diamonds-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 value of diamonds.

0.3 Value Proposition

Give diamond brokers insights into how diamonds are priced. The objective is to provide a tool such as a dashboard that will give greater understanding of how diamonds may be priced.

0.3.1 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?

0.3.2 Solutions

1. There appears to be an inverse pricing pattern with the pricing of diamonds with the 4 C's. When comparing the relationship of best `color` with the best `clarity` diamonds, we see that the average `price` ($8,307) significantly higher to the rest of the pivot table.

Suggestable patterns include: * The inverse pricing pattern is first observed with the average `price` of diamonds by `color` going from lowest to highest, similarities with `cut` and `clarity` continue as well. * The inverse pricing is due the `carat` size increase from best to worst diamonds across `cut`, `color`, and `clarity`. * The worst `cut`, `color`, and `clarity` diamonds have the highest prices. * The best `cut`, `color`, and `clarity` diamonds are among the smallest `carat` in the dataset.

2. There is correlations among the features, and as a whole the data demostrates not normal distributions.
3. Addressed the `cut`, `color`, and `clarity` categorical variables with ordinal encoding of 1-5 (`cut`), 1-7 (`color`), and 1-8 (`clarity`) 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.

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

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

```
[ ]:    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)
```

Almost 54,000 rows in the dataset.

```
[ ]: 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
```

Consolidating `x`, `y`, and `z` into `volume`.

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

[ ]:

	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

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

[ ]:
```
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

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

[ ]:
```
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

[ ]:
```
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
```

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

2 Exploration

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

[ ]:
```
              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
```

Looking at the data we see that the average `carat` size is 0.8 and the largest `carat` is 4.5. The average `price` per diamond is almost $4,000, while the most expensive diamond is priced at $18,823.

2.0.1 Exploring the Categorical Variables

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

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

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

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

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

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

[ ]:
```
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

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

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

According to this printout, the total number of diamonds decrease from best (Ideal) to worst (Fair).

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

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

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

```
[ ]: SI1     13058
     VS2     12250
     SI2      9183
     VS1      8165
     VVS2     5066
     VVS1     3654
     IF       1790
     I1        736
     Name: clarity, dtype: int64
```

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

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

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

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

Average price for cut, color, and clarity

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

```
[ ]:          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` (Ideal) diamonds have the lowest average price.

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

```
[ ]:   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` (J) diamonds have the highest average price.

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

[ ]:
```
  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
```

2.1 Comparing the 4'C's with Pivot Tables

Comparing `cut`, `color`, and `clarity` variables with `price` and `carat` in pivot tables.

2.1.1 Tables of `Cut` and `Clarity`

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

[ ]:
```
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
```

We see that the best `cut` (**Ideal**) and the best `color` (**IF**) diamonds are priced at the third lowest across the entire table.

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

```
[ ]: clarity          IF      VVS1      VVS2       VS1       VS2       SI1  \
     cut
     Ideal      0.455041  0.495960  0.586213  0.674453  0.670213  0.801575
     Premium    0.603478  0.533740  0.654724  0.793308  0.833421  0.907865
     Very Good  0.618769  0.494588  0.566389  0.733683  0.811108  0.845978
     Good       0.616338  0.502312  0.614930  0.757685  0.850787  0.830397
     Fair       0.474444  0.664706  0.691594  0.878284  0.887791  0.962395

     clarity         SI2        I1
     cut
     Ideal      1.007901  1.222671
     Premium    1.143252  1.289212
     Very Good  1.064338  1.281905
     Good       1.034193  1.199895
     Fair       1.204688  1.345048
```

This table indicates that `carat`'s are increasing from the best `clarity` to the worst `clarity` diamonds. What's interesting is we see this pattern across all `cut` diamonds.

2.1.2 Tables of `cut` and `color`

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

```
[ ]: 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
```

An inverse pricing pattern is emerging with the best `cut` and best `color` diamonds being priced the lowest. As we see there is an increase in price almost among all the features going from best to worst (one would expect to see the opposite).

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

[ ]:
```
color            D         E         F         G         H         I  \
cut
Ideal     0.565766  0.578419  0.655612  0.700447  0.799329  0.912673
Premium   0.721248  0.717745  0.826957  0.841250  1.014087  1.144163
Very Good 0.696424  0.676547  0.740961  0.766799  0.915902  1.046952
Good      0.744517  0.745134  0.776075  0.847906  0.914729  1.057222
Fair      0.920123  0.859050  0.901452  1.024355  1.219175  1.198057

color            J
cut
Ideal     1.063564
Premium   1.293094
Very Good 1.133215
Good      1.099544
Fair      1.310085
```

As we see that with the best `cut` (**Ideal**) and the best `color` (**D**) diamonds have an average price lower than the worst `cut` diamonds. This is due to the best `cut` and `color` diamonds are around a half (0.5) carat, while the worst `cut` (**Fair**) and the worst `color` (**J**) diamonds have the highest average carat at **1.31**.

2.1.3 Tables of `color` and `clarity`

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

[ ]:
```
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. Beyond this observation we begin to see that average `price` are among the highest with **SI2** diamonds.

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

[ ]:
```
clarity        IF      VVS1      VVS2       VS1       VS2       SI1       SI2  \
color
D        0.698767  0.475976  0.528590  0.583021  0.558321  0.668401  0.872168
E        0.506266  0.425808  0.475621  0.573732  0.592306  0.711303  0.921576
F        0.460909  0.495327  0.589877  0.681723  0.696311  0.800155  0.987089
G        0.491821  0.536116  0.655107  0.728062  0.797385  0.819534  1.066369
H        0.505385  0.480496  0.582089  0.753647  0.897959  0.990413  1.239353
I        0.515944  0.554930  0.678411  0.902934  1.063020  1.075731  1.395055
J        0.703922  0.843243  1.028473  1.017435  1.134712  1.172827  1.424259

clarity        I1
color
D        1.117143
E        1.106931
F        1.085594
G        1.221419
H        1.440994
I        1.439239
J        1.684082
```

The trend continues with the increase of `carat` size from best to worst diamonds. Except when compared with the best `color` and the best `clarity` diamonds, the `carat` size among the best `clarity` (**IF**) diamonds are almost equal to the highest `carat` across the `color` diamonds. In other words, the best `color` (**D**) diamond is only a fraction less than the largest diamond among the best `clarity` (**IF**) category.

