diamond-prediction

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0.1 # Diamonds Price Prediction

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0.2 Problem Statement

Pricing diamonds is notoriously difficult, especially for brokers. A diamond can be the same size and same weight but priced thousands of dollars differently. This poses significant challenges to setting the fair market price of diamonds.

0.2.1 Problems

The problems faced during this analysis include:

1. Determining the relationship to the 4 C's and pricing, or any identifiable patterns?
2. How are the 4 C's distributed across the data?
3. How to address the `cut`, `color`, and `clarity` categorical variables?
4. How accurate can the price of diamonds be predicted?

0.3 Value Proposition

Give diamonds broker insights into how diamonds are priced. The objective is to provide a tool such as a dashboard that will give greater understanding to how diamonds are priced.

0.3.1 Solutions

1. There is no clear indication of a pattern with the average price of diamonds, only observing that best `color` with the best `clarity` diamonds are priced significantly higher.
2. There is minimal regularities across the features, and as a whole not normal distributions across the data.
3. Addressed the `cut`, `color`, and `clarity` categorical variables with ordinal encoding, from best to worst across the variables.
4. Based on the best performing model, price can be predicted quite accurately with a 99% predicted performance.

[32]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
```

```
sns.set()
```

[33]:
```
diamonds = "https://raw.githubusercontent.com/kyle-w-brown/diamonds-prediction/
↪main/data/diamonds.csv"
df_diamonds = pd.read_csv(diamonds)
df_diamonds.head()
```

[33]:

	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

[ ]:
```
df_diamonds.shape
```

[ ]: (53940, 10)

[ ]:
```
df_diamonds.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 53940 entries, 0 to 53939
Data columns (total 10 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   carat    53940 non-null  float64
 1   cut      53940 non-null  object
 2   color    53940 non-null  object
 3   clarity  53940 non-null  object
 4   depth    53940 non-null  float64
 5   table    53940 non-null  float64
 6   price    53940 non-null  int64
 7   x        53940 non-null  float64
 8   y        53940 non-null  float64
 9   z        53940 non-null  float64
dtypes: float64(6), int64(1), object(3)
memory usage: 4.1+ MB
```

Create `volume` feature by multiplying `x`, `y`, and `z`.

[34]:
```
df_diamonds['volume'] = round(df_diamonds['x'] * df_diamonds['y'] *␣
↪df_diamonds['z'], 2)
df_diamonds.head()
```

[34]:

	carat	cut	color	clarity	depth	table	price	x	y	z	volume
0	0.23	Ideal	E	SI2	61.5	55.0	326	3.95	3.98	2.43	38.20
1	0.21	Premium	E	SI1	59.8	61.0	326	3.89	3.84	2.31	34.51
2	0.23	Good	E	VS1	56.9	65.0	327	4.05	4.07	2.31	38.08

3	0.29	Premium	I	VS2	62.4	58.0	334	4.20	4.23	2.63	46.72
4	0.31	Good	J	SI2	63.3	58.0	335	4.34	4.35	2.75	51.92

1 Data Cleansing

---

[35]:
```
df_diamonds[['x','y','z','volume']] = df_diamonds[['x','y','z','volume']].
 ↪replace(0, np.NaN)
df_diamonds.isnull().sum()
```

[35]:
```
carat       0
cut         0
color       0
clarity     0
depth       0
table       0
price       0
x           8
y           7
z          20
volume     20
dtype: int64
```

Removing missing data

[36]:
```
df_diamonds.dropna(inplace=True)
df_diamonds.isnull().sum()
```

[36]:
```
carat      0
cut        0
color      0
clarity    0
depth      0
table      0
price      0
x          0
y          0
z          0
volume     0
dtype: int64
```

1.0.1 Outliers

Removing the outliers

[37]:
```
df_diamonds = df_diamonds[(df_diamonds["carat"] <= 5)]
df_diamonds = df_diamonds[(df_diamonds["depth"] < 75) & (df_diamonds["depth"] >␣
↪45)]
df_diamonds = df_diamonds[(df_diamonds["table"] < 75) & (df_diamonds["table"] >␣
↪45)]
df_diamonds = df_diamonds[(df_diamonds["x"] < 30) & (df_diamonds["x"] > 2)]
df_diamonds = df_diamonds[(df_diamonds["y"] < 30) & (df_diamonds["y"] > 2)]
df_diamonds = df_diamonds[(df_diamonds["z"] < 30) & (df_diamonds["z"] > 2)]
df_diamonds = df_diamonds[(df_diamonds["volume"] < 3500)]
df_diamonds.shape
```

[37]:
```
(53902, 11)
```

2 Exploration

---

[57]:
```
df_diamonds.describe()
```

[57]:
```
              carat         depth         table         price             x  \
count  53902.000000  53902.000000  53902.000000  53902.000000  53902.000000
mean       0.797555     61.749434     57.455694   3930.426793      5.731398
std        0.473433      1.419670      2.221249   3986.883678      1.119202
min        0.200000     50.800000     49.000000    326.000000      3.730000
25%        0.400000     61.000000     56.000000    949.000000      4.710000
50%        0.700000     61.800000     57.000000   2401.000000      5.700000
75%        1.040000     62.500000     59.000000   5322.000000      6.540000
max        4.500000     73.600000     73.000000  18823.000000     10.230000

                  y             z        volume
count  53902.000000  53902.000000  53902.000000
mean       5.733239      3.539387    129.790389
std        1.111083      0.691292     76.399565
min        3.680000      2.060000     31.710000
25%        4.720000      2.910000     65.190000
50%        5.710000      3.530000    114.840000
75%        6.540000      4.040000    170.840000
max       10.160000      6.720000    698.460000
```

Exploring the categorical variables.

[7]:
```
df_diamonds['cut'].unique()
```

[7]:
```
array(['Ideal', 'Premium', 'Good', 'Very Good', 'Fair'], dtype=object)
```

[8]:
```
df_diamonds['clarity'].unique()
```

[8]:
```
array(['SI2', 'SI1', 'VS1', 'VS2', 'VVS2', 'VVS1', 'I1', 'IF'],
      dtype=object)
```

[9]:
```python
df_diamonds['color'].unique()
```

[9]:
```
array(['E', 'I', 'J', 'H', 'F', 'G', 'D'], dtype=object)
```

[ ]:
```python
df_diamonds.describe(include=object)
```

[ ]:

	cut	color	clarity
count	53902	53902	53902
unique	5	7	8
top	Ideal	G	SI1
freq	21542	11281	13058

Counting the values per unique feature.

[ ]:
```python
df_diamonds['cut'].value_counts()
```

[ ]:
```
Ideal        21542
Premium      13779
Very Good    12079
Good          4902
Fair          1600
Name: cut, dtype: int64
```

[ ]:
```python
df_diamonds['color'].value_counts()
```

[ ]:
```
G    11281
E     9791
F     9535
H     8296
D     6774
I     5419
J     2806
Name: color, dtype: int64
```

[107]:
```python
df_diamonds['clarity'].value_counts()
```

[107]:
```
SI1     13058
VS2     12250
SI2      9183
VS1      8165
VVS2     5066
VVS1     3654
IF       1790
I1        736
```

