💎Diamond Price Prediction

Importing Necessary Libraries

In [1]:
```
import pandas as pd
import numpy as np
from numpy import mean
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_selection import VarianceThreshold
from sklearn.preprocessing import KBinsDiscretizer
from sklearn.model_selection import train_test_split
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
from sklearn.pipeline import Pipeline
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from xgboost import XGBRegressor
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsRegressor
from sklearn.metrics import mean_squared_error
from sklearn import metrics
```

Importing the Dataset

Link to dataset : https://www.kaggle.com/datasets/shubhankitsirvaiya06/diamond-price-prediction (https://www.kaggle.com/datasets/shubhankitsirvaiya06/diamond-price-prediction)

In [2]:
```
df = pd.read_csv('diamonds.csv')
df
```

Out[2]:

	Unnamed: 0	carat	cut	color	clarity	depth	table	price	x	y	z
0	1	0.23	Ideal	E	SI2	61.5	55.0	326	3.95	3.98	2.43
1	2	0.21	Premium	E	SI1	59.8	61.0	326	3.89	3.84	2.31
2	3	0.23	Good	E	VS1	56.9	65.0	327	4.05	4.07	2.31
3	4	0.29	Premium	I	VS2	62.4	58.0	334	4.20	4.23	2.63
4	5	0.31	Good	J	SI2	63.3	58.0	335	4.34	4.35	2.75
...	...	...	...	...	...	...	...	...	...	...	...
53935	53936	0.72	Ideal	D	SI1	60.8	57.0	2757	5.75	5.76	3.50
53936	53937	0.72	Good	D	SI1	63.1	55.0	2757	5.69	5.75	3.61
53937	53938	0.70	Very Good	D	SI1	62.8	60.0	2757	5.66	5.68	3.56
53938	53939	0.86	Premium	H	SI2	61.0	58.0	2757	6.15	6.12	3.74
53939	53940	0.75	Ideal	D	SI2	62.2	55.0	2757	5.83	5.87	3.64

53940 rows × 11 columns

In [3]:
```
df.describe()
```

Out[3]:

	Unnamed: 0	carat	depth	table	price	x	y	z
count	53940.000000	53940.000000	53940.000000	53940.000000	53940.000000	53940.000000	53940.000000	53940.000000
mean	26970.500000	0.797940	61.749405	57.457184	3932.799722	5.731157	5.734526	3.538734
std	15571.281097	0.474011	1.432621	2.234491	3989.439738	1.121761	1.142135	0.705699
min	1.000000	0.200000	43.000000	43.000000	326.000000	0.000000	0.000000	0.000000
25%	13485.750000	0.400000	61.000000	56.000000	950.000000	4.710000	4.720000	2.910000
50%	26970.500000	0.700000	61.800000	57.000000	2401.000000	5.700000	5.710000	3.530000
75%	40455.250000	1.040000	62.500000	59.000000	5324.250000	6.540000	6.540000	4.040000
max	53940.000000	5.010000	79.000000	95.000000	18823.000000	10.740000	58.900000	31.800000

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 53940 entries, 0 to 53939
Data columns (total 11 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   Unnamed: 0  53940 non-null  int64  
 1   carat       53940 non-null  float64
 2   cut         53940 non-null  object 
 3   color       53940 non-null  object 
 4   clarity     53940 non-null  object 
 5   depth       53940 non-null  float64
 6   table       53940 non-null  float64
 7   price       53940 non-null  int64  
 8   x           53940 non-null  float64
 9   y           53940 non-null  float64
 10  z           53940 non-null  float64
dtypes: float64(6), int64(2), object(3)
memory usage: 4.5+ MB
```

In [5]:
```python
df = df.drop('Unnamed: 0',1)
df.head()
```

Out[5]:

	carat	cut	color	clarity	depth	table	price	x	y	z
0	0.23	Ideal	E	SI2	61.5	55.0	326	3.95	3.98	2.43
1	0.21	Premium	E	SI1	59.8	61.0	326	3.89	3.84	2.31
2	0.23	Good	E	VS1	56.9	65.0	327	4.05	4.07	2.31
3	0.29	Premium	I	VS2	62.4	58.0	334	4.20	4.23	2.63
4	0.31	Good	J	SI2	63.3	58.0	335	4.34	4.35	2.75

In [6]:
```python
df.duplicated().sum()
```

Out[6]:
```
146
```

Dropping the duplicate entries from df

In [7]:
```python
df = df.drop_duplicates()
print(df.duplicated().sum())
```