3 Visualization

3.1 Barplots

3.1.1 Barplot of Cut

[ ]:
```
import plotly.express as px

clr = ['rgb(115, 185, 238)', 'rgb(84, 148, 218)', 'rgb(51, 115, 196)', 'rgb(23,␣
↪80, 172)', 'rgb(0, 51, 150)', 'rgb(0, 26, 80)']

fig = px.bar(cut_avg,
             x='cut',
             y='price',
             color='cut',
             color_discrete_sequence=clr)
```

```
fig.update_layout(showlegend=False)
fig.show()
```

3.1.2 Barplot of Color

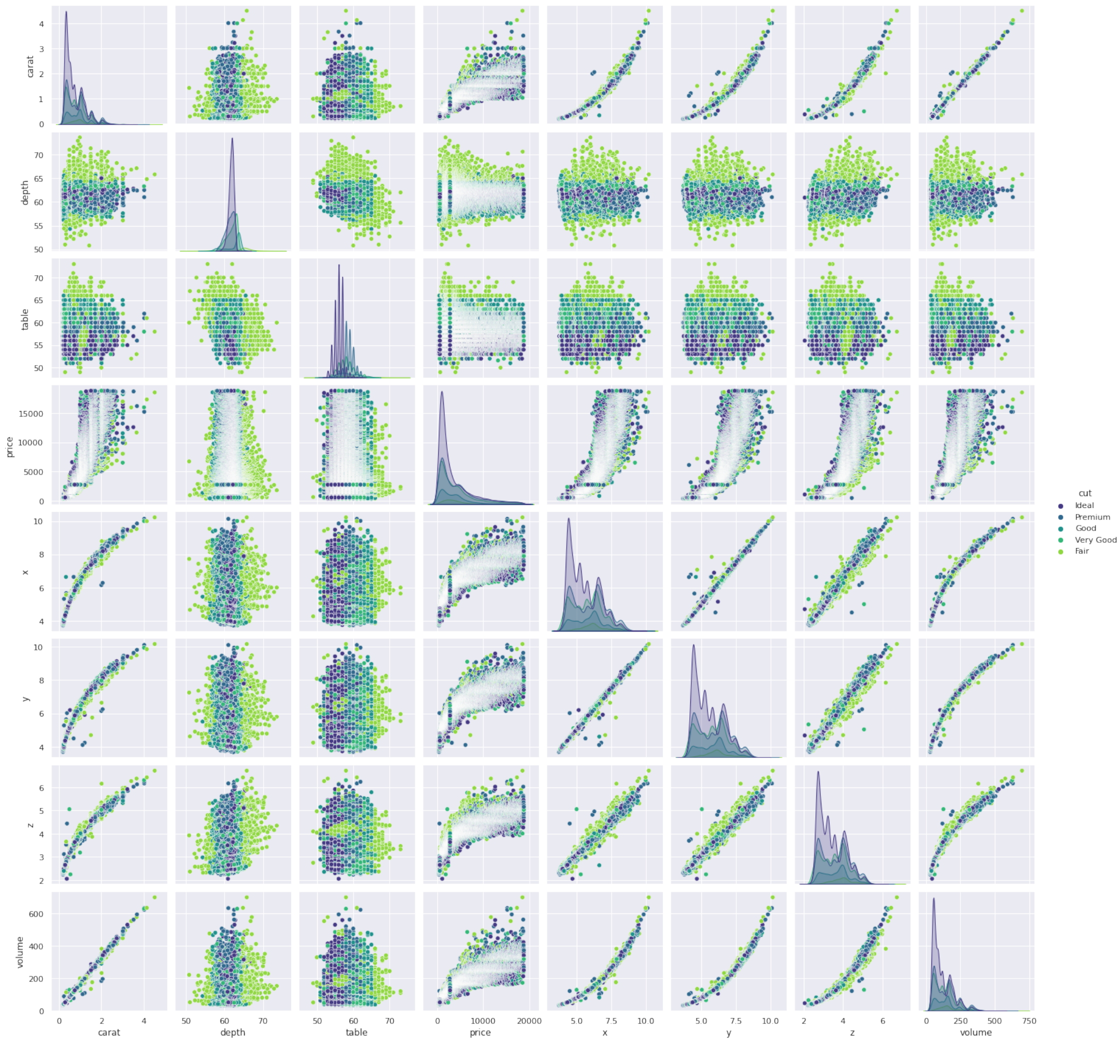
[ ]:
```
import plotly.express as px

color = ['rgb(134, 206, 250)', 'rgb(115, 185, 238)', 'rgb(84, 148, 218)',␣
↪'rgb(51, 115, 196)', 'rgb(23, 80, 172)', 'rgb(0, 51, 150)', 'rgb(0, 26, 80)']

fig = px.bar(color_avg,
             x='color',
             y='price',
             color='color',
             color_discrete_sequence=color)

fig.update_layout(showlegend=False)
fig.show()
```

3.1.3 Barplot of Clarity

[ ]:
```
import plotly.express as px

colors = ['rgb(134, 206, 250)', 'rgb(115, 185, 238)', 'rgb(61, 136, 238)',␣
↪'rgb(84, 148, 218)', 'rgb(51, 115, 196)', 'rgb(23, 80, 172)', 'rgb(0, 51,␣
↪150)', 'rgb(0, 26, 80)']

fig = px.bar(clarity_avg,
             x='clarity',
             y='price',
             color='clarity',
             color_discrete_sequence=colors)

fig.update_layout(showlegend=False)
fig.show()
```

