diamond-price-prediction

November 15, 2023

1 Problem Statements: Diamond Price Prediction

1.1 Description:

- **Diamonds are the hardest naturally occurring substance known to man. They are made of pure carbon, arranged in a crystal structure called diamond cubic.**
- **Diamonds are found in volcanic rock, called kimberlite, which is formed when the Earth's mantle melts and rises to the surface.**
- **Diamonds can be colorless, or they can have a variety of colors, including yellow, brown, pink, blue, green, and red. The color of a diamond is determined by the impurities that are present in the carbon atoms.**
- **Diamonds are used in jewelry and in industrial applications. In jewelry, diamonds are prized for their beauty, durability, and rarity. In industry, diamonds are used for cutting, drilling, and polishing.**
- **The four Cs of diamonds are color, cut, clarity, and carat. These are the factors that determine the value of a diamond.**

2 1.0. Importing Libraries

[3]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.impute import SimpleImputer ## HAndling Missing Values
from sklearn.preprocessing import StandardScaler # HAndling Feature Scaling
from sklearn.preprocessing import OrdinalEncoder # Ordinal Encoding
## pipelines
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
```

3 2.0. The Datasets

3.1 2.1. Reading Datasets

[4]:
```
## Data Ingestions step
df=pd.read_csv('data/gemstone.csv')
df.head()
```

[4]:

	id	carat	cut	color	clarity	depth	table	x	y	z	price
0	0	1.52	Premium	F	VS2	62.2	58.0	7.27	7.33	4.55	13619
1	1	2.03	Very Good	J	SI2	62.0	58.0	8.06	8.12	5.05	13387
2	2	0.70	Ideal	G	VS1	61.2	57.0	5.69	5.73	3.50	2772
3	3	0.32	Ideal	G	VS1	61.6	56.0	4.38	4.41	2.71	666
4	4	1.70	Premium	G	VS2	62.6	59.0	7.65	7.61	4.77	14453

3.2 2.2. Datasets Infromation:

3.2.1 Introduction About the Data :

The dataset The goal is to predict `price` of given diamond (Regression Analysis).

There are 10 independent variables (including `id`):

- `id` : unique identifier of each diamond
- `carat` : Carat (ct.) refers to the unique unit of weight measurement used exclusively to weigh gemstones and diamonds.
- `cut` : Quality of Diamond Cut
- `color` : Color of Diamond
- `clarity` : Diamond clarity is a measure of the purity and rarity of the stone, graded by the visibility of these characteristics under 10-power magnification.
- `depth` : The depth of diamond is its height (in millimeters) measured from the culet (bottom tip) to the table (flat, top surface)
- `table` : A diamond's table is the facet which can be seen when the stone is viewed face up.
- `x` : Diamond X dimension
- `y` : Diamond Y dimension
- `x` : Diamond Z dimension

Target variable: * `price`: Price of the given Diamond.

Dataset Source Link : https://www.kaggle.com/competitions/playground-series-s3e8/data?select=train.csv

4 3.0. Data Exploration

[5]:
```
df.isnull().sum()
```

[5]:
```
id       0
carat    0
cut      0
```

```
color      0
clarity    0
depth      0
table      0
x          0
y          0
z          0
price      0
dtype: int64
```

[6]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 193573 entries, 0 to 193572
Data columns (total 11 columns):
 #   Column    Non-Null Count   Dtype
---  ------    --------------   -----
 0   id        193573 non-null  int64
 1   carat     193573 non-null  float64
 2   cut       193573 non-null  object
 3   color     193573 non-null  object
 4   clarity   193573 non-null  object
 5   depth     193573 non-null  float64
 6   table     193573 non-null  float64
 7   x         193573 non-null  float64
 8   y         193573 non-null  float64
 9   z         193573 non-null  float64
 10  price     193573 non-null  int64
dtypes: float64(6), int64(2), object(3)
memory usage: 16.2+ MB
```

[7]:
```python
df.head()
```

[7]:

	id	carat	cut	color	clarity	depth	table	x	y	z	price
0	0	1.52	Premium	F	VS2	62.2	58.0	7.27	7.33	4.55	13619
1	1	2.03	Very Good	J	SI2	62.0	58.0	8.06	8.12	5.05	13387
2	2	0.70	Ideal	G	VS1	61.2	57.0	5.69	5.73	3.50	2772
3	3	0.32	Ideal	G	VS1	61.6	56.0	4.38	4.41	2.71	666
4	4	1.70	Premium	G	VS2	62.6	59.0	7.65	7.61	4.77	14453

- Lets drop the id column

[8]:
```python
df=df.drop(labels=['id'],axis=1)
df.head()
```

[8]:

	carat	cut	color	clarity	depth	table	x	y	z	price
0	1.52	Premium	F	VS2	62.2	58.0	7.27	7.33	4.55	13619

```
1   2.03  Very Good     J      SI2    62.0    58.0  8.06  8.12  5.05  13387
2   0.70      Ideal     G      VS1    61.2    57.0  5.69  5.73  3.50   2772
3   0.32      Ideal     G      VS1    61.6    56.0  4.38  4.41  2.71    666
4   1.70    Premium     G      VS2    62.6    59.0  7.65  7.61  4.77  14453
```