```
0
```

In [8]:
```python
df.isnull().sum()
```

Out[8]:
```
carat      0
cut        0
color      0
clarity    0
depth      0
table      0
price      0
x          0
y          0
z          0
dtype: int64
```

Separating the X and Y from the df

In [9]:
```python
Y = df[['price']]
X = df.drop(['price'], axis = 1)
```

In [10]:
```python
num = X.select_dtypes(include=[np.number])
cat = X.select_dtypes(exclude=[np.number])
```

Numerical Feature Engineering

In [11]:
```
num.head()
```

Out[11]:

	carat	depth	table	x	y	z
0	0.23	61.5	55.0	3.95	3.98	2.43
1	0.21	59.8	61.0	3.89	3.84	2.31
2	0.23	56.9	65.0	4.05	4.07	2.31
3	0.29	62.4	58.0	4.20	4.23	2.63
4	0.31	63.3	58.0	4.34	4.35	2.75

In [12]:
```
num.describe(percentiles=[0.01,0.05,0.10,0.25,0.30,0.40,0.50,0.60,0.75,0.85,0.9,0.99]).T
```

Out[12]:

	count	mean	std	min	1%	5%	10%	25%	30%	40%	50%	60%	75%	85%	90%	99%	max
carat	53794.0	0.797780	0.473390	0.2	0.24	0.30	0.31	0.40	0.42	0.54	0.70	0.90	1.04	1.24	1.51	2.18	5.01
depth	53794.0	61.748080	1.429909	43.0	57.90	59.30	60.00	61.00	61.20	61.60	61.80	62.10	62.50	62.90	63.30	65.60	79.00
table	53794.0	57.458109	2.233679	43.0	53.00	54.00	55.00	56.00	56.00	57.00	57.00	58.00	59.00	60.00	60.00	64.00	95.00
x	53794.0	5.731214	1.120695	0.0	4.02	4.29	4.36	4.71	4.82	5.23	5.70	6.08	6.54	6.91	7.30	8.35	10.74
y	53794.0	5.734653	1.141209	0.0	4.04	4.30	4.36	4.72	4.83	5.24	5.71	6.08	6.54	6.90	7.30	8.33	58.90