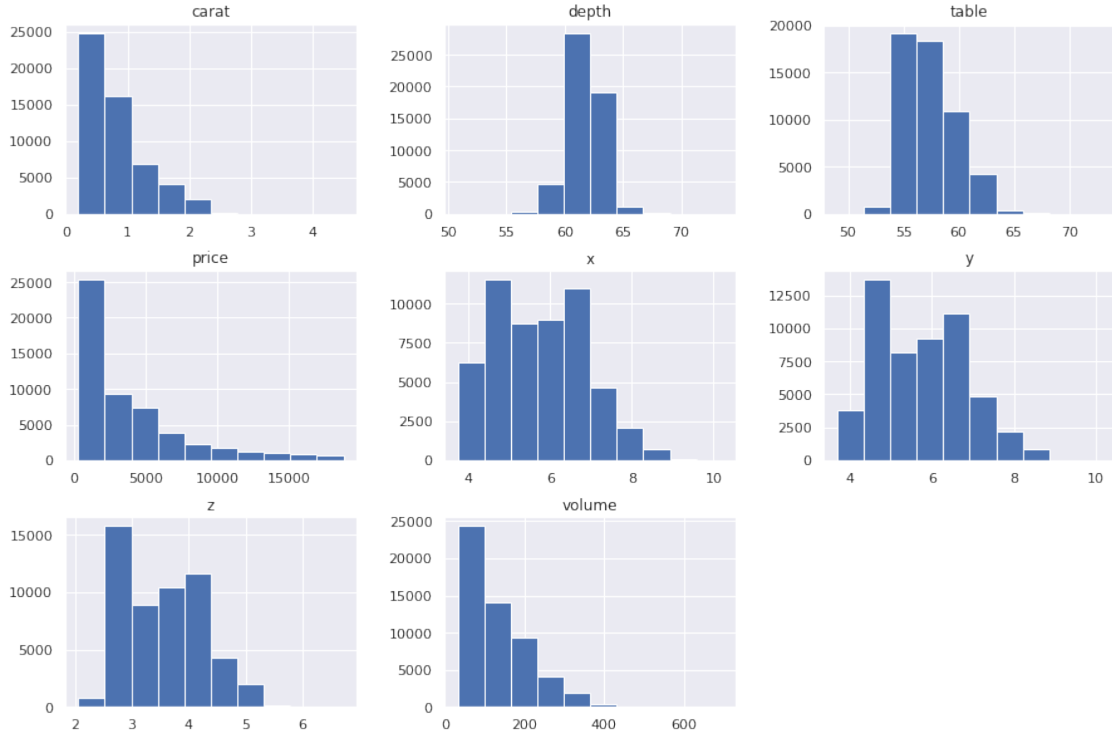
3.2 Pairplot

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



3.3 Historgram

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



3.4 Histogram carat

Taking a closer look at `carat`'s distribution.

[ ]:
```
import plotly.express as px

fig = px.histogram(df_diamonds,
                   x="carat",
                   marginal="violin",
                   color_discrete_sequence=['rgb(115, 185, 238)'],
                   hover_data=df_diamonds.columns)
fig.show()
```

Notice that the `carat`'s are distributed in increments?

Normalizing `carat`

[ ]:
```
import plotly.express as px

fig = px.histogram(df_diamonds,
                   x="carat",
                   histnorm='probability',
                   color_discrete_sequence=['rgb(115, 185, 238)']
                   )
```

```
fig.show()
```

The highest probability of `carat`'s fall between 0.3 and 1.1

3.5 Boxplots

```
[ ]: from plotly.subplots import make_subplots
import plotly.graph_objects as go
import plotly.express as px

vars = ['carat', 'depth', 'table', 'price', 'x', 'y', 'z', 'volume']
fig = make_subplots(rows=1, cols=len(vars))
for i, var in enumerate(vars):
    fig.add_trace(
        go.Box(y=df_diamonds[var],
        name=var),
        row=1, col=i+1
    )

fig.update_layout(width=1100, height=600)
fig.update_traces(showlegend=False)
```

3.5.1 Boxplot of Cut

```
[ ]: import plotly.express as px

fig = px.box(data_frame = df_diamonds,
             x = 'cut',
             y = 'price',
             color='cut',
             category_orders={"cut": ["Ideal", "Premium", "Very Good", "Good",␣
 ↪"Fair"]},
             color_discrete_sequence=clr)

fig.update_layout(showlegend=False)
fig.show()
```

3.5.2 Boxplot of Color

```
[ ]: import plotly.express as px

fig = px.box(data_frame = df_diamonds,
             x = 'color',
             y = 'price',
             color='color',
             category_orders={"color": ["D", "E", "F", "G", "H", "I", "J"]},
```

```
             color_discrete_sequence=color)

fig.update_layout(showlegend=False)
fig.show()
```

3.5.3 Boxplot of Clarity

[ ]:
```
import plotly.express as px

fig = px.box(data_frame = df_diamonds,
             x = 'clarity',
             y = 'price',
             color='clarity',
             category_orders={"clarity": ["IF", "VVS1", "VVS2", "VS1", "VS2",␣
 ↪"SI1", "SI2", "I1"]},
             color_discrete_sequence=colors)

fig.update_layout(showlegend=False)
fig.show()
```

It's unique that VS1 and VS2 have the same exact inner quartile ranges considering they may be priced thousands of dollars differently.

3.5.4 Ordinal Encoding

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

[ ]:
```
# 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}})
```

[ ]:
```
# 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}})
```

[ ]:
```
# 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}})
```

3.5.5 Examining the Ranks of cut, color, and clarity

[ ]:
```
from plotly.subplots import make_subplots
import plotly.graph_objects as go
import plotly.express as px

vars = ['cut_rk', 'color_rk', 'clarity_rk']
fig = make_subplots(rows=1, cols=len(vars))
for i, var in enumerate(vars):
    fig.add_trace(
        go.Box(y=df_diamonds[var],
        name=var),
        row=1, col=i+1
    )
#width=1100, height=600
fig.update_layout()
fig.update_traces(showlegend=False)
```

3.6 Correlation Heatmap

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

df_corr = df_diamonds.corr()

fig = go.Figure()

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

[ ]:
```
df_diamonds.to_csv('diamonds-new.csv', index=False)
```

4 Models

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

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

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

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

[ ]:
```
       carat  depth  table  price  volume  cut_rk  color_rk  clarity_rk
43633   0.43   61.8   55.0   1433   71.39       1         4           1
32320   0.30   60.4   60.0    789   48.71       2         5           1
40084   0.33   62.1   55.0   1114   53.85       1         5           1
49503   0.55   61.5   55.0   2120   90.26       1         5           1
53911   0.57   59.8   60.0   2753   94.36       2         2           1
```

With `price` reaching as high as $18,823 and `carat` as low as 0.21, we will need to scale the features.