```
Name: clarity, dtype: int64
```

2.0.1 Reordering cut, color, and clarity categorical variables from best to worst

[10]:
```python
df_diamonds['cut'] = pd.Categorical(df_diamonds['cut'], ["Ideal", "Premium",␣
↪"Very Good", "Good", "Fair"])
df_diamonds = df_diamonds.sort_values('cut')
```

[11]:
```python
df_diamonds['color'] = pd.Categorical(df_diamonds['color'], ["D", "E", "F",␣
↪"G", "H", "I", "J"])
df_diamonds = df_diamonds.sort_values('color')
```

[12]:
```python
df_diamonds['clarity'] = pd.Categorical(df_diamonds['clarity'], ["IF", "VVS1",␣
↪"VVS2", "VS1", "VS2", "SI1", "SI2", "I1"])
df_diamonds = df_diamonds.sort_values('clarity')
```

Looking at the average price for `cut`, `color`, and `clarity`.

[13]:
```python
round(df_diamonds.groupby('cut')['price'].mean().reset_index(), 2)
```

[13]:
```
         cut    price
0      Ideal  3456.21
1    Premium  4579.13
2  Very Good  3982.12
3       Good  3926.40
4       Fair  4350.67
```

The best `cut` diamonds have the lowest average price.

[14]:
```python
round(df_diamonds.groupby('color', as_index=False)['price'].mean(), 2)
```

[14]:
```
  color    price
0     D  3168.11
1     E  3077.52
2     F  3723.99
3     G  3997.05
4     H  4479.38
5     I  5089.27
6     J  5319.49
```

The worst `color` diamonds have the highest average price.

[15]:
```python
round(df_diamonds.groupby('clarity', as_index=False)['price'].mean(), 2)
```

[15]:
```
  clarity    price
0      IF  2864.84
1    VVS1  2519.51
```

```
2    VVS2  3283.74
3     VS1  3839.14
4     VS2  3923.01
5     SI1  3993.02
6     SI2  5059.96
7      I1  3910.66
```

Comparing variables to `price` with pivot tables.

[16]:
```python
df_diamonds.pivot_table('price', index='cut', columns='clarity')
```

[16]:
```
clarity             IF         VVS1         VVS2          VS1          VS2  \
cut
Ideal      2272.913366  2468.129458  3250.290100  3487.972393  3281.928374
Premium    3856.143478  2810.304065  3795.122989  4485.462041  4546.261919
Very Good  4396.216418  2459.441065  3037.765182  3808.267343  4215.403089
Good       4098.323944  2254.774194  3079.108392  3801.445988  4262.236196
Fair       1912.333333  3871.352941  3349.768116  4152.029586  4187.647287

clarity            SI1          SI2           I1
cut
Ideal      3750.394860  4755.876396  4335.726027
Premium    4448.621886  5539.047910  3958.881773
Very Good  3932.391049  4988.688095  4078.226190
Good       3689.533333  4571.627087  3584.694737
Fair       4191.592593  5180.094624  3646.451923
```

[17]:
```python
df_diamonds.pivot_table('price', index='cut', columns='color')
```

[17]:
```
color                D            E            F            G            H  \
cut
Ideal      2629.094566  2597.684008  3373.863755  3718.469070  3887.452152
Premium    3623.767790  3538.914420  4325.099571  4502.207806  5195.375531
Very Good  3470.467284  3216.314012  3778.820240  3872.753806  4535.059243
Good       3405.382175  3423.644159  3498.761852  4105.907940  4276.254986
Fair       4291.061350  3703.248869  3801.087097  4241.022581  5135.683168

color                I            J
cut
Ideal      4449.548541  4918.343017
Premium    5939.557814  6294.591584
Very Good  5255.879568  5103.513274
Good       5078.532567  4574.172638
Fair       4685.445714  4865.127119
```

[18]:
```python
df_diamonds.pivot_table('price', index='color', columns='clarity')
```

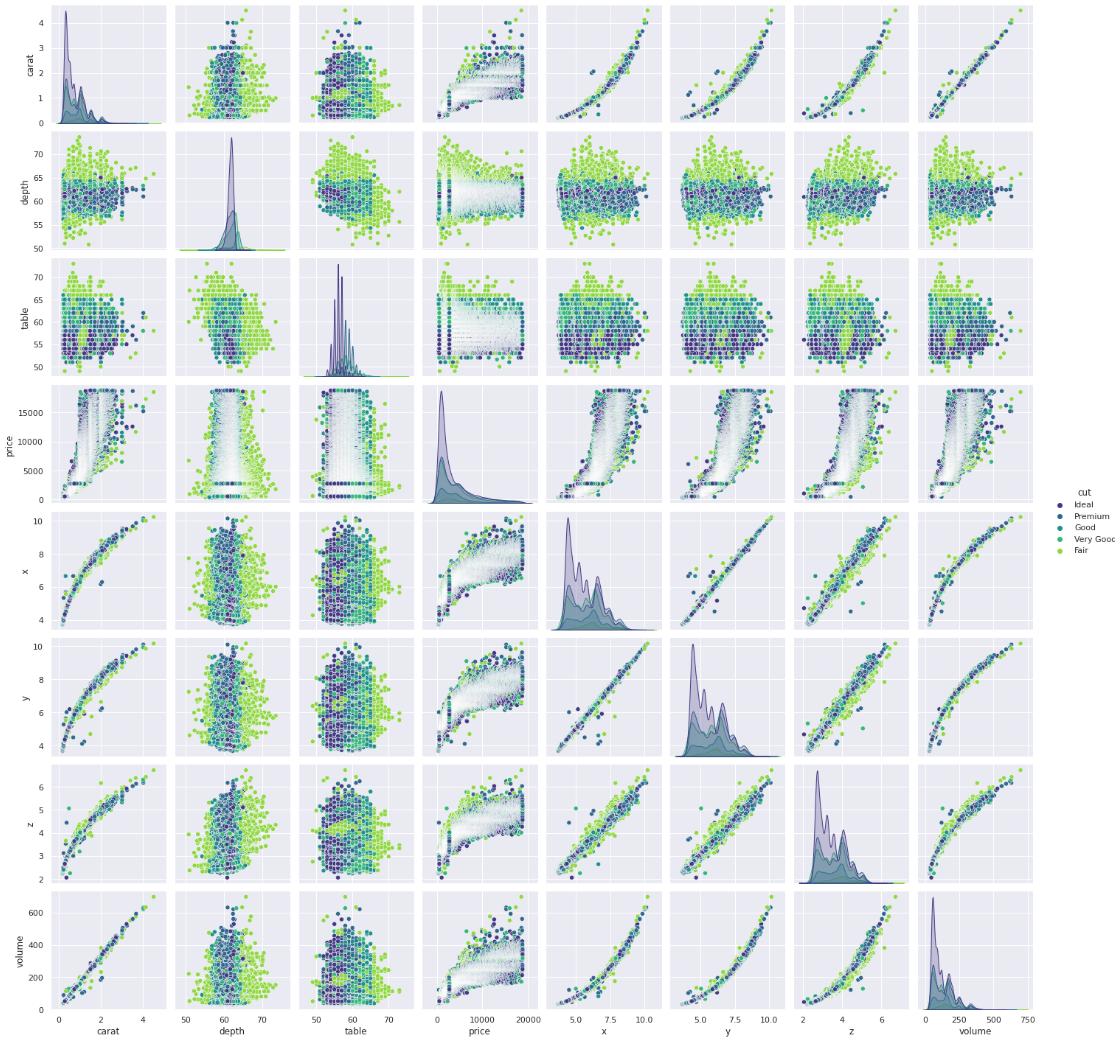
```
[18]: clarity           IF         VVS1         VVS2          VS1          VS2  \
      color
      D          8307.369863  2897.163347  3351.128391  3030.158865  2587.225692
      E          3668.506329  2219.820122  2499.674067  2859.463224  2751.081037
      F          2750.836364  2804.276567  3475.512821  3796.717742  3756.795093
      G          2558.033774  2866.820821  3845.283437  4130.314392  4412.354096
      H          2287.869565  1845.658120  2649.067434  3775.576199  4713.943327
      I          1994.937063  2034.861972  2968.232877  4632.805411  5690.505560
      J          3363.882353  4034.175676  5142.396947  4884.461255  5311.789041

