

'''

Iris flower has three species; setosa, versicolor, and virginica, which differs according to their measurements. Now assume that you have the measurements of the iris flowers according to their species, and here your task is to train a machine learning model that can learn from the measurements of the iris species and classify them

Although the Scikit-learn library provides a dataset for iris flower classification, you can also download the same dataset from here for the task of iris flower classification with Machine Learning.

'''

```
'''
Iris flower has three species; setosa, versicolor, and virginica, which differs according to their
measurements. Now assume that you have the measurements of the iris flowers according to
their species, and here your task is to train a machine learning model that can learn from the
measurements of the iris species and classify them
Although the Scikit-learn library provides a dataset for iris flower classification, you can also
download the same dataset from here for the task of iris flower classification with Machine
Learning.
'''
```

```
import pandas as pd
import numpy as np
import seaborn as sns
```

```
df=sns.load_dataset('iris')
```

```
df.head()
```

```
'''
sepal_length sepal_width petal_length petal_width species
0          5.1         3.5         1.4         0.2    setosa
1          4.9         3.0         1.4         0.2    setosa
2          4.7         3.2         1.3         0.2    setosa
3          4.6         3.1         1.5         0.2    setosa
4          5.0         3.6         1.4         0.2    setosa
'''
```

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```
df['species'].unique()
```

```
'''
array(['setosa', 'versicolor', 'virginica'], dtype=object)
```

```
df.isnull().sum()
```

```
'''
0
sepal_length 0
sepal_width  0
petal_length 0
petal_width  0
species      0

dtype: int64
```

```
df.duplicated().sum()
```

```
'''
np.int64(1)
```

```
df.shape
```

```
'''
(150, 5)
```

```
df.drop_duplicates(inplace=True)
```

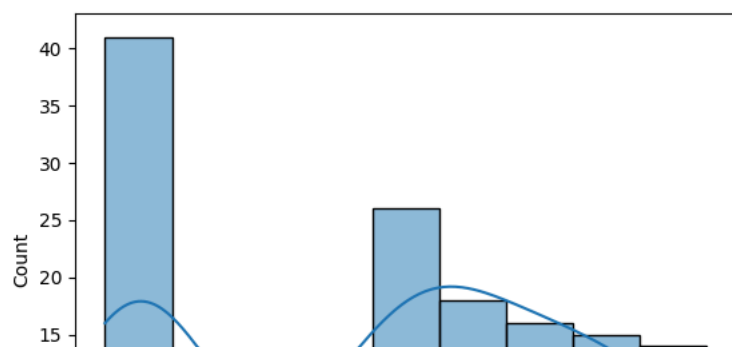
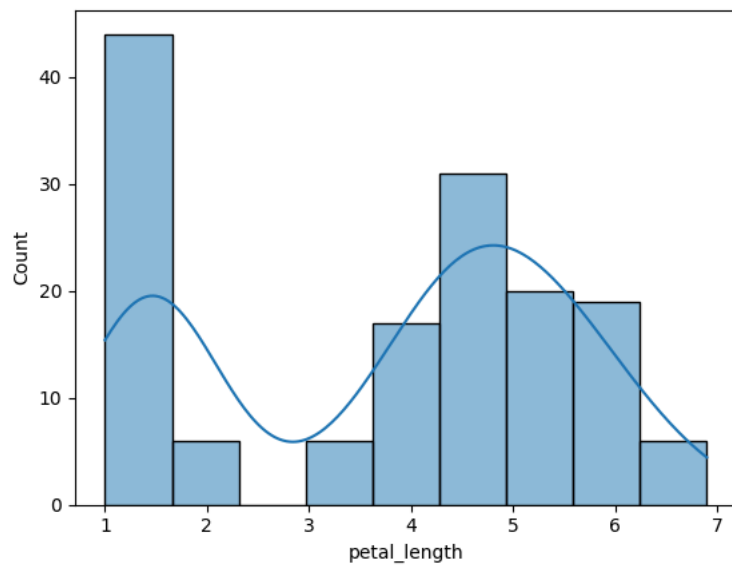
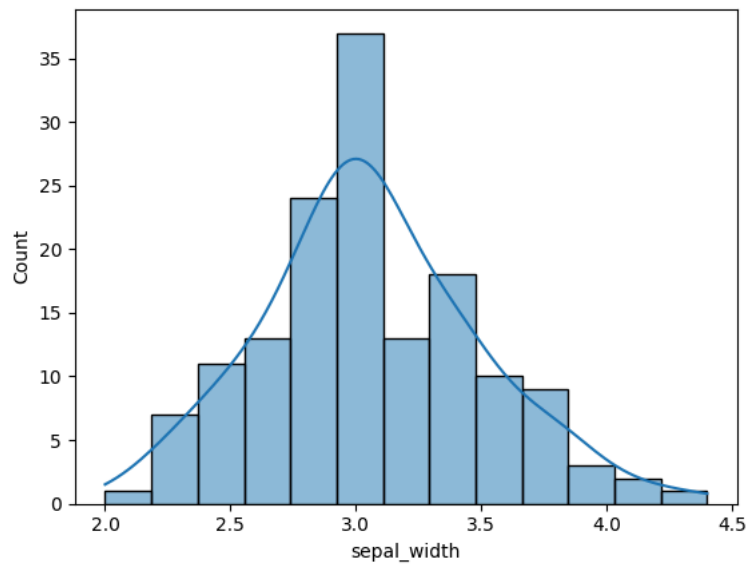
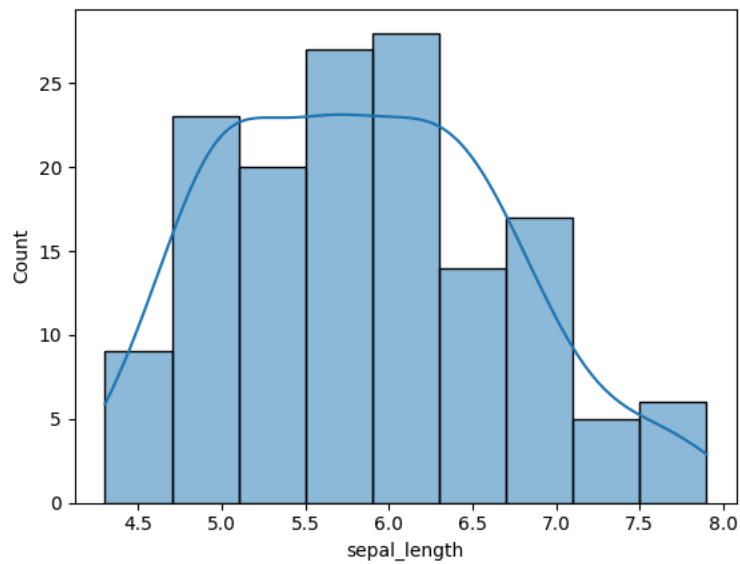
```
df.shape
```

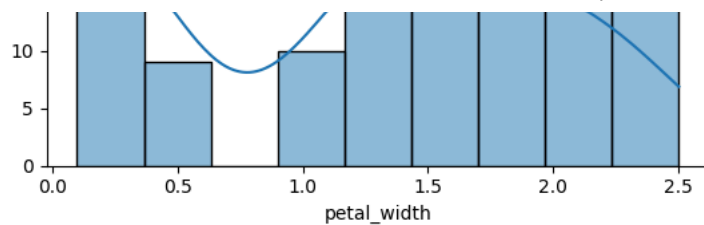
```
'''
(149, 5)
```

```
import matplotlib.pyplot as plt
```

```
for i in df.columns:
    if df[i].dtypes=='object':
```

```
continue  
sns.histplot(data=df, x=i, kde=True)  
plt.show()
```





```
df.columns
```

```
Index(['sepal_length', 'sepal_width', 'petal_length', 'petal_width',  
      'species'],  
      dtype='object')
```