z	53794.0	3.538714	0.705037	0.0	2.48	2.65	2.69	2.91	2.98	3.22	3.53	3.77	4.03	4.26	4.52	5.15	31.80

Clipping function below excludes the outliers present.

In [13]:
```
def outlier_cap(x):
    x = x.clip(lower = x.quantile(0.01))
    x = x.clip(upper = x.quantile(0.99))
    return(x)
```

In [14]:
```
num=num.apply(lambda x : outlier_cap(x))
```

In [15]:
```
num.describe(percentiles=[0.01,0.05,0.10,0.25,0.30,0.40,0.50,0.60,0.75,0.85,0.9,0.99]).T
```

Out[15]:

	count	mean	std	min	1%	5%	10%	25%	30%	40%	50%	60%	75%	85%	90%	99%	max
carat	53794.0	0.795562	0.464987	0.24	0.24	0.30	0.31	0.40	0.42	0.54	0.70	0.90	1.04	1.24	1.51	2.18	2.18
depth	53794.0	61.744691	1.340372	57.90	57.90	59.30	60.00	61.00	61.20	61.60	61.80	62.10	62.50	62.90	63.30	65.60	65.60
table	53794.0	57.446609	2.173349	53.00	53.00	54.00	55.00	56.00	56.00	57.00	57.00	58.00	59.00	60.00	60.00	64.00	64.00
x	53794.0	5.729885	1.111137	4.02	4.02	4.29	4.36	4.71	4.82	5.23	5.70	6.08	6.54	6.91	7.30	8.35	8.35
y	53794.0	5.731981	1.103578	4.04	4.04	4.30	4.36	4.72	4.83	5.24	5.71	6.08	6.54	6.90	7.30	8.33	8.33
z	53794.0	3.537896	0.685907	2.48	2.48	2.65	2.69	2.91	2.98	3.22	3.53	3.77	4.03	4.26	4.52	5.15	5.15

In [16]:
```
varselector= VarianceThreshold(threshold=0)
varselector.fit_transform(num)
# Get columns to keep and create new dataframe with those only
cols = varselector.get_support(indices=True)
num_1 = num.iloc[:,cols]
```

In [17]:
```
num_1
```

Out[17]:

	carat	depth	table	x	y	z
0	0.24	61.5	55.0	4.02	4.04	2.48