      clarity          SI1          SI2           I1
      color
      D          2976.146423  3931.101460  3863.023810
      E          3161.838005  4173.826036  3510.465347
      F          3708.651480  4476.996259  3342.181818
      G          3775.574468  5014.848544  3545.540541
      H          5027.035620  6084.141667  4461.403727
      I          5345.414909  7002.649123  4302.184783
      J          5186.048000  6520.958246  4993.571429
```

The best `color` and best `clarity` diamonds have an average price that is significantly higher than the rest of the variables.

3 Visualization

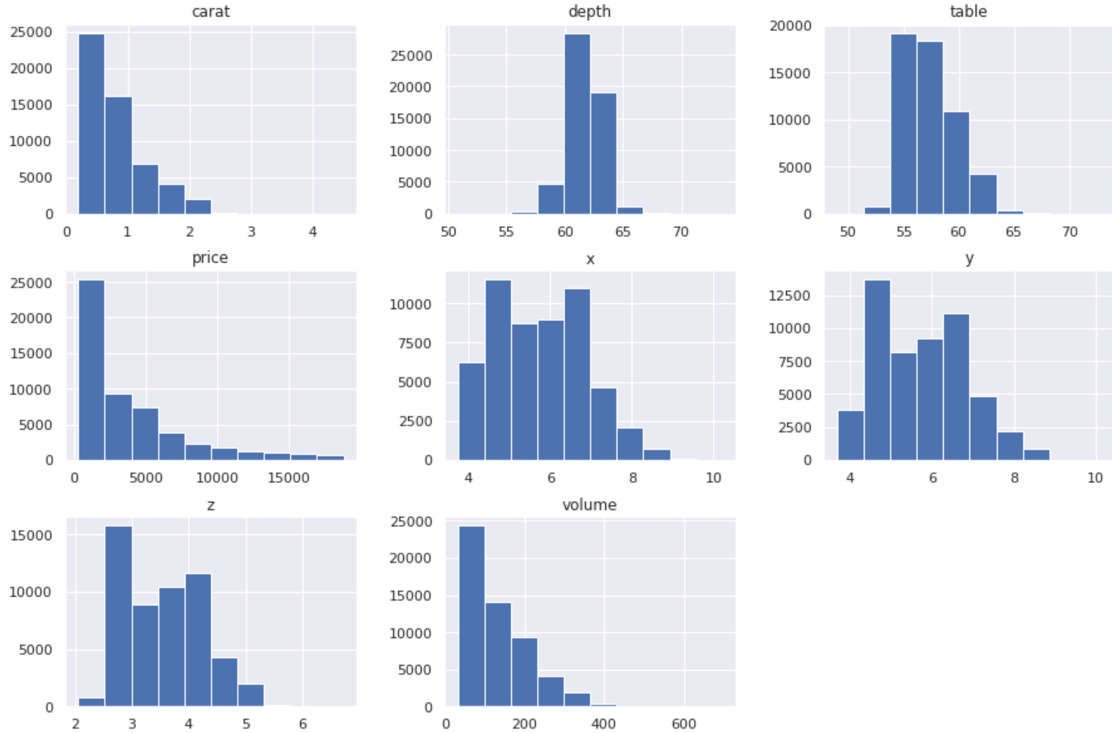
3.1 Pairplot