```
df['petal_length']=np.log(df['petal_length'])
```

```
df['petal_width']=np.sqrt(df['petal_width'])
```

```
df['sepal_length']=np.log(df['sepal_length'])
```

```
np.mean(np.log(df['petal_width']))
```

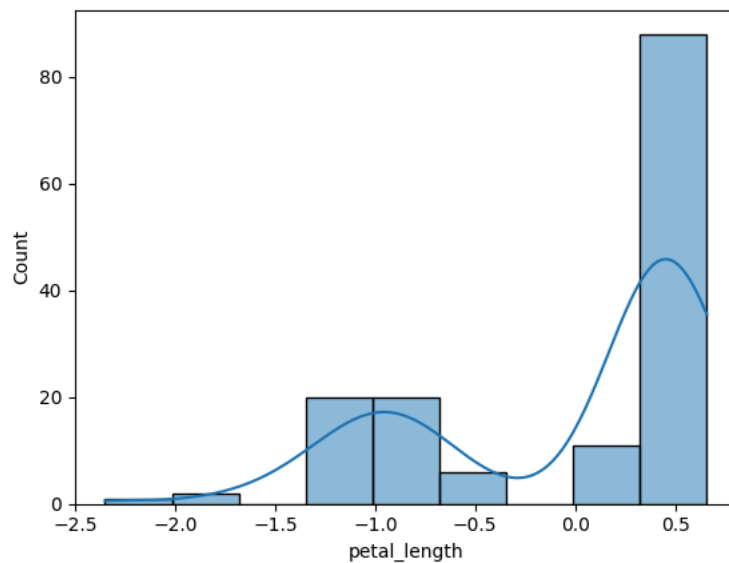
```
np.float64(-0.08889346431188545)
```

```
np.mean(np.sqrt(df['petal_width']))
```

```
np.float64(0.983830888077141)
```

```
sns.histplot(data=df,x=np.log(df['petal_length']),kde=True)  
plt.show()
```

```
/usr/local/lib/python3.11/dist-packages/pandas/core/arraylike.py:399: RuntimeWarning: divide by zero encountered in log  
result = getattr(ufunc, method)(*inputs, **kwargs)
```



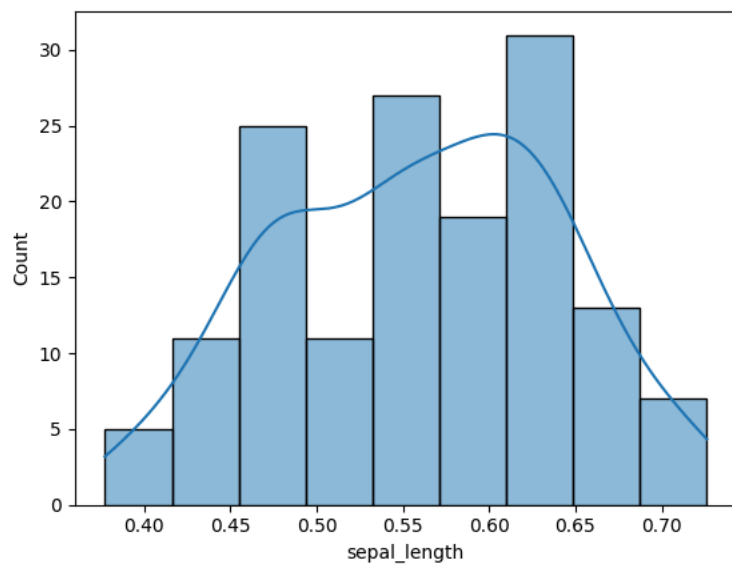
```
np.mean(np.sqrt(df['petal_length']))
```

```
np.float64(1.0333140332764557)
```

```
np.mean(np.log(df['petal_length']))
```

```
/usr/local/lib/python3.11/dist-packages/pandas/core/arraylike.py:399: RuntimeWarning: divide by zero encountered in log  
result = getattr(ufunc, method)(*inputs, **kwargs)  
np.float64(-inf)
```

```
sns.histplot(data=df,x=np.log(df['sepal_length']),kde=True)  
plt.show()
```



```
np.mean(np.sqrt(df['sepal_length']))
```



```
np.float64(1.323831781280919)
```

```
np.mean(np.log(df['sepal_width']))
```



```
np.float64(1.1082055251621128)
```

```
df.head()
```



	sepal_length	sepal_width	petal_length	petal_width	species
0	1.629241	3.5	0.336472	0.447214	setosa
1	1.589235	3.0	0.336472	0.447214	setosa
2	1.547563	3.2	0.262364	0.447214	setosa
3	1.526056	3.1	0.405465	0.447214	setosa
4	1.609438	3.6	0.336472	0.447214	setosa

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```
df.shape
```



```
(149, 5)
```

Start coding or [generate](#) with AI.

```
df['species'].value_counts()
```



```

count
species
setosa    50
versicolor 50
virginica  49

```

```
dtype: int64
```

## ✓ MODEL BUILDING

```
X=df.drop('species',axis=1)
```

```
y=df['species']
```

```

from sklearn.preprocessing import LabelEncoder
lb=LabelEncoder()

```


```
df['species']=lb.fit_transform(df['species'])
```

```
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)
```

```
from sklearn.model_selection import GridSearchCV
```

```
para={
    'C':[0.01,0.1,1],
    'solver':['liblinear','saga','newton-cg'],
    'penalty':['l1','l2']
}
```

```
from sklearn.linear_model import LogisticRegression
lg=LogisticRegression(C=1,penalty='l1',solver='saga')
lg.fit(X_train,y_train)
```


 /usr/local/lib/python3.11/dist-packages/sklearn/linear\_model/\_sag.py:348: ConvergenceWarning: The max\_iter was reached which means 1 warnings.warn(

▼ LogisticRegression ⓘ ?  
LogisticRegression(C=1, penalty='l1', solver='saga')


```
gd=GridSearchCV(estimator=lg,param_grid=para,cv=5,scoring='accuracy')
gd.fit(X_train,y_train)
```

[https://colab.research.google.com/drive/1xY7tVVdo3\\_uF0JCU29c6E\\_73AE3MBQDo#scrollTo=4078Q3Y\\_oa0q&printMode=true](https://colab.research.google.com/drive/1xY7tVVdo3_uF0JCU29c6E_73AE3MBQDo#scrollTo=4078Q3Y_oa0q&printMode=true) 7/24


auc

 np.float64(1.0)

confusion\_matrix(Y\_test,y\_pred)

 array([[10, 0, 0],  
[ 0, 9, 0],  
[ 0, 0, 11]])

print(classification\_report(Y\_test,y\_pred))



	precision	recall	f1-score	support
setosa	1.00	1.00	1.00	10
versicolor	1.00	1.00	1.00	9
virginica	1.00	1.00	1.00	11
accuracy			1.00	30
macro avg	1.00	1.00	1.00	30
weighted avg	1.00	1.00	1.00	30

## UNEMPLOYMENT IN INDIA AT THE TIME OF CORONA

df1=pd.read\_csv(r'/content/Unemployment in India.csv')

df1.head()



	Region	Date	Frequency	Estimated Unemployment Rate (%)	Estimated Employed	Estimated Labour Participation Rate (%)	Area
0	Andhra Pradesh	31-05-2019	Monthly	3.65	11999139.0	43.24	Rural
1	Andhra Pradesh	30-06-2019	Monthly	3.05	11755881.0	42.05	Rural
2	Andhra Pradesh	31-07-2019	Monthly	3.75	12086707.0	43.50	Rural