1	0.24	59.8	61.0	4.02	4.04	2.48
2	0.24	57.9	64.0	4.05	4.07	2.48
3	0.29	62.4	58.0	4.20	4.23	2.63
4	0.31	63.3	58.0	4.34	4.35	2.75
...	...	...	...	...	...	...
53935	0.72	60.8	57.0	5.75	5.76	3.50
53936	0.72	63.1	55.0	5.69	5.75	3.61
53937	0.70	62.8	60.0	5.66	5.68	3.56
53938	0.86	61.0	58.0	6.15	6.12	3.74
53939	0.75	62.2	55.0	5.83	5.87	3.64

53794 rows × 6 columns

There are no columns with zero variance so none of the column got dropped.

In [18]:
```
discrete = KBinsDiscretizer(n_bins=10, encode='ordinal', strategy='uniform')
num_binned = pd.DataFrame(discrete.fit_transform(num_1), index=num_1.index, columns=num_1.columns).add_suffix('_Rank')
num_binned
```

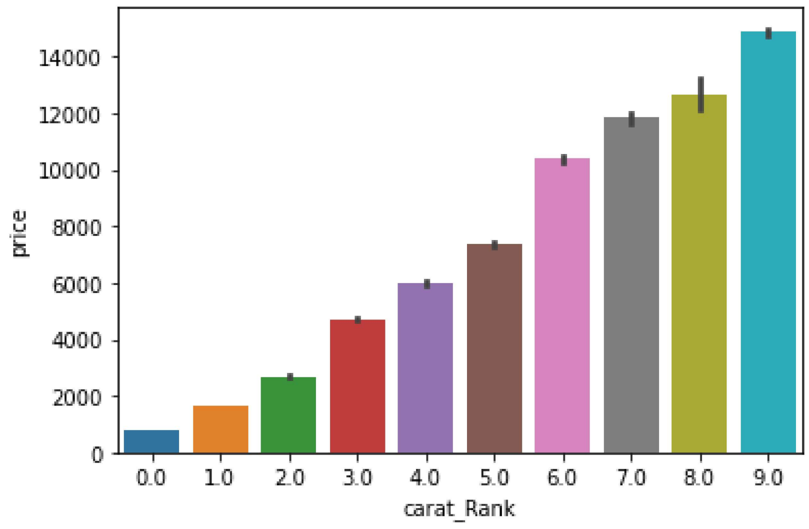
Out[18]:

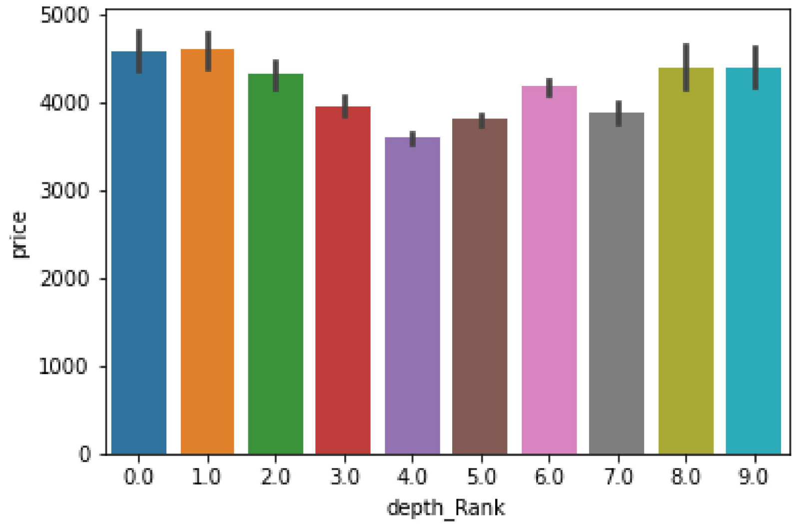
	carat_Rank	depth_Rank	table_Rank	x_Rank	y_Rank	z_Rank
0	0.0	4.0	1.0	0.0	0.0	0.0
1	0.0	2.0	7.0	0.0	0.0	0.0
2	0.0	0.0	9.0	0.0	0.0	0.0
3	0.0	5.0	4.0	0.0	0.0	0.0
4	0.0	7.0	4.0	0.0	0.0	1.0
...	...	...	...	...	...	...
53935	2.0	3.0	3.0	3.0	4.0	3.0
53936	2.0	6.0	1.0	3.0	3.0	4.0
53937	2.0	6.0	6.0	3.0	3.0	4.0
53938	3.0	4.0	4.0	4.0	4.0	4.0
53939	2.0	5.0	1.0	4.0	4.0	4.0

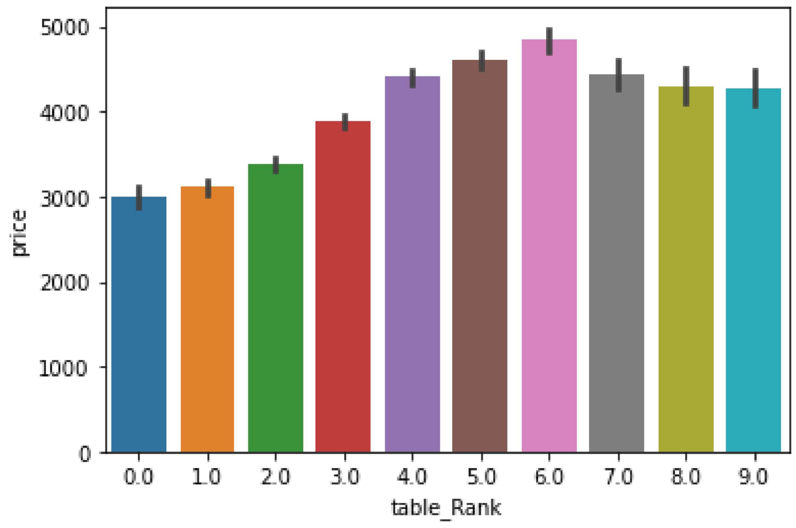
53794 rows × 6 columns

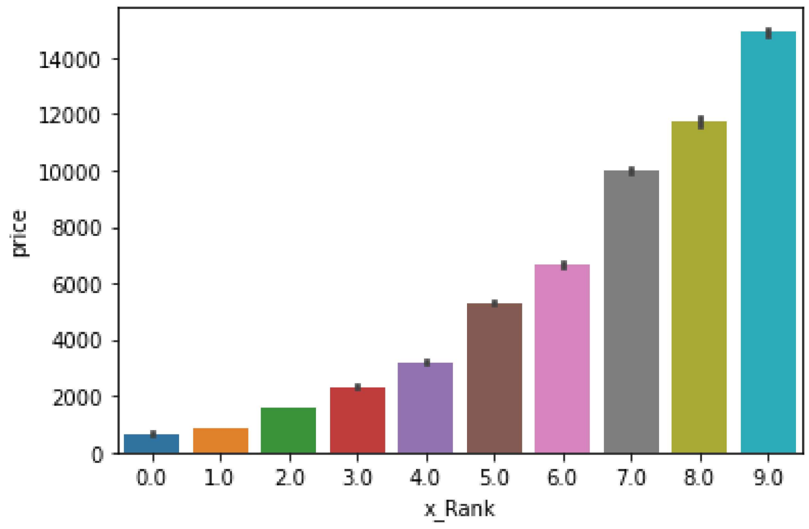
KbinDiscretizer is used here to make a graph of each feature in num_1 vs the target feature (i.e. price).

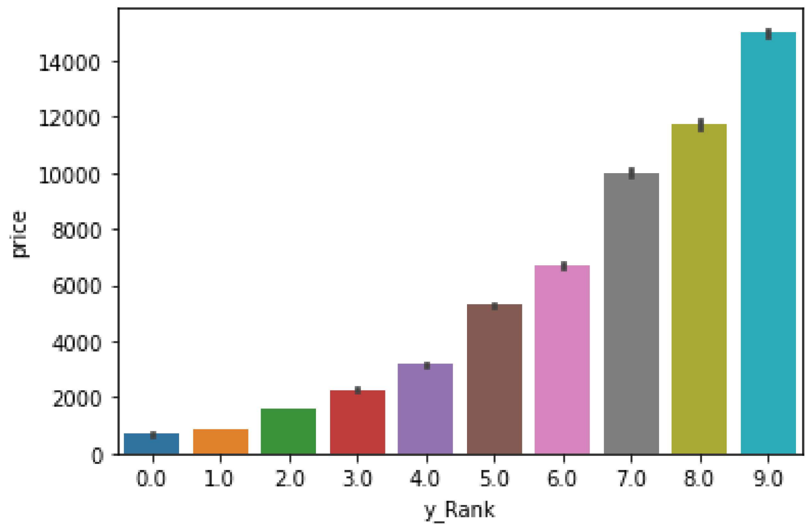
In [19]:
```
Xbinned = pd.concat([Y,num_binned], axis=1, join='inner')