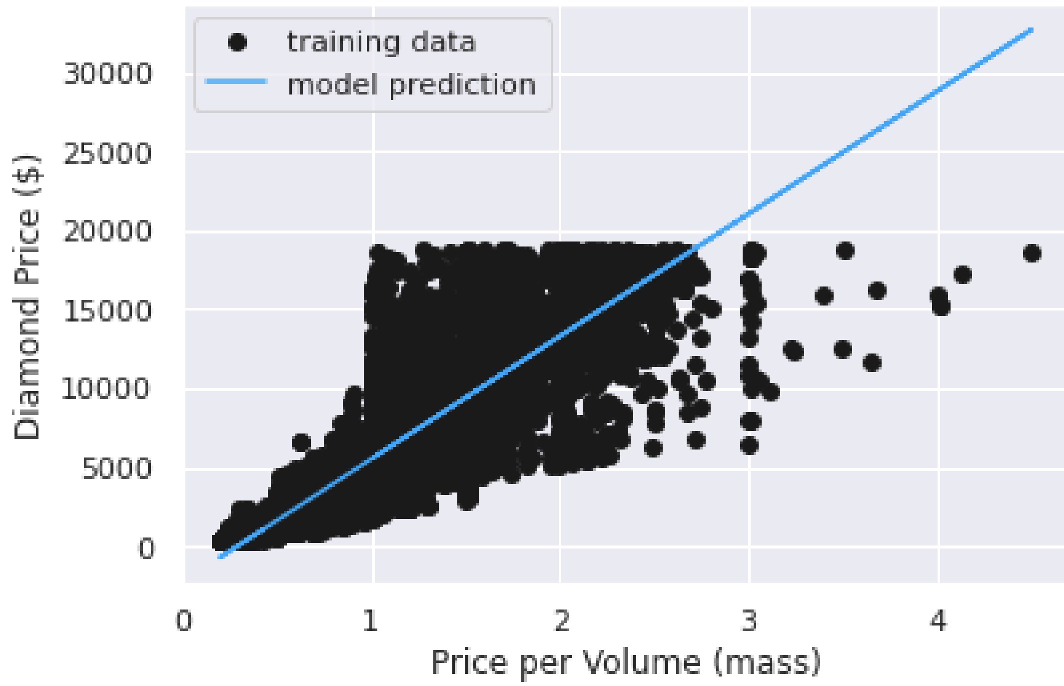
[ ]:
```
from sklearn.preprocessing import StandardScaler

standard_scaler = StandardScaler()

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

[ ]:
```
      carat     depth     table     price    volume    cut_rk  color_rk  \
0 -0.776367  0.035618 -1.105557 -0.626417 -0.764414 -0.981476  0.238680
1 -1.050960 -0.950535  1.145450 -0.787948 -1.061278 -0.085459  0.826487
2 -0.987592  0.246937 -1.105557 -0.706430 -0.993999 -0.981476  0.826487
3 -0.522897 -0.175700 -1.105557 -0.454100 -0.517421 -0.981476  0.826487
4 -0.480652 -1.373172  1.145450 -0.295328 -0.463755 -0.085459 -0.936934

   clarity_rk
0   -2.397184
1   -2.397184
2   -2.397184
3   -2.397184
4   -2.397184
```

4.1 Linear Regression

[ ]:
```
from sklearn.linear_model import LinearRegression
from numpy import *

X = df_diamonds[['carat']]
y = df_diamonds['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('Price per Volume (mass)')
plt.ylabel('Diamond Price ($)')
plt.legend();
```



[ ]:
```
from sklearn import metrics

# Using scaled features
X = df_diamonds_scaled[['carat']]
y = df_diamonds_scaled['price']

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

y_pred = lr.predict(X)

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): 0.252631690580942
Mean squared error (MSE): 0.15029971977032106
Root Mean squared error (RMSE): 0.3876850780857074
R^2: 0.8497002802296789
```

4.2 Multiple Linear Regression

```
[ ]: 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);
```

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

```
prediction = -1.0455101613761209e-16 +
0.11935791009746087 * carat +
0.0036623212292048457 * depth +
-0.0006422984576671814 * table +
0.9229942229753505 * volume +
-0.03152197675314965 * cut_rk +
-0.1359159833047961 * color_rk +
-0.21507245231196492 * clarity_rk
```

```
[ ]: 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

```
[ ]: 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)
```

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

     forest  = RandomForestRegressor(random_state = random.seed(1234))
     model = forest.fit(X_train,y_train)
     y_pred = model.predict(X_test)
```

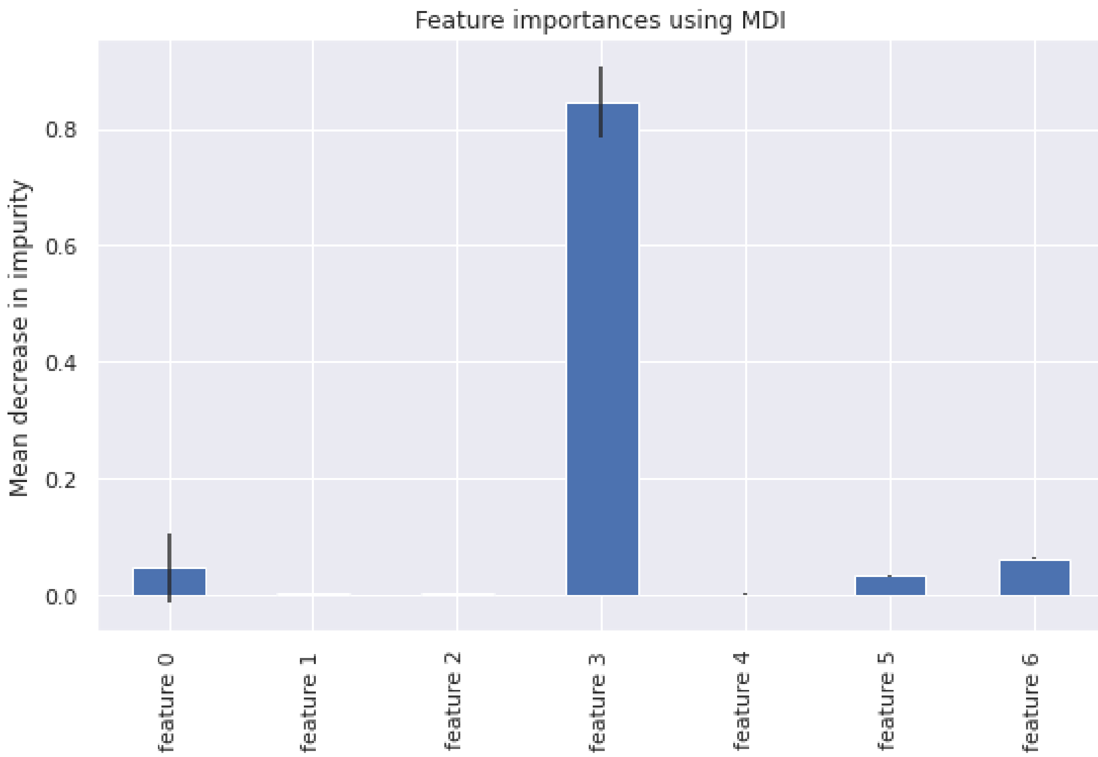
[ ]:
```
from sklearn.metrics import mean_squared_error