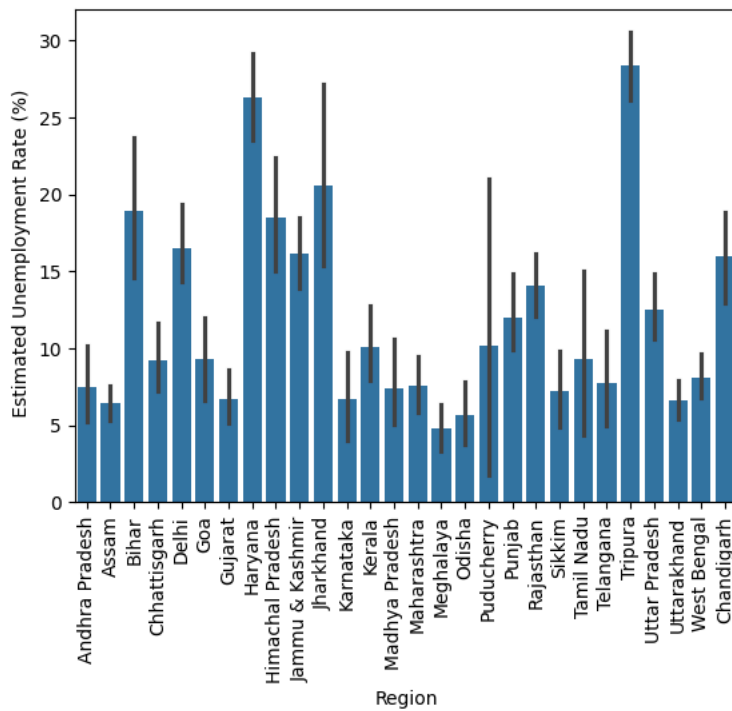
Next steps:

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## EXPLORATORY DATA ANALYSIS

```
sns.barplot(data=df1, x='Region', y=' Estimated Unemployment Rate (%)')
plt.xticks(rotation=90)
plt.show()
```





df1.head()




	Region	Date	Frequency	Estimated Unemployment Rate (%)	Estimated Employed	Estimated Labour Participation Rate (%)	Area
0	Andhra Pradesh	31-05-2019	Monthly	3.65	11999139.0	43.24	Rural
1	Andhra Pradesh	30-06-2019	Monthly	3.05	11755881.0	42.05	Rural
2	Andhra Pradesh	31-07-2019	Monthly	3.75	12086707.0	43.50	Rural

Next steps:

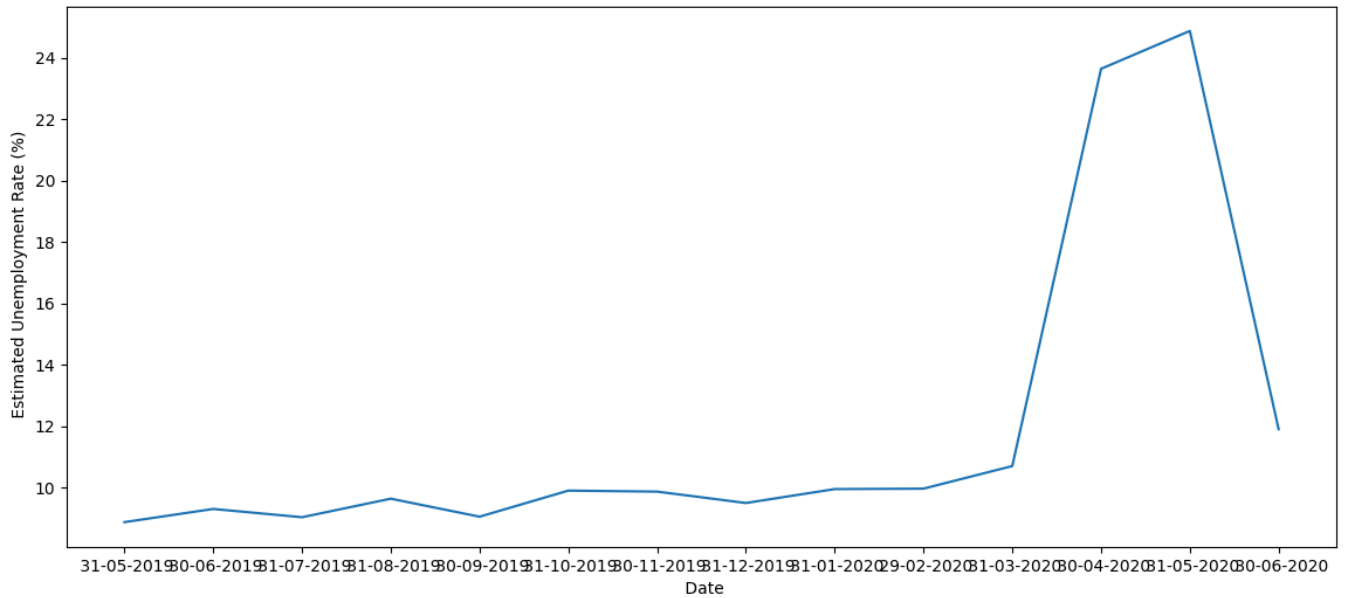
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```
fig, ax = plt.subplots(figsize=(14, 6))
sns.lineplot(data=df1, x='Date', y='Estimated Unemployment Rate (%)', ci=None)
plt.show()
```


 <ipython-input-111-ca29d06e5dbc>:2: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

```
sns.lineplot(data=df1,x=' Date',y=' Estimated Unemployment Rate (%)',ci=None)
```

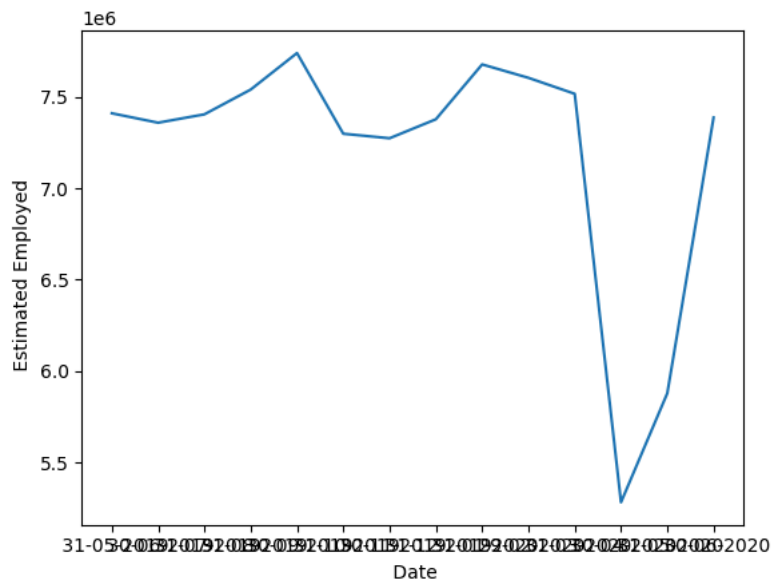


```
sns.lineplot(data=df1,x=' Date',y=' Estimated Employed',ci=None)
plt.show()
```

 <ipython-input-112-10d3bc17e3bc>:1: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

```
sns.lineplot(data=df1,x=' Date',y=' Estimated Employed',ci=None)
```

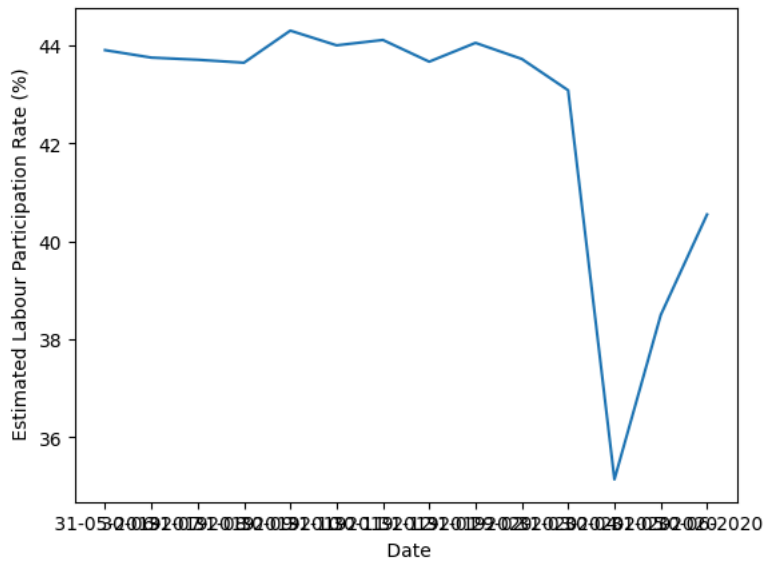