- check for duplicated records

[9]:
```python
df.duplicated().sum()
```

[9]:
```
0
```

segregate numerical and categorical columns

[10]:
```python
numerical_columns=df.columns[df.dtypes!='object']
categorical_columns=df.columns[df.dtypes=='object']
print("Numerical columns:",numerical_columns)
print('Categorical Columns:',categorical_columns)
```

```
Numerical columns: Index(['carat', 'depth', 'table', 'x', 'y', 'z', 'price'],
dtype='object')
Categorical Columns: Index(['cut', 'color', 'clarity'], dtype='object')
```

[11]:
```python
df[categorical_columns].describe()
```

[11]:

	cut	color	clarity
count	193573	193573	193573
unique	5	7	8
top	Ideal	G	SI1
freq	92454	44391	53272

[12]:
```python
df['cut'].value_counts()
```

[12]:
```
Ideal        92454
Premium      49910
Very Good    37566
Good         11622
Fair          2021
Name: cut, dtype: int64
```

[13]:
```python
df['color'].value_counts()
```

[13]:
```
G    44391
E    35869
F    34258
H    30799
D    24286
I    17514
J     6456
```

```
Name: color, dtype: int64
```

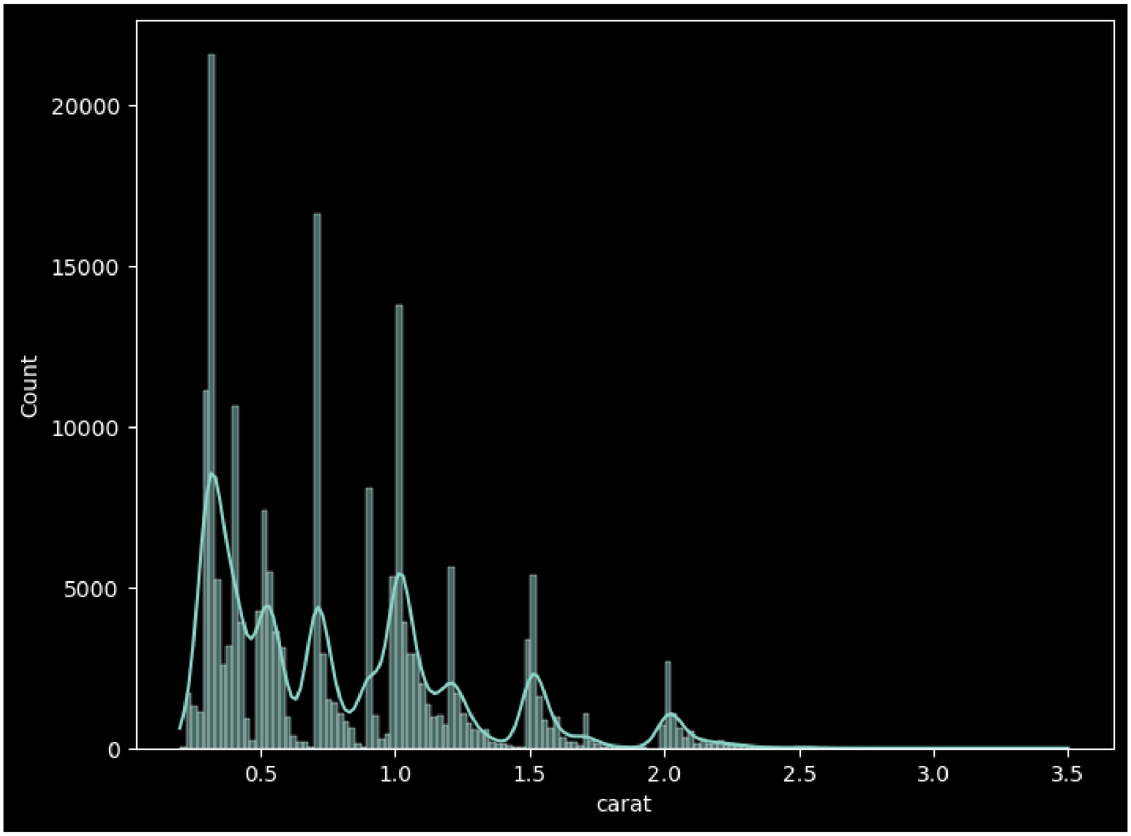
[14]:
```
df['clarity'].value_counts()
```

[14]:
```
SI1     53272
VS2     48027
VS1     30669
SI2     30484
VVS2    15762
VVS1    10628
IF       4219
I1        512
Name: clarity, dtype: int64
```