```
[58]: ax = sns.pairplot(df_diamonds,
                        hue= "cut",
                        palette = 'viridis')
```



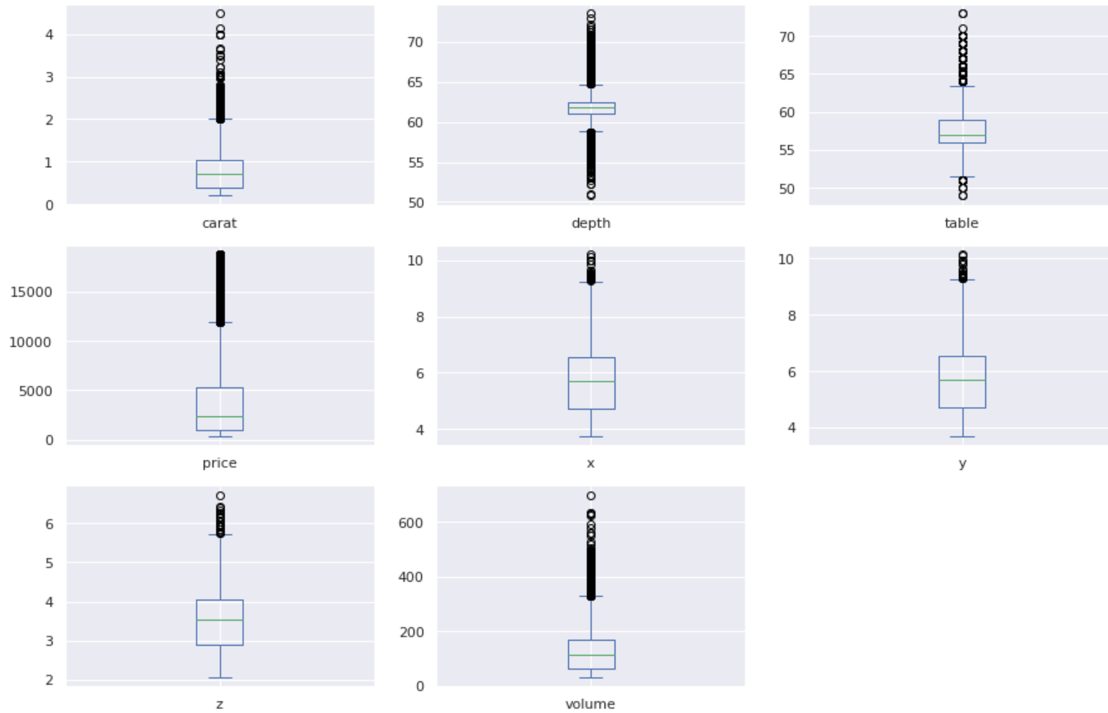
3.2 Historgram

[59]:
```
df_diamonds.hist(layout=(3,3), figsize=(15,10))
plt.show()
```



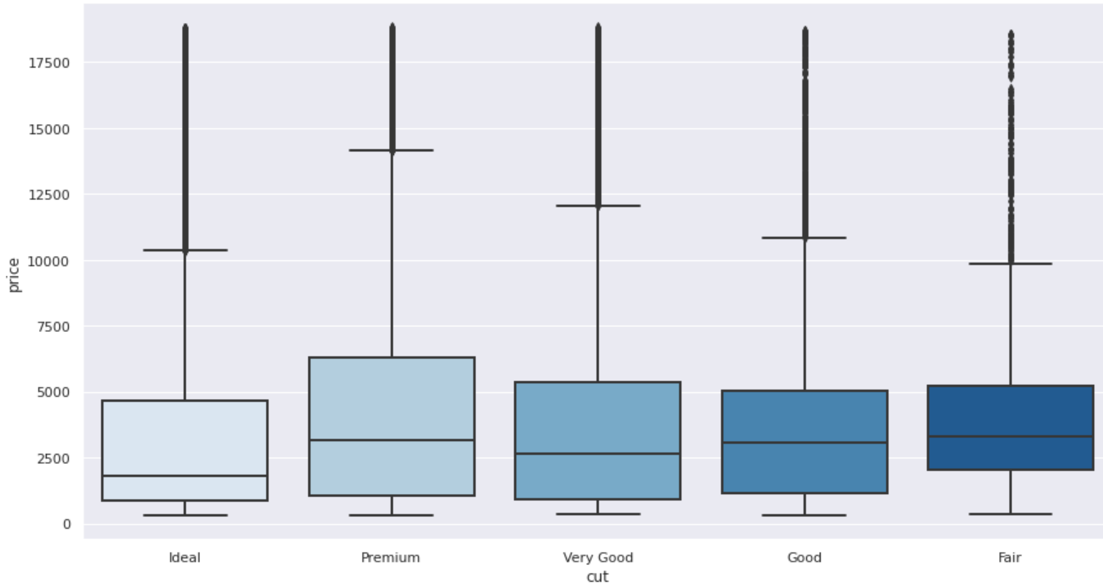
3.3 Boxplots

[60]:
```
df_diamonds.plot(kind='box',figsize=(15,10),subplots=True,layout=(3,3))
plt.show()
```



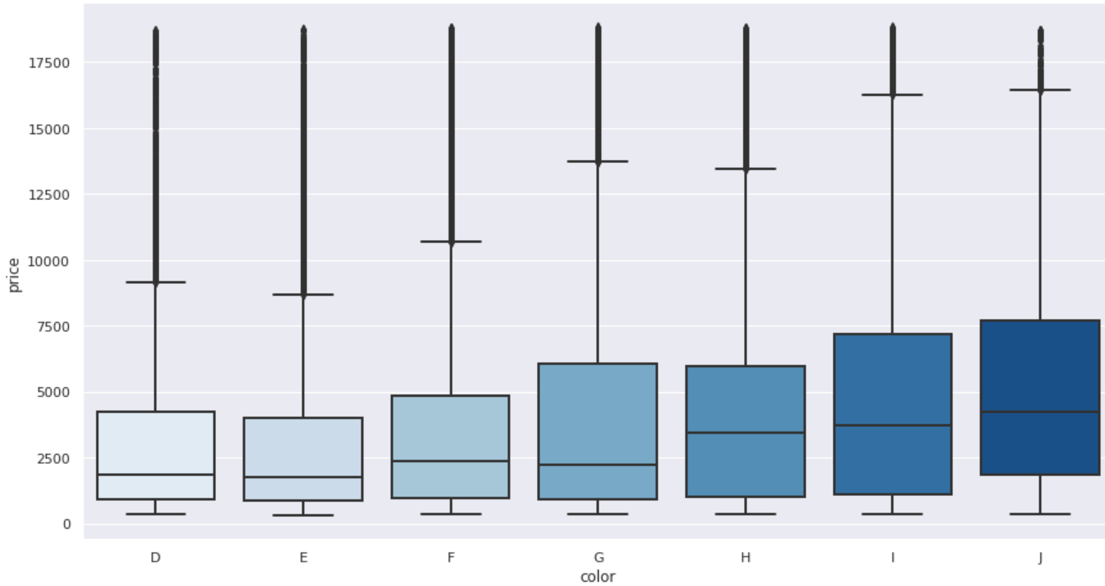
3.3.1 Boxplot of Cut, Color, Clarity

[102]:
```
%matplotlib inline

sns.set_theme(style="dark")
sns.set_theme(rc = {'figure.figsize':(15,8)})

sns.boxplot(x=df_diamonds["cut"],
            y=df_diamonds["price"],
            linewidth=2,
            order=['Ideal','Premium', 'Very Good', 'Good', 'Fair'],
            palette="Blues")

plt.show();
```

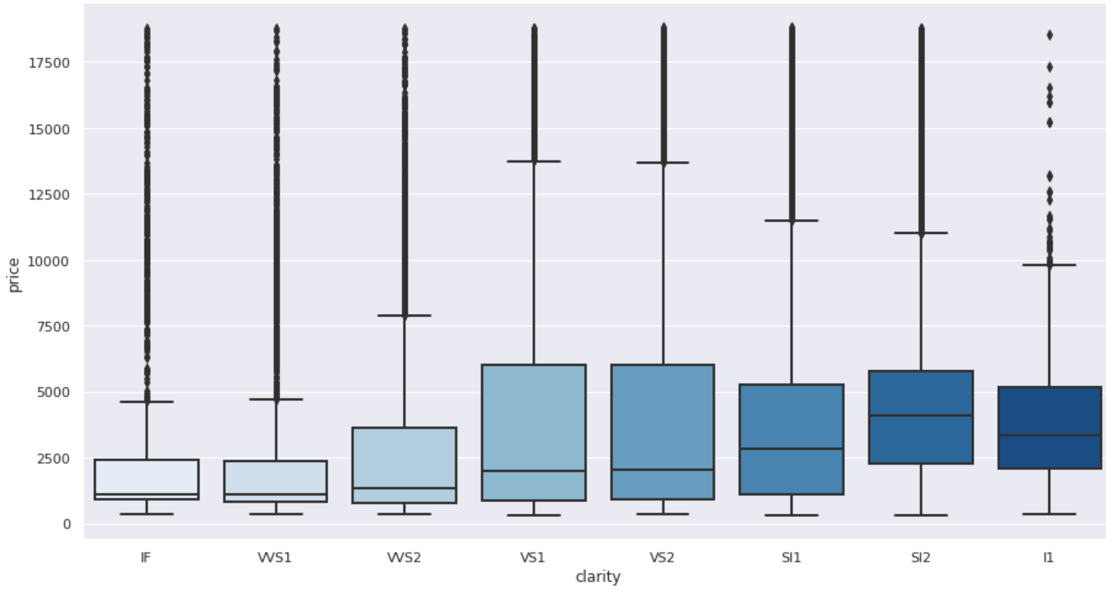


[103]:

```
%matplotlib inline

sns.set_theme(style="dark")
sns.set_theme(rc = {'figure.figsize':(15,8)})

sns.boxplot(x=df_diamonds["color"],
            y=df_diamonds["price"],
            order=['D', 'E', 'F', 'G', 'H', 'I', 'J'],
            linewidth=2,
            palette="Blues")

plt.show();
```



[104]:
```
%matplotlib inline

sns.set_theme(style="dark")
sns.set_theme(rc = {'figure.figsize':(15,8)})

sns.boxplot(x=df_diamonds["clarity"],
            y=df_diamonds["price"],
            order=['IF', 'VVS1', 'VVS2', 'VS1', 'VS2', 'SI1', 'SI2', 'I1'],
            linewidth=2,
            palette="Blues")
plt.show();
```



3.3.2 Ordinal Encoding

Creating a rank system for `cut`, `color`, and `clarity`.

[40]:
```
# Cut rank
cut_two = pd.DataFrame(df_diamonds['cut'])
df_diamonds['cut_rk']= cut_two.replace({'cut':{'Ideal' : 1, 'Premium' : 2,␣
↪'Very Good' : 3, 'Good' : 4, 'Fair' : 5}})
```

[41]:
```
# Color rank
color_two = pd.DataFrame(df_diamonds['color'])
df_diamonds['color_rk']= color_two.replace({'color':{'D' : 1, 'E' : 2, 'F' : 3,␣
↪'G' : 4, 'H' : 5, 'I' : 6, 'J' : 7}})
```

[42]:
```
# Clarity rank
clarity_two = pd.DataFrame(df_diamonds['clarity'])
df_diamonds['clarity_rk']= clarity_two.replace({'clarity':{'IF' : 1, 'VVS1' :␣
↪2, 'VVS2' : 3, 'VS1' : 4, 'VS2' : 5, 'SI1' : 6, 'SI2' : 7, 'I1' : 8}})
```

3.4 Correlation Heatmap

[22]:
```
import plotly.express as px
import plotly.graph_objects as go
import numpy as np

df_corr = df_diamonds.corr()
```

```python
fig = go.Figure()

fig.add_trace(
    go.Heatmap(
        x = df_corr.columns,
        y = df_corr.index,
        z = np.array(df_corr),
        colorscale='Viridis'
    )
)
```

[10]:
```python
df_diamonds.to_csv('diamonds_new.csv', index=False)
```

4 Models

---

[38]:
```python
import warnings
from sklearn.exceptions import ConvergenceWarning

warnings.simplefilter("ignore", ConvergenceWarning)
```

Slicing the data on for numeric columns and removing highly correlated x, y, and z.

[43]:
```python
df = df_diamonds.drop(df_diamonds.columns[[1, 2, 3, 7, 8, 9]], axis=1)
df.head()
```

[43]:

	carat	depth	table	price	volume	cut_rk	color_rk	clarity_rk
0	0.23	61.5	55.0	326	38.20	1	2	7
1	0.21	59.8	61.0	326	34.51	2	2	6
2	0.23	56.9	65.0	327	38.08	4	2	4
3	0.29	62.4	58.0	334	46.72	2	6	5
4	0.31	63.3	58.0	335	51.92	4	7	7

Scaling the features

[44]:
```python
from sklearn.preprocessing import StandardScaler

standard_scaler = StandardScaler()

df_diamonds_scaled = pd.DataFrame(standard_scaler.fit_transform(df),
                                  columns=df.columns)
df_diamonds_scaled.head()
```

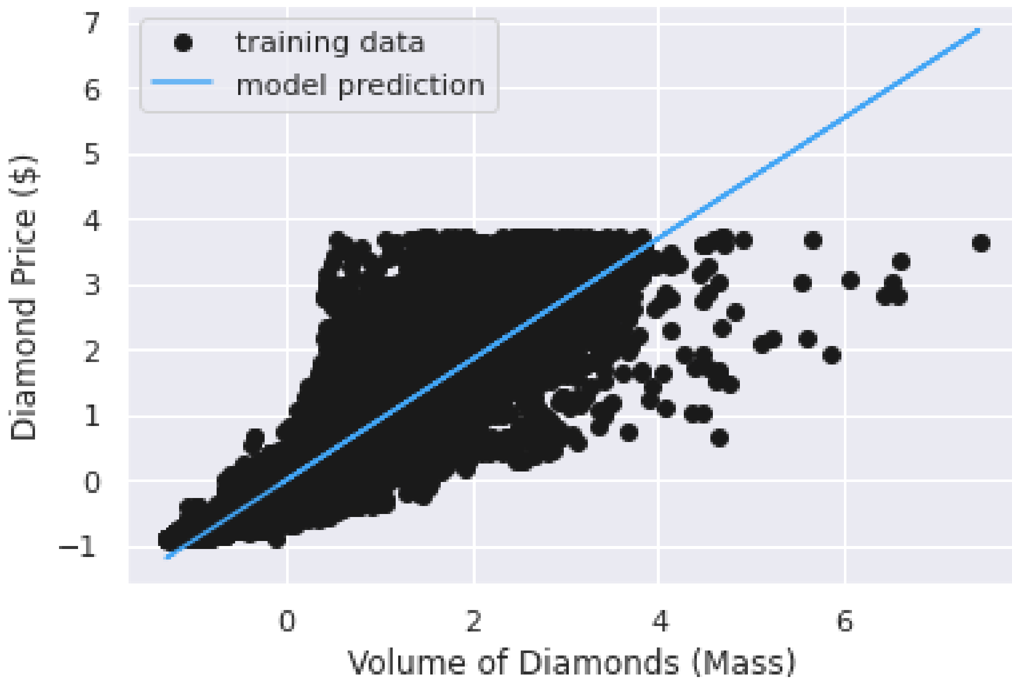
[44]:

```
      carat     depth     table     price    volume    cut_rk  color_rk  \
0 -1.198817 -0.175700 -1.105557 -0.904080 -1.198845 -0.981476 -0.936934
1 -1.241062 -1.373172  1.595652 -0.904080 -1.247144 -0.085459 -0.936934
```

```
2 -1.198817 -3.415919  3.396457 -0.903829 -1.200416  1.706574 -0.936934
3 -1.072082  0.458256  0.245047 -0.902073 -1.087325 -0.085459  1.414295
4 -1.029837  1.092211  0.245047 -0.901822 -1.019261  1.706574  2.002102

   clarity_rk
0    1.245681
1    0.638536
2   -0.575752
3    0.031392
4    1.245681
```

4.1 Linear Regression

[45]:
```
from sklearn.linear_model import LinearRegression

X = df_diamonds_scaled[['volume']]
y = df_diamonds_scaled['price']

lr = LinearRegression()
lr.fit(X, y)

y_pred = lr.predict(X)

plt.plot(X, y, 'o', color = 'k', label='training data')
plt.plot(X, y_pred, color='#42a5f5ff', label='model prediction')
plt.xlabel('Volume of Diamonds (Mass)')
plt.ylabel('Diamond Price ($)')
plt.legend();
```



[28]:
```
from sklearn import metrics

print("Mean absolute error (MAE):", metrics.mean_absolute_error(y, y_pred))
print("Mean squared error (MSE):", metrics.mean_squared_error(y, y_pred))
print("Root Mean squared error (RMSE):", np.sqrt(metrics.mean_squared_error(y,␣
 ↪y_pred)))
print("R^2:", metrics.r2_score(y, y_pred))
```