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: 0.13225034160421884
R2  : 0.9911725406670384
```

[ ]:
```
import time

start_time = time.time()
importances = forest.feature_importances_
std = np.std([tree.feature_importances_ for tree in forest.estimators_], axis=0)
elapsed_time = time.time() - start_time

print(f"Elapsed time to compute the importances: {elapsed_time:.3f} seconds")
```

```
Elapsed time to compute the importances: 0.470 seconds
```

[ ]:
```
plt.rcParams["figure.figsize"] = (8,5.5)

feature_names = [f"feature {i}" for i in range(X.shape[1])]
forest_importances = pd.Series(importances, index=feature_names)

fig, ax = plt.subplots()
forest_importances.plot.bar(yerr=std, ax=ax)
ax.set_title("Feature importances using MDI")
ax.set_ylabel("Mean decrease in impurity")
fig.tight_layout()
```

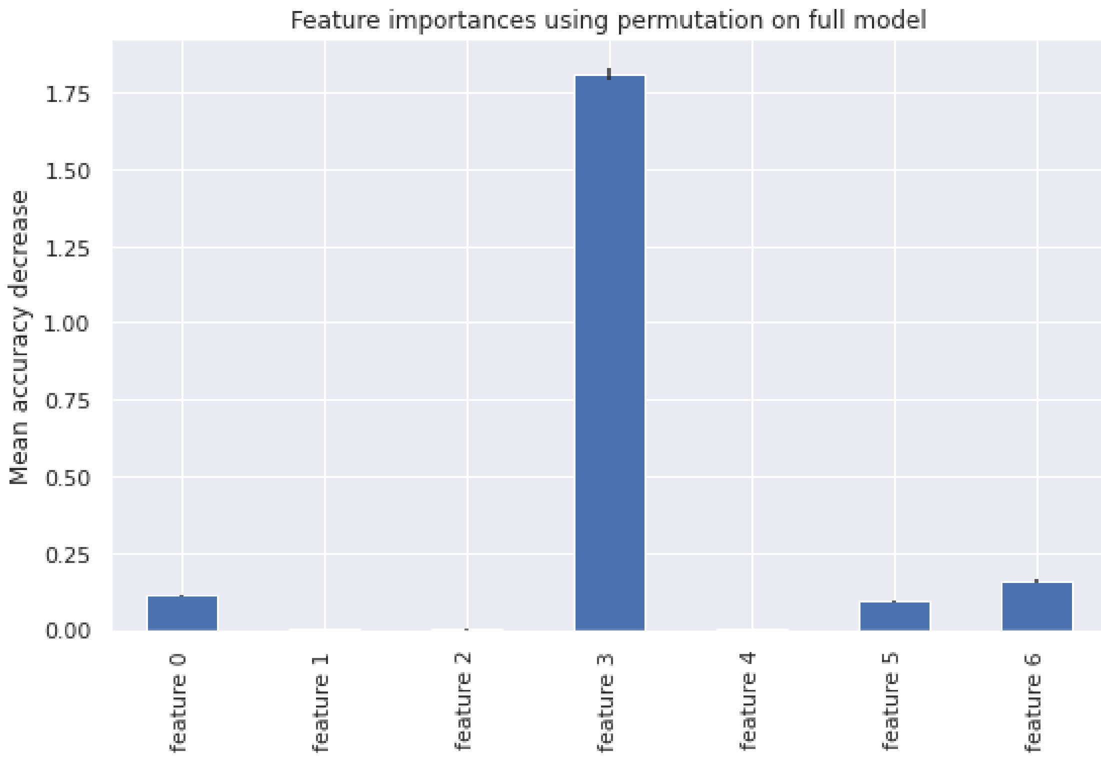


The feature `volume` appears to the highest importance among the Random Forest model.

[ ]:
```
from sklearn.inspection import permutation_importance

start_time = time.time()
result = permutation_importance(
    forest, X_test, y_test, n_repeats=10, random_state=42, n_jobs=2
)
elapsed_time = time.time() - start_time
print(f"Elapsed time to compute the importances: {elapsed_time:.3f} seconds")

forest_importances = pd.Series(result.importances_mean, index=feature_names)
```

```
Elapsed time to compute the importances: 45.103 seconds
```

[ ]:
```
fig, ax = plt.subplots()
forest_importances.plot.bar(yerr=result.importances_std, ax=ax)
ax.set_title("Feature importances using permutation on full model")
ax.set_ylabel("Mean accuracy decrease")
fig.tight_layout()
plt.show()
```



The `volume` feature remains the highest with permutation feature importance which indicates do not have a bias toward high-cardinality features and can be computed on a left-out test set. This demonstrates the `volume` overcomes limitations of the impurity-based feature importance.

4.4 Hyperparameter Tuning Random Forest

[ ]:
```
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
```

[ ]:
```
{'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]}
```

[ ]:
```
from sklearn.model_selection import RandomizedSearchCV
from numpy import *
```