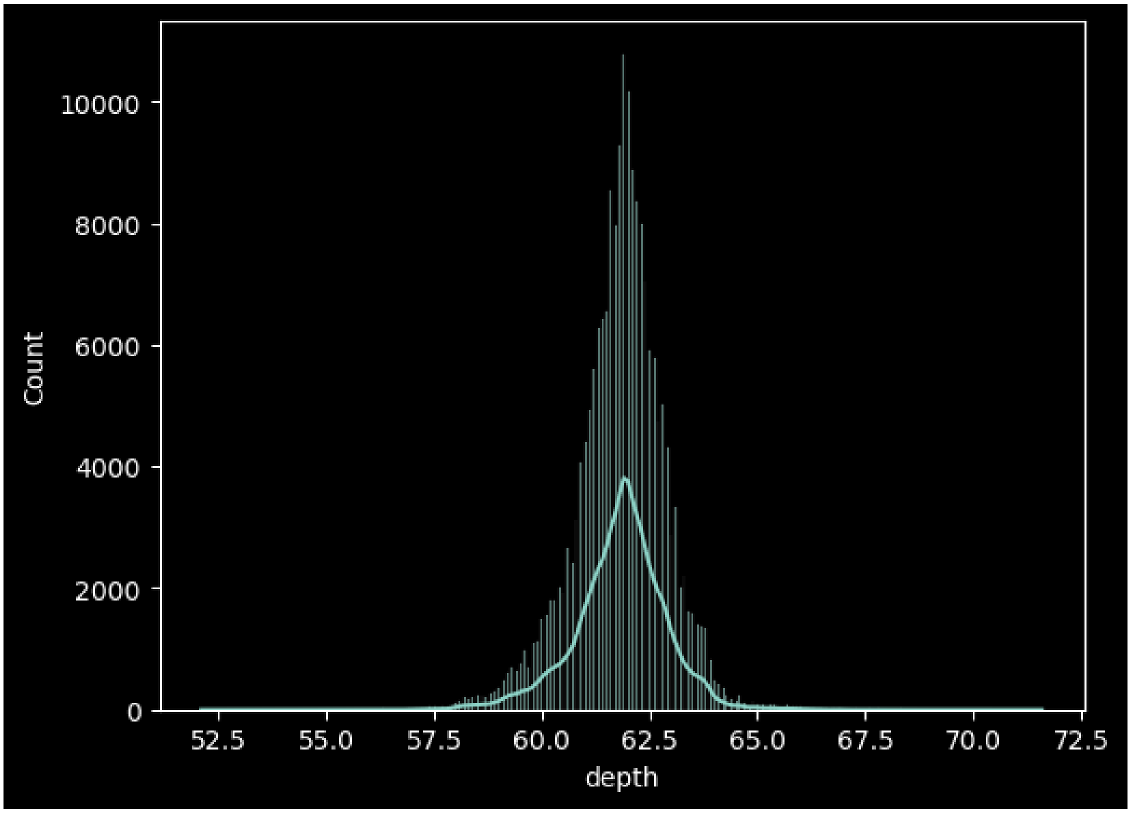
5 4.0. Data Visualization

[15]:
```
plt.style.use('dark_background')
```

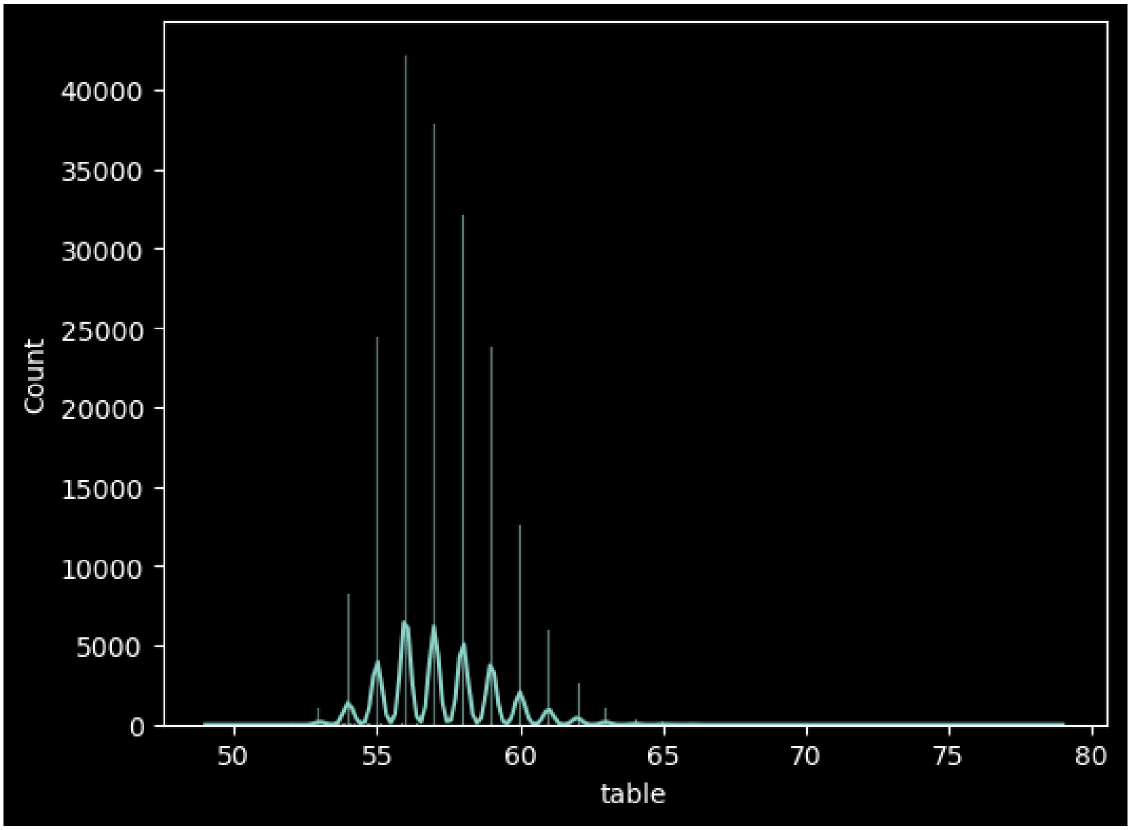
[16]:
```
plt.figure(figsize=(8,6))
x=0
for i in numerical_columns:
    sns.histplot(data=df,x=i,kde=True)
    print('\n')
    plt.show()
```