```
Mean absolute error (MAE): 0.2505992415063422
Mean squared error (MSE): 0.1465545262843114
Root Mean squared error (RMSE): 0.3828244065943437
R^2: 0.8534454737156886
```

4.2 Multiple Linear Regression

[46]:
```
features = ['carat', 'depth','table', 'volume', 'cut_rk', 'color_rk',␣
 ↪'clarity_rk']
X = df_diamonds_scaled[features]
y = df_diamonds_scaled['price']

lr_many_features = LinearRegression()
lr_many_features.fit(X, y);
```

```
[30]: print(('prediction = ' +
       '{} +\n'.format(lr_many_features.intercept_) +
       ' +\n'.join(['{} * {}'.format(n, f) for f, n in zip(features,␣
 ↪lr_many_features.coef_)])))
```

```
prediction = 2.589476119376005e-16 +
0.11935791009746609 * carat +
0.0036623212292045126 * depth +
-0.0006422984576668067 * table +
0.9229942229753453 * volume +
-0.031521976753149175 * cut_rk +
-0.13591598330479643 * color_rk +
-0.21507245231196492 * clarity_rk
```

```
[52]: print('Multiple features linear model R^2 on training data set: {}'.
 ↪format(lr_many_features.score(X, y)))
```

```
Multiple features linear model R^2 on training data set: 0.9059466891034228
```

4.3 Random Forest

```
[165]: 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=321)
```

```
[166]: from sklearn.ensemble import RandomForestRegressor

forest  = RandomForestRegressor()
model = forest.fit(X_train,y_train)
y_pred = model.predict(X_test)
```

```
[167]: from sklearn.metrics import mean_squared_error

print("RMSE: {}".format(np.sqrt(mean_squared_error((y_test),(y_pred)))))
print("R2  : {}".format(np.sqrt(metrics.r2_score((y_test),(y_pred)))))
```

```
RMSE: 0.13191401153332313
R2  : 0.9912175810216939
```

```
[168]: n_estimators = [int(x) for x in np.linspace(10,200,10)]
max_depth = [int(x) for x in np.linspace(10,100,10)]
min_samples_split = [2,3,4,5,10]
min_samples_leaf = [1,2,4,10,15,20]
random_grid = {'n_estimators':n_estimators,'max_depth':max_depth,
               'min_samples_split':min_samples_split,'min_samples_leaf':
 ↪min_samples_leaf}
```

```
random_grid
```

[168]:
```
{'max_depth': [10, 20, 30, 40, 50, 60, 70, 80, 90, 100],
 'min_samples_leaf': [1, 2, 4, 10, 15, 20],
 'min_samples_split': [2, 3, 4, 5, 10],
 'n_estimators': [10, 31, 52, 73, 94, 115, 136, 157, 178, 200]}
```

[169]:
```
from sklearn.model_selection import RandomizedSearchCV

rf = RandomForestRegressor()
rf_random = RandomizedSearchCV(estimator=rf,
                               param_distributions=random_grid,
                               cv = 3)

rf_random.fit(X_train,y_train)
y_pred = rf_random.predict(X_test)

print("RMSE: {}".format(np.sqrt(mean_squared_error((y_test),(y_pred)))))
print("R2  : {}".format(np.sqrt(metrics.r2_score((y_test),(y_pred)))))
```

```
RMSE: 0.13224621848979198
R2  : 0.9911730935294353
```

[170]:
```
rf_random.best_params_
```

[170]:
```
{'max_depth': 100,
 'min_samples_leaf': 2,
 'min_samples_split': 2,
 'n_estimators': 178}
```

[171]:
```
rf = RandomForestRegressor(max_depth = 100,
                           min_samples_leaf = 2,
                           min_samples_split = 2,
                           n_estimators = 178)
rf.fit(X_train,y_train)
y_pred = rf.predict(X_test)

print("RMSE: {}".format(np.sqrt(mean_squared_error((y_test),(y_pred)))))
print("R2  : {}".format(np.sqrt(metrics.r2_score((y_test),(y_pred)))))
```

```
RMSE: 0.1320848174143195
R2  : 0.9911947217783478
```

4.4 AutoML using H2O

[ ]:
```
!apt-get install openjdk-8-jdk
```

[ ]:
```
!pip install H2O
```

[53]:
```
import h2o
h2o.init()
```

```
Checking whether there is an H2O instance running at http://localhost:54321
… not found.
Attempting to start a local H2O server…
  Java Version: openjdk version "11.0.15" 2022-04-19; OpenJDK Runtime
Environment (build 11.0.15+10-Ubuntu-0ubuntu0.18.04.1); OpenJDK 64-Bit Server VM
(build 11.0.15+10-Ubuntu-0ubuntu0.18.04.1, mixed mode)
  Starting server from /usr/local/lib/python3.7/dist-
packages/h2o/backend/bin/h2o.jar
  Ice root: /tmp/tmpjj_kvf9p
  JVM stdout: /tmp/tmpjj_kvf9p/h2o_unknownUser_started_from_python.out
  JVM stderr: /tmp/tmpjj_kvf9p/h2o_unknownUser_started_from_python.err
  Server is running at http://127.0.0.1:54321
Connecting to H2O server at http://127.0.0.1:54321 … successful.

--------------------------  ----------------------------------
H2O_cluster_uptime:         02 secs
H2O_cluster_timezone:       Etc/UTC
H2O_data_parsing_timezone:  UTC
H2O_cluster_version:        3.36.1.1
H2O_cluster_version_age:    1 month and 11 days
H2O_cluster_name:           H2O_from_python_unknownUser_inkqa6
H2O_cluster_total_nodes:    1
H2O_cluster_free_memory:    3.172 Gb
H2O_cluster_total_cores:    2
H2O_cluster_allowed_cores:  2
H2O_cluster_status:         locked, healthy
H2O_connection_url:         http://127.0.0.1:54321
H2O_connection_proxy:       {"http": null, "https": null}
H2O_internal_security:      False
Python_version:             3.7.13 final
--------------------------  ----------------------------------
```

[2]:
```
diamonds = h2o.import_file("/content/diamonds_new.csv")
```

```
Parse progress:
|                                   | (done) 100%
```

[82]:
```
diamonds.describe()
```

```
Rows:53902
Cols:14
```

[3]:

```python
diamonds = diamonds[:, ["carat", "depth", "table", "price", "volume",␣
 ↪"cut_rk",         "color_rk", "clarity_rk"]]
print(diamonds)
```

4.4.1 GBM Model

[6]:

```python
from h2o.estimators.gbm import H2OGradientBoostingEstimator

# set the predictor names and the response column name
predictors = ["carat",         "depth",         "table",         "volume",␣
 ↪"cut_rk",         "color_rk",         "clarity_rk"]

response = "price"

# split into train and validation sets
train, valid = diamonds.split_frame(ratios = [.8], seed = 1234)

# train a GBM model
diamonds_gbm = H2OGradientBoostingEstimator(distribution = "poisson", seed =␣
 ↪1234)
diamonds_gbm.train(x = predictors,
               y = response,
               training_frame = train,
               validation_frame = valid)