for col in (num_binned.columns):
    plt.figure()
    sns.barplot(x = col, y = 'price', data = Xbinned, estimator = mean)
plt.show()
```

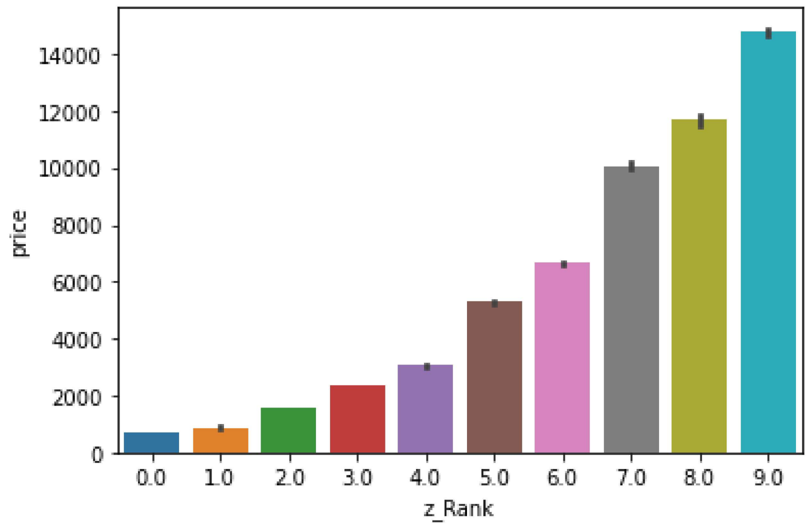












In [20]:
```
num_1 = num_1.drop('depth', 1)
num_1.head()
```

Out[20]:

	carat	table	x	y	z
0	0.24	55.0	4.02	4.04	2.48
1	0.24	61.0	4.02	4.04	2.48
2	0.24	64.0	4.05	4.07	2.48
3	0.29	58.0	4.20	4.23	2.63
4	0.31	58.0	4.34	4.35	2.75

In num_1 we dropped depth feature because from figure, we can see there is not much slope to be seen as other columns. Rest features show a good slope giving an intuition that those are having an good amount of effect on the target feature (i.e. price)

Categorical Feature Engineering

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

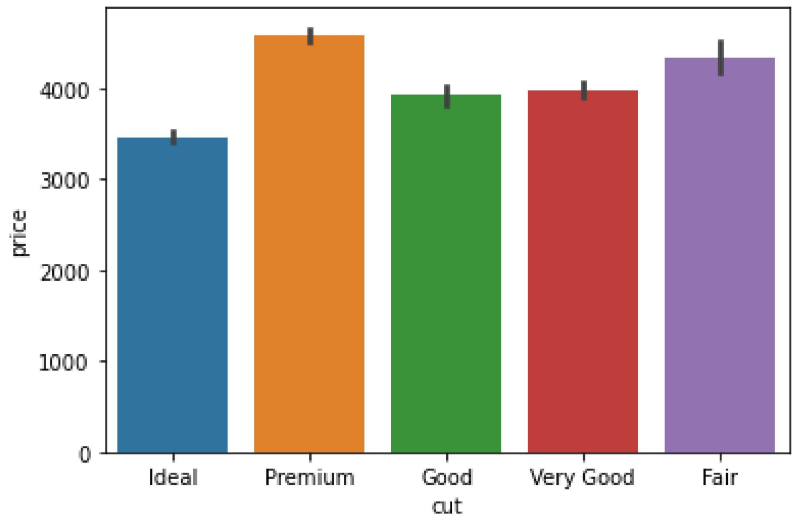
Out[21]:

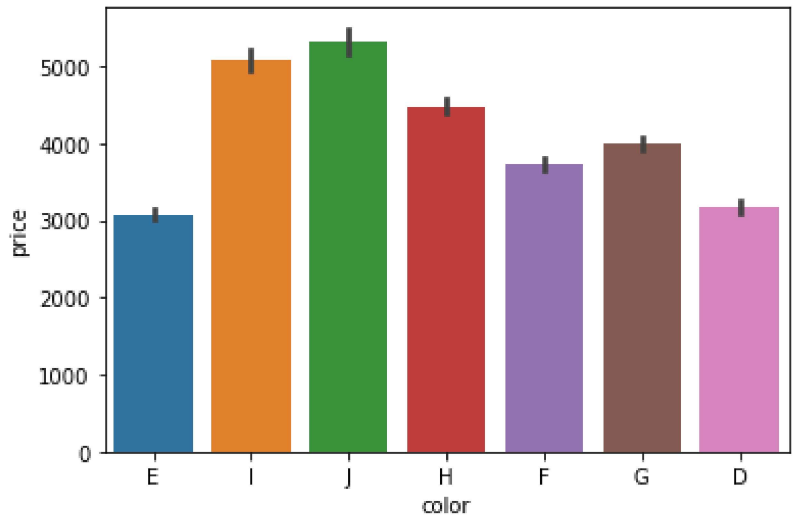
	cut	color	clarity
0	Ideal	E	SI2
1	Premium	E	SI1
2	Good	E	VS1
3	Premium	I	VS2
4	Good	J	SI2

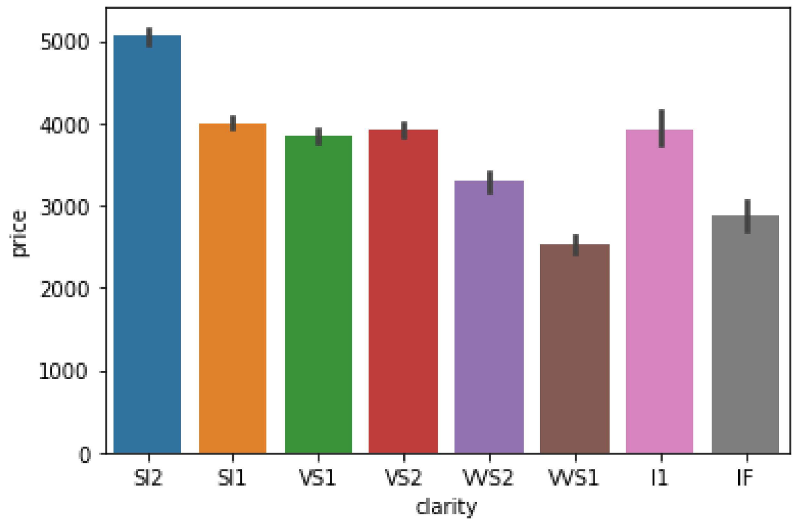
In [22]:
```
cat.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 53794 entries, 0 to 53939
Data columns (total 3 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   cut       53794 non-null  object
 1   color     53794 non-null  object
 2   clarity   53794 non-null  object
dtypes: object(3)
memory usage: 3.7+ MB
```

In [23]:
```
Xchar = pd.concat([Y,cat], axis=1, join='inner')