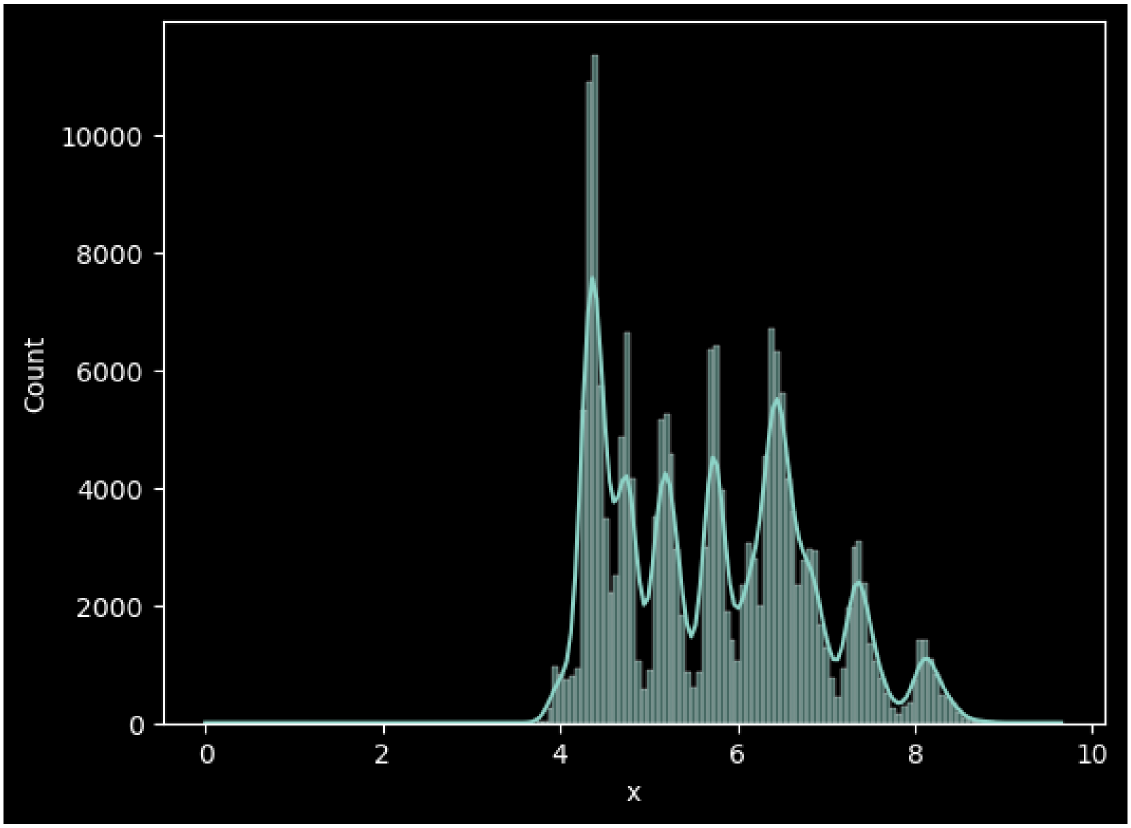
20000
15000
10000
5000
0
Count
0.5
1.0
1.5
2.0
2.5
3.0
3.5
carat