```
plt.show()
sns.lineplot(data=df1,x=' Date',y=' Estimated Labour Participation Rate (%)',ci=None)
```

```
<ipython-input-113-1227a9dac27d>:2: FutureWarning:
```

The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

```
sns.lineplot(data=df1,x=' Date',y=' Estimated Labour Participation Rate (%)',ci=None)
<Axes: xlabel=' Date', ylabel=' Estimated Labour Participation Rate (%)'>
```



```
df1[' Frequency'].unique()
```

```
array([' Monthly', nan, 'Monthly'], dtype=object)
```

```
df1.isnull().sum().sum()
```

```
np.int64(196)
```

```
df1.shape
```

```
(768, 7)
```

```
df.duplicated().sum()
```

```
np.int64(0)
```

```
df1.dropna(inplace=True)
```

```
df1
```

	Region	Date	Frequency	Estimated Unemployment Rate (%)	Estimated Employed	Estimated Labour Participation Rate (%)	Area
0	Andhra Pradesh	31-05-2019	Monthly	3.65	11999139.0	43.24	Rural
1	Andhra Pradesh	30-06-2019	Monthly	3.05	11755881.0	42.05	Rural
2	Andhra Pradesh	31-07-2019	Monthly	3.75	12086707.0	43.50	Rural
3	Andhra Pradesh	31-08-2019	Monthly	3.32	12285693.0	43.97	Rural
4	Andhra Pradesh	30-09-2019	Monthly	5.17	12256762.0	44.68	Rural
...	...	...	...	...	...	...	...
749	West Bengal	29-02-2020	Monthly	7.55	10871168.0	44.09	Urban
750	West Bengal	31-03-2020	Monthly	6.67	10806105.0	43.34	Urban

Next steps:

[Generate code with df1](#)
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✓ THIS TO BE CONTINUED AFTER SOME DAYS THE ABOVE

df1.head()

	Region	Date	Frequency	Estimated Unemployment Rate (%)	Estimated Employed	Estimated Labour Participation Rate (%)	Area
0	Andhra Pradesh	31-05-2019	Monthly	3.65	11999139.0	43.24	Rural
1	Andhra Pradesh	30-06-2019	Monthly	3.05	11755881.0	42.05	Rural
2	Andhra Pradesh	31-07-2019	Monthly	3.75	12086707.0	43.50	Rural

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df1.columns

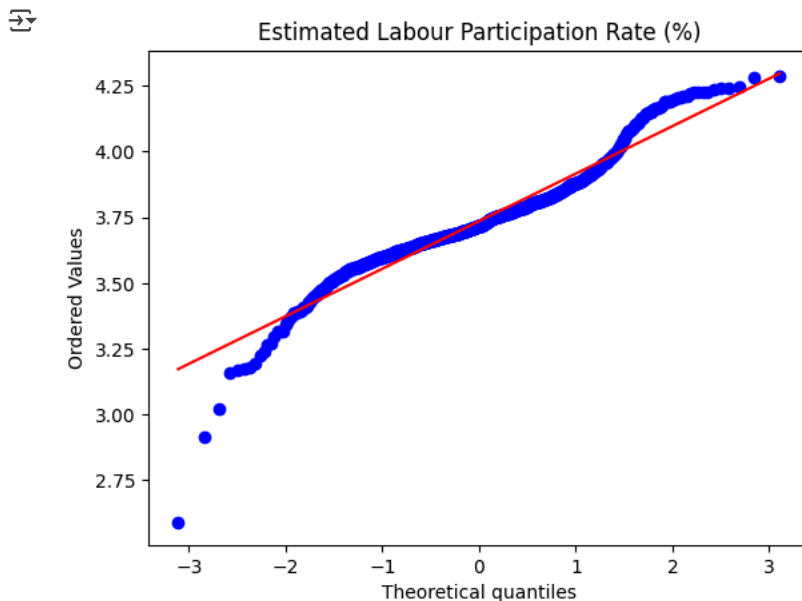
```
Index(['Region', 'Date', 'Frequency', 'Estimated Unemployment Rate (%)',
      'Estimated Employed', 'Estimated Labour Participation Rate (%)',
      'Area'],
      dtype='object')
```

```
from sklearn.preprocessing import StandardScaler
s=StandardScaler()
```

```
df1['Estimated Employed']=s.fit_transform(df1['Estimated Employed'].values.reshape(-1,1))
```

```
import scipy.stats as stats
```

```
stats.probplot(np.log(df1['Estimated Labour Participation Rate (%)']), dist="norm", plot=plt)
plt.title('Estimated Labour Participation Rate (%)')
plt.show()
```



df1.isnull().sum()

	0
Region	0
Date	0
Frequency	0
Estimated Unemployment Rate (%)	0
Estimated Employed	0
Estimated Labour Participation Rate (%)	0
Area	0

dtype: int64

## PREPROCESSING

```
df1.dropna(inplace=True)
```

```
from sklearn.preprocessing import LabelEncoder
le1=LabelEncoder()
```

```
for i in df1.columns:
    if df1[i].dtypes=='object':
        df1[i]=le1.fit_transform(df1[i])
```

```
x1=df1.drop([' Estimated Employed','Area'],axis=1)
```

```
x1.isnull().sum()
```

```

0
Region      0
Date        0
Frequency   0
Estimated Unemployment Rate (%)  0
Estimated Labour Participation Rate (%)  0

dtype: int64
```

```
y1=df1[' Estimated Employed']
```

```
y1.isnull().sum()
```

```
np.int64(0)
```

## MODEL BUILDING

```
X1_train,X1_test,y1_train,y1_test=train_test_split(x1,y1,test_size=0.2,random_state=43)
```

```

para1={
    'n_estimators':[10,20,30,40],
    'max_depth':[4,6,7],
    'min_samples_split':[30,40],
    'min_samples_leaf':[4,5,6],
    'criterion':['squared_error','absolute_error']
}
```

```

from sklearn.ensemble import RandomForestRegressor
rf=RandomForestRegressor()
```

```

g=GridSearchCV(estimator=rf,param_grid=para1,cv=5,n_jobs=-1,scoring='neg_mean_squared_error')
g.fit(X1_train,y1_train)
```

```

GridSearchCV
└─ best_estimator_: RandomForestRegressor
   └─ RandomForestRegressor
      RandomForestRegressor(max_depth=7, min_samples_leaf=4, min_samples_split=30,
                             n_estimators=20)
```

```
g.best_score_
```

```
np.float64(-0.3933487557143115)
```

```

rf=RandomForestRegressor(max_depth=8, min_samples_leaf=5, min_samples_split=20,
                          n_estimators=18)
```

```
rf.fit(X1_train,y1_train)
```



```
RandomForestRegressor
RandomForestRegressor(max_depth=8, min_samples_leaf=5, min_samples_split=20,
n_estimators=18)
```

```
mean_squared_error(rf.predict(X1_test),y1_test)
```



```
0.6019545686377283
```

```
x1.columns
```



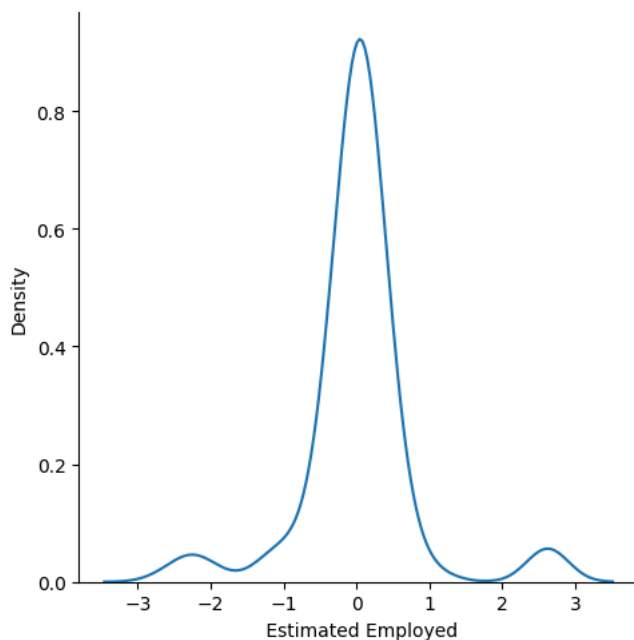
```
Index(['Region', ' Date', ' Frequency', ' Estimated Unemployment Rate (%)',
' Estimated Labour Participation Rate (%)'],
dtype='object')
```