for col in (cat.columns):
    plt.figure()
    sns.barplot(x = col, y = 'price', data = Xchar, estimator = mean)
plt.show()
```







In [24]:
```
X_char_dum = pd.get_dummies(cat, drop_first = True)
X_char_dum.shape
```

Out[24]: (53794, 17)

In [25]:
```
X_char_dum.head()
```

Out[25]:

	cut_Good	cut_Ideal	cut_Premium	cut_Very Good	color_E	color_F	color_G	color_H	color_I	color_J	clarity_IF	clarity_SI1	clarity_SI2	clarity_V
0	0	1	0	0	1	0	0	0	0	0	0	0	1	
1	0	0	1	0	1	0	0	0	0	0	0	1	0	
2	1	0	0	0	1	0	0	0	0	0	0	0	0	
3	0	0	1	0	0	0	0	0	1	0	0	0	0	
4	1	0	0	0	0	0	0	0	0	1	0	0	1	

In [26]:
```
selector = SelectKBest(chi2, k=15)
```

Here we are using KBest to select best features out of all the categorical features. Here, k = 15 denotes no of top features to be selected.

In [27]:
```
selector.fit_transform(X_char_dum, Y)
```

Out[27]:
```
array([[0, 0, 1, ..., 0, 0, 0],
       [0, 0, 1, ..., 0, 0, 0],
       [1, 0, 1, ..., 0, 0, 0],
       ...,
       [0, 1, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0]], dtype=uint8)
```

In [28]:
```
cols = selector.get_support(indices=True)
select_features_df_char = X_char_dum.iloc[:,cols]
```

In [29]:
```
select_features_df_char.head()
```

Out[29]:

	cut_Good	cut_Very Good	color_E	color_F	color_G	color_H	color_I	color_J	clarity_IF	clarity_SI1	clarity_SI2	clarity_VS1	clarity_VS2	clarity_V
0	0	0	1	0	0	0	0	0	0	0	1	0	0	
1	0	0	1	0	0	0	0	0	0	1	0	0	0	
2	1	0	1	0	0	0	0	0	0	0	0	1	0	
3	0	0	0	0	0	0	1	0	0	0	0	0	1	
4	1	0	0	0	0	0	0	1	0	0	1	0	0	

In [30]:
```
cat_1 = pd.DataFrame(select_features_df_char)
cat_1.shape
```

Out[30]: (53794, 15)

In [31]:
```
Xall = pd.concat([num_1, cat_1], axis=1, join='inner')
Xall.head()
```

Out[31]:

	carat	table	x	y	z	cut_Good	cut_Very Good	color_E	color_F	color_G	color_H	color_I	color_J	clarity_IF	clarity_SI1	clarity_SI2	cl
0	0.24	55.0	4.02	4.04	2.48	0	0	1	0	0	0	0	0	0	0	1	
1	0.24	61.0	4.02	4.04	2.48	0	0	1	0	0	0	0	0	0	1	0	
2	0.24	64.0	4.05	4.07	2.48	1	0	1	0	0	0	0	0	0	0	0	
3	0.29	58.0	4.20	4.23	2.63	0	0	0	0	0	0	1	0	0	0	0	
4	0.31	58.0	4.34	4.35	2.75	1	0	0	0	0	0	0	1	0	0	1	

In [32]:
```
print(Xall.columns)
```