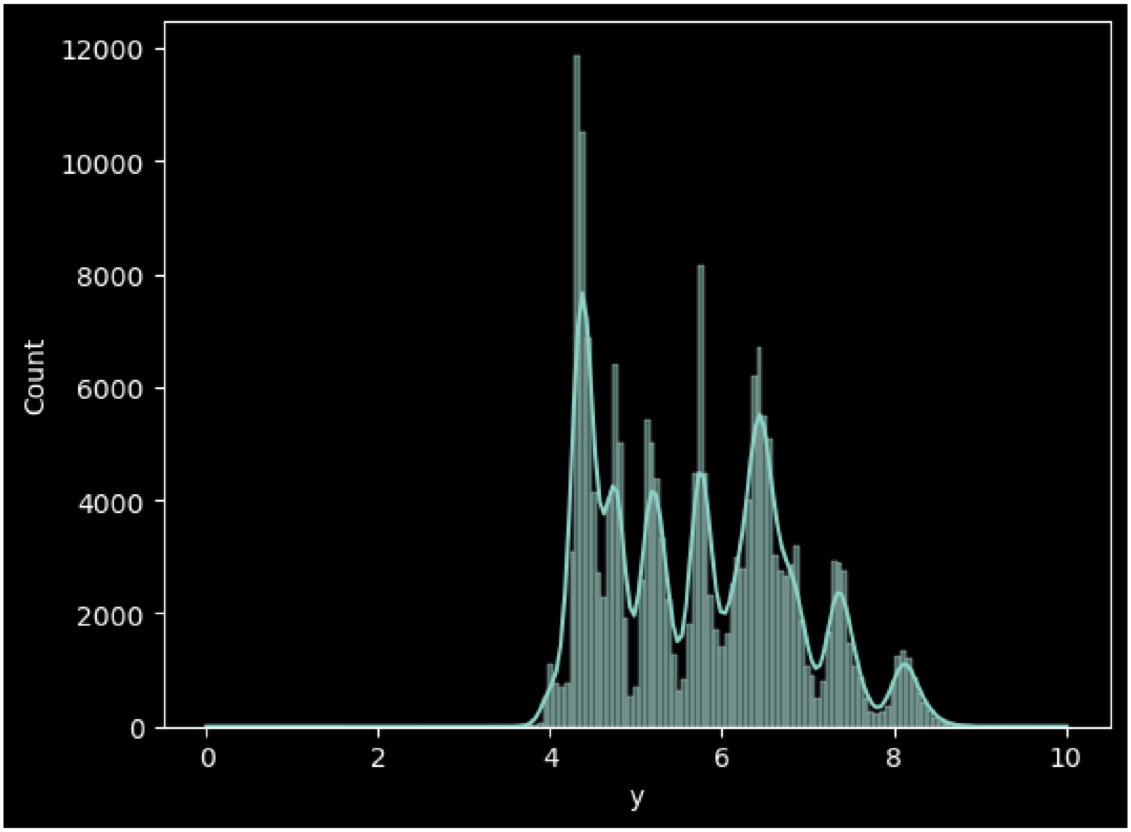
10000
8000
6000
4000
2000
0
Count
52.5
55.0
57.5
60.0
62.5
65.0
67.5
70.0
72.5
depth



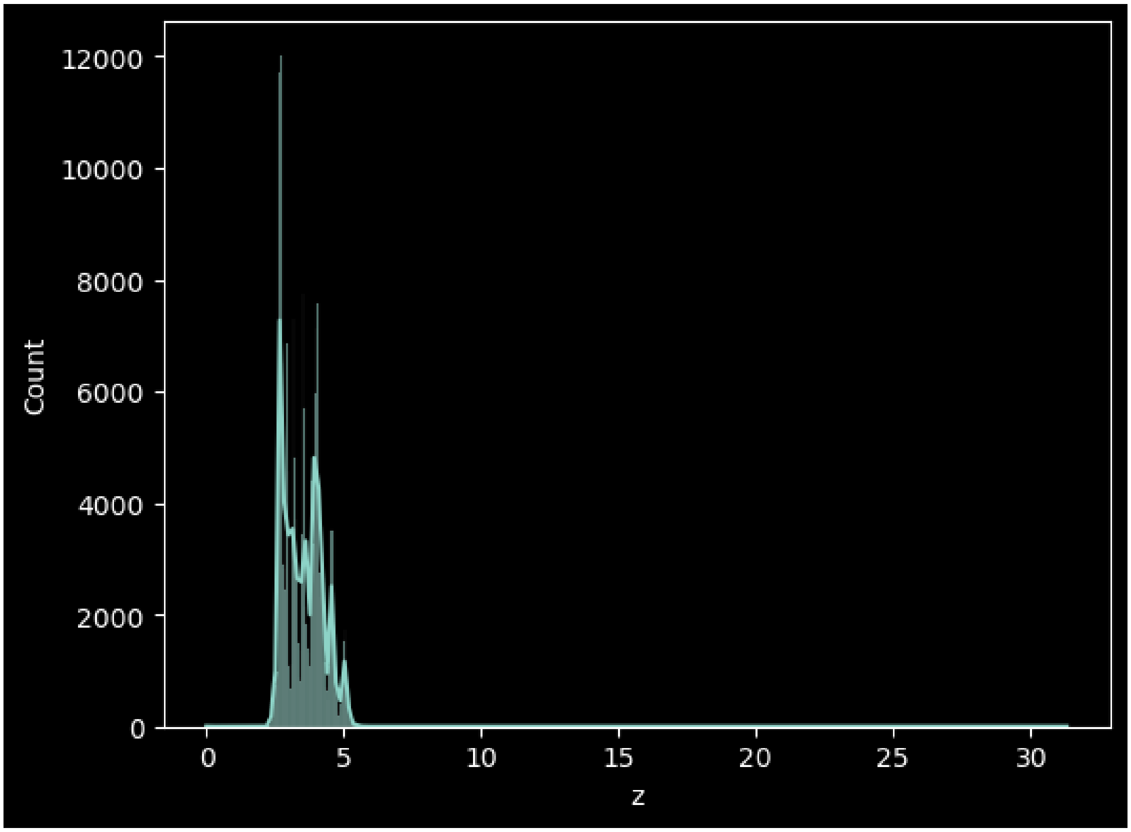
40000
35000
30000
25000
20000
15000
10000
5000
0
Count
50
55
60
65
70
75
80
table