```python
rf = RandomForestRegressor(random_state = random.seed(1234))
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: 0.13627217704239236
R2  : 0.9909164510584496
```

[ ]:
```python
rf_random.best_params_
```

[ ]:
```
{'max_depth': 30,
 'min_samples_leaf': 2,
 'min_samples_split': 3,
 'n_estimators': 94}
```

[ ]:
```python
rf = RandomForestRegressor(max_depth = 30,
                           min_samples_leaf = 2,
                           min_samples_split = 3,
                           n_estimators = 94,
                           random_state = random.seed(1234))
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)))))
```

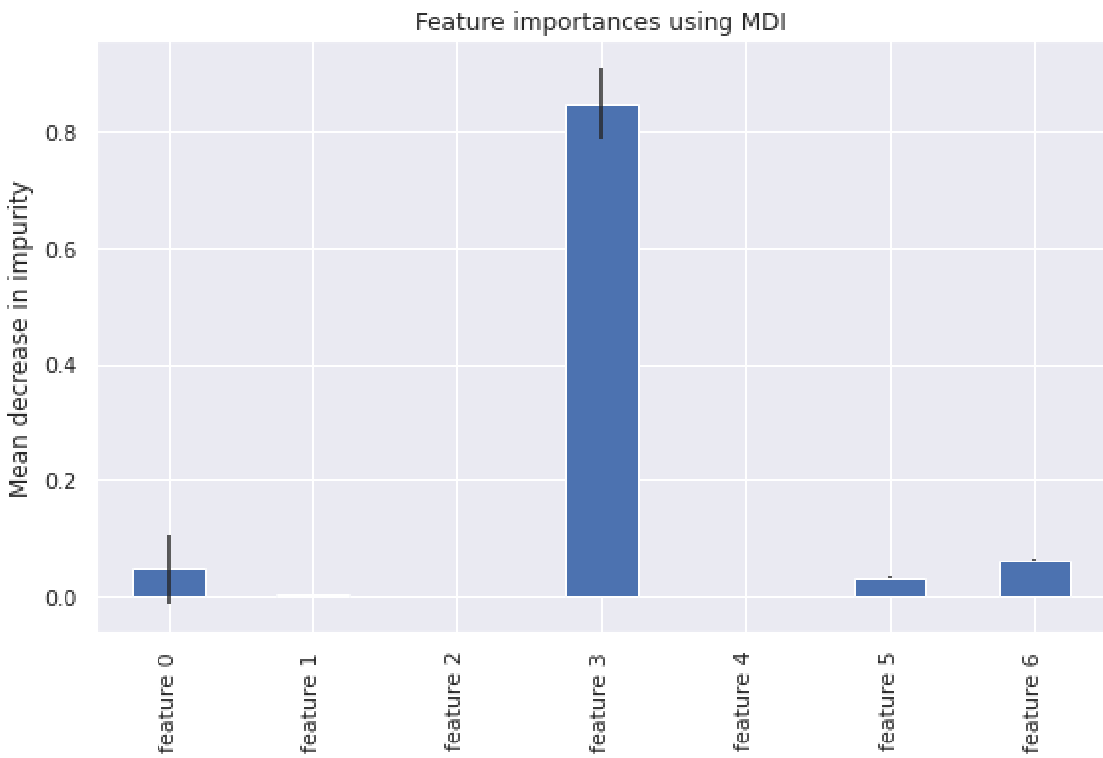
```
RMSE: 0.1371532785575916
R2  : 0.9907980602434069
```

[ ]:
```python
start_time = time.time()
importances = rf.feature_importances_
std = np.std([tree.feature_importances_ for tree in forest.estimators_], axis=0)
elapsed_time = time.time() - start_time

print(f"Elapsed time to compute the importances: {elapsed_time:.3f} seconds")
```

```
Elapsed time to compute the importances: 0.269 seconds
```

[ ]:
```python
feature_names = [f"feature {i}" for i in range(X.shape[1])]
forest_importances = pd.Series(importances, index=feature_names)
```

```
fig, ax = plt.subplots()
forest_importances.plot.bar(yerr=std, ax=ax)
ax.set_title("Feature importances using MDI")
ax.set_ylabel("Mean decrease in impurity")
fig.tight_layout()
```

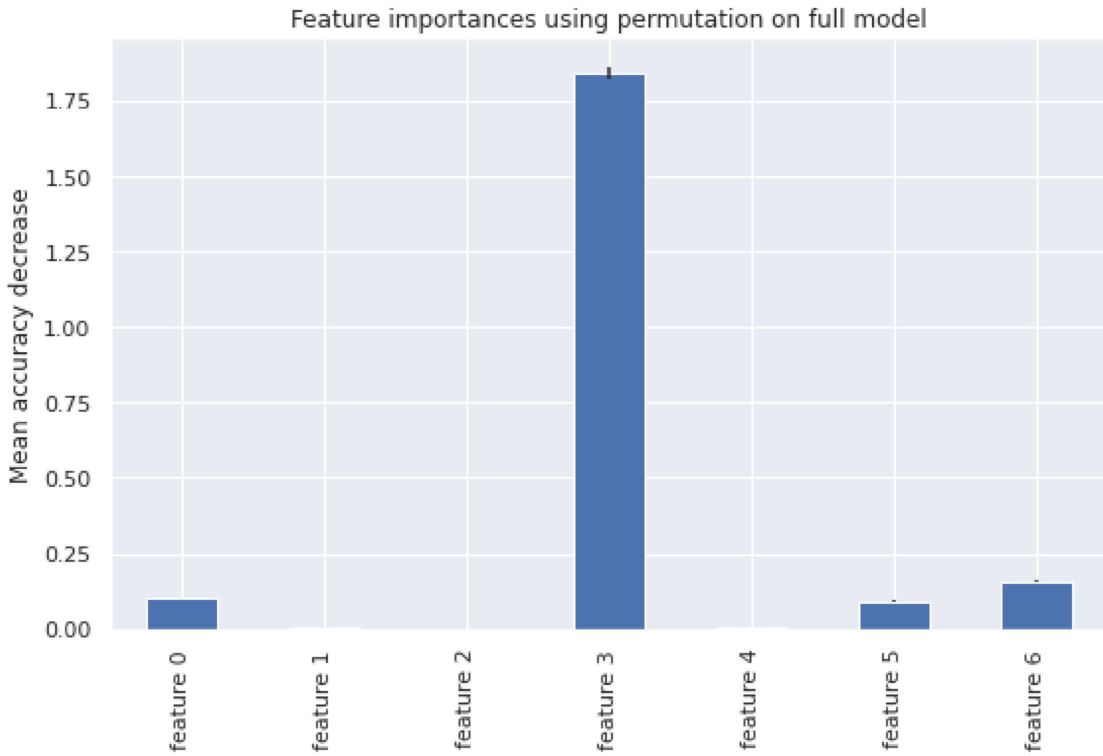


[ ]:
```
start_time = time.time()
result = permutation_importance(
    rf, X_test, y_test, n_repeats=10, random_state=42, n_jobs=2
)
elapsed_time = time.time() - start_time
print(f"Elapsed time to compute the importances: {elapsed_time:.3f} seconds")

forest_importances = pd.Series(result.importances_mean, index=feature_names)
```

```
Elapsed time to compute the importances: 23.421 seconds
```

[ ]:
```
fig, ax = plt.subplots()
forest_importances.plot.bar(yerr=result.importances_std, ax=ax)
ax.set_title("Feature importances using permutation on full model")
ax.set_ylabel("Mean accuracy decrease")
fig.tight_layout()
```

```
plt.show()
```



4.5 AutoML using H20

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

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

[ ]:
```
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/tmpcavk4j6w
  JVM stdout: /tmp/tmpcavk4j6w/h2o_unknownUser_started_from_python.out
  JVM stderr: /tmp/tmpcavk4j6w/h2o_unknownUser_started_from_python.err
```

```
  Server is running at http://127.0.0.1:54321
Connection to H2O server at http://127.0.0.1:54321 … successful.
```