```
r2_score(rf.predict(X1_test),y1_test)
```



```
0.157928096623694
```

```
sns.displot(rf.predict(X1_test)-y1_test,kind='kde')
plt.show()
```



## ✓ CAR PRICE PRIDITION

```
df3=pd.read_csv(r'/content/car data.csv')
```

```
df3.head()
```



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

Next steps:

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## ✓ EXPLORATORY DATA ANALYSIS

```
df3['Fuel_Type'].unique()
```

```
array(['Petrol', 'Diesel', 'CNG'], dtype=object)
```

```
df3['Selling_type'].unique()
```

```
array(['Dealer', 'Individual'], dtype=object)
```

```
df3['Transmission'].unique()
```

```
array(['Manual', 'Automatic'], dtype=object)
```

```
df3['Owner'].unique()
```

```
array([0, 1, 3])
```

```
df3.shape
```

```
(301, 9)
```

```
df3.isnull().sum()
```

```

0
Car_Name    0
Year        0
Selling_Price    0
Present_Price    0
Driven_kms    0
Fuel_Type      0
Selling_type    0
Transmission    0
Owner          0

dtype: int64
```

```
df3.duplicated().sum()
```

```
np.int64(2)
```

```
df3[df3.duplicated()]
```

```

Car_Name  Year  Selling_Price  Present_Price  Driven_kms  Fuel_Type  Selling_type  Transmission  Owner
17    eriga  2016           7.75          10.79      43000      Diesel        Dealer        Manual         0
93  fortun  2015          23.00          30.61      40000      Diesel        Dealer        Automatic        0
```

```
df3.drop(93,axis=0,inplace=True)
```

```
df3.info()
```

```

<class 'pandas.core.frame.DataFrame'>
Index: 300 entries, 0 to 300
Data columns (total 9 columns):
#   Column          Non-Null Count  Dtype
---  ---
0   Car_Name        300 non-null    object
1   Year            300 non-null    int64
2   Selling_Price   300 non-null    float64
3   Present_Price   300 non-null    float64
4   Driven_kms      300 non-null    int64
5   Fuel_Type       300 non-null    object
6   Selling_type    300 non-null    object
7   Transmission    300 non-null    object
8   Owner          300 non-null    int64
dtypes: float64(2), int64(3), object(4)
memory usage: 23.4+ KB
```

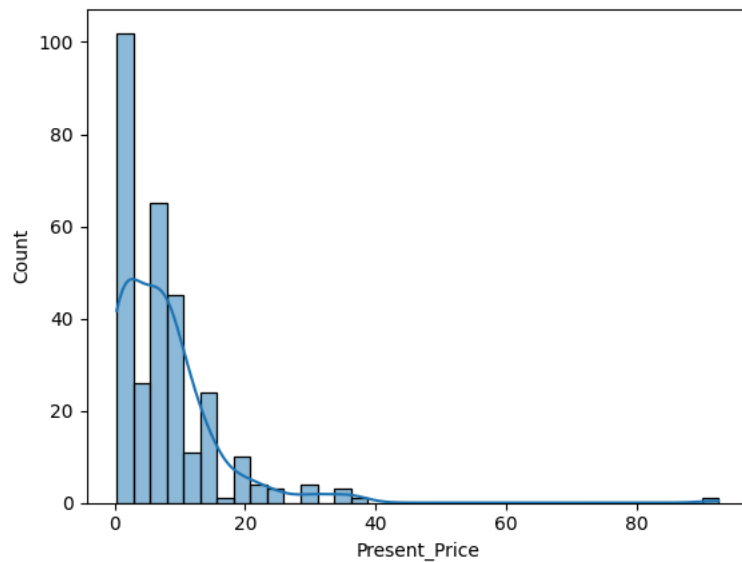
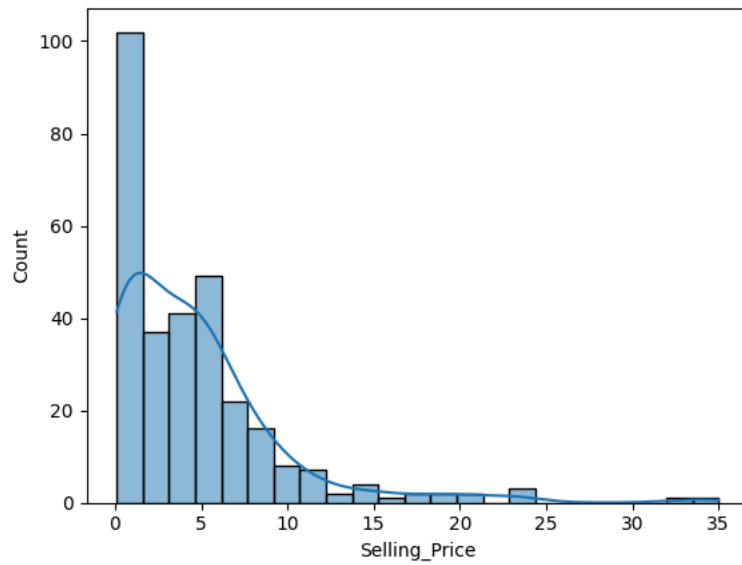
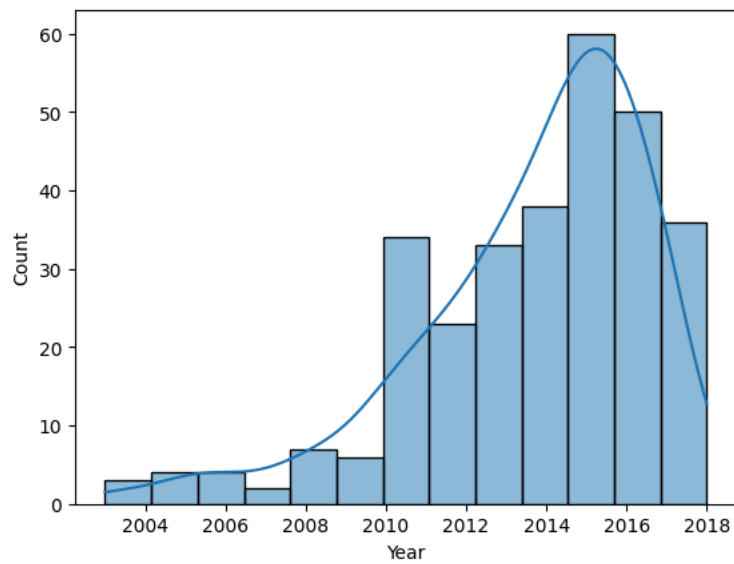
```
import numpy as np
```

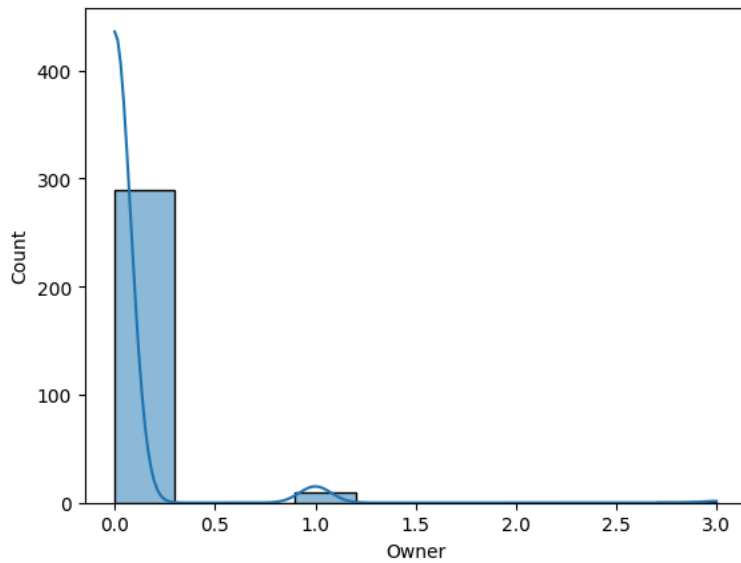
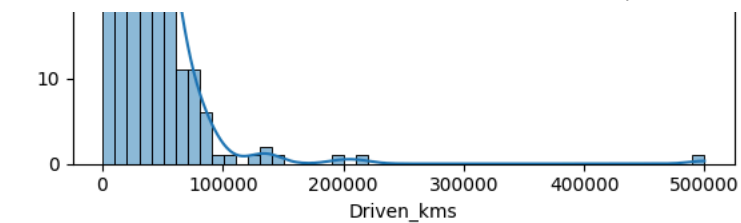
```