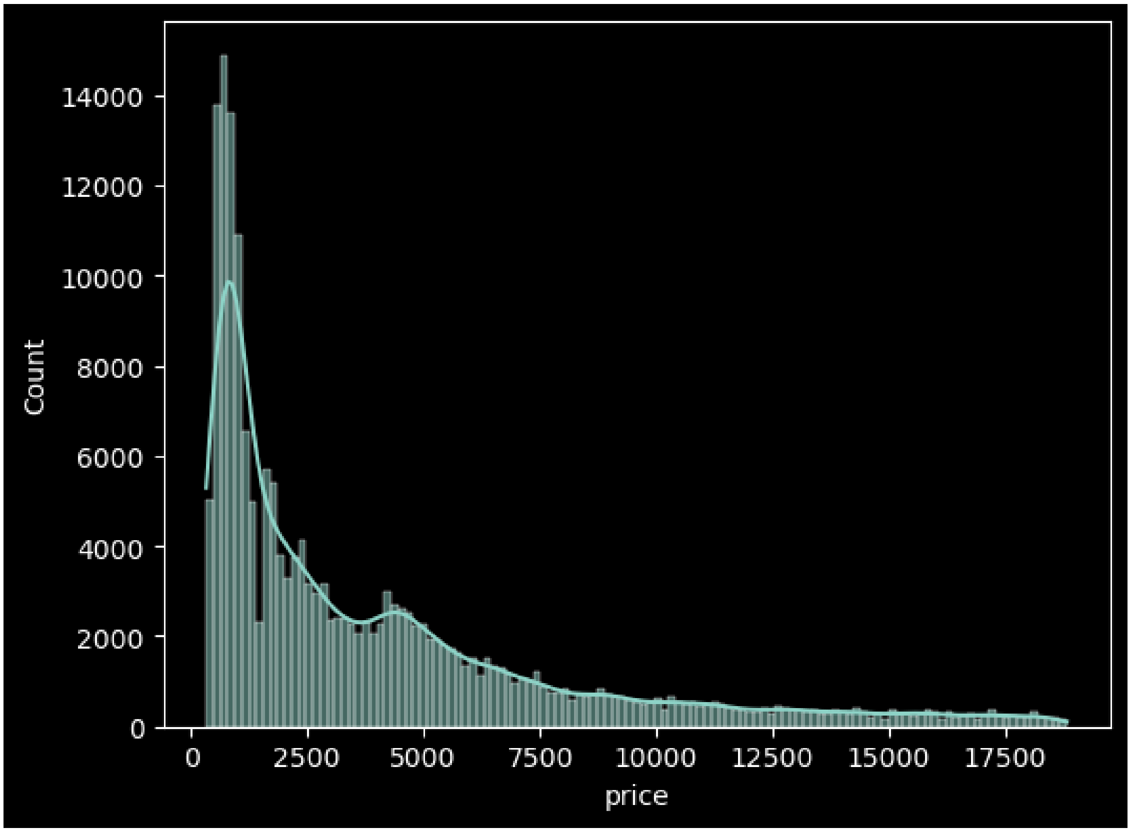


10000
8000
6000
4000
2000
0
Count
0
2
4
6
8
10
x



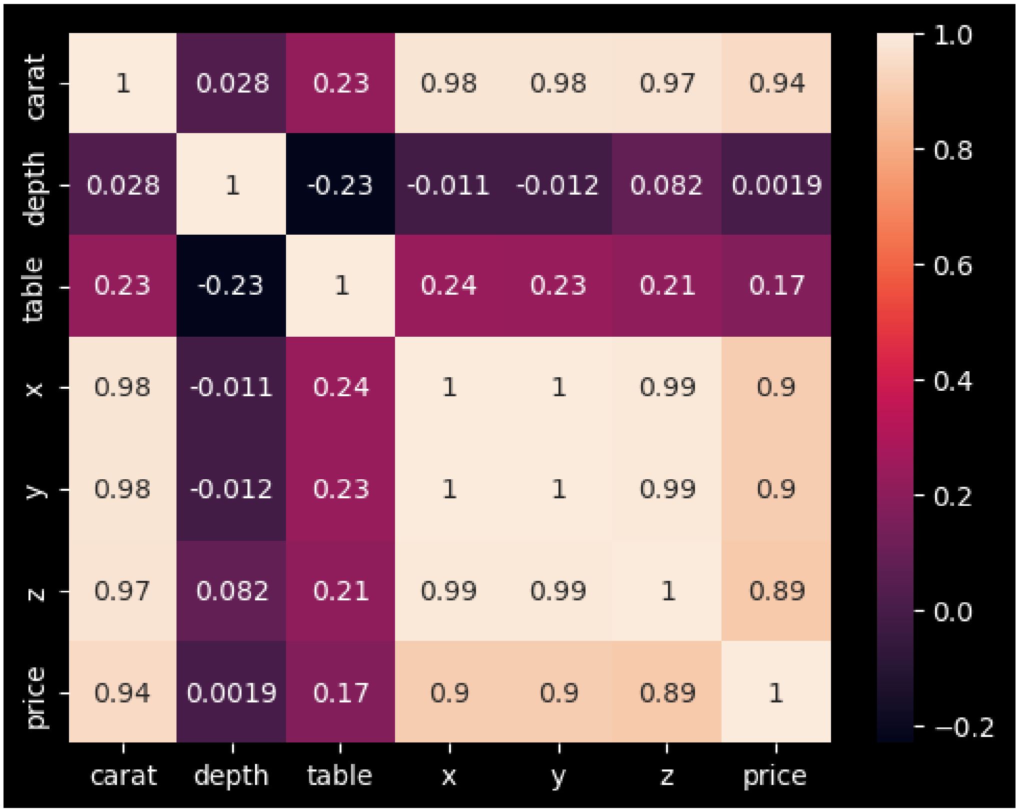
Count
12000
10000
8000
6000
4000
2000
0
0
2
4
6
8
10
y