```
--------------------------  ----------------------------------
H2O_cluster_uptime:         03 secs
H2O_cluster_timezone:       Etc/UTC
H2O_data_parsing_timezone:  UTC
H2O_cluster_version:        3.36.1.2
H2O_cluster_version_age:    1 day
H2O_cluster_name:           H2O_from_python_unknownUser_vyy7c7
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
--------------------------  ----------------------------------
```

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

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

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

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

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

4.5.1 GBM Model

[ ]:
```
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
```

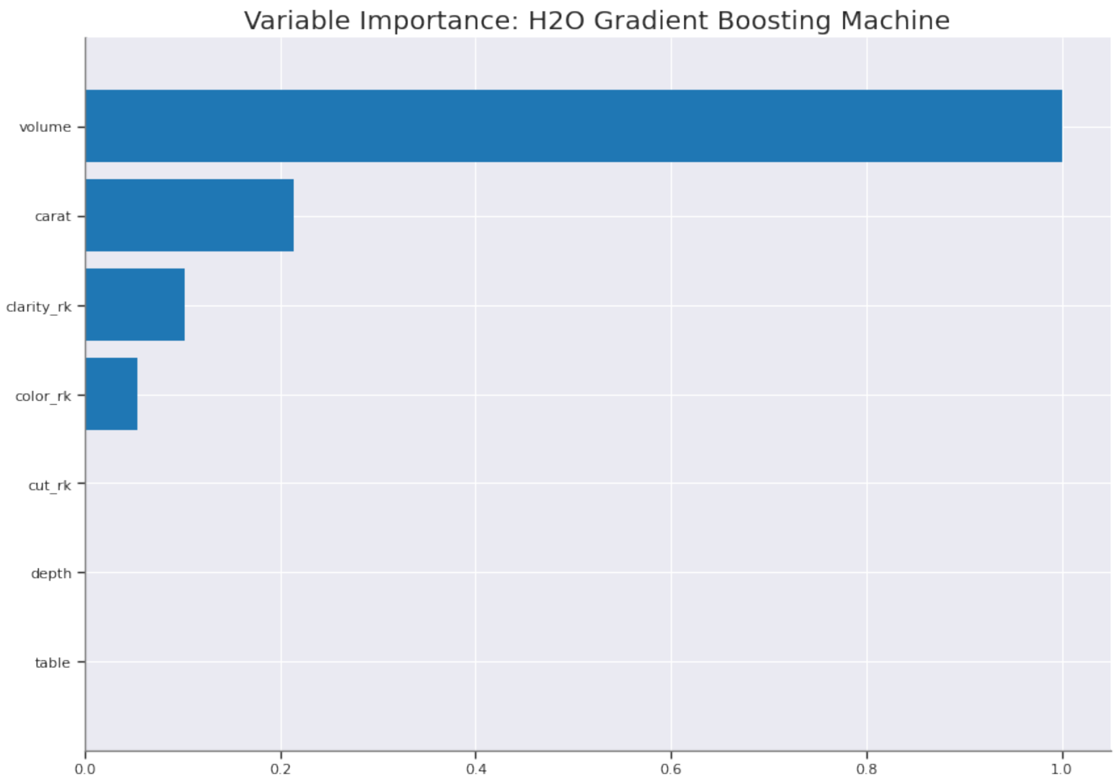
[ ]:

[ ]:
```
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
```

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

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

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



<Figure size 432x288 with 0 Axes>

4.5.2 AutoML Search

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

y = "price"

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

```
[ ]: 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_20220527_213545
```

```
No model summary for this model

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

MSE: 163376.48303073455
RMSE: 404.198568813318
MAE: 221.74431915028975
RMSLE: 0.08811328250901963
R^2: 0.9896274225811342
Mean Residual Deviance: 163376.48303073455
Null degrees of freedom: 10063
Residual degrees of freedom: 10060
Null deviance: 158518164125.60925
Residual deviance: 1644220925.2213125
AIC: 149376.76408165455

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

MSE: 293111.1409579319
RMSE: 541.3973965193514
MAE: 278.7109268472651
RMSLE: 0.10113636742699597
R^2: 0.9823457864836054
Mean Residual Deviance: 293111.1409579319
Null degrees of freedom: 4424
Residual degrees of freedom: 4421
Null deviance: 73479405051.87427
Residual deviance: 1297016798.7388484
AIC: 68270.86509898382
```

[ ]:

[ ]:

```
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_3_AutoML_2_20220527_213720

No model summary for this model

ModelMetricsRegressionGLM: stackedensemble
```

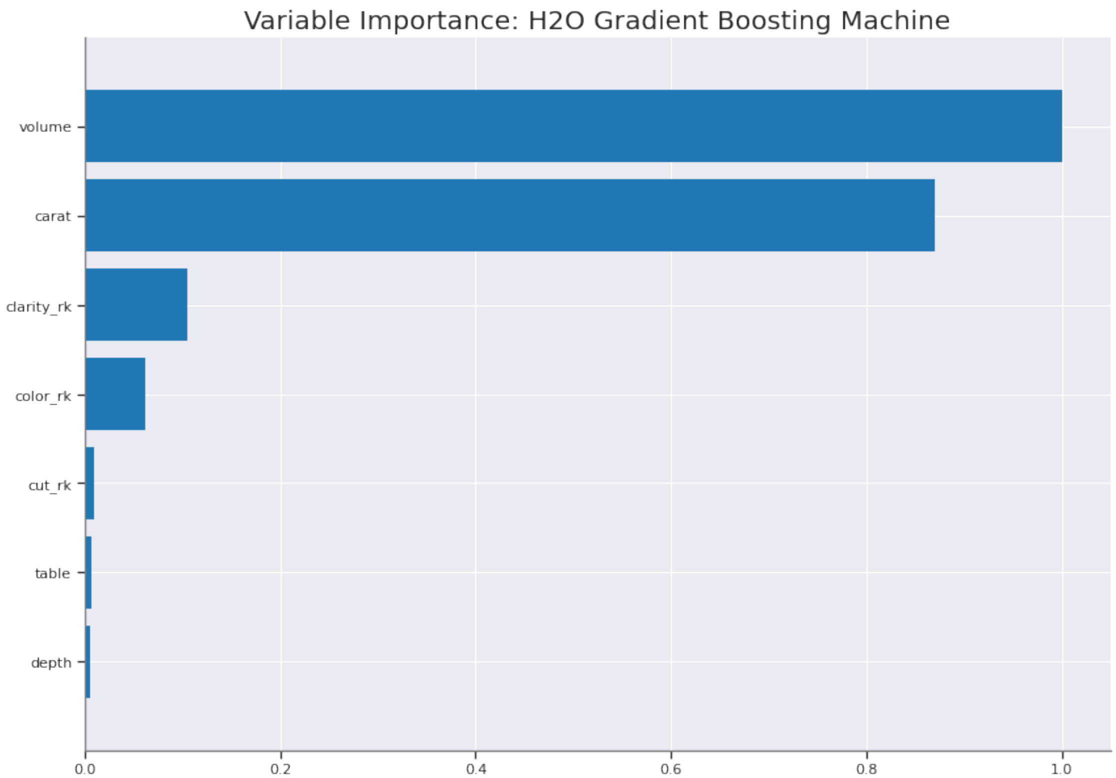
```
** Reported on train data. **