# retrieve the model performance
perf = diamonds_gbm.model_performance(valid)
perf
```

```
gbm Model Build progress:
|                             | (done) 100%

ModelMetricsRegression: gbm
** Reported on test data. **

MSE: 297175.9346014002
RMSE: 545.1384545245365
MAE: 298.17434419493014
RMSLE: 0.12287040514285516
Mean Residual Deviance: -59961.81794308857
```

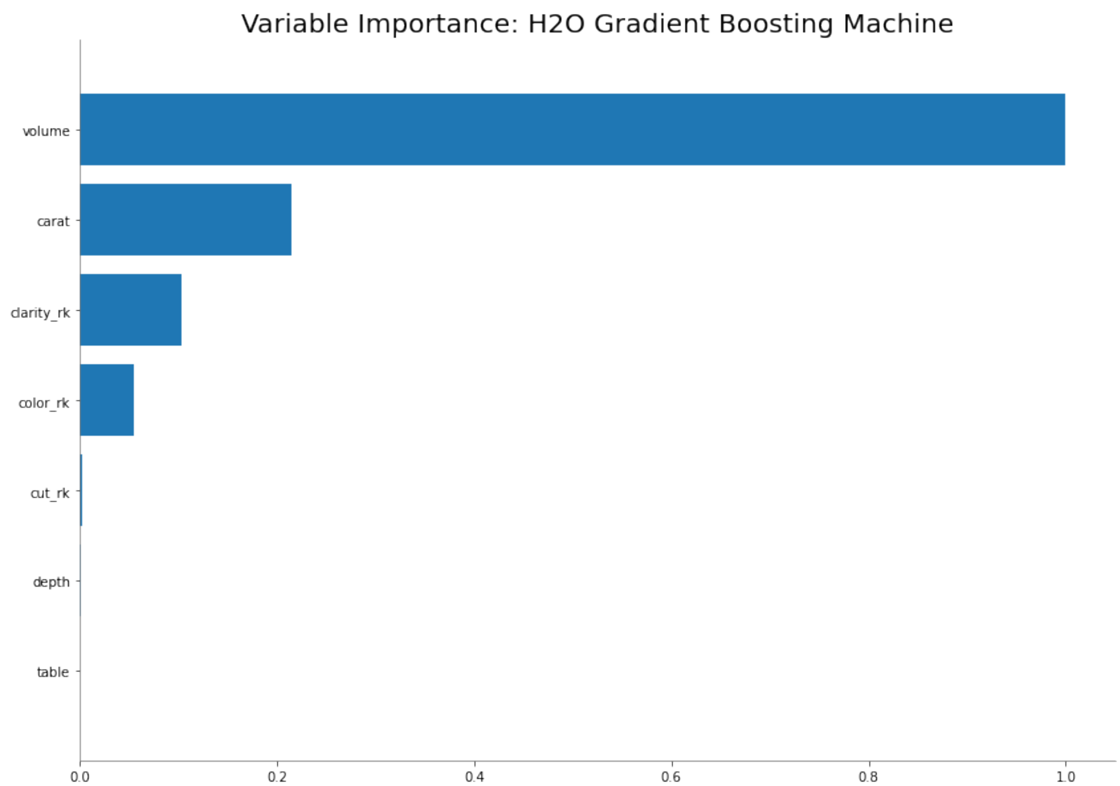
[6]:

[7]:
```
print('R^2:', diamonds_gbm.r2())
print('R^2 on validation data:', diamonds_gbm.r2(valid=True))
```

```
R^2: 0.9814291623069304
R^2 on validation data: 0.9812236569623808
```

[8]:
```
import matplotlib.pyplot as plt
%matplotlib inline

import warnings
import matplotlib.cbook
warnings.filterwarnings("ignore", category = matplotlib.cbook.mplDeprecation)
```

[9]:
```
diamonds_gbm.varimp_plot();
```




```
<Figure size 432x288 with 0 Axes>
```

4.4.2 AutoML Search

[10]:
```
from h2o.automl import H2OAutoML

y = "price"

splits = diamonds.split_frame(ratios = [0.8], seed = 1)
train = splits[0]
test = splits[1]
```

[11]:
```
aml = H2OAutoML(max_runtime_secs = 60, seed = 1, project_name =␣
 ↪"diamonds_lb_frame")
aml.train(y = y, training_frame = train, leaderboard_frame = test)
```

```
AutoML progress:
|                                  | (done) 100%
Model Details
=============
H2OStackedEnsembleEstimator :  Stacked Ensemble
Model Key:  StackedEnsemble_BestOfFamily_2_AutoML_1_20220524_162247

No model summary for this model

ModelMetricsRegressionGLM: stackedensemble
** Reported on train data. **

MSE: 161938.39018806818
RMSE: 402.4156932676311
MAE: 220.7877598599966
RMSLE: 0.08778344307949035
R^2: 0.9897187253749596
Mean Residual Deviance: 161938.39018806818
Null degrees of freedom: 10063
Residual degrees of freedom: 10060
Null deviance: 158518164125.60925
Residual deviance: 1629747958.852718
AIC: 149287.78529932746

ModelMetricsRegressionGLM: stackedensemble
** Reported on validation data. **

MSE: 292904.99543856416
RMSE: 541.2069802197345
MAE: 278.4709657509555
RMSLE: 0.10112574270266088
R^2: 0.982358202719312
Mean Residual Deviance: 292904.99543856416
Null degrees of freedom: 4424
```

```
Residual degrees of freedom: 4421
Null deviance: 73479405051.87427
Residual deviance: 1296104604.8156464
AIC: 68267.7518947419
```

[11]:

[12]:
```
aml2 = H2OAutoML(max_runtime_secs = 60, seed = 1, project_name =␣
 ↪"diamonds_full_data")
aml2.train(y = y, training_frame = diamonds)
```

```
AutoML progress:
|                                   | (done) 100%
Model Details
=============
H2OStackedEnsembleEstimator :  Stacked Ensemble
Model Key:  StackedEnsemble_BestOfFamily_2_AutoML_2_20220524_162357

No model summary for this model

ModelMetricsRegressionGLM: stackedensemble
** Reported on train data. **

MSE: 138826.82775252234
RMSE: 372.59472319468284
MAE: 204.39755930071115
RMSLE: 0.08147085766295006
R^2: 0.9913322116029226
Mean Residual Deviance: 138826.82775252234
Null degrees of freedom: 10060
Residual degrees of freedom: 10057
Null deviance: 161145712751.90436
Residual deviance: 1396736714.0181272
AIC: 147694.0070222262