12000
10000
8000
6000
4000
2000
0
Count
0
5
10
15
20
25
30
z



[17]:
```
## correlation
sns.heatmap(df[numerical_columns].corr(),annot=True)
```

[17]: <AxesSubplot: >



6 5.0. Feature Selection

[18]:
```
df.head()
```

[18]:

	carat	cut	color	clarity	depth	table	x	y	z	price
0	1.52	Premium	F	VS2	62.2	58.0	7.27	7.33	4.55	13619
1	2.03	Very Good	J	SI2	62.0	58.0	8.06	8.12	5.05	13387
2	0.70	Ideal	G	VS1	61.2	57.0	5.69	5.73	3.50	2772
3	0.32	Ideal	G	VS1	61.6	56.0	4.38	4.41	2.71	666
4	1.70	Premium	G	VS2	62.6	59.0	7.65	7.61	4.77	14453

[19]:
```
df['cut'].unique()
```

[19]:
```
array(['Premium', 'Very Good', 'Ideal', 'Good', 'Fair'], dtype=object)
```

[20]:
```
cut_map={"Fair":1,"Good":2,"Very Good":3,"Premium":4,"Ideal":5}
```

[21]:
```
df['clarity'].unique()
```

[21]:
```
array(['VS2', 'SI2', 'VS1', 'SI1', 'IF', 'VVS2', 'VVS1', 'I1'],
      dtype=object)
```

[22]:
```
df['clarity'].unique()
```

[22]:
```
array(['VS2', 'SI2', 'VS1', 'SI1', 'IF', 'VVS2', 'VVS1', 'I1'],
      dtype=object)
```

[23]:
```
df['clarity'].unique()
```

[23]:
```
array(['VS2', 'SI2', 'VS1', 'SI1', 'IF', 'VVS2', 'VVS1', 'I1'],
      dtype=object)
```

[24]:
```
df['color'].unique()
```

[24]:
```
array(['F', 'J', 'G', 'E', 'D', 'H', 'I'], dtype=object)
```

[25]:
```
color_map = {"D":1 ,"E":2 ,"F":3 , "G":4 ,"H":5 , "I":6, "J":7}
```

[27]:
```
df.head()
```

[27]:

	carat	cut	color	clarity	depth	table	x	y	z	price
0	1.52	4	F	VS2	62.2	58.0	7.27	7.33	4.55	13619
1	2.03	3	J	SI2	62.0	58.0	8.06	8.12	5.05	13387
2	0.70	5	G	VS1	61.2	57.0	5.69	5.73	3.50	2772
3	0.32	5	G	VS1	61.6	56.0	4.38	4.41	2.71	666
4	1.70	4	G	VS2	62.6	59.0	7.65	7.61	4.77	14453

7 5.0. Model Training

[32]:
```
df2 = pd.read_csv('./data/gemstone.csv')
df.head()
```

[32]:

	carat	cut	color	clarity	depth	table	x	y	z	price
0	1.52	Premium	F	VS2	62.2	58.0	7.27	7.33	4.55	13619
1	2.03	Very Good	J	SI2	62.0	58.0	8.06	8.12	5.05	13387
2	0.70	Ideal	G	VS1	61.2	57.0	5.69	5.73	3.50	2772
3	0.32	Ideal	G	VS1	61.6	56.0	4.38	4.41	2.71	666
4	1.70	Premium	G	VS2	62.6	59.0	7.65	7.61	4.77	14453

[33]:
```
df2=df2.drop(labels=['id'],axis=1)
## Independent and dependent features
X = df.drop(labels=['price'],axis=1)
Y = df[['price']]
Y
```

[33]:

	price
0	13619
1	13387

```
2          2772
3           666
4         14453
…          …
193568    1130
193569    2874
193570    3036
193571     681
193572    2258

[193573 rows x 1 columns]
```

7.0.1 Segregating and categorical variables

[34]:
```
categorical_cols = X.select_dtypes(include='object').columns
numerical_cols = X.select_dtypes(exclude='object').columns
```