for i in df3.columns:
    if df3[i].dtypes=='object':
        continue
```

```
sns.histplot(data=df3,x=(i),kde=True)  
plt.show()
```







```
np.mean(df3['Selling_Price'])
```

```
np.float64(4.6001666666666665)
```

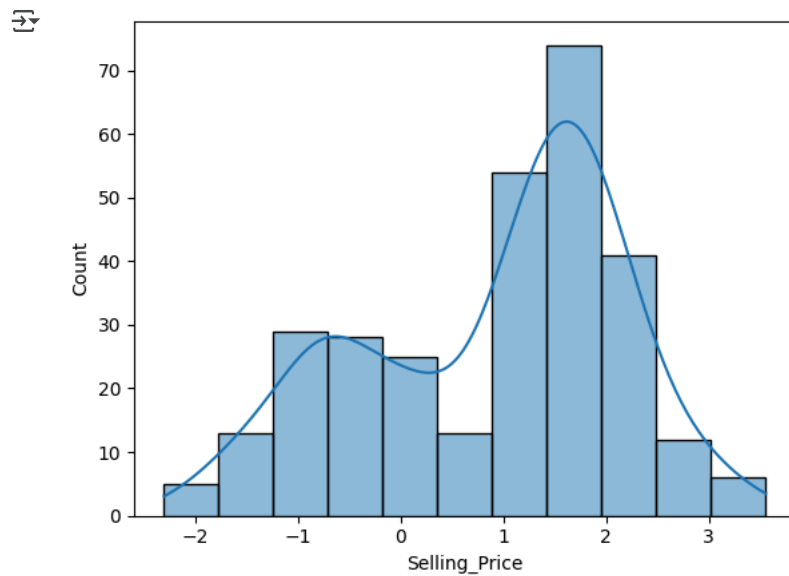
```
np.mean(np.sqrt(df3['Selling_Price']))
```

```
np.float64(1.8761384695271879)
```

```
np.mean(np.log(df3['Selling_Price']))
```

```
np.float64(0.9039446587834338)
```

```
sns.histplot(data=df3,x=np.log(df3['Selling_Price']),kde=True)
plt.show()
```



```
df3['Selling_Price']=np.log(df3['Selling_Price'])
```

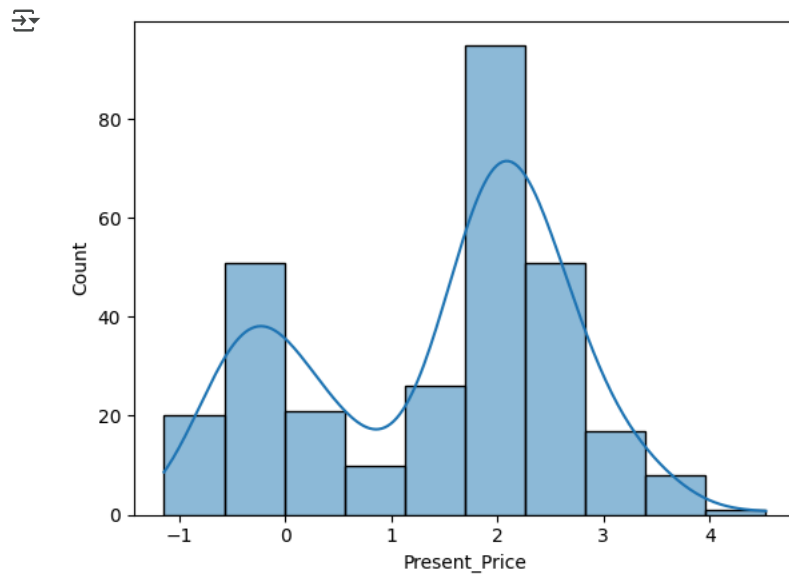
```
np.mean(np.sqrt(df3['Present_Price']))
```

```
np.float64(2.4119916890364816)
```

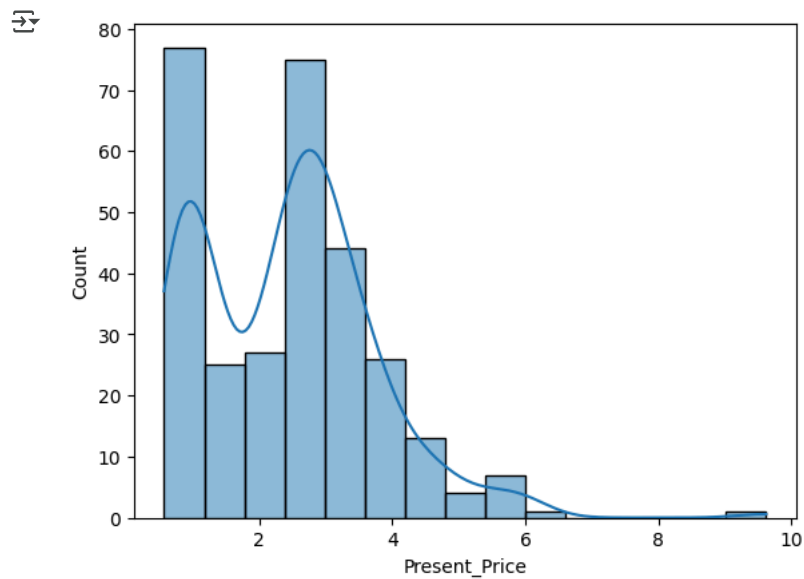
```
np.mean(np.log(df3['Present_Price']))
```

```
np.float64(1.4265831790876917)
```

```
sns.histplot(data=df3,x=np.log(df3['Present_Price']),kde=True)  
plt.show()
```



```
sns.histplot(data=df3,x=np.sqrt(df3['Present_Price']),kde=True)  
plt.show()
```



df3

	Car_Name	Year	Selling_Price	Present_Price	Driven_kms	Fuel_Type	Selling_type	Transmission	Owner	
0	ritz	2014	1.208960	5.59	27000	Petrol	Dealer	Manual	0	
1	sx4	2013	1.558145	9.54	43000	Diesel	Dealer	Manual	0	
2	ciaz	2017	1.981001	9.85	6900	Petrol	Dealer	Manual	0	
3	wagon r	2011	1.047319	4.15	5200	Petrol	Dealer	Manual	0	
4	swift	2014	1.526056	6.87	42450	Diesel	Dealer	Manual	0	
...	...	...	...	...	...	...	...	...	...	
296	city	2016	2.251292	11.60	33988	Diesel	Dealer	Manual	0	
297	brio	2015	1.386294	5.90	60000	Petrol	Dealer	Manual	0	
298	city	2009	1.208960	11.00	87934	Petrol	Dealer	Manual	0	
299	city	2017	2.442347	12.50	9000	Diesel	Dealer	Manual	0	
300	brio	2016	1.667707	5.90	5464	Petrol	Dealer	Manual	0	

300 rows × 9 columns

Next steps:

[Generate code with df3](#)[View recommended plots](#)[New interactive sheet](#)

## VISUALIZATION

'''

What is the average selling price of used cars?

Which car models are the most frequently sold?

How does the fuel type affect the selling price?

Are older cars (based on Year) priced significantly lower?

What is the distribution of Driven\_kms – are most cars lightly used?

How many cars are sold by Dealers vs. Individuals?

What's the proportion of manual vs. automatic transmission?

'''