ModelMetricsRegressionGLM: stackedensemble
** Reported on validation data. **

MSE: 282593.98661155737
RMSE: 531.5956984509538
MAE: 271.81878422685537
RMSLE: 0.09838611409008427
R^2: 0.9828973674669435
Mean Residual Deviance: 282593.98661155737
Null degrees of freedom: 5459
Residual degrees of freedom: 5456
Null deviance: 90264416715.4349
Residual deviance: 1542963166.8991032
```

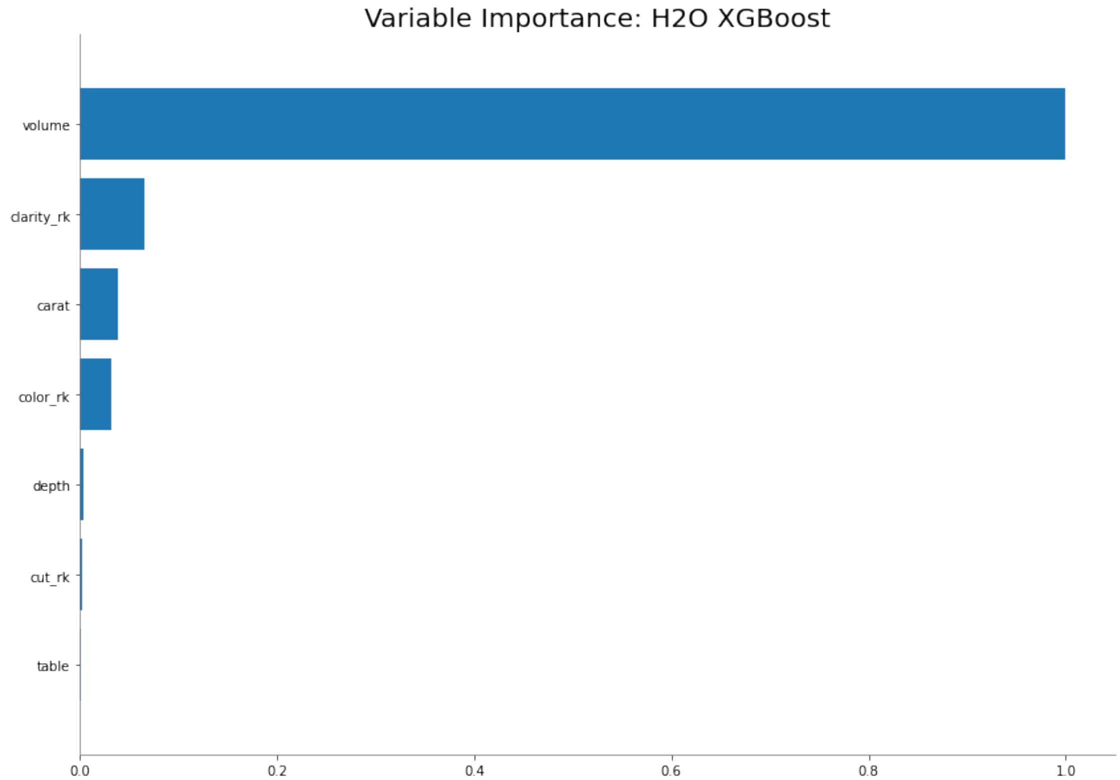
```
AIC: 84037.45370992915
```

[12]:

[13]:
```
aml.leaderboard.head()
```

[13]:

[18]:
```
best_model_aml = h2o.get_model(aml.leaderboard[9,'model_id'])

best_model_aml.varimp_plot();
```




```
<Figure size 432x288 with 0 Axes>
```

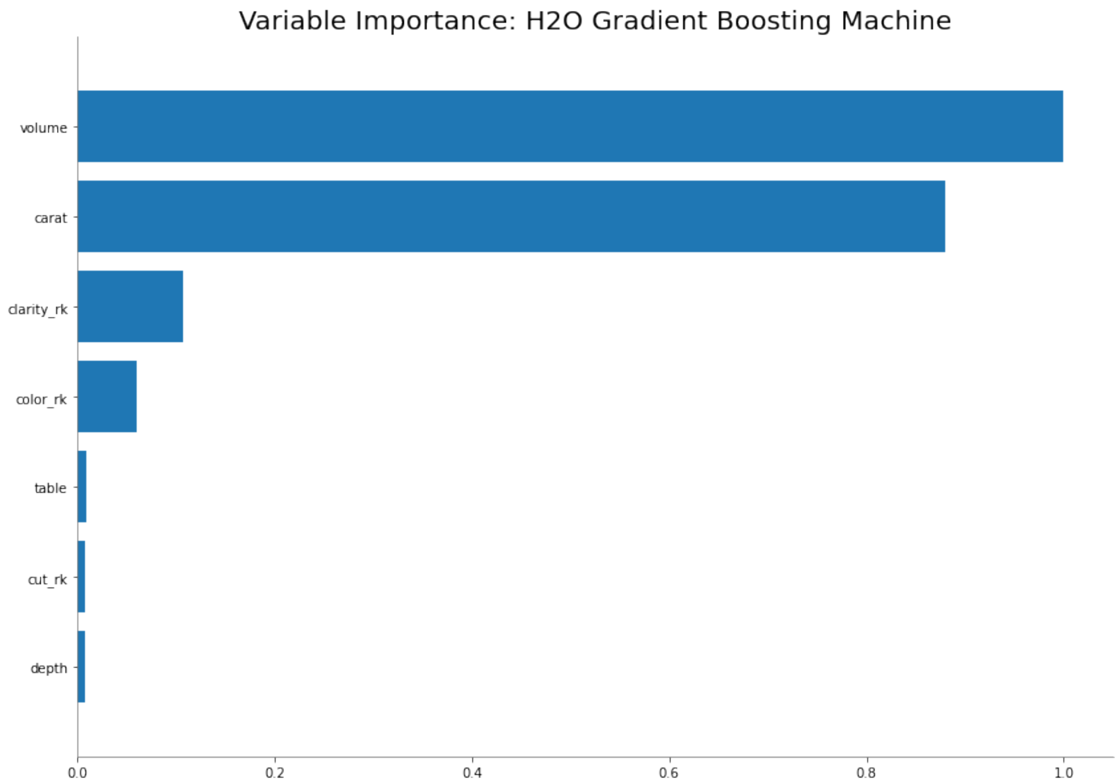
[56]:
```
print('XGBoost_3_AutoML R^2:', best_model_aml.r2())
print('XGBoost_3_AutoML R^2 on validation data:', best_model_aml.r2(valid=True))
```

```
XGBoost_3_AutoML R^2: 0.9870193028366475
XGBoost_3_AutoML R^2 on validation data: 0.9802658257424989
```

[16]:
```
aml2.leaderboard.head()
```

[16]:

[17]:
```
best_model_aml2 = h2o.get_model(aml2.leaderboard[4,'model_id'])

best_model_aml2.varimp_plot();
```




```
<Figure size 432x288 with 0 Axes>
```

[55]:
```
print('GBM_2_AutoML R^2:', best_model_aml2.r2())
print('GBM_2_AutoML R^2 on validation data:', best_model_aml2.r2(valid=True))
```

```
GBM_2_AutoML R^2: 0.9861479432667472
GBM_2_AutoML R^2 on validation data: 0.9824892967917611
```

[23]:
```
h2o.cluster().shutdown()
```

```
H2O session _sid_8a0f closed.
```

5 Conclusion

- An analysis was performed using the classic `Diamonds` dataset, in which the objective was determining how to best price diamonds for brokers.
- Through exploration and visualization of the data, observed small generalized patterns, accompanied with not normal distributions.
- The clearest indication is the combination of best `color` and best `clarity` diamonds are priced significantly higher.

- After scaling and slicing, the baseline linear regression captured a modest 90% accuracy, while the Random Forest model scored the highest with 99.11%.
- Of the 4 C's `carat`'s coefficient level in the multiple linear regression, and among the variable importance compared favorable against the other 4 C's.

[ ]:
```

```