7.0.2 Define the custom ranking for each ordinal variable

[35]:
```
cut_categories = ['Fair', 'Good', 'Very Good','Premium','Ideal']
color_categories = ['D', 'E', 'F', 'G', 'H', 'I', 'J']
clarity_categories = ['I1','SI2','SI1','VS2','VS1','VVS2','VVS1','IF']
```

7.0.3 Numerical Pipeline

[36]:
```
num_pipeline=Pipeline(
    steps=[
    ('imputer',SimpleImputer(strategy='median')),
    ('scaler',StandardScaler())

    ]

)

# Categorigal Pipeline
cat_pipeline=Pipeline(
    steps=[
    ('imputer',SimpleImputer(strategy='most_frequent')),
   ␣
 ↪('ordinalencoder',OrdinalEncoder(categories=[cut_categories,color_categories,clarity_catego
    ('scaler',StandardScaler())
    ]

)

preprocessor=ColumnTransformer([
```

```
('num_pipeline',num_pipeline,numerical_cols),
('cat_pipeline',cat_pipeline,categorical_cols)
])
```

7.0.4 Train test split

[37]:
```
from sklearn.model_selection import train_test_split

X_train,X_test,y_train,y_test=train_test_split(X,Y,test_size=0.
 ↪30,random_state=30)
```

[38]:
```
X_train=pd.DataFrame(preprocessor.fit_transform(X_train),columns=preprocessor.
 ↪get_feature_names_out())
X_test=pd.DataFrame(preprocessor.transform(X_test),columns=preprocessor.
 ↪get_feature_names_out())
```

[39]:
```
X_train.head()
```

[39]:
```
   num_pipeline__carat  num_pipeline__depth  num_pipeline__table  \
0            -0.975439            -0.849607            -0.121531
1             0.235195             1.833637            -0.121531
2             0.494617             0.815855             0.399800
3            -1.018676             0.260701             0.921131
4            -0.953821            -0.664555            -0.642862

   num_pipeline__x  num_pipeline__y  num_pipeline__z  cat_pipeline__cut  \
0        -1.042757        -1.080970        -1.123150           0.874076
1         0.318447         0.279859         0.485354          -2.144558
2         0.570855         0.606458         0.673737          -0.132136
3        -1.214034        -1.244270        -1.195605          -0.132136
4        -1.069801        -1.044681        -1.094168           0.874076

   cat_pipeline__color  cat_pipeline__clarity
0             1.528722               1.352731
1            -0.935071              -0.646786
2             0.296826               0.686225
3             0.296826               0.019720
4             2.144670               1.352731
```

[40]:
```
## Model Training

from sklearn.linear_model import LinearRegression,Lasso,Ridge,ElasticNet
from sklearn.metrics import r2_score,mean_absolute_error,mean_squared_error
```

[41]:
```
regression=LinearRegression()
regression.fit(X_train,y_train)
```

[41]: LinearRegression()

[42]:
```
regression.coef_
```

[42]:
```
array([[ 6433.66003594,  -132.75843566,   -70.42922179, -1720.30971463,
         -499.29302619,   -63.39317848,    72.44537247,  -460.41604642,
          650.76431652]])
```

[43]:
```
regression.intercept_
```

[43]:
```
array([3970.76628955])
```

[44]:
```
def evaluate_model(true, predicted):
    mae = mean_absolute_error(true, predicted)
    mse = mean_squared_error(true, predicted)
    rmse = np.sqrt(mean_squared_error(true, predicted))
    r2_square = r2_score(true, predicted)
    return mae, rmse, r2_square
```

7.0.5 Train multiple models

7.0.6 Model Ecaluation

[45]:
```
models={
    'LinearRegression':LinearRegression(),
    'Lasso':Lasso(),
    'Ridge':Ridge(),
    'Elasticnet':ElasticNet()
}
trained_model_list=[]
model_list=[]
r2_list=[]

for i in range(len(list(models))):
    model=list(models.values())[i]
    model.fit(X_train,y_train)

    #Make Predictions
    y_pred=model.predict(X_test)

    mae, rmse, r2_square=evaluate_model(y_test,y_pred)

    print(list(models.keys())[i])
    model_list.append(list(models.keys())[i])

    print('Model Training Performance')
    print("RMSE:",rmse)
```

```
    print("MAE:",mae)
    print("R2 score",r2_square*100)

    r2_list.append(r2_square)

    print('='*35)
    print('\n')
```

```
LinearRegression
Model Training Performance
RMSE: 1013.9047094344002
MAE: 674.025511579685
R2 score 93.68908248567512
===================================


Lasso
Model Training Performance
RMSE: 1013.8784226767013
MAE: 675.0716923362162
R2 score 93.68940971841704
===================================


Ridge
Model Training Performance
RMSE: 1013.9059272771628
MAE: 674.0555800798244
R2 score 93.6890673250594
===================================


Elasticnet
Model Training Performance
RMSE: 1533.4162456064048
MAE: 1060.7368759154729
R2 score 85.56494831165182
===================================
```

8 Reference:

PWSKILLS

9 Thank You!