```

'''
What is the average selling price of used cars?
Which car models are the most frequently sold?
How does the fuel type affect the selling price?
Are older cars (based on Year) priced significantly lower?
What is the distribution of Driven_kms – are most cars lightly used?
How many cars are sold by Dealers vs. Individuals?
What's the proportion of manual vs. automatic transmission?
'''

```

df3['Year'].unique()

```

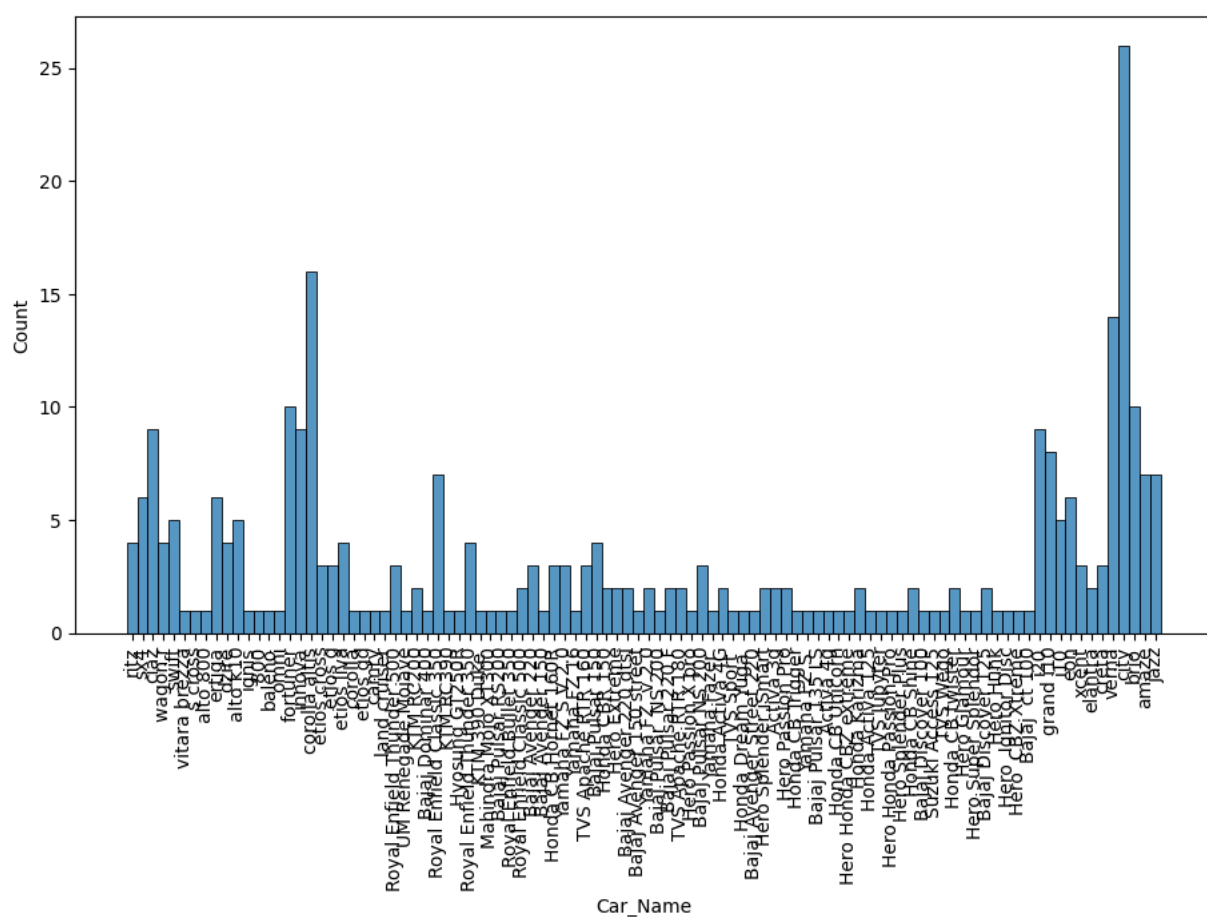
array([2014, 2013, 2017, 2011, 2018, 2015, 2016, 2009, 2010, 2012, 2003,
       2008, 2006, 2005, 2004, 2007])

```

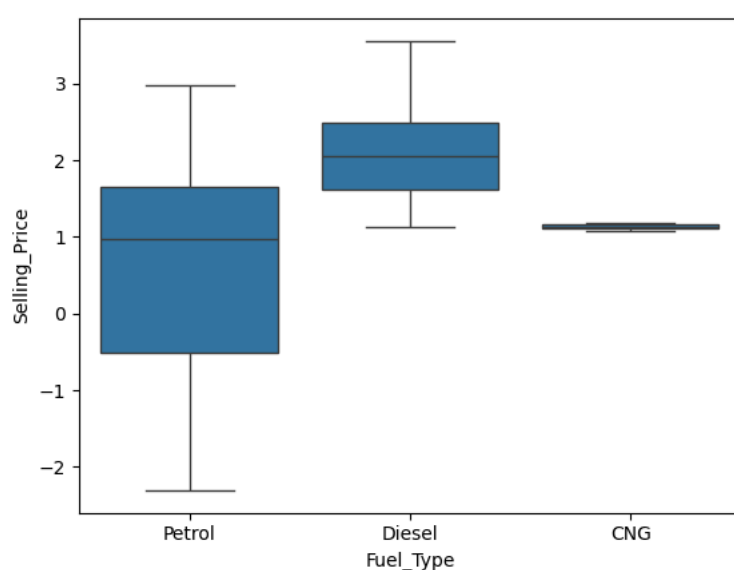
```

plt.figure(figsize=(11,6))
sns.histplot(data=df3,x=df3['Car_Name'])
plt.xticks(rotation=90)
plt.show()

```



```
sns.boxplot(data=df3,x='Fuel_Type',y='Selling_Price')
plt.show()
```



```
df31=df3.groupby('Year')['Selling_Price'].mean().reset_index()
```

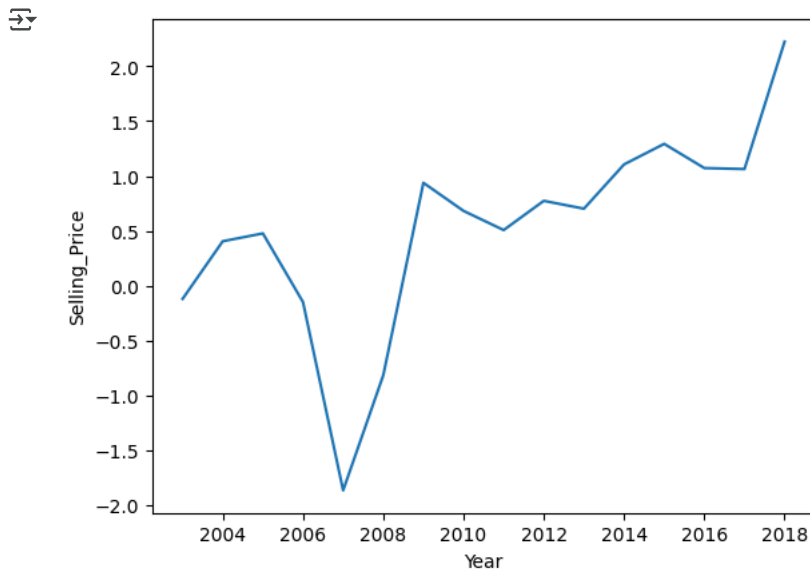
```
df31
```

	Year	Selling_Price	
0	2003	-0.119446	
1	2004	0.405465	
2	2005	0.476920	
3	2006	-0.148892	
4	2007	-1.864851	
5	2008	-0.815614	
6	2009	0.938180	
7	2010	0.682096	
8	2011	0.507475	
9	2012	0.773808	
10	2013	0.702343	
11	2014	1.105755	
12	2015	1.293036	
13	2016	1.072335	
14	2017	1.063544	
15	2018	2.224624	

Next steps:

[Generate code with df31](#)[View recommended plots](#)[New interactive sheet](#)