MSE: 143032.15302056298
RMSE: 378.1959188311833
MAE: 207.24916737663557
RMSLE: 0.08235619094213531
R^2: 0.9910408992276571
Mean Residual Deviance: 143032.15302056298
Null degrees of freedom: 10060
Residual degrees of freedom: 10057
Null deviance: 160625531552.78574
Residual deviance: 1439046491.539884
AIC: 147994.2487763461

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

MSE: 283749.631509217
RMSE: 532.6815479338636
MAE: 272.7611077737793
RMSLE: 0.09844370443884244
R^2: 0.9828274276559079
Mean Residual Deviance: 283749.631509217
Null degrees of freedom: 5459
Residual degrees of freedom: 5456
Null deviance: 90264416715.4349
Residual deviance: 1549272988.040325
AIC: 84059.73640085015
```

[ ]:

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

[ ]:

[ ]:
```
best_model_aml = h2o.get_model(aml.leaderboard[2,'model_id'])

best_model_aml.varimp_plot();
```



<Figure size 432x288 with 0 Axes>

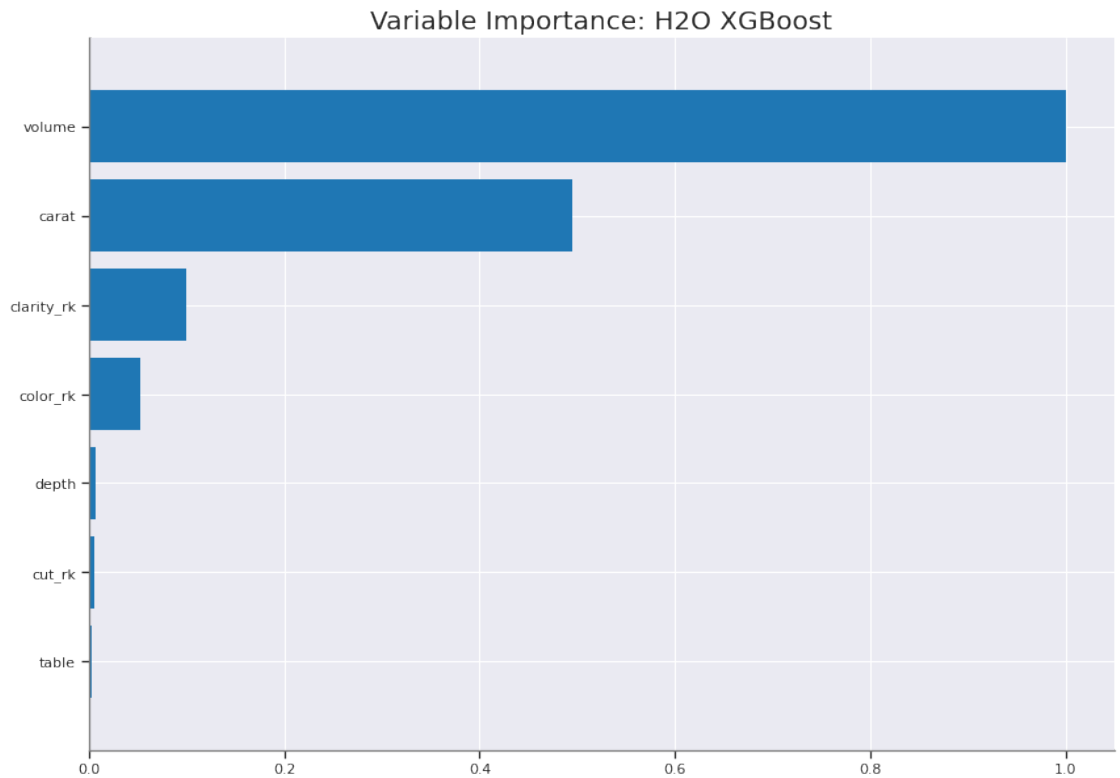
```
[ ]: print('GBM_2_AutoML_1 R^2:', best_model_aml.r2())
     print('GBM_2_AutoML_1 R^2 on validation data:', best_model_aml.r2(valid=True))
```

```
XGBoost_1_AutoML_1 R^2: 0.9868201213956783
XGBoost_1_AutoML_1 R^2 on validation data: 0.9822494320805603
```

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

```
[ ]:
```

```
[ ]: best_model_aml2 = h2o.get_model(aml2.leaderboard[9,'model_id'])

     best_model_aml2.varimp_plot();
```




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

[ ]:
```
print('XGBoost_2_AutoML_2 R^2:', best_model_aml2.r2())
print('XGBoost_2_AutoML_2 R^2 on validation data:', best_model_aml2.
  ↪r2(valid=True))
```

```
XGBoost_2_AutoML_2 R^2: 0.9909054467211048
XGBoost_2_AutoML_2 R^2 on validation data: 0.98091389302047
```

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

```
H2O session _sid_b971 closed.
```

5 Model Results

Model	r2
Linear_Regression	84.97%
Multiple_Linear_Regression	90.59%
XGBoost_2_AutoML_2	98.09%
GBM_Estimator	98.12%

Model	r2
StackedEnsemble_BestOfFamily_2_AutoML_1	98.23%
GBM_2_AutoML_1	98.22%
StackedEnsemble_BestOfFamily_3_AutoML_2	98.28%
Random_Forest	99.07%

6 Conclusion

An analysis was performed using the classic `Diamonds` dataset, in which the objective was determining the relationship of 4 C's to price, any identifiable patterns, and how to best price diamonds for brokers. - Through exploration and visualization of the data, observed generalized pattern of inverse pricing accompanied with not normal distributions. - The clearest indication is the combination of best `color` and best `clarity` diamonds are priced significantly higher, while `cut`, `color`, `clarity` are priced highest from the worst diamonds.
- 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. - After scaling the features, the baseline linear regression captured a modest 84.97% accuracy, while the Random Forest model scored the highest with 99.07%. - The final deliverable was a Tableau Dashboard, to assist brokers with visualizations and a potential pricing mechanism to the `Diamonds` dataset. The dashboard can be viewed here