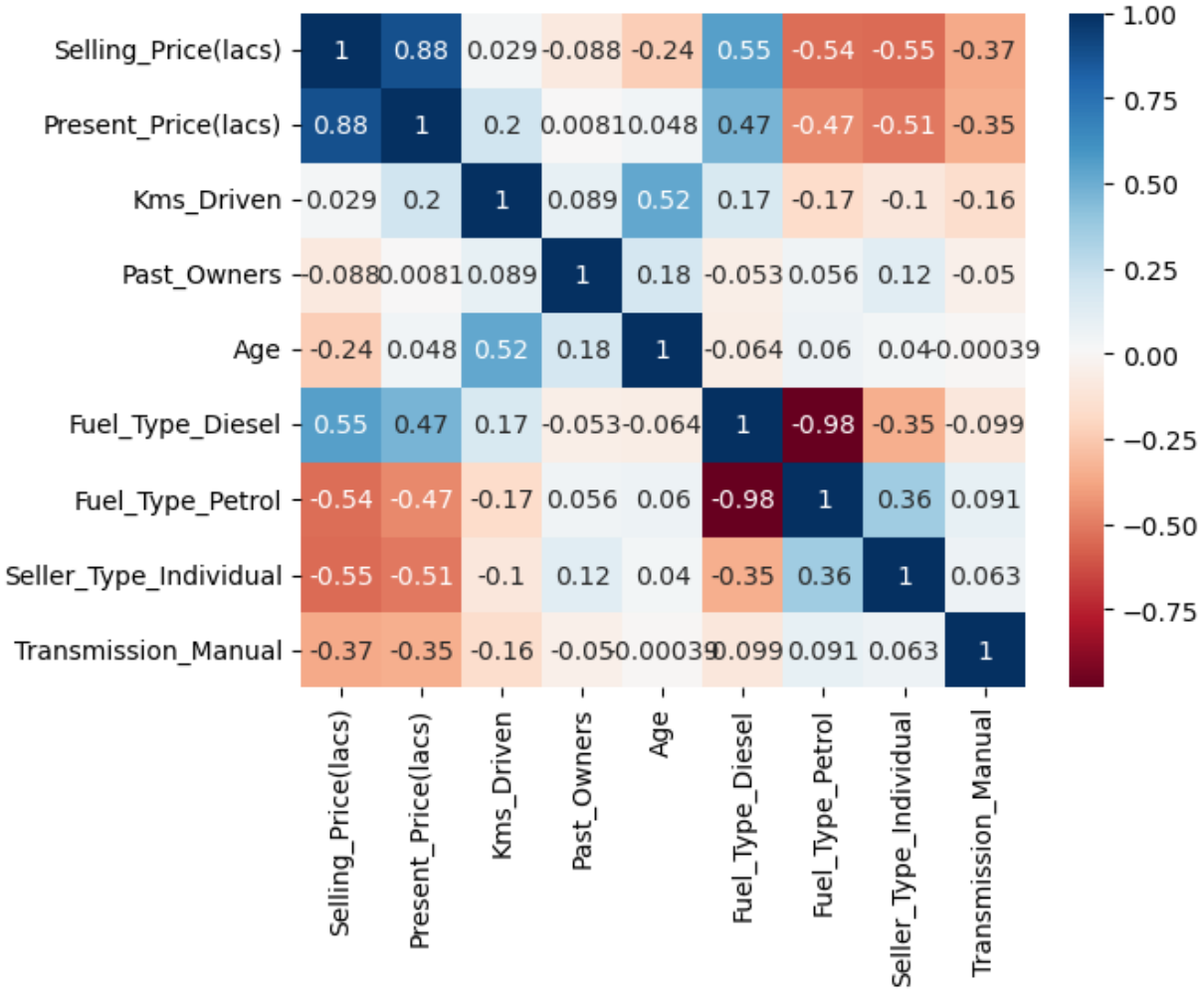
```
    sns.boxplot(x=num_cols[i], data=data)
    i += 1

    #ax2.title.set_text(num_cols[i])
    plt.subplot(1,2,2)
    sns.boxplot(x=num_cols[i], data=data)
    i += 1

    plt.show()
```



In [15]:
```
data.drop(labels='Car_Name',axis= 1, inplace = True)
```

In [16]:
```
data = pd.get_dummies(data = data,drop_first=True)
```

In [17]:
```
sns.heatmap(data.corr(), annot=True, cmap="RdBu")
plt.show()
```



In [18]:
```
data.corr()['Selling_Price(lacs)']
```

Out[18]:
```
Selling_Price(lacs)       1.000000
Present_Price(lacs)       0.878983
Kms_Driven                0.029187
Past_Owners              -0.088344
Age                      -0.236141
Fuel_Type_Diesel          0.552339
Fuel_Type_Petrol         -0.540571
Seller_Type_Individual   -0.550724
Transmission_Manual      -0.367128
Name: Selling_Price(lacs), dtype: float64
```

Train-Test Split

In [19]:
```
# Separating target variable and its features

x = data.drop('Selling_Price(lacs)',axis=1)
y = data['Selling_Price(lacs)']
```

In [20]:
```
x.head()
```

Out[20]:

	Present_Price(lacs)	Kms_Driven	Past_Owners	Age	Fuel_Type_Diesel	Fuel_Type_Petrol	Seller_Type_
0	5.59	27000	0	10	False	True	
1	9.54	43000	0	11	True	False	
2	9.85	6900	0	7	False	True	
3	4.15	5200	0	13	False	True	
4	6.87	42450	0	10	True	False	

In [21]:
```
y.head()
```

Out[21]:
```
0    3.35
1    4.75
2    7.25
3    2.85
4    4.60
Name: Selling_Price(lacs), dtype: float64
```

In [22]:
```
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=
print("x train: ",X_train.shape)
print("x test: ",X_test.shape)
print("y train: ",y_train.shape)
print("y test: ",y_test.shape)
```

```
x train:  (240, 8)
x test:  (61, 8)
y train:  (240,)
y test:  (61,)
```

In [23]:
```
# Create a Linear Regression model
model = LinearRegression()
# Train the model on the training data
model.fit(X_train, y_train)
# Make predictions on the test data
y_pred = model.predict(X_test)
```

In [24]:
```
# Print the model coefficients and intercept
print("Coefficients:", model.coef_)
print("Intercept:", model.intercept_)
```

```
Coefficients: [ 4.37233976e-01 -5.30613944e-06  3.45912849e-01 -4.13270098e-01
  2.23050770e+00  4.58549217e-01 -1.20927814e+00 -1.87014327e+00]
Intercept: 7.073759933489658
```

In [25]:
```
# Evaluate the model using Mean Squared Error
from sklearn.metrics import mean_squared_error
mse = mean_squared_error(y_test, y_pred)
print("Mean Squared Error:", mse)
```

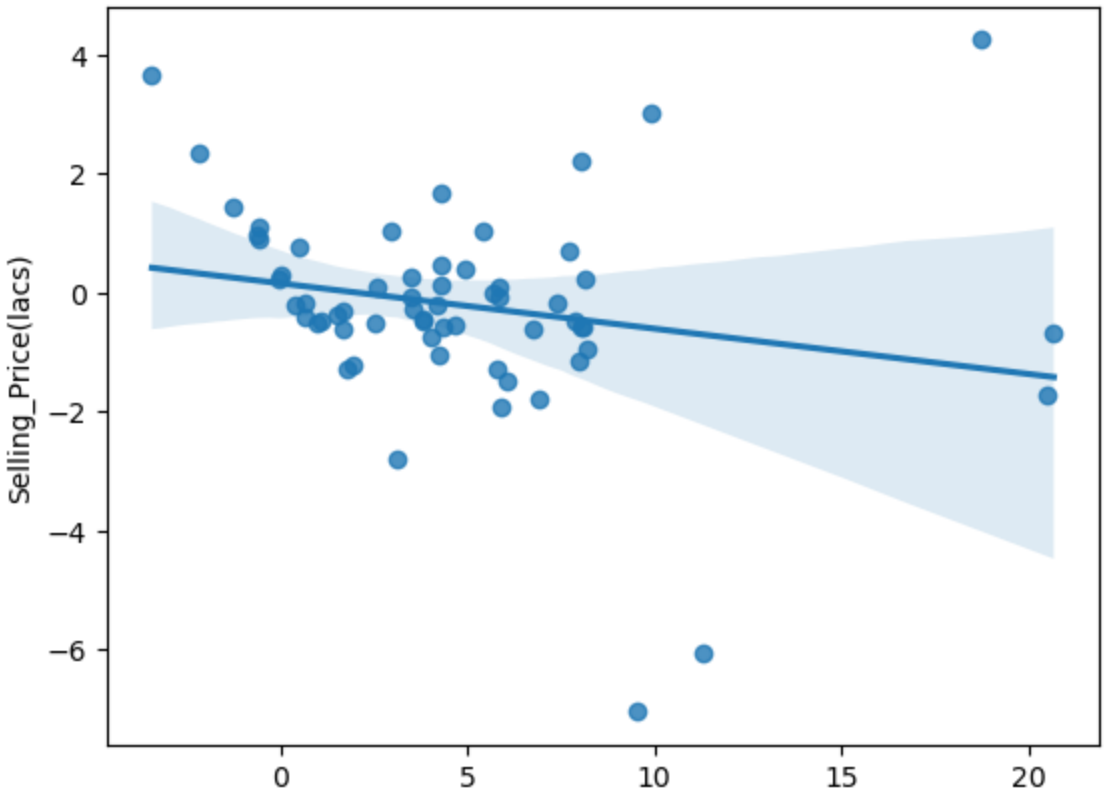
```
Mean Squared Error: 2.98238486185975
```

In [30]:
```
error= y_test-y_pred
print(error)
```

```
285   -0.462732
248    1.031713
150    1.090305
217   -1.063360
107    0.766824
         ...
62    -1.730622
154   -0.162504
218    1.049726
286   -0.008562
186   -0.397876
Name: Selling_Price(lacs), Length: 61, dtype: float64
```

In [32]:
```
sns.regplot(x=y_pred, y=error, data=data)
```

Out[32]:
```
<Axes: ylabel='Selling_Price(lacs)'>
```



In [ ]:
```

```

In [ ]:

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