```
Index(['carat', 'table', 'x', 'y', 'z', 'cut_Good', 'cut_Very Good', 'color_E',
       'color_F', 'color_G', 'color_H', 'color_I', 'color_J', 'clarity_IF',
       'clarity_SI1', 'clarity_SI2', 'clarity_VS1', 'clarity_VS2',
       'clarity_VVS1', 'clarity_VVS2'],
      dtype='object')
```

Above are all the columns that are being considered during model development

In [33]:
```
Xall.shape
```

Out[33]: (53794, 20)

Test Train Split

In [34]:
```
Xtrain, Xtest, Ytrain, Ytest = train_test_split(Xall, Y, test_size=0.2, random_state=101)
```

Having a look at shape of training, testing data and mean of target variable

In [35]:
```
print("Shape of Training Data",Xtrain.shape)
print("\nShape of Testing Data",Xtest.shape)
print("\nMean price in Training Data",Ytrain.mean())
print("\nMean price in Testing Data",Ytest.mean())
```

```
Shape of Training Data (43035, 20)

Shape of Testing Data (10759, 20)

Mean price in Training Data price    3933.958569
dtype: float64

Mean price in Testing Data price    3929.491217
dtype: float64
```

Making Pipelines and fitting models

In [36]:
```
pipeline_lr=Pipeline([("lr_regressor",LinearRegression())])
pipeline_dt=Pipeline([("dt_regressor",DecisionTreeRegressor())])
pipeline_rf=Pipeline([("rf_regressor",RandomForestRegressor())])
pipeline_svm=Pipeline([("svm_regressor", SVR(kernel = 'rbf'))])
pipeline_kn=Pipeline([("kn_regressor",KNeighborsRegressor())])
pipeline_xgb=Pipeline([("xgb_regressor",XGBRegressor())])
pipelines = [pipeline_lr, pipeline_dt, pipeline_rf, pipeline_svm, pipeline_kn,pipeline_xgb]
pipe_dict = {0: "LinearRegression", 1: "DecisionTree", 2: "RandomForest", 3: "SVMRegressor", 4: "KNeighbor",5:"XGBoost
for pipe in pipelines:
    pipe.fit(Xtrain, Ytrain)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\pipeline.py:346: DataConversionWarning: A column-vector y was pas
sed when a 1d array was expected. Please change the shape of y to (n_samples,), for example using ravel().
  self._final_estimator.fit(Xt, y, **fit_params_last_step)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py:63: DataConversionWarning: A column-vector y
was passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel().
  return f(*args, **kwargs)
```

Training Accuracy of each model

In [40]:
```
for i, model in enumerate(pipelines):
    print(f'\n{pipe_dict[i]} Training Accuracy: {model.score(Xtrain,Ytrain)}')
```

```
LinearRegression Training Accuracy: 0.9280194017816433

DecisionTree Training Accuracy: 0.9991578743921723

RandomForest Training Accuracy: 0.9957792356657483

SVMRegressor Training Accuracy: -0.11282677118314455

KNeighbor Training Accuracy: 0.9723810676139834

XGBoost Training Accuracy: 0.9877016436183174
```

Testing Accuracy of each model

In [41]:
```
for i, model in enumerate(pipelines):
    print(f'\n{pipe_dict[i]} Test Accuracy: {model.score(Xtest,Ytest)}')
```