```
sns.lineplot(data=df31,x='Year',y='Selling_Price')  
plt.show()
```



```
df3['Car_Name'].value_counts()
```

```

count
Car_Name
city      26
corolla altis  16
verna      14
brio       10
fortuner    10
...
Honda Activa 125  1
Hero Hunk      1
Hero Ignitor Disc  1
Hero CBZ Xtreme  1
Bajaj ct 100    1

98 rows x 1 columns

dtype: int64

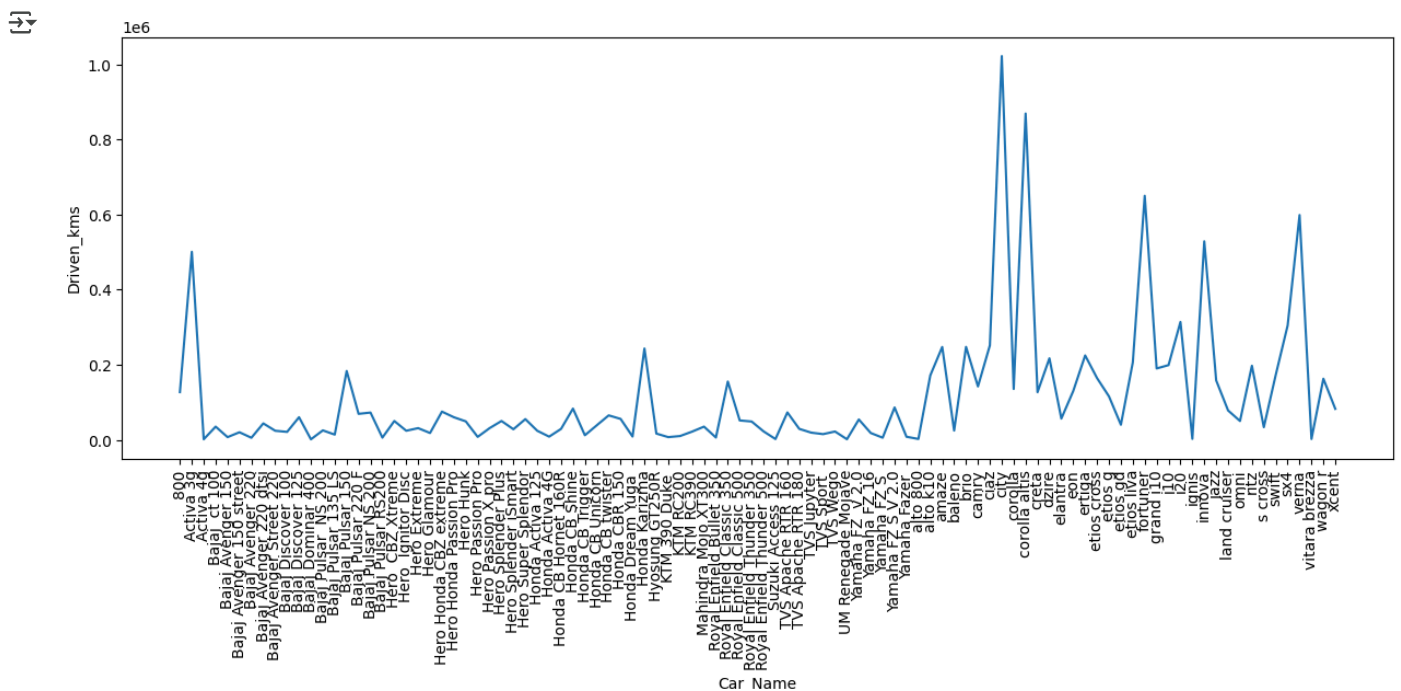
```

```
df32=df3.groupby('Car_Name')['Driven_kms'].sum().reset_index()
```

```

plt.figure(figsize=(15,5))
sns.lineplot(data=df32,x='Car_Name',y='Driven_kms')
plt.xticks(rotation=90)
plt.show()

```



```
df3.head(2)
```

```

Car_Name  Year  Selling_Price  Present_Price  Driven_kms  Fuel_Type  Selling_type  Transmission  Owner
0      ritz   2014      1.208960          5.59      27000      Petrol      Dealer          Manual          0
1      sx4    2013      1.558145          9.54      43000      Diesel      Dealer          Manual          0

```

Next steps:

[Generate code with df3](#)[View recommended plots](#)[New interactive sheet](#)

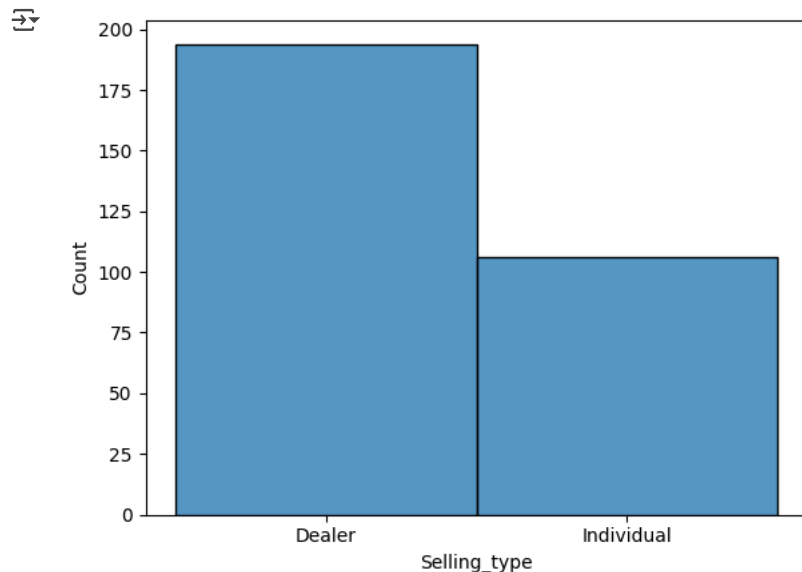
```
df3.groupby('Selling_type')['Car_Name']
```

```
<pandas.core.groupby.generic.SeriesGroupBy object at 0x785fe4ffe250>
```

```
k=df3['Selling_type'].value_counts()
```

```
sns.histplot(data=df3, x='Selling_type')
```

```
plt.show()
```



```
df3['Transmission'].value_counts()
```

count	
Transmission	
Manual	261
Automatic	39

dtype: int64

```
df3['Current_Year']=2025-df3['Year']
```

```
df3.head()
```

	Car_Name	Year	Selling_Price	Present_Price	Driven_kms	Fuel_Type	Selling_type	Transmission	Owner	Current_Year
0	ritz	2014	1.208960	5.59	27000	Petrol	Dealer	Manual	0	11
1	sx4	2013	1.558145	9.54	43000	Diesel	Dealer	Manual	0	12
2	ciaz	2017	1.981001	9.85	6900	Petrol	Dealer	Manual	0	8
3	wagon r	2011	1.047319	4.15	5200	Petrol	Dealer	Manual	0	14
4	swift	2014	1.526056	6.87	42450	Diesel	Dealer	Manual	0	11

Next steps:

[Generate code with df3](#)[View recommended plots](#)[New interactive sheet](#)

```
df3=df3.sort_values(by='Year')
```

```
df3.head(2)
```

	Car_Name	Year	Selling_Price	Present_Price	Driven_kms	Fuel_Type	Selling_type	Transmission	Owner	Current_Year
39	sx4	2003	0.810930	7.98	62000	Petrol	Dealer	Manual	0	22
37	800	2003	-1.049822	2.28	127000	Petrol	Individual	Manual	0	22

Next steps:

[Generate code with df3](#)[View recommended plots](#)[New interactive sheet](#)

```
from sklearn.preprocessing import LabelBinarizer
```