```
LinearRegression Test Accuracy: 0.9265250099911464

DecisionTree Test Accuracy: 0.9577040217306393

RandomForest Test Accuracy: 0.9728303222615093

SVMRegressor Test Accuracy: -0.11491688375173603

KNeighbor Test Accuracy: 0.9563631536246787

XGBoost Test Accuracy: 0.9765602918234914
```

Best Model with respect to accuracy

In [42]:
```
best_accuracy=0.0
best_pipeline=''
best_classifier=0


for i, model in enumerate(pipelines):
    if model.score(Xtest,Ytest)>best_accuracy:
        best_accuracy = model.score(Xtest, Ytest)
        best_pipeline = model
        best_classifier = i
print(f'Model with best accuracy: {pipe_dict[best_classifier]}')
```

```
Model with best accuracy: XGBoost
```

Predictions of each model

In [43]:
```
for i, model in enumerate(pipelines):
    print(f'\n{pipe_dict[i]} prediction: {model.predict(Xtest)}')
```

```

LinearRegression prediction: [[6601.26764206]
 [1894.89550334]
 [ 558.62526067]
 ...
 [3762.79369878]
 [-694.16261731]
 [2946.92516229]]

DecisionTree prediction: [7365. 1323.  802. ... 3619.  558. 2602.]

RandomForest prediction: [7492.95 1401.75  742.14 ... 3526.02  546.36 2705.97]

SVMRegressor prediction: [2448.73789034 2369.57554265 2329.45876863 ... 2421.31473876 2302.68126495
 2398.75889088]

KNeighbor prediction: [[6174.4]
 [1412.8]
 [ 613.8]
 ...
 [3913.6]
 [ 506.6]
 [2472.2]]

XGBoost prediction: [7568.843  1433.8162  656.0665 ... 3663.9822  592.7593 2555.7563]
```

Other Matrices to find Best Model

R Squared Value of each model

In [44]:
```
for i, model in enumerate(pipelines):
    print(f"\nR^2 {pipe_dict[i]} :",metrics.r2_score(Ytest, model.predict(Xtest) ))
```

```

R^2 LinearRegression : 0.9265250099911464

R^2 DecisionTree : 0.9577040217306393

R^2 RandomForest : 0.9728303222615093

R^2 SVMRegressor : -0.11491688375173603

R^2 KNeighbor : 0.9563631536246787

R^2 XGBoost : 0.9765602918234914
```

Mean Absolute Error of each model

In [45]:
```
for i, model in enumerate(pipelines):
    print(f"\nMAE {pipe_dict[i]}:",metrics.mean_absolute_error(Ytest, model.predict(Xtest)))
```

```
MAE LinearRegression: 716.8572009212276

MAE DecisionTree: 383.4269430526099

MAE RandomForest: 302.6974654751749

MAE SVMRegressor: 2733.32549189663

MAE KNeighbor: 415.0480713820987

MAE XGBoost: 308.174219499823
```

Mean Square Error of each model

In [46]:
```
for i, model in enumerate(pipelines):
    print(f"\nMSE {pipe_dict[i]}:",metrics.mean_squared_error(Ytest, model.predict(Xtest) ))
```

```
MSE LinearRegression: 1147063.7663534656

MSE DecisionTree: 660308.8224906351

MSE RandomForest: 424162.7371921752

MSE SVMRegressor: 17405660.888055008

MSE KNeighbor: 681241.9484375871

MSE XGBoost: 365931.8625280836
```

Root Mean Square Error of each model

In [47]:
```
for i, model in enumerate(pipelines):
    print(f"\nRMSE {pipe_dict[i]}:",np.sqrt(metrics.mean_squared_error(Ytest, model.predict(Xtest))))
```

```
RMSE LinearRegression: 1071.0106284969659

RMSE DecisionTree: 812.5938853391866

RMSE RandomForest: 651.2777726839564

RMSE SVMRegressor: 4172.009214761517

RMSE KNeighbor: 825.3738234506757

RMSE XGBoost: 604.9230219855115
```

Conclusion

- Diamond price prediction is a regression problem
- Most important Numerical features are:-

    `"carat", "table", "x", "y" and "z".`

- Most important Categorical features are:-

    `'cut_Good', 'cut_Very Good', 'color_E', 'color_F', 'color_G', 'color_H', 'color_I', 'color_J', 'clarity_IF', 'clarity_SI1', 'clarity_SI2', 'clarity_VS1', 'clarity_VS2', 'clarity_VVS1' and 'clarity_VVS2'.`

- Testing Accuracy is maximum for XGBoost model with accuracy 97.65%.
- Other metrics such as R2 , Mean Absolute Error, Mean Squared Error, Root Mean Squared Error confirm that XGBoost is indeed optimum than that of other models.